Research in Economics 76 (2022) 264–276

Contents lists available at ScienceDirect

Research in Economics

journal homepage: www.elsevier.com/locate/rie

The impact of health insurance on households' financial choices: Evidence from Vietnam

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A R T I C L E I N F O

Article history:
Received 9 February 2022
Accepted 15 July 2022
Available online 18 July 2022

JEL codes:
I13
G51
G52

Keywords:
Impact
Health insurance
Multivariate probit
Financial services

A B S T R A C T

This paper investigates the impact of health insurance on families' financial service choices in Vietnam using TVSEP data from three waves in 2013, 2016, and 2017. The endogeneity is handled via a recursive multivariate probit model. The findings indicate that while health insurance has no effect on private health insurance, it has a positive effect on savings and investments and a negative effect on credit choice. The multivariate probit model's results are robust to both the instrumental variable two-stage least squares model and the bivariate probit model. In addition, correlations between error components in financial service choice equations indicate a possible pattern of household financial usage. The results suggest that health insurance improves households' financial well-being. The implication of the findings is that when developing social security policies aimed at achieving universal health insurance, the influence of health insurance on household finances should not be underestimated.

1. Introduction

Many governments in low-and middle-income countries (LMICs) have implemented national health insurance reforms in recent years in order to move toward universal health coverage (Kutzin, 2012; Lagomarsino et al., 2012). In accordance with this, numerous studies on the effects of health insurance policies have been conducted. In line with the purpose of health insurance, which is to increase access and use, improve health status, and mitigate the financial consequences of ill health (Escobar et al., 2010), previous impact evaluation studies have primarily focused on outcomes such as utilization of health services, financial protection, and health status. For example, Erlangga et al. (2019) conducted a systematic review of 68 studies, 40 of which looked at utilization, 46 at out-of-pocket health spending and catastrophic health spending, and 12 at health status. And, more recently, all studies in the systematic reviews by Docrat et al. (2020) and Zhang et al. (2020) focused solely on the effects of insurance on health care utilization.

Health insurance enrollment is viewed as an ex-ante measure for individuals to mitigate the effects of future risks (Jorgensen & Siegel, 2019). It could thus be argued that households' participation in health insurance affects their choices of financial services both before and after risks occur. On the one hand, when members of a household have health insurance, it is likely that their choices of other ex-ante risk management instruments, such as savings and investments, will be influenced to some extent. We can imagine two opposing ways in which insurance take-up would impact savings and investments; for example, households may decrease them because they perceive a lower need for future medical costs, or

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https://doi.org/10.1016/j.rie.2022.07.005
1090-9443/

increase them because their current out-of-pocket payments on health care are reduced, allowing them to increase both other expenditures and savings at the same time (Kirdruang & Glewwe, 2018). On the other hand, when a household suffers an income shock, such as the death of an income-earning household member, demand for insurance and savings falls, while demand for ex-post instruments such as credit rises (Bendig et al., 2009). Therefore, it is conceivable that households' insurance status have an impact on other financial choices, and as such, studying the impact of health insurance in LMICs will only provide an incomplete picture if it focuses solely on outcomes such as utilization of health services, financial protection, and health status and ignores this area.

In reality, a number of studies have been conducted to confirm the impact of health insurance on household financial tools, with a small part of them coming from LMICs. In the United States, Gallagher et al. (2020) investigated the impact of Medicaid, a subsidized health insurance program, on savings behavior. The findings revealed significant heterogeneity in savings responses to Medicaid across households. Households that are not in financial distress save less through Medicaid. Medicaid eligibility, on the other hand, increases refund savings rates among households experiencing financial hardship. Besides, Bornstein & Indarte (2020) estimated the causal effect of expanded insurance on household debt by utilizing Medicaid's staggered expansions, and shown that Medicaid increased credit card borrowing. In Thailand, Kirdruang & Glewwe (2018) finds no decline in total household savings following the implementation of the Universal Health Coverage Scheme; however, the considerable increase in consumption of durables suggests a change in households' consumption-smoothing patterns, such that they spend more on goods with installment plans and thus save less for precautionary purposes. Kumar (2019) proved the positive impact of health insurance on life insurance in Finland. Most notably, Farrell et al. (2016) adopted a multivariate model to investigate the role of financial self-efficacy in explaining women's personal finance behavior in Australia. A system of six equations of financial products, including private health insurance, investments, mortgages, savings accounts, credit cards, and loans, were used in the model. Although the primary focus of the research was not on the relationship between financial products, the correlations between the error terms for each pair of equations were positive and statistically significant, implying that health insurance and financial products are supplementary to some extent.

