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Can health insurance reduce household vulnerability? Evidence from Viet Nam

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ABSTRACT

This study provides new evidence on the impact of health insurance coverage on household vulnerability using the Vietnam Access to Resources Household Surveys (VARHS) for 2010 and 2012. We apply propensity score matching to address the non-random selection of households into health insurance status. The VARHS data allow us to include risk preference as a predictor of health insurance propensity, an important source of endogeneity between health insurance coverage and vulnerability. We estimate that health insurance helps rural households in Vietnam reduce the idiosyncratic component of utility loss by 81 per cent and the probability of becoming poor by 19 per cent. Our results are robust to alternative statistical specifications. To the best of our knowledge, this is the first paper measuring the impact of health insurance coverage on household *ex-ante* vulnerability. Our findings suggest that expanding access, reducing costs and improving efficiency in health care would have big benefits of reducing vulnerability for the poor.

1. Introduction

One of the worst shocks to households is a serious illness of one of its members. Illness introduces two important economic costs: the cost of medical care and income loss due to reduced labor supply. The unpredictable nature of the shocks and these two costs makes it difficult for households to smooth consumption over periods of major illness. This is particularly true in developing countries where few individuals have health insurance or access the formal credit markets. Instead, the poor typically have to rely on informal coping mechanisms such as drawing on savings, selling assets, transfers from family or social support networks. Low-income households who cannot access these channels are more likely to fall into poverty. The burden of health care can push individuals into poverty or into deeper poverty.

In this paper, we estimate the impact of health insurance on a household's vulnerability—measured as the probability of falling into poverty and the expected loss in utility—using data from the Vietnam Access to Resources Household Surveys (VARHS) for 2010–2012. Health insurance can help households reduce the unexpected financial loss from health care and can also reduce losses in human capital from going without medical treatment. Our estimates show that health insurance has a large effect on household vulnerability, reducing the idiosyncratic component of utility loss by 81 per cent and reducing the probability of becoming poor by 19 per cent.

In estimating the causal impact of health insurance on vulnerability we must address the possible endogeneity of the two variables. Factors such as an individual's health or wealth will likely be correlated with a household's health insurance status as well as its vulnerability. We use insurance propensity scores to match individuals that have health insurance to those that do not and estimate the treatment effect of health insurance as the differences in vulnerability between matched observations.

Unlike other household datasets, the VARHS contain information on individuals' attitudes toward risk. Risk preferences are of course an important determinant of an individual's health insurance status and is also associated with vulnerability.[1] With this data, we are able to include measures of risk preferences in estimat-

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[1] The relationship between individuals' risk preference and health insurance demand has been investigated in Friedman (1974),leichrodt and Pinto (2000, 2002) and Barseghyan, Molinari, O'Donoghue, and Teitelbaum (2013). The relationship between an individuals' economic behaviour and risk aversion has been investigated in many empirical studies. For example, Bowman, Minehart, and Rabin (1999, 2008) with consumption behaviour; labor supply (Camerer, Babcock, Loewenstein, & Thaler, 1997; Goette, Huffman, & Fehr, 2004). In addition, the relationship of risk preference and other aspects of health choice has been studied in Andersen, Harrison, Lau, and Rutström (2008), BBleichrodt and Gafnileichrodt and Gafni (1996), Bridges (2003), Lusk and Coble (2005), Nightingale (1988), Nightingale and Grant (1988), Picone, Sloan, and Taylor (2004), Richardson (1994), and Zhang and Rashad (2008).

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ing health insurance propensities. This methodology allows us to address an important source of bias unlike past studies on the effect of health insurance using other datasets.

While past studies have investigated the impact of health insurance on health status, health service use or out-of-pocket payment in developing countries (see, for example, Jowett, Contoyannis, & Vinh (2003), Nguyen et al. (2012), Sepehri, Sarma, & Simpson (2006), Thanh, Löfgren, Phuc, Chuc, & Lindholm (2010)) or the relationship between health insurance coverage and *ex-post* poverty (see Wagstaff & Doorslaer (2003) and Wagstaff (2007)), none have looked explicitly at the impact of health insurance on vulnerability. Other studies have examined the impact of money transfers such as micro-finance access and remittances on *ex-ante* vulnerability (see Khandker (1998), Morduch (1999), Zaman (1999)), but none have looked at the effect of health insurance coverage on vulnerability. Our paper fills this gap in the empirical literature which is important from a policy perspective as health insurance has been considered to be a crucial strategy for coping with vulnerability arising from idiosyncratic shocks.

The remainder of the paper is organized as follows. Section 2 provides an overview of health insurance schemes in Vietnam. Section 3 describes the data and Section 4 details the analytical framework. Section 5 discusses the results. We conclude in Section 6.

2. Overview of health insurance in Vietnam

When Vietnam launched economic reforms in 1986, the health care system was transformed from a centralized system with free universal access to a user-pay system. The pharmaceutical industry was also privatized. Out-of-pocket (OOP) spending on health care increased rapidly reaching 71 per cent of health spending in 1993 and 80 per cent in 1998, creating a big burden on households especially the poor (Lieberman & Wagstaff, 2009). In 1993, Vietnam introduced a compulsory health insurance (CHI) program initially aimed at formal sector workers. A voluntary health insurance scheme was later added to cover the self-employed, informal sector employees, and dependents of CHI members.

In the early 2000s, other important changes in health insurance were introduced: copayments were scrapped and benefits were made more generous. Insurers were also permitted to contract with private providers and some hospitals were given greater autonomy. In 2002, the central government launched the Health Care Fund for the Poor (HCFP) program to provide insurance coverage for the poor and other disadvantaged groups. Later, the government continued to expand coverage through a decree called Decision 139, which asked local governments to provide free health care to the poor, ethnic minority households living in the remote areas and households living in communes officially classified as "special poor". In 2008, the government enacted the Health Insurance Law which aimed to achieve universal health insurance coverage.

According to Ministry of Health (2013), the household out-of-pocket payment share of total health spending in Vietnam is much higher than the WHO recommendation (30–40%).[2] Households without health insurance cards, households in rural areas and poor households have lower out-of-pocket spending on health, but higher catastrophic spending and impoverishment due to health spending. According to Ministry of Health (2016), out-of-pocket costs were still high after 2010, but catastrophic health spending and impoverishment by health spending fell in 2012.[3] Data from the Vietnam Household Living Standard Survey (see Table 19) and the World Health Organization's website confirm this trend. Ministry of Health (2013) and Somanathan, Tandon, Lan, Hurt, and Fuenzalida-Puelma (2014) note that rich households account for the bulk of all OOP spending. While the top economic decile of the population accounts for 25% of total OOP spending, the bottom two economic deciles account for 4%. OOP spending of the bottom groups is more likely to result in catastrophic and impoverishing expenditure which health insurance coverage can hopefully be a way to lower the negative impact (Chaudhuri & Roy, 2008; Sepehri et al., 2006; Wagstaff & Doorslaer, 2003; Wagstaff, 2010). The health insurance share of total health spending and the volume of medical services reimbursed by insurance have both increased over time (Ministry of Health, 2013).

The government fully subsidizes health insurance premiums for over 27 million beneficiaries of social assistance policies, including the poor and children under age 6; and has continuously expanded entitlements and increased health insurance premium subsidies for the near poor, pupils and students. In 2012, about 59.31 million people were insured, accounting for 66.8 per cent of the population. In some mountainous provinces with a large number of poor and ethnic minorities population coverage was over 75 per cent. Frequency of use of medical services reimbursed by insurance reached 2.02 visits per person. There were 15.6 inpatient visits for every 100 people in the population. The health insurance fund has become an important funding source for health care. In 2012, the health insurance fund reimbursed facilities for medical services worth approximately 1.7 billion USD (Somanathan et al., 2014).

Health insurance coverage has increased considerably. In 1993, only 5.4 per cent of the population was covered; in 2010 60 per cent was covered; by 2012, the figure had grown to 66.8 per cent. Around 60 per cent of the insured have been completely or partially financed by the state budget (Matsushima & Yamada, 2014; Ministry of Health, 2013). However, Vietnam's health insurance system in 2010 covered only 21.1 per cent of the voluntary group which includes non-poor workers and families in the informal sector (see as can be seen in Table 1). The enrollment rate was only 53.4 per cent for workers in private enterprises. While most of the poor and the recipients of social allowance were covered, about 20 per cent of children under 6 years old were uninsured despite the fact that their enrollment costs were fully paid by the state budget. Similarly, the enrollment rate for the near poor was just 11.38 per cent, although this targeted group was eligible for at least 50 per cent of subsidies from the government. More importantly, coverage for the unemployed remained zero. Many vulnerable people are still without health insurance (Matsushima & Yamada, 2014).

Reasons for the low coverage vary among eligible groups. While the Law of Health Insurance does not stipulate effective measure compliance in the formal sector, the amount of state budget supporting health insurance contributions among the near poor and informal sector workers is inadequate to encourage their enrollment in health insurance. Quality of medical services at the grassroots level does not meet need and required out-of-pocket payments are still high. Beneficiaries also have poor understanding of insurance entitlements, particularly co-payment policies (Matsushima & Yamada, 2014; Ministry of Health, 2013).

3. Data

Our analysis uses the 2010 and 2012 waves of the Vietnam Access to Resources Household Survey (VARHS). The VARHS are longitudinal datasets constructed biannually by the University of Copenhagen (Denmark) in collaboration with the Centre Institute of Economic Management (CIEM), the Institute for Labor Studies

[2] Household out-of-pocket spending on health accounts for 8.3–11.0% of household capacity to pay and approximately 4.6–6.0% of total household expenditure.

[3] There were 3.9–5.7% of households, or approximately 1 million households facing catastrophic spending and 2.5–4.1% of households, or approximately 600,000 households facing impoverishment due to health spending between 2002 and 2010. The numbers of catastrophic and impoverishment households respectively reduced to 2.5% and 1.8% in 2012.

Table 1
Breakdown of the insured population in 2010.