When assessing the impact of health insurance, one important issue that previous research has generally overlooked is the interconnectedness of financial services. That is, in estimation strategies for drawing causal effects of health insurance, separate equations were typically used for each service choice (Bornstein & Indarte, 2020; Gallagher et al., 2020; Kirdruang & Glewwe, 2018). In practice, households may use a variety of financial services, some of which correlate with one another (Farrell et al., 2016; Giesbert et al., 2011; Viganò & Castellani, 2020). The correlations occurs when there are unobserved household-specific characteristics that influence several financial service decisions but are difficult to capture with measurable proxies (Belderbos et al., 2004). Hence, in the presence of correlations, estimates from separate equations of financial service choices are inefficient (Belderbos et al., 2004; Greene, 2012); additionally, these estimates do not tell the whole story of how health insurance affects financial tools in households' risk management basket.

Controlling for endogeneity is a task that researchers investigating the impact of health insurance coverage on financial service choice have to perform. Estimates will be biased if there are unobserved characteristics that affect both health insurance status and household financial service choice. A variety of strategies can be employed to control such unobserved characteristics. For instance, Gallagher et al. (2020), and Bornstein & Indarte (2020) utilized two-stage least-squares to account for the unobserved heterogeneity that jointly determine health insurance and financial choice. Kirdruang & Glewwe (2018) used the difference-in-difference method to account for endogeneity caused by unobserved characteristics that could bias the causal effect. In this study, we use a recursive multivariate probit model to circumvent endogeneity issues caused by unobserved heterogeneity.

The primary goal of this research is to determine the impact of health insurance on the choice of household financial services in Vietnam, including private insurance, savings, investments, and credit. This paper contributes to the current limited literature in a number of ways. First, it investigates the impact of health insurance on household financial choices, an area that is still unclear in Vietnam and in LMICs in general. Second, unlike previous research that disregarded the correlations between financial services, this research captures potential jointly determining processes by incorporating health insurance, private insurance, savings, investments, and credit simultaneously into a multivariate probit model that allows error terms to correlate. This method is expected to produce more efficient estimates and to provide a more comprehensive picture of the health insurance impact. Third, to the best of our knowledge, this is the first research of its kind to use an recursive multivariate probit model to control for endogeneity in assessing the impact of health insurance on household financial decisions.

This paper is structured as follows. The next section displays and examines the data utilized in the analysis, as well as the variables' descriptive statistics. Section three discusses the empirical approach adopted. The fourth section provides results from the multivariate probit model. The fifth section is the robustness checks. The conclusion is the last section.

2. Data and variables

2.1. Data source

This research is based on data from the Thailand-Vietnam Socioeconomic Panel (TVSEP) project. The project's goal is to investigate and compare long-term development dynamics in these emerging economies, such as agricultural production and rural–urban migration (Nguyen et al., 2019). Since 2007, the TVSEP project has conducted regular surveys among

Table 1
Definitions of dependent variables.

Variables	Definitions
Health insurance	Dummy variable, 1 if household had government or private health insurance over the past 12 months, 0 otherwise
Private insurance	Dummy variable, 1 if household had insurance from private companies (life insurance, property insurance, disability health insurance, livestock insurance, crop insurance, funeral insurance, accident insurance and others) over the past 12 months, 0 otherwise
Savings	Dummy variable, 1 if household saved parts of their income over the past 12 months, 0 otherwise
Credit	Dummy variable, 1 if household had loans over the past 12 months, 0 otherwise
Investments	Dummy variable, 1 if household invested in durable goods over the past 12 months, 0 otherwise

rural households in Thailand and Vietnam. Thai data was collected in the provinces of Buriram, Nakhon Panom, and Ubon Ratchathani, while Vietnamese data was collected in the provinces of Thua Thien Hue, Ha Tinh, and Dak Lak. The data was gathered using a three-stage cluster sampling procedure, with the primary sampling units being sub-districts (Gloede et al., 2015; Priebe et al., 2017). The information in the data is rich in terms of household backgrounds and various financial behaviors, including insurance, savings, investments, and credit. The data is representative of rural households in Thailand and Vietnam (Liebenehm et al., 2018). We use data from three waves, in 2013, 2016, and 2017, but limit our sample to Vietnamese households that supply the relevant information. As a consequence, an unbalanced panel dataset comprising 5,701 observations from 2,052 households is constructed, in which 116 households appear just once, 223 households appear twice, and 1,713 households appear three times.

2.2. Variable definitions and descriptive statistics

In the estimations below, we include five dependent variables. The status of health insurance is the most important dependent variable. It is a binary indicator that denotes whether a family is covered by either government or private health insurance, but not by the government's free health card. Four financial service choices are also dependent variables. These variables indicate whether households used private insurance, savings, investments, or credit in the previous year. Assuming that household characteristics influence the likelihood of obtaining financial services, the vector of control variables in our analysis contains a range of socio-demographic factors. Among the important covariates is risk attitude. We elicit respondents' risk attitudes through a survey question that asks them to rate their overall willingness to take risks on an eleven-point Likert scale, as described by (Dohmen et al., 2011). All monetary values in this paper are converted to Purchasing Power Parity USD equivalents in 2007. Variables are defined in Tables 1 and 2.

Table 3 provides summaries of the statistical data for variables. In terms of dependent variables, 54% of families had health insurance, 61% had private insurance, 41% saved a portion of their income, 44% invested, and 67% had credit. The average risk attitude score was 6, which indicates some degree of risk-taking. Respondents who resided in households with health insurance had an average score of 6.20, compared to 5.77 for those who lived in households without health insurance. The characteristics of household heads show that the average age of heads is 54.98 years, that 80% of heads are men, that 81% were married, that 79% were from the Kinh group, and that the average number of years of schooling was 6.45 years. Regarding households' characteristics, on average, each household had 5.32 members. The average asset value was 19,400 USD, while the average remittance received by households in the previous 12 months was 8,600 USD. There were an average of 1.16 people in each family who had a serious illness or injury, 2.22 people who joined a sociopolitical group, and 1.26 who worked for a wage. In respect of shocks, 49% of households reported experiencing natural shocks, 47% economic shocks, 14% crime shocks, and 9% social shocks. The mean percentage of families in districts with government health insurance was 49%.

Pairwise correlations between dependent variables are presented in Table 4. Correlations are computed using tetrachoric coefficients for couples of dichotomous variables. The coefficients between pairs of financial decisions are statistically significant, implying a potential pattern of financial service usage. And notably, health insurance correlates positively with private insurance, savings, and investments but negatively with credit, suggesting that health insurance may have an effect on these services. However, these correlations are not interpreted as conclusive evidence of health insurance's causal effect on financial choices. Indeed, there are several possible explanations for the correlations. One rationale is that risk-averse households acquire more insurance (both health and private), save and invest more, yet have less credit. In this context, positive correlations between health insurance and private insurance, savings, and investments, and negative correlations between health insurance and credit, should be seen, even if health insurance has no effect on financial choices.

3. Hypotheses and methods

3.1. Research hypotheses

Households' decision to choose health insurance is dependent on their choice of other types of insurance, such as life insurance, crop insurance, or property insurance. In terms of minimizing the consequences of future risks, private insurance

Table 2
Definitions of control variables.