Target groups	Target populations (thousand)	Covered people (thousand)	Percent covered (%)
Total	**85,666**	**51,903**	**59.64**
Compulsory groups	67,114	47,176	70.29
Employees of enterprises and other companies	11,911	6,361	53.40
Civil servants	3,142	3,142	100.00
Foreign students	3	3	100.00
Part-time officers at commune level	182	0	0.00
Pensioners	920	920	100.00
Recipients of social allowances	1,305	1,254	96.09
Unemployed people	80	0	0.00
Local authorities	41	40	97.56
Meritorious people	2,113	2,113	100.00
Veterans	374	350	93.58
Members of national assembly and people's council	123	119	96.75
Privileged social groups	843	384	45.55
The poor	13,945	13,511	96.89
Dependents of meritorious people	869	0	0.00
Dependents of army and police officers	1,281	297	23.19
Children under 6	10,103	8,183	81.00
Near poor people	6,081	692	11.38
Students and pupils	13,798	9,807	71.08
Voluntary groups	18,552	3,917	21.11
Relatives of employees	6,820	0	0.00
Farmers, self-employees, members of cooperatives	11,732	3,917	33.39

Source: VSS (2011) cited in Tien et al. (2011).

and Social Affairs (ILSSA), and the Institute of Policy and Strategy for Agriculture and Rural Development (IPSARD). The surveys were carried out in rural areas of 12 provinces[4] in the summer of each year, producing a balanced panel of 2,045 households spread over 161 districts and 456 communes. All surveys were conducted during the same three-month period each year to ensure consistency and facilitate comparisons across time. The VARHS investigates issues surrounding Vietnamese rural households' access to resources and the constraints that these households face in managing their livelihoods. Along with detailed demographic information on household members, the surveys include sections on household assets, savings, credit (both formal and informal), formal insurance, shocks and risk-coping, informal safety nets and the structure of social capital (Wainwright & Newman, 2011). There is also a variety of information on communes where households lived at the time they were surveyed.

The VARHS contains information on all the types of insurance that a household held at the time of interview. There are three categories of health insurance: health insurance, free health insurance for the poor and free health insurance for children under six-years-old. Other types of insurance consist of farmer insurance, fire insurance, life insurance, social insurance, unemployment insurance, education insurance and vehicle insurance. In this study, we focus on the impact of health insurance in general which is essential for a universal health insurance policy in Vietnam. While the data do not distinguish between compulsory and voluntary health insurance, we later show in a number of robustness exercises that our results are not affected by possible underlying differences between these two groups.

[4] These areas are evenly distributed throughout Vietnam: Ha Tay in the Red River Delta; Lao Cai and Phu Tho in the Northeast; Lai Chau and Dien Bien in the Northwest; Nghe An in North Central Coast; Quang Nam and Khanh Hoa in the South Central Coast; Dac Lac, Dac Nong and Lam Dong in the Central Highland; and Long An in the Mekong River Delta. However, the VARHS is not nationally representative.

The 2010 and 2012 waves of the VARHS contain questions that allow us to measure an individual's risk aversion (See Appendix B). Observing risk preferences allows us to address an important source of endogeneity between health insurance and vulnerability.

4. Methodology

In this section, we describe the measurement of vulnerability which is the outcome of interest, propensity score matching which is our identification method, and calculation of risk aversion which is potentially an important determinant of health insurance status as well as vulnerability.

4.1. Measuring vulnerability

Vulnerability is typically quantified in one of two ways: vulnerability as expected poverty and vulnerability based on expected utility.

Introducing the expected poverty approach, Chaudhuri (2003) defined vulnerability as the likelihood that a household will fall into poverty:

$$v_{i,Chaudhuri} \equiv \Pr(c_i < z|X_i) \tag{1}$$

where c_i is per capita consumption expenditure for household i, X_i is a vector of observable household and commune characteristics and z is some poverty line.

Suppose consumption depends on household observables in a log-linear way:

$$\ln c_i = \alpha + \beta X_i + e_i, \tag{2}$$

where e_i is a mean-zero idiosyncratic shock that leads to different levels of per capita consumption across households. Assuming e_i is normally distributed, we can rewrite vulnerability as:

$$v_{i,Chaudhuri} = \Phi\left(\frac{\ln z - \alpha - \beta X_i}{\sigma_i}\right) \tag{3}$$

where σ^2 is the variance of the disturbance term e_i. To estimate vulnerability as expected poverty, we must estimate α, β, and σ^2. Chaudhuri, Jalan, and Suryahadi (2002) and Chaudhuri (2003) acknowledge that the disturbance (e_i) is likely to be heteroskedastic and thus estimating Eq. (2) directly using ordinary least squares will lead to biased estimates. Instead, we follow the three-step Feasible Generalized Least Squares (FGLS) technique proposed by Amemiya (1977) to estimate α, β, and σ^2. The details of this procedure are given in the appendix.

We use total household income instead of consumption as the latter is not available in the VARHS. There are two accepted approaches to poverty measurement in Vietnam using national poverty lines. The first approach, developed by the Ministry of Labor, Invalids, and Social Affairs (MOLISA), is based on income and is used primarily for targeting social programs. The second was developed by the General Statistical Office and the World Bank, is based on consumption and is used chiefly for monitoring poverty over time. The poverty lines used in this study are the national poverty lines generated from household income by MOLISA: 1917, 2077 and 2566 thousand VND/person/year for the years of 2002, 2004 and 2006, respectively.

The second way to measure vulnerability takes a welfare-based approach. Ligon and Schechter (2003) define vulnerability as the difference between the utility derived from a certainty-equivalent consumption level, z_{ce}, and the expected utility of actual consumption:

$$V_i = U_i(z_{ce}) - EU_i(c_i) \tag{4}$$

where U_i is a weakly concave, strictly increasing function. z_{ce} is akin to z in the expected poverty formulation described above. The researcher can set the value of z_{ce} equal to a poverty line to measure *absolute* vulnerability or equal to a statistic from the distribution of consumption to arrive at a *relative* vulnerability measure. To complement the *absolute* measure of expected poverty vulnerability above, we measure *relative* vulnerability below by setting z_{ce} equal to average consumption in the population. In this formulation, households have vulnerability zero when they receive the average consumption expenditure with certainty.

If household consumption is stochastic but with mean equal to the population average, then vulnerability would be positive and increasing in the variance of consumption. Thus, under this expected utility based formulation, vulnerability has two distinct sources: (relative) poverty and uncertainty/risk.

We can rewrite Eq. (4) in the following way to explicitly see these two contributions to vulnerability:

$$V_i = [U_i(z_{ce}) - U_i(Ec_i)] + [U_i(Ec_i) - EU_i(c_i)]. \tag{5}$$

The first bracketed term is 'poverty' vulnerability given as the difference between utility at z_{ce} and utility at the household's mean level of consumption, c_i. The second term captures 'risk' vulnerability as the difference between utility at household's mean level of consumption and the expected utility of consumption. The first terms increases as average consumption falls while the second term increases with the variance of consumption. The second risk term can be further decomposed into aggregate risk and risk idiosyncratic to the household:

$$\begin{aligned} V_i = {} & [U_i(z_{ce}) - U_i(Ec_i)] \quad \text{[Poverty or inequality]} \\ & + [U_i(Ec_i) - EU_i(E(c_i|x_t))] \quad \text{[Covariate or aggregate risk]} \\ & + [EU_i(E(c_i|x_t)) - EU_i(c_i|x_t, x_{it})] \quad \text{[Idiosyncratic risk]} \\ & + [EU_i(c_i|x_t, x_{it}) - EU_i(c_i)] \quad \text{[Unexplained risk and measurement error]} \end{aligned} \tag{6}$$

where $E(c_i|x_t)$ is the commune expected value of consumption, conditional on a vector of commune variables x_t and $E(c_i|x_t, x_{it})$ is the household expected value of consumption conditional on a vector of commune variables x_t and household characteristics x_{it}. We normalize the average consumption expenditure over all households in all periods, z_{ce}, to unity.

Estimating vulnerability in this way requires panel data and assumption of a specific functional form for utility.[5] Ligon and Schechter (2003) propose the following form for utility:

$$U(c) = \frac{c^{1-\gamma}}{1-\gamma} \tag{7}$$

where γ is a coefficient of relative risk aversion. We follow the existing empirical literature and assume $\gamma = 2$.

Components of Eq. (6) can be estimated by applying restricted least squares for expected consumption and then substituting each of them into utility function 7: Ec_i is household i's average consumption over all time periods; $E(c_{it}|x_t)$ is predicted from an estimation with commune level covariates; and $E(c_{it}|x_t, x_{it})$ is predicted from an estimation with household and commune level covariates with household and year fixed effects. In the last estimation of consumption household income may be endogenous so we instrument for income using total land area owned by a household and productive assets per capita.

[5] Hoddinott and Quisumbing (2010) argue that the relative components of the decomposition are not likely to be affected by functional form even though the cardinal measures may be.

4.2. Calculating risk aversion

The VARHS include a number of hypothetical lotteries the responses to which we use to measure an individual's risk aversion. We do this in two ways. First, applying the cumulative prospect theory of Tversky and Kahneman (1992), individuals will be indifferent between accepting and rejecting the lottery if:

$$w^+(0.5) \cdot v(G) = w^-(0.5)\lambda^{risk} v(L) \tag{8}$$

where G is the gain and L is the loss in a given lottery; $v(\cdot)$ is a utility function, λ^{risk} is the coefficient of risk aversion in the choice task; $w^+(0.5)$ and $w^-(0.5)$ represent the probability weights for the 0.5 chance of gaining G or losing L, respectively (Gächter, Johnson, & Herrmann, 2010). Cumulative risk aversion can be calculated as follows:[6]

$$\lambda^{risk} = \frac{w^+(0.5)}{w^-(0.5)} \times \frac{v(G)}{v(L)}. \tag{9}$$

Second, we also estimate risk aversion under expected utility theory by employing the methods of Arrow (1965) and Pratt (1964). Following these studies, we assume that households are initially endowed with income w and have a twice differentiable, concave utility function $U, U' > 0$ and $U < 0$. The prize of the lottery is defined by z and the probability of winning that prize is α. The maximum price that an individual is willing to pay for the lottery ticket, or the reservation price, is λ. Therefore, the initial wealth will become $w - \lambda$ after purchasing the lottery ticket and increase to $w - \lambda + z$ if he or she wins the prize.