Variables	Definitions
Age	Age of household head
Age squared	Squared age of household head
Gender	Dummy variable, 1 if gender of household head is male, 0 otherwise
Marital status	Dummy variable, 1 if household head is married, 0 otherwise
Education	Years of schooling of household head
Ethnicity	Dummy variable, 1 if ethnicity of the household head is King group, 0 otherwise
Household size	Number of household members
Asset (10,000USD-PPP)	The value of assets owned by household
Remittance (10,000USD-PPP)	Value of remittances received by household over the past 12 months
Coverage rate	The fraction of household enrollment in government health insurance in the district in which the household resides.
Risk attitude	How willing the respondent is to take risks in general (on a scale of 0 to 10)
Health status	The number of household members who have suffered from a serious illness or injury over the last 12 months
Wage-employee	Number of household members who worked as wage-employees over the last 12 months
Natural shock	Dummy variable, 1 if household experienced natural shocks over the past 12 months, 0 otherwise. Natural shocks comprise house damage, flooding of agricultural land, drought, pests and livestock diseases, landslides, erosion, storms, flooding on the house/homestead.
Social shock	Dummy variable, 1 if household experienced social shocks over the past 12 months, 0 otherwise. Social shocks include having to spend money on a ceremony and having conflict with village neighbors.
Economic shock	Dummy variable, 1 if household experienced economic shocks over the past 12 months, 0 otherwise. Economic shocks involve illness of household member, household member left the household, accident, being cheated at work/business, job loss, collapse of business, strong decrease of prices for output, strong increase of prices for input.
Crime shock	Dummy variable, 1 if household experienced crime shocks over the past 12 months, 0 otherwise. Crime shocks include theft of transportation (car, motorcycle, bicycle), theft of livestock, theft of crops or agricultural products, theft of other items, burglary, robbery, vandalism.
Member of social groups	Number of people in a household who are members of a sociopolitical organization
Wave 2013	Dummy variable, 1 if year 2013, 0 otherwise
Wave 2016	Dummy variable, 1 if year 2016, 0 otherwise
Wave 2017	Dummy variable, 1 if year 2017, 0 otherwise

and health insurance serve the same function as satisfying the same need for households. They are thus referred to as substitutes (Aaker & Keller, 1990). However, Kumar (2019) showed that health and life insurance, two financial risk-managing goods, are complements as health insurance and life insurance choice are positively correlated in Finland. In the Vietnamese context, we conjecture that health insurance and other insurance choices can be complemented if decision-makers understand insurance. Taking all these together, based on previous studies, we propose the following hypothesis:

Hypothesis I. : Health insurance positively affects private insurance

Savings can be considered as a form of self-insurance that households can utilize to insure against health shocks in the future. Health insurance purchases, therefore, may lead to lower savings, especially for precautionary savings. On the other hand, access to health insurance may reduce out-of-pocket health care payments and thus increase savings as well as investments. Gallagher et al. (2020) found mixed results, i.e., the sign of a relationship depends on whether the household experienced financial hardship or not. In the Vietnamese context, we tend to think that health insurance has a positive effect on both investments and savings. This is because health insurance helps lower the direct out-of-pocket costs of health care for Vietnamese households, which have always been high, making up 50–70% of total health care costs (Van Minh et al., 2013). Therefore, this gives households a chance to invest and save simultaneously.

Hypothesis II. : Health insurance has a positive impact on savings

Hypothesis III. : Health insurance has a positive impact on investments

Health insurance access can mitigate the financial impact of adverse events and thus help households avoid default, raising credit demand as well as supply via higher lenders' expected returns. This positive relationship has been confirmed by empirical studies in developed countries such as Gallagher et al. (2020) and Bornstein & Indarte (2020). However, in the context of Vietnam, health insurance often leads to a reduction in out-of-pocket costs of health care, which in turn may help households avoid borrowing. Therefore, we propose a hypothesis as follows:

Hypothesis IV. : Health insurance has a negative impact on credit choice

3.2. Research methods

One major issue when examining the causal effect of health insurance on family financial choices is the possibility of estimation bias due to reverse causality. For example, health insurance helps families decrease their out-of-pocket expenses;

Table 3
Descriptive statistics of variables (mean, standard deviation).