To deduce the value of the Pratt-Arrow measure of absolute risk aversion $A(w) = -U(w)/U'(w)$, the utility of wealth w, without participation in the lottery, is equal to expected utility when participating at reservation price λ: (Hartog, Ferrer-i Carbonell, & Jonker, 2002)

$$U(w) = (1-\alpha) \cdot U(w-\lambda) + \alpha \cdot U(w - \lambda + z). \tag{10}$$

A second order Taylor series expansion of $U(w-\lambda)$ and $U(w - \lambda + z)$ around $U(w)$ gives:

$$\begin{aligned} U(w) = {} & U(w) + \alpha \cdot z \cdot U'(w) - \lambda U''(w) + 0.5 \cdot U''(w) \\ & \times \left[(1-\alpha) \cdot \lambda^2 + \alpha \cdot (z-\lambda)^2\right] \end{aligned} \tag{11}$$

The Pratt-Arrow measure of absolute risk aversion is calculated as follows:

$$A(w) = -\frac{U''}{U'} = \frac{\alpha \cdot z - \lambda}{0.5 \cdot \lambda^2 + 0.5 \cdot \alpha z^2 - \alpha \cdot \lambda \cdot z}. \tag{12}$$

We only consider monotonic acceptance decisions (99.47% of respondents in our analytical data show monotonicity). The results of our cumulative risk aversion estimation, using different assumptions on the probability weighting and diminishing sensitivities for gains and losses, are presented in the first four rows of Table 15 in the Appendix. Absolute risk aversion estimates are provided in the next two rows of Table 15 of the Appendix. There is a strong correlation between the risk parameters calculated by the prospect theory and by expected utility theory (see Table 16). We classify households into groups of high, medium and low aversion and summarize the results in Table 17 and Table 18 of the Appendix.

[6] If we assume that the same weighting function is used for both gains and losses, $w^+ = w^-$, then the ratio $v(G)/v(L) = \lambda^{risk}$ will define an individual's implied risk aversion in the lottery choice task. Using a linear assumption on $v(x)$ that $v(x) = x$ for small amounts, we would have a simple measure of risk aversion: $\lambda^{risk} = G/L$.

4.3. Propensity score matching

To estimate the effect of health insurance coverage, we compare vulnerability of households with health insurance (the treated group) with that of households without health insurance (the control group). Because health insurance status is not randomly assigned to households, selection into treatment and control might be determined by factors that are correlated with vulnerability which would bias our estimates. We can minimize this potential bias with appropriate choice of control and treatment observations using the method of propensity score matching.[7]

The treatment group includes households that had health insurance in 2012. The control group includes households who do not have health insurance in 2012, but have the observed characteristics (X variables) and health insurance status in 2010 (H_{2010} variable) similar to those of the treatment group. We thus control not only for usual individual and household characteristics such as age, education, income, assets, and exposure to natural disasters but also earlier health insurance status. By controlling for earlier health insurance status we are more able to argue that the change in insurance status from 2010 to 2012 was due to exogenous shocks not among the factors already controlled for. And by using the VARHS, we are also able to control for individual's risk preferences which past studies have not been able to do using other datasets. In this way, we are able to better to satisfy the condition of unconfoundedness or conditional independence—that selection into treatment and control groups are not due unobserved factors that are also correlated with vulnerability.

We match an uninsured observation to an insured observation using the probability of being insured (the propensity score) in 2012 conditional on the controlling factors described above. In this study, we use kernel matching estimators. The standard errors are calculated using bootstrap techniques.

On the question of adverse selection into health insurance, we control for many household risks, including health risk in our PSM specification. Therefore, the treatment insured and the control uninsured should have similar health risks. Moreover, the remaining voluntary insured in our sample that are selected adversely for reasons not correlated with the observable characteristics that determine the propensity to obtain insurance are likely to have high health risks or chronic diseases and would thus be more vulnerable. As a result, adverse selection, if present, would bias our results downward and we would underestimate the impact of health insurance on vulnerability.

The validity of propensity score matching also requires sizable common support or overlap in propensity scores across treatment and control groups (or enough nonparticipants to match with participants). This common support assumption states that there is an available control group that has similar control variables as the treatment group. We report the results for the matched observations across treatment and control groups in the next section.

5. Results and discussion

5.1. Measuring vulnerability as expected poverty

Results for our estimates of vulnerability as expected poverty (VEP) using feasible generalized least squares in the years 2010 and 2012 (Eqs. (18) and (19)) are shown in Table 2. Households with an older head or more education tend to have higher per capita income while those with a higher share of females has a lower per capita income. As expected, the coefficients of dependency burden are negative and significant in both surveys—a household with many old or many young members tends to have lower income. Agricultural households are more likely to have a higher income—all households in this data set are from rural areas. Households living in communes with higher incidence of poverty or residing in areas farther away from bus stations tend to have lower income. Households with a married household head have higher income but the estimate is not statistically significant.

From the estimates of consumption and the variance of disturbance term in Table 2, we adopt Chaudhuri's measure to calculate each household's vulnerability. A summary of the estimated VEP—the probability of becoming poor using the national poverty lines for 2010 and 2012 from MOLISA—is presented in Table 3. On average, rural households in Vietnam had a 12.95 per cent probability of falling into poverty in 2010, This number increased to 27.36 per cent in 2012.

5.2. Measuring vulnerability as low expected utility (VEU)

Estimates of $E(c_{it}|x_t)$ using a random effects model are presented in Table 4. Communes with higher population have higher food consumption—possibly because of higher average incomes and more available consumption activities. The positive and significant coefficient on the regular market variable supports this explanation. Similarly, communes with a secondary school can be expected to have a higher level of food consumption. If a commune is one of the targeted communes or has a higher incidence of poverty, it has a lower average level of food consumption.

Table 5 provides the results from the Panel IV estimation for $E(c_{it}|x_t, x_{it})$. After controlling for household and commune characteristics, there is likely to be little time variation for household observations. We thus follow Gaiha and Imai (2008) and Jha, Dang, and Tashrifov (2010) and use a random effects model in our estimation. In the first stage, total land area owned by a household, and per capita of productive assets (including feed grinding machine, rice milling machine, grain harvesting machine, tractor and plough) are used as instruments for income. These instruments for income are also used in Gaiha and Imai (2008), Jha et al. (2010) and Jha, Kang, Nagarajan, and Pradhan (2013).

The first stage estimation shows strong evidence of a relationship between productive assets and household income. Similarly, having more land increases household income. Households with an older head tend to have higher incomes but the effect tapers off with age of the head. If the head is married or any household member experienced higher education, then household income tends to increase. However, a household with a higher share of females or dependents will face a lower level of per capita income. As can be seen from Table 5, in the second stage, the income coefficient is highly significant and positive. This result suggests that per capita income largely determines household food consumption. Marital status of the household head and the education levels of household members both affect household food consumption positively while dependents and agriculture as the only source of income are factors which reduce food consumption. Living in a more populated area contributes slightly to a higher level of household food consumption. In addition, if households reside in a commune with a regular market, their food consumption may increase. As expected, households in poorer communes and targeted communes have lower food consumption. Surprisingly, distance to a bus station is positively correlated with food consumption.

The results above are used to predict $E(c_{it}|x_t)$ and $E(c_{it}|x_t, x_{it})$. We calculate the mean of normalized food consumption Ec_{it} and together with the utility function we estimate the four components of VEU shown in Eq. (6). Estimates of aggregate VEU and its components are presented in Table 6. We estimate an average VEU vulnerability of 0.71 over all households. This means that the utility of

[7] See Cuong (2012) for an application of propensity score matching in a study of health insurance on out-of-pocket payments in Vietnam.

Table 2
Estimates of Vulnerability as Expected Poverty in Vietnam 2010 and 2012.

	2010		2012	
Variable	Log (Income)	Variance	Log (Income)	Variance
headage	0.017*	0.055*	0.029**	0.019
	(1.74)	(1.70)	(2.52)	(0.55)
married	0.042	0.026	0.056	−0.239
	(0.80)	(0.15)	(1.05)	(−1.11)
headage2	−0.0001	−0.0005	−0.0002**	−0.0001
	(−1.55)	(−1.57)	(−2.04)	(−0.34)
femaleshare	−0.249***	0.149	−0.217**	0.224
	(−2.61)	(0.52)	(−2.45)	(0.72)
dependshare	−0.651***	−0.048	−0.534***	−0.929***
	(−8.57)	(−0.19)	(−6.27)	(−3.60)
highestedu	0.145***	0.028	0.108***	0.068
	(7.43)	(0.50)	(5.45)	(1.14)
agrhh	0.108**	0.153	0.265***	0.083
	(2.47)	(1.35)	(5.65)	(0.61)
totalhousehold	0.00002	0.0001	−0.000	−0.00004
	(0.61)	(1.43)	(−0.12)	(−0.61)
targetcommune	0.088	0.083	0.090*	0.402
	(1.64)	(0.65)	(1.81)	(3.08)
povertyrate	−1.378***	0.126	−0.983***	−0.462
	(−6.35)	(0.21)	(−5.83)	(−1.38)
regularmarket	−0.076	−0.024	−0.106	0.172
	(−1.52)	(−0.17)	(−1.58)	(0.97)
secondaryschool	0.153*	0.095	0.093	0.060
	(1.71)	(0.44)	(1.15)	(0.33)
distance2bus	−0.004**	−0.008*	−0.002	−0.002**
	(−2.25)	(−1.91)	(−3.26)	(−2.31)
_cons	8.785***	−4.096***	8.214***	−2.918**
	(28.49)	(−4.12)	(22.74)	(−2.51)
N	1975	1975	1977	1977
R^2	0.2195	0.0081	0.1950	0.0228
F	30.46	1.04	20.62	2.99
Prob > F	0.000	0.4076	0.000	0.0003

Note: The estimation method used is three-step Feasible Generalized Least Squares. The dependent variable is logarithm of household per capita income and its variance. t statistics in parentheses.
$*p < 0.05, **\ p < 0.01, ***p < 0.001$.

Table 3
Summary of estimated VEP in 2010 and 2012.

	VEP 2010	VEP 2012
Observation	1942	1944
Mean	0.1295347	0.2736287
Standard Deviation	0.1911949	0.2527675
Min	0.00000183	0.0009027
Max	0.9881003	0.9997653

Source: Authors' calculations based on the panel sample of the VARHS 2010 and 2012.