Variable	Full sample		Insured by health insurance		Uninsured by health insurance	
Health insurance	0.54	(0.50)	1.00	(0.00)	0.00	(0.00)
Private insurance	0.61	(0.49)	0.71	(0.45)	0.50	(0.50)
Savings	0.41	(0.49)	0.48	(0.50)	0.33	(0.47)
Investments	0.44	(0.50)	0.51	(0.50)	0.36	(0.48)
Credit	0.67	(0.47)	0.65	(0.48)	0.69	(0.46)
Risk attitude	6.00	(2.51)	6.20	(2.48)	5.77	(2.53)
Gender	0.80	(0.40)	0.84	(0.37)	0.75	(0.43)
Age	54.98	(13.01)	54.07	(11.56)	56.05	(14.45)
Marital status	0.81	(0.39)	0.85	(0.36)	0.76	(0.43)
Ethnicity	0.79	(0.41)	0.92	(0.27)	0.65	(0.48)
Education	6.45	(4.34)	7.19	(4.48)	5.59	(4.00)
Health status	1.16	(1.14)	1.06	(1.08)	1.28	(1.19)
Household size	5.32	(2.10)	5.38	(1.90)	5.25	(2.30)
Asset (10,000USD-PPP)	1.94	(52.85)	2.89	(69.94)	0.83	(18.69)
Remittance (10,000USD-PPP)	0.86	(3.19)	0.99	(3.84)	0.70	(2.19)
Member of social groups	2.22	(1.58)	2.45	(1.62)	1.95	(1.49)
Wage-employee	1.26	(1.18)	1.37	(1.18)	1.13	(1.16)
Natural shock	0.49	(0.50)	0.44	(0.50)	0.54	(0.50)
Social shock	0.09	(0.28)	0.08	(0.27)	0.09	(0.29)
Economic shock	0.47	(0.50)	0.46	(0.50)	0.49	(0.50)
Crime shock	0.14	(0.35)	0.13	(0.34)	0.16	(0.36)
Coverage rate	0.49	(0.21)	0.56	(0.20)	0.40	(0.17)
Wave 2013	0.34	(0.47)	0.33	(0.47)	0.37	(0.48)
Wave 2016	0.33	(0.47)	0.28	(0.45)	0.38	(0.48)
Wave 2017	0.33	(0.47)	0.39	(0.49)	0.26	(0.44)

Table 4
Pairwise tetrachoric correlations between dependent variables.

	Health insurance	Private insurance	Savings	Investments	Credit
Health insurance	1.0000				
Private insurance	0.3332 (0.0000)	1.0000			
Savings	0.2456 (0.0000)	0.2479 (0.0000)	1.0000		
Investments	0.2321 (0.0000)	0.2074 (0.0000)	0.1167 (0.0000)	1.0000	
Credit	-0.0600 (0.0057)	0.1512 (0.0000)	-0.2532 (0.0000)	0.0700 (0.0012)	1.0000

Note: P-values are reported in parentheses.

hence, households with health insurance may have greater opportunities to save and invest, but less access to credit. On the other hand, families with substantial savings and investments but few borrowings may feel secure in purchasing less insurance. To address the issue of endogeneity, following Stanciole (2008), we apply a recursive multivariate probit model using a pooled cross-sectional dataset of three-wave TVSEP surveys. This model jointly estimates a system of probits and allows for residual correlation. An extra benefit of using a multivariate probit model is that correlation coefficients between the residuals of the system's equations can give some clues about how financial services are related to each other.

The model in this study is a recursive five-equation system with a reduced equation for health insurance coverage and structural form equations for each of the four financial service choices: private insurance, savings, investments, and credit. Health insurance is included as an explanatory variable in the financial service equations, and the error terms in each equation are allowed to be freely correlated. Let $Y_{h,1,2,3,4i} = \{Y_{hi}, Y_{1i}, Y_{2i}, Y_{3i}, Y_{4i}\}$ denote to a vector of five dummies representing, in that order, health insurance, private insurance, savings, investments, and credit.

$$Y^*_{hi} = \beta_h X'_i + \gamma_h R_i + \varepsilon_{hi} \tag{1}$$

$$Y^*_{1i} = \alpha_1 Y_{hi} + \beta_1 X'_i + \varepsilon_{1i} \tag{2}$$

$$Y^*_{2i} = \alpha_2 Y_{hi} + \beta_2 X'_i + \varepsilon_{2i} \tag{3}$$

$$Y^*_{3i} = \alpha_3 Y_{hi} + \beta_3 X'_i + \varepsilon_{3i} \tag{4}$$

$$Y^*_{4i} = \alpha_4 Y_{hi} + \beta_4 X'_i + \varepsilon_{4i} \tag{5}$$

$$Y_{hi} = \begin{cases} 1, & if\ \ Y^*_{hi} > 0 \\ 0, & if\ \ Y^*_{hi} \le 0 \end{cases}$$

$$Y_{1,2,3,4i} = \begin{cases} 1, & if\ Y^*_{1,2,3,4i} > 0 \\ 0, & if\ Y^*_{1,2,3,4i} \leq 0 \end{cases}$$

X'_i is a vector of exogenous variables that is identical in all five equations. R_i is an instrumental variable (IV) which is the government health insurance coverage rate in a district. The error terms $\varepsilon_{hi},\ \varepsilon_{1i}, \varepsilon_{2i},\ \varepsilon_{3i}$, and ε_{4i} follow a multivariate normal distribution, each with a mean of zero, and variance–covariance matrix with values of 1 on the leading diagonal and correlations ρ_{jk} as off-diagonal elements (Cappellari & Jenkins, 2003). The correlation coefficients ρ_{jk} represent the correlation between the error terms in the equations due to omited factors (Greene, 2012, p.747). If equations from (1) to (5) are estimated separately, ignoring the unobserved heterogeneity and assuming that the error terms are uncorrelated ($\rho_{jk} \neq\ 0$ for all $j \neq k$), the estimates for the effect of insurance on financial choices are biased (Stanciole, 2008). However, if $\varepsilon_{hi},\ \varepsilon_{1i}, \varepsilon_{2i},\ \varepsilon_{3i}$, and ε_{4i} are mutually independent ($\rho_{jk} =\ 0$ for all $j \neq k$), the multivariate model's estimate results are identical to those of single equations.

$$\begin{pmatrix} \varepsilon_{hi} \\ \varepsilon_{1i} \\ \varepsilon_{2i} \\ \varepsilon_{3i} \\ \varepsilon_{4i} \end{pmatrix} \sim N(0, \Sigma),\ \text{of which,}\ \ \Sigma = \begin{pmatrix} 1 & & & & \\ \rho_{1h} & 1 & & & \\ \rho_{2h} & \rho_{21} & 1 & & \\ \rho_{3h} & \rho_{32} & \rho_{32} & 1 & \\ \rho_{4h} & \rho_{42} & \rho_{42} & \rho_{43} & 1 \end{pmatrix}$$

The multivariate probit model was estimated using a simulated maximum likelihood method that employs the Geweke–Hajivassiliou–Keane smooth recursive conditioning simulator to evaluate multivariate normal probabilities. This method's detailed algorithm can be found in (Cappellari & Jenkins, 2003; Greene, 2012, p.627-29). The simulated maximum likelihood estimator is consistent as the number of draws and observations approaches infinity. According to Cappellari & Jenkins (2003), when the number of draws is increased in proportion to the sample size, simulation bias is reduced to negligible levels, and the number of draws must be at least equal to the square root of the sample size. This rule is followed in this paper to improve the stability of the estimated coefficients.