Table 4
Covariate risk component.

Variable	Per capita food consumption
totalhousehold	0.0000496
	(3.33)***
targetcommune	−0.0662523
	(−2.96)***
povertyrate	−0. 6435118
	(−9.22)***
regularmarket	0.0479312
	(1.70)*
secondaryschool	0.0818515
	(1.86)*
distance2bus	−0.0005328
	(1.33)
_cons	0.908447
	(12.16)***
Number of observations	3963
Number of groups	1988
Join significance	Wald chi^2 (6) = 250.01
	Prob> chi^2 = 0.0000

Notes: The estimation method used is the random-effects model for panel data. The dependent variable is normalized food consumption. Standard error adjusted for 1988 clusters. Robust z statistics in parentheses. $p \leqslant 0.1; **\ p \leqslant 0.05; ***p \leqslant 0.01$.

the average household is 71 per cent less than the hypothetical situation without any risk or inequality in consumption. This level of utility vulnerability is lower than the estimate of 0.75 in Gaiha and Imai (2008) but much higher than (Jha et al.'s, 2013) estimate of 0.30 for rural India. Idiosyncratic shocks contribute about 60 per cent to utility loss. The negative sign on the aggregate risk component indicates that economic growth offsets the negative covariate shocks.

5.3. Impact of health insurance on VEU and VEP

To estimate the impact of health insurance on vulnerability, we first estimate a household's propensity to have health insurance using a probit regression. The dependent variable is an binary variable with value one if a household has health insurance coverage in 2012 and zero if not. The regressors include variables from the 2010 VARHS: health insurance status in 2010, health status, risk aversion, income, assets, age of household head, marital status of the head, female share of the household, dependent share of the household, occupation and distance to the nearest bus station. Other commune variables representing the covariate shocks that might affect health insurance decision such as drought, flood, epidemic, livestock disease and other shocks are also included as explanatory variables.

Table 5
Idiosyncratic risk component.

Variable	First stage (normalized income)	Second stage (normalized food consumption)
ntotalincome		0.3191125
		(6.71)***
headage	0.0326934	0.0103375
	(4.53)***	(1.59)
married	0.2094052	0.1413307
	(5.71)***	(4.13)***
headage2	−0.0002982	−0.0000812
	(−4.51)***	(−1.36)
femaleshare	−0.2029016	−0.0313423
	(−3.00)***	(−0.52)
dependshare	−0.1901757	−0.136678
	(−3.35)***	(−2.69)***
highestedu	0.0967099	0.0868081
	(6.86)***	(6.63)***
agrhh	0.0066595	−0.1872426
	(0.25)	(−8.02)***
totalhousehold	0.0000121	0.0000405
	(0.95)	(3.64)***
targetcommune	0.135024	−0.1037634
	(5.53)***	(−4.48)***
povertyrate	−1.01589	−0.3393418
	(−13.44)***	(−4.21)***
regularmarket	−0.0011191	0.0565362
	(−0.04)	(2.12)**
secondaryschool	0.0356218	0.06378
	(0.88)***	(1.79)*
distance2bus	−0.0017999	0.001261
	(−2.81)***	(2.23)**
totalland	0.1040897	
	(17.11)***	
productiveasset	0.4654674	
	(4.93)***	
_cons	−0.0316537	0.1290584
	(−0.14)	(0.66)
Number of observations	3952	3952
Join significance	Wald $chi(15)$ = 884	Wald $chi^2(14) = 663.15$
Prob> chi^2	0.0000	0.0000
Sargan-Hansen test for over-identification restriction	$Chi^2(1) = 1.210$ Prob> $chi^2 = 0.2713$	

Notes: The estimation method used is the random-effects model with instrumental variables for panel data. The dependent variables in the first and second stages are normalized income and normalized food consumption, respectively. Robust z statistics in parentheses. $p \leq 0.1; * * p \leq 0.05; * * * p \leq 0.01$.

Table 6
Decomposition of average vulnerability during 2010–2012.

VEU	Poverty	Covariate risk	Idiosyncratic risk	Unexplained risk
0.7108	0.4314	−0.3410	0.4288	0.1905

Source: Author's calculations based on the panel sample of the VARHS, 2010 and 2012.

In our sample, the insured include both those with voluntary and compulsory insurance. Those with compulsory insurance might in principle have insurance because of factors not among the regressors in our probit regression. However, during the years covered in our data sample, the two groups of insured might not be different in ways that would bias our estimates of the effect of insurance on vulnerability. First, the compulsory health insurance scheme in Vietnam is not strictly compulsory. The coverage rate of this scheme is not 100 per cent for those households in this category (see Table 1). Households that are not fully subsidized in compulsory groups are likely to go through a decision making process similar to households in the voluntary group. Second, premiums for households in the compulsory groups that are partly subsidized are not much different from that of households in the voluntary scheme. Third, the poor and children under six years of age, who are compulsorily insured and fully subsidized, are excluded from the analysis to keep the incentive gap at the minimal level. Fourth, for households with formal employment that offer health insurance, some employers might actually not provide health insurance despite the law. Employees can choose to stay or find a better job with health insurance (Monheit & Vistnes, 2008). Hence, their probability of having a health insurance card might depend on their risk preference or factors representing their negotiating power such as education, age which are among our regressors.

Table 7 shows results from the probit regressions for health insurance. Households that have health insurance in 2010 are more likely to have health insurance in 2012. Households with higher income and higher proportion of females increase the probability of having health insurance. Similarly, households living in an area with a high incidence of epidemics tend to have health insurance. However, living in a commune with a high incidence of drought and livestock disease reduce the probability of have insurance. Households with agricultural jobs or with a higher dependent share are less likely to have health insurance. In our study, health status defined by the number of days on sick leave during the past 12 months (in survey 2010) does not affect health insurance status in 2012.

The risk aversion indexes (both cumulative risk aversion and absolute risk aversion) do not affect the decision to purchase health insurance because the estimated coefficients are negative and insignificant (Table 7).[8] This result contrasts with Condliffe and Fiorentino (2014) where individuals in the U.S. who are less risk averse are less likely to carry health insurance. There are four possible reasons for this. First, the risk aversion effect in our paper is offset by a "rigidity effect" where individuals are less likely to change from their current insurance plan (Costa-Font & Garcia-Villar, 2009; Friedman, 1974; Marquis & Holmer, 1996).[9] Health insurance status in 2010 which could be correlated with risk preferences, is significant in predicting status in 2012. Second, households might prefer other types of insurance over health insurance because the gain from health insurance is uncertain and ambiguous (Marquis & Holmer, 1996; Matsushima & Yamada, 2014). Third, the effect of individual risk aversion might be stronger for decisions taken in the near future and then might reduce considerably in next two years (which is the duration between the two surveys). When we estimate the impact of risk aversion on an individual acquiring any type of insurance coverage, we find positive and significant effects in the same year but not significant in the next two years.[10] Fourth, this might reflect the fact that the market for health insurance is limited and mainly provided by a few state companies. A health insurance purchasing decision is constrained not only by limited health insurance choices, but also by a complicated purchasing process. For instance, households are required to enroll all household members listed on the household certificate even in the common situation of some members having migrated to other places. The complications associated with enrollment hinders the expansion of coverage as pointed out in Matsushima and Yamada (2014).

[8] When we classified households into three different groups of risk attitude, we found that households with low risk aversion (i.e. prefer taking risk) are more likely to have health insurance. The results are not shown and can be provided upon request.

[9] Thaler (1980) calls this the "endowment effect"; Samuelson and Zeckhauser (1988) call this a "status quo" bias; and Costa-Font and Garcia-Villar (2009) call this the "captive preference".

[10] The estimated results can be provided upon request. However, we cannot deny that simultaneity bias with this specification because the independent variable and dependent variables in the probit model are collected in the same survey.

Table 7
Probit regression for health insurance propensity.

	Cumulative risk aversion index		Absolute risk aversion index	
insurance2012	Coefficient	Std. Err.	Coefficient	Std. Err.
insurance2010	0.4493***	0.1096	0.4529***	0.1093
healthstatus	−0.0001	0.0004	−0.0002	0.0004
riskaversion	−0.0123	0.0284		
abriskaversion			−0.0716	0.0606
lpcincome	0.2422***	0.0461	0.2428***	0.0460
headage	0.0061	0.0196	0.0060	0.0196
married	0.1101	0.0978	0.1111	0.0978
headage2	0.0001	0.0002	0.0001	0.0002
femaleshare	0.3939**	0.1867	0.3981**	0.1868
dependshare	−0.3992***	0.1543	−0.4028***	0.1543
agrhh	−0.2118***	0.0748	−0.2154***	0.0749
distance2bus	−0.0048	0.0030	−0.0047	0.0030
asset	−0.0890	0.0590	−0.0881	0.0590
drought	−0.0126**	0.0051	−0.0127**	0.0050
flood	−0.0016	0.0039	−0.0018	0.0039
epidemic	0.1712*	0.0891	0.1664*	0.0890
livestock	−0.0114***	0.0042	−0.0112***	0.0042
othershock	0.0197	0.0131	0.0195	0.0131
_cons	−3.2029***	0.6870	−3.1893***	0.6843
Number of obs	1988		Number of obs	1988
LR $chi^2(17)$	195.46		LR $chi^2(17)$	196.65
Prob > chi^2	0.0000		Prob > chi^2	0.0000
Log likelihood	−1100.671		Log likelihood	−1100.074
Pseudo R^2	0.0815		Pseudo R^2	0.0820

Notes: The estimation method used is the probit model. The dependent variable is a dummy indicating whether the household possesses at least one health insurance card in 2012 or not. Column (2) and (4) provide results with cummulative risk aversion and absolute risk aversion, respectively. $*p < 0.05, **p < 0.01, ***p < 0.001$.

Differences in the features of the households that owned a health insurance card and households that did not are presented in Table 8. The last column reports the *p*-value for the test of the null hypothesis that the means of the treatment and control groups are equal. Before the match, the *p*-values suggest that there is significant difference between the treatment and control samples with respect to farm-level and household characteristics. In particular, households with a health insurance card are more likely to be older and to have a higher income than households without a health insurance card. After the match, the treatment and control groups are well balanced across the observed characteristics as the *p*-values are statistically insignificant.

Table 9 reports the health insurance impact on vulnerability using propensity score matching. The kernel-matching estimator is applied with a bandwidth of 0.06. The first and second columns present the difference between treatment and control groups in 2012 and 2010 respectively. The last column reports the difference in these differences which is our estimate of the health insurance impact. Health insurance coverage has significantly reduced household vulnerability: the impact of health insurance on the idiosyncratic component of VEU is −0.35. Recall that in the estimates from our whole sample, the idiosyncratic component contributes about 0.43 to utility loss (Table 6). So on average, health insurance helps rural households in Vietnam reduce the idiosyncratic component of utility loss by 81 per cent. The impact of health insurance on the probability of falling into income poverty (VEP) is −0.05. From our previous estimates in Table 3, on average, households in 2012 have a 27 per cent probability of falling into poverty. That means health insurance helps rural households in Vietnam reduce the probability of becoming poor by about 19 per cent.

5.4. Robustness analysis

We perform two additional exercises to check the robustness of the results from the matching method. Table 10 reports the results using panel data regressions to estimate the impact of health insurance coverage on household idiosyncratic vulnerability. Controlling for absolute risk aversion health status and income, a random effects model estimate effect of health insurance is −0.26. When we control for other household and commune characteristics, the effect is a little lower at −0.23. Using the between variations model, the estimates are −0.56 without and −0.49 with household and commune controls. All estimates are statistically significant. We can thus say that health insurance reduces vulnerability coming from idiosyncratic shocks by between 23 to 56 per cent with 35 per cent being our preferred estimate of this effect using propensity score matching.

Because of the data collection timing, we do not know when households bought health insurance. It could have been at the beginning or at the end of the year. Therefore, we assume that the impact of health insurance coverage should be the impact of total health insurance during the time between the two surveys. Therefore, in one set of regressions, we specify the explanatory variable as the total health insurance that a household has during 2010 and 2012, that is the sum of health insurance cards a household has in the 2010 survey and in the 2012 survey. As seen in Table 11, with the random effect estimator, having a health insurance will reduce utility loss by about −0.21. Similarly, with the between estimator, the impact of health insurance is about −0.24. Although these results are not exactly the same as the estimates from the matching method, they reinforce our findings of the negative and significant impact of health insurance coverage on household vulnerability.

Although we control for many commune and household factors including risk preferences in our estimations and the difference-in-difference calculation helps to eliminate the effects from unobserved time-invariant factors, there might still be concern about other unobservables that could affect both health insurance enrollment and vulnerability. To address this concern, we also perform a sensitivity analysis proposed by Ichino, Mealli, and Nannicini (2008) building on Rosenbaum and Rubin (1983) and Rosenbaum (1987). The idea is that if conditional independence is not satisfied given observables but *is* satisfied if one could observe an additional

Table 8
Balance test in the matched samples.

		Mean			%reduct	t-test	
		Treated	Control	%bias	—bias—	t	p > t
lpcincome	U	9.2153	8.9195	40.6		8.12	0.00
	M	9.2153	9.2604	−6.2	84.7	−1.07	0.29
headage	U	53.3560	48.5580	37.4		7.59	0.00
	M	53.3560	53.2530	0.8	97.8	0.14	0.89
married	U	0.8391	0.8709	−9.0		−1.87	0.06
	M	0.8391	0.8443	−1.5	83.7	−0.24	0.81
femaleshare	U	0.5092	0.4992	5.7		1.14	0.25
	M	0.5092	0.5143	−2.9	49.0	−0.48	0.63
dependshare	U	0.2569	0.3102	−20.9		−4.32	0.00
	M	0.2569	0.2493	3.0	85.7	0.50	0.62
agrhh	U	0.2076	0.2851	−18.0		−3.58	0.00
	M	0.2076	0.2197	−2.8	84.4	−0.50	0.62
distance2bus	U	9.0187	11.1020	−19.5		−3.83	0.00
	M	9.0187	8.5758	4.1	78.7	0.81	0.42
asset	U	0.2145	0.2752	−11.2		−2.26	0.02
	M	0.2145	0.2128	0.3	97.1	0.06	0.95
drought	U	7.1471	9.1376	−28.4		−5.85	0.00
	M	7.1471	6.8166	4.7	83.4	0.81	0.42
flood	U	9.5830	10.7830	−13.5		−2.76	0.01
	M	9.5830	8.6972	10.0	26.2	1.74	0.08
epidemic	U	0.0779	0.0511	7.7		1.64	0.10
	M	0.0779	0.0761	0.5	93.5	0.07	0.94
livestock	U	5.7907	7.9156	−25.9		−5.19	0.00
	M	5.7907	5.8754	−1.0	96.0	−0.18	0.85
othershock	U	0.6107	0.6092	0.1		0.01	0.99
	M	0.6107	0.6609	−2.1	−3230.0	−0.33	0.74
healthstatus	U	38.5280	39.4840	−1.3		−0.27	0.79
	M	38.5280	34.5090	5.7	−320.0	1.04	0.30
riskavermed	U	0.2439	0.2844	−9.2		−1.84	0.07
	M	0.2439	0.2786	−7.9	14.5	−1.34	0.18
riskaverlow	U	0.0934	0.0617	11.9		2.50	0.01
	M	0.0934	0.0761	6.5	45.5	1.06	0.29

Notes: The region of common support is [.05686186,.79890357]. The final number of blocks is 8. Test of balancing property of the propensity score is satisfied. The balance test is generated by the Stata command *pstest*. U and M represent for Unmatched and Matched, respectively.

Table 9
Impact of health insurance on vulnerability.

	2012	2010	Difference-in-difference
Covariate risk	0.16***	0.22***	−0.06***
	(4.941)	(6.976)	(−13.338)
Idiosyncratic risk	−0.51**	−0.16***	−0.35**
	(−2.131)	(−4.202)	(−2.243)
VEP	-0.08***	-0.03***	−0.05***
	(−9.446)	(−4.736)	(−7.95)

Notes: The kernel-matching estimator is applied with a bandwidth of 0.06. The first and second columns present the difference between treatment and control groups in 2012 and 2010 respectively. The last column shows the difference in these differences, or the health insurance impact.

binary variable (call it a confounder), then this potential confounder could be simulated in the data and used as an additional covariate in combination with the preferred matching estimator.

We use two covariates to simulate the confounder: young (age of household head is less than 47, or in the 25*th* centile of the age distribution) and low education (with no diploma). These covariates are selected to capture the effect of unobservable factors like ability and experience. We employ the kernel matching algorithm with between-imputation standard errors. Since our outcome variable is continuous, the confounders are simulated on the basis of the binary transformation of the outcome along the 75*th* centile. The results of the sensitivity analysis are presented in Tables 12 and 13. For both confounders, the simulated average treatment effect estimates are very close to our preferred matching estimates. The outcome and selection effect on vulnerability are positive but not very large.

While the data does not distinguish between compulsory and voluntary health insurance, we added a number of exercises to minimize the potential differences between the compulsory and voluntary groups. First, we excluded from our analytical sample the 236 households with an employment contract, an eligibility condition for compulsory health insurance. With this sample, health insurance enrollment in 2010 no longer affects the probability of having health insurance in 2012. This suggests that most households with health insurance in both 2010 and 2012 belong to the compulsory group (which is now omitted from the sample). Therefore, after controlling for enrollment in 2010, we have mostly captured the differences between the compulsory group and the voluntary group that affect the health insurance decision. The PSM and difference-in-difference estimates of the impact of health insurance on vulnerability are nearly the same in both samples (See Tables 21b and 22b).

Second, we test our assumption about the close relationship between health insurance enrollment and the employment contract by adding a dummy variable representing the household employment contract into the original propensity score probit regression. The coefficient on the employment contract dummy is statistically significant. Once again, The PSM and difference-in-difference estimates of the impact of health insurance on vulnerability do not change much (See Tables 21a and 22a).

6. Concluding remarks

Health shocks are one of the major causes of vulnerability and poverty in Vietnam. Therefore, the government of Vietnam has

Table 10
Impact of health insurance coverage on idiosyncratic VEU.

	Random effect	Between variation	Random effect	Between variation
Health insurance	−0.261***	−0.558***	−0.231***	−0.486**
(Yes/No at the time of interview)	(0.043)	(0.160)	(0.069)	(0.167)
Absolute risk aversion	−0.164*	−0.082	−0.129*	−0.104
	(0.088)	(0.165)	(0.076)	(0.163)
Health status	−0.030	−0.009	−0.068	−0.067
	(0.032)	(0.065)	(0.059)	(0.066)
Per capita income (log)	−0.270***	−0.251***	−0.174***	−0.163**
	(0.058)	(0.060)	(0.045)	(0.066)
Household characteristics	No	No	Yes	Yes
Commune characteristics	No	No	Yes	Yes
N	3952	3952	3952	3952
R^2		0.019		0.066
F		9.524		5.991
p	0.000	0.000	0.000	0.000

Notes: Both random–effects and between variation models are used. The dependent variable is a dummy indicating if the household has a health insurance card at the time of interview or not. Absolute risk aversion index is used in this case. Standard errors in parentheses. $*p < 0.05, **\ p < 0.01, ***p < 0.001$.

Table 11
Impact of health insurance coverage on idiosyncratic VEU (total health insurances across surveys, absolute risk aversion).

	Random effect	Between variation	Random effect	Between variation
Health insurance	−0.274***	−0.269***	−0.214***	−0.235**
(Total insurance across surveys)	(0.044)	(0.080)	(0.057)	(0.084)
Absolute risk aversion	−0.164*	−0.082	−0.133*	−0.105
	(0.088)	(0.165)	(0.077)	(0.163)
Health status	−0.029	−0.008	−0.070	−0.066
	(0.032)	(0.065)	(0.059)	(0.066)
Per capita income (log)	−0.239***	−0.251***	−0.161***	−0.163**
	(0.055)	(0.060)	(0.043)	(0.067)
Household characteristics	No	No	Yes	Yes
Commune characteristics	No	No	Yes	Yes
N	3952	3952	3952	3952
R^2		0.018		0.065
F		9.273		5.961
p	0.000	0.000	0.000	0.000

Notes: Standard errors in parentheses.
$*p < 0.05, **\ p < 0.01, ***p < 0.001$.