Identification of a recursive multivariate probit model has long been a source of debate in the literature. Maddala (1983) contended that in the absence of exclusion restrictions, the parameters of the structural equation are not identified, and that at least one covariate must be present in the reduced form equation but not in the structural equations. These covariates are known as IVs because, in this study's context, they have no direct impact on the financial choices and do not correlate with error terms (Chib & Greenberg, 2007). Nevertheless, Wilde (2000) argued that in recursive bivariate probit models, identification can be achieved even when the same exogenous variables appear in both equations, and that additional IVs in the reduced form equation are not required. According to Wilde (2000), if the data is sufficiently varied, no exclusion restrictions for the exogenous variables are required for identification in multivariate probit.

This research follows the exclusion restriction approach by including an IV (R_i) in the health insurance equation. Although, in Wilde's view, this task is unnecessary, an IV will aid in increasing the power of parameter identification (Chen et al., 2014). An IV must satisfy two assumptions in order to be considered valid: (1) it must be correlated with the treatment; and (2) it must not have a direct impact on the outcome (exclusion restriction) (Greene, 2012). In this study, we choose to use the district's coverage rate of government health insurance as an IV. This choice is supported by two arguments. To begin with, households who live in districts with a higher coverage rate are more likely to enroll in insurance. Second, while the coverage rate of government health insurance in a district is related to whether a household has insurance, it has no effect on household financial choices, including private insurance, savings, investments, and credit. In this study, we also estimate univariate probit results for comparison with multivariate probit results.

3.2.1. Empirical strategy for robustness checks

To test the robustness of the coefficients in the multivariate probit model, we treat the data set as a panel data set. We examine the effect of health insurance on private insurance, savings, investments, and credit using an IV two-stage least-squares model that ignores the binary nature of treatment and outcome variables as well as their interconnectedness. Thus, we adopt the model:

$$Y_{hit} = \pi_0 + \theta_h X'_{it} + \ \varphi_h R_{it} + \varepsilon_{hit} \tag{6}$$

$$Y_{1it} = \lambda_0 + \omega_1 \hat{Y}_{hit} + \theta_1 X'_{it} + \varepsilon_{1it} \tag{7}$$

$$Y_{2it} = \lambda_0 + \omega_2 \hat{Y}_{hit} + \theta_2 X'_{it} + \varepsilon_{2it} \tag{8}$$

$$Y_{3it} = \lambda_0 + \omega_3 \hat{Y}_{hit} + \theta_3 X'_{it} + \varepsilon_{3it} \tag{9}$$

$$Y_{4it} = \lambda_0 + \omega_4 \hat{Y}_{hit} + \theta_4 X'_{it} + \varepsilon_{4it} \tag{10}$$

Where Y_{hit} is health insurance status of household i at time t, X′ denotes a vector of exogenous variables. R is the IV, which is the district's coverage rate of government health insurance. $Y_{1,2,3,4it} = \{Y_{1it}, Y_{2it}, Y_{3it}, Y_{4it}\}$ is a vector of four dummies representing, in that order, private insurance, savings, investments, and credit of household i at time t. In the first stage, the IV and all covariates are regressed on health insurance status, equation (6), and then the predicted health insurance status replaces health insurance in the second stage, equations (7), (8), (9), and (10).

In sociology, the two common models for panel data are fixed-and random-effects models (Bollen & Brand, 2010). The fixed-effects model has been widely recognized as a powerful tool for controlling unobserved time-invariant heterogeneity (Hill et al., 2020; Vaisey & Miles, 2017). However, fixed-effects methods are incapable of estimating coefficients for variables that do not vary within subjects (Allison, 2009) and perform poorly when attempting to predict a variable from a near constant (Treiman, 2009). In these cases, the random-effects model will produce better estimates (Clark & Linzer, 2015). Because some covariates in this study, such as ethnicity, gender, marital status, and family background, remain constant (Hill et al., 2020; Vaisey & Miles, 2017) or change little over time, the random-effects method is used. With random-effects, error terms ε_{it} are assumed to be uncorrelated with any covariates in the model (Greene, 2012).