Table 12
Simulation-based sensitivity analysis for matching estimators (2010, confounders: young and low education).

	ATT_{2010}	Standard error	Outcome effect	Selection effect
Young	−0.147	0.008	1.623	0.456
Low education	−0.154	0.004	3.552	0.582

Notes: Based on the sensitivity analysis with kernel matching algorithm with between-imputation standard error. The binary transformation of the outcome is along the 75 centile. Young variable (=1 if age is less than 41 years, or the 25 centile) and low education (=1 if households do not have any certificate). Both the outcome and the selection effect are odds ratios from probit estimations.

Table 13
Simulation-based sensitivity analysis for matching estimators (2012, confounders: young and low education)

	ATT_{2012}	Standard error	Outcome effect	Selection effect
Young	−0.512	0.043	1.206	0.440
Low education	−0.508	0.039	2.572	0.565

Notes: Based on the sensitivity analysis with kernel matching algorithm with between-imputation standard error. The binary transformation of the outcome is along the 75 centile. Young variable (=1 if age is less than 41 years, or the 25 centile) and low education (=1 if households do not have any certificate). Both the outcome and the selection effect are odds ratios from probit estimations.

tried to achieve its goal of universal health insurance coverage partly to address this issue. In this paper we provide empirical evidence for the positive effect that health insurance has on reducing household vulnerability. To the best of our knowledge, this study is the first paper measuring the impact of health insurance coverage on household *ex-ante* vulnerability.

Using propensity score matching and data from the Vietnam Access to Resources Household Surveys (VARHS) 2010–2012, we estimate that health insurance helps rural households in Vietnam reduce the idiosyncratic component of utility loss by 81 per cent and the probability of becoming poor by 19 per cent. Our findings are robust to alternative specifications. The VARHS allows us to include risk preferences in our analysis, a possible source of endogeneity between health insurance coverage and vulnerability. Interestingly, risk aversion is not a significant predictor of health insurance status even though it is a significant predictor of other types of insurance purchases. This result suggests a persistence in health insurance status and the presence of frictions in the market for health insurance consistent with anecdotal evidence. Health insurance status in 2010 is an important predictor of status in 2012.

Our findings suggest that the expansion of health insurance coverage in Vietnam has clear benefits, especially for the vulnerable poor. These benefits can be weighed against potential program costs to design informed policies. However, efficiency improvements in the dissemination of information, education and communication about health insurance would have immediate gains to boost the demand for insurance. On the supply side, government can reduce unnecessary bureaucracy in the issuance of insurance. Extending beyond health insurance, our results also suggest that other measures to improve access to health care services for the poor or to reduce costs for health services would have similar benefits of reducing vulnerability.

Appendix A. Vulnerability as expected poverty (VEP)

Vulnerability as expected poverty is a vulnerability measure which was first proposed and applied to Indonesian household data by Chaudhuri (2003). This household vulnerability is defined as the likelihood that a household will fall into poverty in the next period. VEP can be estimated through the following procedures, beginning with the consumption function:

$$\ln c_i = \alpha + \beta \cdot X_i + e_i \tag{13}$$

where c_i is per capita consumption expenditure for household i, X_i represents a vector of observable household characteristics and commune characteristics (e.g. characteristics of head, location, assets, shocks), β is a vector of parameters to be estimated, and e_i is a mean-zero disturbance term that captures idiosyncratic shocks that lead to different levels of per capita consumption.

The variance of the disturbance term is:

$$\sigma^2_{e,i} = \theta \cdot X_i \tag{14}$$

Chaudhuri et al. (2002) and Chaudhuri (2003) acknowledge that the error term (e_i) is not the same for all households (heteroskedasticity). Therefore, we adopt the three-step Feasible Generalized Least Squares (FGLS) technique proposed by Amemiya (1977).

Firstly, we estimate Eq. (14) by employing the ordinary least squares (OLS) technique. Next we predict the residuals from the regression and regress the predicted residuals on the same covariates included in the specification of the consumption process. Then we have the error variance estimating process as follows:

$$\hat{e}^2_{i,OLS} = \rho + \hat{\delta} \cdot X_i + \eta_i \tag{15}$$

The prediction of Eq. (15) is used to weight the previous equation, thus leading to the transformed version:

$$\frac{\hat{e}^2_i}{\hat{e}^2_{i,OLS}} = \frac{\rho}{\hat{e}^2_{i,OLS}} + \frac{\hat{\delta} X_i}{\hat{e}^2_{i,OLS}} + \frac{\eta_i}{\hat{e}^2_{i,OLS}} \tag{16}$$

According to Chaudhuri (2003), the OLS estimation of Eq. (16) generates an asymptotically FGLS estimate, δ^{FGLS}, and thus e^2_i is a consistent estimate of the variance of the idiosyncratic component of household consumption. Having obtained an efficient estimate of the variance as the predicted value of Eq. (16), $\left(\hat{\delta}^2_{i,FGLS}\right)$, we now take the square root and transform Eq. (13) as follows:

$$\frac{\ln c_i}{\hat{\delta}_{i,FGLS}} = \frac{\alpha}{\hat{\delta}_{i,FGLS}} + \frac{\beta \cdot X_i}{\hat{\delta}_{i,FGLS}} + \frac{e_i}{\hat{\delta}_{i,FGLS}} \tag{17}$$

An OLS estimation of Eq. (17) generates a consistent and asymptotically efficient estimate of $\alpha^{FGLS}, \beta^{FGLS}$. Once we obtain these estimates, it is possible to predict both the expected log consumption and its variance:

$$\hat{E}[\ln C_i|X_i] = \alpha^{FGLS} + \beta^{FGLS} \cdot X_i \tag{18}$$

$$\hat{V}[\ln C_i|X_i] = \rho^{FGLS} + \delta^{FGLS} \cdot X_i \tag{19}$$

Chaudhuri (2003) assumes that lnc_i is normally distributed. Then the estimated probability that a household will be poor in the future (for example, at time $t+1$) is given by:

$$\hat{v}_{i,Chaudhuri} = \widehat{Pr}(\ln c_i < \ln z|X_i) = \Phi\left(\frac{\ln z - \hat{E}[\ln C_i|X_i]}{\sqrt{\hat{V}[\ln C_i|X_i]}}\right) \tag{20}$$

where $\Phi(.)$ is the cumulative function of the standard normal and z is the actual poverty line.[11]

Unfortunately, household consumption expenditure is not available in the VARHS. As a result, we decide to use total income as a substitution for household consumption. The poverty lines used in this study are the national poverty line generated from household income by MOLISA.[12] Then the vulnerability index is the probability of falling into poverty according the national standard.

Appendix B. Questions about risk preferences

In the 2010 and 2012 waves of the VARHS, there are three questions that allow us to assign a measure of risk aversion for each individual. The first question is a simple unpaid lottery experiment in which respondents are required to accept or reject each of six lotteries with different payoffs. In each lottery, the winning prize is unchanged at VND 6,000 and the loss varies from VND 2,000 to VND 7,000 (Table 14).

That exact question in the questionnaire is:

"You are given the opportunities of playing a game where you have a 50:50 chance of winning or losing (for example, a coin is tossed so that you have an equal chance of it turning up either heads or tails). In each case choose whether you would accept or reject the option of playing:".

The VARHS dataset in 2010 and 2012 also contain information that we can use to estimate absolute risk aversion. The exact two questions in the VARHS questionnaire are:

"Consider an imaginary situation where you are given the chance of entering a state-run lottery where only 10 people can enter

[11] The poverty lines in this study are calculated from the VHLSS and released by the GSO and the WB. The poverty line measure takes account of the regional price differences and monthly price changes over the survey periods. The poverty lines are 1917, 2077 and 2566 thousand VND/person/year for the years of 2002, 2004 and 2006, respectively.

[12] There are two parallel approaches to poverty measurement in Vietnam using national poverty lines. The first approach developed and led by the Ministry of Labor, Invalids, and Social Affairs (MOLISA), is based on income and is used primarily for targeting social programs. The second was developed by the General Statistical Office and the World Bank, is based on consumption and is used chiefly for monitoring poverty over time.

and 1 person will win the prize. How much would you be willing to pay for a 1 in 10 chance of winning a prize of 2,000,000 VND?".

and,

"How much would you be willing to pay for a 1 in 10 chance of winning a prize of 20,000,000 VND?".

The answers to these questions are regarded as reservation prices above which households reject the lottery.

Appendix C. Estimates of risk aversion

Tables 15–22.

Table 14
Questionaires about risk preference in VARHS.

	Lottery	Accept	Decline
a.	You have a 50% chance of losing 2,000 VND and a 50% chance of winning 6,000 VND	○	○
b.	You have a 50% chance of losing 3,000 VND and a 50% chance of winning 6,000 VND	○	○
c.	You have a 50% chance of losing 4,000 VND and a 50% chance of winning 6,000 VND	○	○
d.	You have a 50% chance of losing 5,000 VND and a 50% chance of winning 6,000 VND	○	○
e.	You have a 50% chance of losing 6,000 VND and a 50% chance of winning 6,000 VND	○	○
f.	You have a 50% chance of losing 7,000 VND and a 50% chance of winning 6,000 VND	○	○

Source: VARHS 2010 and 2012.

Table 15
Summary of risk aversion in 2010 and 2012.

		2010				2012			
Variable	Obs	Mean	Std.Dev	Min	Max	Mean	Std.Dev	Min	Max
riskaversion1	1988	3.2334	1.1089	0.8571	4	3.2097	1.0804	0.8571	4
riskaversion2	1988	3.8019	1.2262	1.1266	4.6477	3.7771	1.1950	1.1266	4.6477
riskaversion3	1988	2.7807	0.9536	0.7371	3.44	2.7603	0.9291	0.7371	3.44
riskaversion4	1988	3.2697	1.0545	0.9688	3.9970	3.2483	1.0277	0.9688	3.9970
abriskaversion1	1988	0.8198	0.4959	−1.6471	1	0.7533	0.1957	0.1110	1
abriskaversion2	1988	0.8756	0.4437	−1.6471	1	0.9533	0.0864	0.2759	1

Note: We involve a different assumption on probability weighting and diminishing sensitivities for gains and losses to estimate the cumulative risk aversion. In our benchmark model (1), both probability weighting and diminishing sensitivity are not important. Model (2) assumes the same probability weighting for gains and losses, or $w^{+}(0.5)/w^{-}(0.5) = 1$, but allows for diminishing sensitivities for gains and losses (this study uses the median estimates of Booij and Van de Kuilen (2009) where $\alpha = 0.95$ and $\beta = 0.92$). Model (3) assumes indifferent diminishing sensitivity but allows for differences in probability weights for gains and losses. We use the estimates from Abdellaoui (2000) in which $w^{+}(0.5) = 0.394$ and $w^{-}(0.5) = 0.456$ for the median individual, implying $w^{+}(0.5)/w^{-}(0.5) = 0.86$. This probability weighting difference is one of the largest gaps between gains and losses in the literature, providing an upper bound for our estimation. Model (4) simultaneously assumes that both probability weighting and diminishing sensitivities are essential. The smaller the value is, the more likely the respondent is to engage risk behaviors.

Table 16
Pairwise correlation of risk parameters in 2010.

Variable	riskaver1	riskaver2	riskaver3	riskaver4	abriskaver1	abriskaver2
riskaversion1	1					
riskaversion2	1.0000*	1				
riskaversion3	1.0000*	1.0000*	1			
riskaversion4	1.0000*	1.0000*	1.0000*	1		
abriskaversion1	0.3349*	0.3339*	0.3339*	0.3339*	1	
abriskaversion2	0.2552*	0.2560*	0.2552*	0.2560*	0.7104*	1

Notes: * Statistically significant at 5 percent.

Table 17
Cumulative risk aversion in groups.

	2010		2012	
Cumulative risk aversion	Freq.	Percent	Freq.	Percent
high	1,305	65.64	1,214	61.07
medium	542	27.26	638	32.09
low	141	7.09	136	6.84
Total	1,988	100.00	1,988	100.00

Table 18
Absolute risk aversion in groups.

	2010		2012	
Cumulative risk aversion	Freq.	Percent	Freq.	Percent
high	1,154	58.05	108	5.43
medium	776	39.03	1,880	94.57
low	58	2.92		
Total	1,988	100.00	1,988	100.00

Table 19
Monthly out-of-pocket by household characteristics.

	2010			2012		
	OOP	CTP	$\frac{OOP}{CTP}\%$	OOP	CTP	$\frac{OOP}{CTP}\%$
Household health insurance						
No	255.47	1,950.11	14.29	349.57	2,500.69	13.06
Yes	258.18	2,211.71	11.74	320.36	2,733.26	11.00
Total	257.73	2,168.47	12.16	324.47	2,700.50	11.29
Type of health insurance						
No health insurance	290.28	2,159.78	14.23	356.72	2,706.05	12.74
Free health insurance						
For children aged 6 or less	207.40	2,055.52	10.67	275.73	2,618.51	9.36
For the poor	165.67	798.42	14.15	230.30	1,100.49	13.38
For the near-poor	175.05	980.99	16.77	179.35	1,326.74	12.14
Free healthcare	123.92	1,186.12	10.16	217.74	1,954.02	9.31
For policy beneficiaries	248.09	1,748.34	11.78	304.17	2,250.15	12.25
Compulsory health insurance						
State-run health insurance	303.33	3,587.23	9.37	442.41	4,452.26	8.94
Non-state health insurance	255.47	3,283.72	9.07	395.45	3,372.66	10.58
Voluntary health insurance						
Health insurance for student	263.79	2,811.79	9.14	271.71	3,248.73	8.22
Other health insurance	358.90	2,474.42	13.13	415.70	3,191.83	12.59
Others	163.39	1,802.95	9.38	252.48	2,042.15	12.51
Total	257.73	2,168.47	12.16	324.47	2,700.50	11.29
Urban						
Rural	238.83	1,751.27	12.75	294.22	2,241.45	11.80
Urban	305.69	3,227.33	10.68	396.59	3,794.82	10.10
Total	257.73	2,168.47	12.16	324.47	2,700.50	11.29

Note: Out-of-pocket (OOP) includes in- and out-patient costs of households. We use member ID to match OOP with type of health insurance. Capacity to pay (CTP) is calculated as household's income after subtracting subsistence expenditure. Catastrophic expenditure occurs when OOP/CTP exceeds 40%.
Source: Author's calculation from VHLSS.

Table 20
Household employment contract and health insurance statistics.

(a) Household employment contract and health insurance in 2012

	Employment Contract																			
	2010										2012									
	No		Yes		Self-employed		Unemployed		Total		No		Yes		Self-employed		Unemployed		Total	
Household Insurance 2012	No.	C%	No.	C%	No.	C%	No.	C%	No.	C%	No.	C%	No.	C%	No.	C%	No.	C%	No.	C%
No	624	75	186	55	597	73	3	75	1,410	71	656	82	188	44	561	75	5	50	1,410	71
Yes	205	25	152	45	220	27	1	25	578	29	148	18	236	56	189	25	5	50	578	29
Total	829	100	338	100	817	100	4	100	1,988	100	804	100	424	100	750	100	10	100	1,988	100

(b) Health insurance and household employment contract in 2012

	Health Insurance															
	2010						2012						Has Health Insurance			
	No		Yes		Total		No		Yes		Total		in both 2010 and 2012			
Employment contract 2012	No.	C%	No.	C%	Freq	C%	No.	C%	No.	C%	No.	C%	No.	C%	No.	C%
No	789	43	15	10	804	40	656	47	148	26	804	40	8	10%	5	6%
Yes	322	18	102	65	424	21	188	13	236	41	424	21	64	79%	64	79%
Self-employed	711	39	39	25	750	38	561	40	189	33	750	38	9	11%	12	15%
Unemployed	10	1	0	0	10	1	5	0	5	1	10	1	0	0%	0	0%
Total	1,832	100	156	100	1,988	100	1,410	100	578	100	1,988	100	81	100%	81	100%

Source: Author's calculation from VARHS.

Table 21
Probit regression for health insurance propensity score with employment contract.

(a) Added households employment contract variable

	Risk Aversion Index	
	Cumulative	Absolute
riskaversion1	−0.0120	
	(0.029)	
abriskaversion1		−0.0676
		(0.062)
insurance20101	0.123	0.127
	(0.12)	(0.12)
employ_contract	0.806	0.806
	(0.078)***	(0.078)***
healthstatus	-0.0000558	-0.0000544
	(0.00045)	(0.00045)
lpcincome	0.229	0.230
	(0.047)***	(0.047)***
headage	0.0106	0.0104
	(0.020)	(0.020)
headage2	0.0000478	0.0000500
	(0.00018)	(0.00018)
married	0.0745	0.0754
	(0.10)	(0.10)
femaleshare	0.415	0.419
	(0.19)*	(0.19)*
dependshare	−0.203	−0.207
	(0.16)	(0.16)
agrhh	−0.121	−0.124
	(0.077)	(0.077)
distance2bus	−0.00430	−0.00409
	(0.0030)	(0.0030)
asset	−0.0823	−0.0817
	(0.059)	(0.059)
drought	−0.0114	−0.0115
	(0.0052)*	(0.0052)*
flood	−0.00219	−0.00235
	(0.0039)	(0.0039)
epidemic	0.145	0.141
	(0.092)	(0.092)
livestock	−0.0126	−0.0124
	(0.0043)**	(0.0043)**
othershock	0.0167	0.0165
	(0.013)	(0.013)
_cons	−3.406	−3.392
	(0.71)***	(0.70)***
N	1988	1988
chi2	304.2	305.2

(b) Dropped households with both employment contract and health insurance

	Risk Aversion Index	
	Cumulative	Absolute
riskaversion1	0.0151	
	(0.033)	
abriskaversion1		−0.0423
		(0.068)
insurance20101	−0.258	−0.256
	(0.16)	(0.16)
healthstatus	0.000131	0.000145
	(0.00049)	(0.00049)
lpcincome	0.244	0.244
	(0.053)***	(0.053)***
headage	0.0101	0.0110
	(0.023)	(0.023)
headage2	0.0000527	0.0000461
	(0.00021)	(0.00021)
married	0.0631	0.0625
	(0.11)	(0.11)
femaleshare	0.354	0.366
	(0.21)	(0.21)
dependshare	−0.0561	−0.0550
	(0.18)	(0.17)
agrhh	−0.0888	−0.0927
	(0.082)	(0.082)
distance2bus	−0.00332	−0.00338
	(0.0035)	(0.0035)
asset	−0.0270	−0.0281
	(0.064)	(0.064)
drought	−0.0112	−0.0111
	(0.0059)	(0.0059)
flood	-0.000305	-0.000493
	(0.0044)	(0.0044)
epidemic	0.0936	0.0959
	(0.11)	(0.11)
livestock	−0.0130	−0.0126
	(0.0049)**	(0.0049)**
othershock	0.0182	0.0170
	(0.015)	(0.015)
_cons	−3.745	−3.692
	(0.79)***	(0.79)***
N	1752	1752
chi2	96.85	97.02

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.
Dependent variable is Insurance in 2012 Standard errors in parentheses.

Table 22
Impact of health insurance on vulnerability (controlling for the emlpyment contract).

(a) Added employment contract variable

	2012	2010	Diff-in-diff
Covariate risk	0.103**	0.157**	−0.052***
	(2.956)	(4.722)	(−9.671)
Idiosyncratic risk	−0.425*	−0.117**	−0.306*
	(−2.054)	(−2.917)	(−1.881)
VEP	−0.079***	−0.03**	−0.049***
	(−8.023)	(−4.363)	(−8.557)

(b) Dropped households with both employment contract and health insurance

	2012	2010	Diff-in-diff
Covariate risk	0.077*	0.145**	−0.069***
	(1.48)	(3.294)	(−13.012)
Idiosyncratic risk	−0.318*	−0.102*	−0.214*
	(−2.117)	(−1.969)	(−2.102)
VEP	−0.09***	−0.03**	−0.06***
	(−8.735)	(−3.311)	(−10.098)

References

Abdellaoui, M. (2000). Parameter-free elicitation of utility and probability weighting functions. *Management Science, 46*(11), 1497–1512.
Amemiya, T. (1977). The maximum likelihood and the nonlinear three-stage least squares estimator in the general nonlinear simultaneous equation model. *Econometrica, 45*(4), 955–968.
Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2008). Eliciting risk and time preferences. *Econometrica, 76*(3), 583–618.
Arrow, K. J. (1965). *Aspects of the theory of risk-bearing*. Helsinki: Yrjö Jahnssonin Säätiö.
Barseghyan, L., Molinari, F., O'Donoghue, T., & Teitelbaum, J. C. (2013). The nature of risk preferences: Evidence from insurance choices. *American Economic Review, 103*(6), 2499–2529.
Bleichrodt, H., & Gafni, A. (1996). Time preference, the discounted utility model and health. *Journal of Health Economics, 15*(1), 49–66.
Bleichrodt, H., & Pinto, J. L. (2000). A parameter-free elicitation of the probability weighting function in medical decision analysis. *Management Science, 46*(11), 1485–1496.
Bleichrodt, H., & Pinto, J. L. (2002). Loss aversion and scale compatibility in two-attribute trade-offs. *Journal of Mathematical Psychology, 46*(3), 315–337.
Booij, A. S., & Van de Kuilen, G. (2009). A parameter-free analysis of the utility of money for the general population under prospect theory. *Journal of Economic Psychology, 30*(4), 651–666.
Bowman, D., Minehart, D., & Rabin, M. (1999). Loss aversion in a consumption–savings model. *Journal of Economic Behavior & Organization, 38*(2), 155–178.
Bridges, J. (2003). Stated preference methods in health care evaluation: an emerging methodological paradigm in health economics. *Applied Health Economics and Health Policy, 2*(4), 213–224.
Camerer, C., Babcock, L., Loewenstein, G., & Thaler, R. (1997). Labor supply of New York city cabdrivers: One day at a time. *The Quarterly Journal of Economics*, 407–441.

Chaudhuri, A., & Roy, K. (2008). Changes in out-of-pocket payments for healthcare in Vietnam and its impact on equity in payments, 1992–2002. *Health Policy, 88*(1), 38–48.

Chaudhuri, S. (2003). *Assessing vulnerability to poverty: Concepts, empirical methods and illustrative examples*. New York: Department of Economics,Columbia University.

Chaudhuri, S., Jalan, J., & Suryahadi, A. (2002). *Assessing household vulnerability to poverty from cross-sectional data: A methodology and estimates from Indonesia*. Columbia University Discussion Paper.

Condliffe, S., & Fiorentino, G. T. (2014). The impact of risk preference on health insurance and health expenditures in the united states. *Applied Economics Letters, 21*(9), 613–616.

Costa-Font, J., & Garcia-Villar, J. (2009). Risk attitudes and the demand for private health insurance: the importance of captive preferences. *Annals of Public and Cooperative Economics, 80*(4), 499–519.

Cuong, N. V. (2012). The impact of voluntary health insurance on health care utilization and out-of-pocket payments: New evidence for Vietnam. *Health Economics, 21*(8), 946–966.

Friedman, B. (1974). Risk aversion and the consumer choice of health insurance option. *The Review of Economics and Statistics*, 209–214.

Gächter, S., Johnson, E. J., & Herrmann, A. (2010). *Individual-level loss aversion in riskless and risky choices, Discussion papers 2010–20*. The Centre for Decision Research and Experimental Economics, School of Economics, University of Nottingham.

Gaiha, R., & Imai, K. (2008). *Measuring vulnerability and poverty: Estimates for rural india, UNU-WIDER Research paper 2008/040*. Helsinki, Finland: World Institute for Development Economic Research, United Nation University.

Goette, L., Huffman, D., & Fehr, E. (2004). Loss aversion and labor supply. *Journal of the European Economic Association, 2*(2–3), 216–228.

Hartog, J., Ferrer-i Carbonell, A., & Jonker, N. (2002). Linking measured risk aversion to individual characteristics. *Kyklos, 55*(1), 3–26.

Heidhues, P., & Köszegi, B. (2008). Competition and price variation when consumers are loss averse. *The American Economic Review*, 1245–1268.

Hoddinott, J., & Quisumbing, A. (2010). Methods for microeconometric risk and vulnerability assessment. In R. Fuentes-Nieva & P. A. Seck (Eds.), *Risk, Shocks, and Human Development* (pp. 62–100). Springer.

Ichino, A., Mealli, F., & Nannicini, T. (2008). From temporary help jobs to permanent employment: What can we learn from matching estimators and their sensitivity? *Journal of Applied Econometrics, 23*(3), 305–327.

Jha, R., Dang, T., & Tashrifov, Y. (2010). Economic vulnerability and poverty in Tajikistan. *Economic Change and Restructuring, 43*(2), 95–112.

Jha, R., Kang, W., Nagarajan, H. K., & Pradhan, K. C. (2013). *Vulnerability and responses to risks in rural india, Working paper 2012/05*. Canberra, Australia: Australia South Asia Research Centre, The Australian National University.

Jowett, M., Contoyannis, P., & Vinh, N. D. (2003). The impact of public voluntary health insurance on private health expenditures in Vietnam. *Social Science & Medicine, 56*(2), 333–342.

Khandker, S. R. (1998). *Fighting poverty with microcredit: Experience in Bangladesh*. Oxford University Press.

Lieberman, S. S., & Wagstaff, A. (2009). *Health financing and delivery in Vietnam: Looking forward*. Washington, D.C.: World Bank Publications.

Ligon, E., & Schechter, L. (2003). Measuring vulnerability. *The Economic Journal, 113*(486), C95–C102.

Lusk, J. L., & Coble, K. H. (2005). Risk perceptions, risk preference, and acceptance of risky food. *American Journal of Agricultural Economics, 87*(2), 393–405.

Marquis, M. S., & Holmer, M. R. (1996). Alternative models of choice under uncertainty and demand for health insurance. *The Review of Economics and Statistics*, 421–427.

Matsushima, M., & Yamada, H. (2014). Public health insurance in Vietnam towards universal coverage: Identifying the challenges, issues, and problems in its design and organisational practices. *Kokusai Hoken Iryo (Journal of International Health), 29*(4), 289–297.

Ministry of Health (2013). *Towards universal health coverage, Joint annual health review 2013*. Hanoi: Ministry of Health of Vietnam, Health Partnership Group.

Ministry of Health (2016). *Strengthening primary health care at the grassroots towards universal health coverage, Joint annual health review 2015*. Hanoi: Ministry of Health of Vietnam, Health Partnership Group.

Monheit, A. C., & Vistnes, J. P. (2008). Health insurance enrollment decisions: preferences for coverage, worker sorting, and insurance take-up. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing, 45*(2), 153–167.

Morduch, J. (1999). The microfinance promise. *Journal of Economic Literature, 37*(4), 1569–1614.

Nguyen, K. T., Khuat, O. T. H., Ma, S., Pham, D. C., Khuat, G. T. H., & Ruger, J. P. (2012). Coping with health care expenses among poor households: Evidence from a rural commune in Vietnam. *Social Science & Medicine, 74*(5), 724–733.

Nightingale, S. (1988). Risk preference and admitting rates of emergency room physicians. *Medical Care, 26*(1), 84–87.

Nightingale, S., & Grant, M. (1988). Risk preference and decision making in critical care situations. *Chest, 93*(4), 684–687.

Picone, G., Sloan, F., & Taylor, D. (2004). Effects of risk and time preference and expected longevity on demand for medical tests. *Journal of Risk and Uncertainty, 28*(1), 39–53.

Pratt, J. W. (1964). Risk aversion in the small and in the large. *Econometrica, 34*(1/2), 122–136.

Richardson, J. (1994). Cost utility analysis: What should be measured? *Social Science & Medicine, 39*(1), 7–21.

Rosenbaum, P. R. (1987). Sensitivity analysis for certain permutation inferences in matched observational studies. *Biometrika, 74*(1), 13–26.

Rosenbaum, P. R., & Rubin, D. B. (1983). Assessing sensitivity to an unobserved binary covariate in an observational study with binary outcome. *Journal of the Royal Statistical Society: Series B (Methodological), 45*(2), 212–218.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of Risk and Uncertainty, 1*(1), 7–59.

Sepehri, A., Sarma, S., & Simpson, W. (2006). Does non-profit health insurance reduce financial burden? evidence from the Vietnam living standards survey panel. *Health Economics, 15*(6), 603–616.

Somanathan, A., Tandon, A., Lan, D. H., Hurt, K. L., & Fuenzalida-Puelma, H. L. (2014). *Moving toward universal coverage of social health insurance in Vietnam: Assessment and options*. Washington, D.C.: World Bank Publications.

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization, 1*(1), 39–60.

Thanh, N., Löfgren, C., Phuc, H., Chuc, N., & Lindholm, L. (2010). An assessment of the implementation of the health care funds for the poor policy in rural Vietnam. *Health Policy, 98*(1), 58–64.

Tien, T. V., Phuong, H. T., Mathauer, I., & Phuong, N. T. K. (2011). *A health financing review of Viet Nam with a focus on social health insurance*. Geneva: World Health Organization.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty, 5*(4), 297–323.

Wagstaff, A. (2007). The economic consequences of health shocks: Evidence from Vietnam. *Journal of Health Economics, 26*(1), 82–100.

Wagstaff, A. (2010). Estimating health insurance impacts under unobserved heterogeneity: The case of Vietnam's health care fund for the poor. *Health Economics, 19*(2), 189–208.

Wagstaff, A., & Doorslaer, E. V. (2003). Catastrophe and impoverishment in paying for health care: with applications to Vietnam 1993–1998. *Health Economics, 12*(11), 921–933.

Wainwright, F., & Newman, C. (2011). *Income shocks and household risk coping strategies: Evidence from rural Vietnam, IIIS Discussion Paper 2011/358*. Ireland: Institute for International Integration Studies, The University of Dublin.

Zaman, H. (1999). *Assessing the poverty and vulnerability impact of micro-credit in Bangladesh: A case study of BRAC*. Washington, D.C.: World Bank Publications.

Zhang, L., & Rashad, I. (2008). Obesity and time preference: The health consequences of discounting the future. *Journal of Biosocial Science, 40*(01), 97–113.