As another robustness check, this research estimates recursive bivariate probit regressions for each pair of insurance and financial choices. The structure of the bivariate probit is similar to that of the multivariate probit, but there are only two equations in a system (Greene, 2012; Stanciole, 2008). Bivariate probit, unlike multivariate probit, does not rely on a simulation-based method and can thus be used to test the robustness of multivariate coefficients (Stanciole, 2008).

4. Results

Coefficients from multivariate regressions are shown in Table 6. To assure the stability of computed coefficients, we set the simulation process to 150 draws, which is nearly twice the square root of our sample of 5,701 observations.

4.1. Impacts of covariates

Table 6 shows a positive and statistically significant coverage rate coefficient, indicating that the percentage of homes covered by government health insurance in a district is positively connected with the chance of a household getting health insurance in that district. Risk attitude has a positive correlation with savings, investments, and credit. Surprisingly, risk attitude is positively related to two forms of insurance, which seems to contradict the expectation that risk-averse families would purchase more insurance, but is consistent with findings from Farrell et al. (2016), Giesbert et al. (2011), and Giné et al. (2008). A likely interpretation of this finding is that there exist other variables' impacts that overshadow the risk aversion impact in deciding whether to acquire insurance.

With reference to household heads' characteristics, male-headed families are less likely to have credit than female-headed households. Households with an older head have a larger likelihood of purchasing private insurance; however, the negative coefficients of age squared suggest that this likelihood declines at a certain age. Married heads of household have a positive association with private insurance. In comparison to families headed by members of ethnic minorities, households headed by members of the King majority were more likely to have health insurance. This is consistent with the Vietnamese context, in which ethnic minority families get more free health cards than Kinh majority homes (The National Assembly of Vietnam, 2008), and thus ethnic households are less inclined to purchase health insurance at a price. Furthermore, Kinh households have a greater likelihood of investing than ethnic minority families. This may be because Kinh families often earn more money than minority households. The number of school years spent by household heads is positively associated with the chance of the household purchasing insurance, saving, and investing.

Regarding households' characteristics, interestingly, insurance is adversely connected with the health status of family members. These relationships stand in stark contrast to the adverse selection theory that poor health households acquire more insurance than healthy families (Doiron et al., 2008). However, when looking at the positive coefficients of the health status variable in the equation credit, perhaps there is a pattern in how families react to financial risks in which they increase credit in order to cope with risks rather than purchasing insurance. Households with a greater number of members are more likely to purchase insurance, invest, and utilize credit than households with fewer members. Asset value is positively correlated with health insurance but negatively correlated with investments. Families who receive a greater amount of remittance are more likely to save and invest. The number of members of sociopolitical organizations contributes to the likelihood of obtaining insurance, investing, and credit. Households with more wage earners had a higher probability of purchasing insurance and obtaining credit, but a lower probability of saving. In terms of shocks, natural shocks reduce the likelihood of having health insurance and savings, but raise the likelihood of investing and obtaining credit. Social shocks decrease both the propensity to get private insurance and to save. Households that have been subjected to economic shocks tend to purchase less insurance and save less, but have more credit. Crime shocks have a negative relationship with savings but a positive relationship with credit.

4.2. Impact of health insurance on financial choices

Let us start with the estimated coefficients from the univariate probit regressions. Table 5 contains coefficients estimated using five distinct and independent univariate probit models. As can be noticed, health insurance significantly affects each

Table 5
Univariate probit coefficients.

	Health insurance (1)	Private insurance (2)	Savings (3)	Investments (4)	Credit (5)
Health insurance		0.3778***	0.3108***	0.1558***	-0.0983**
		(0.0476)	(0.0416)	(0.0392)	(0.0501)
Coverage rate	2.6271***				
	(0.2094)				
Risk attitude	0.0274***	0.0556***	0.0357***	0.0182**	0.0177**
	(0.0092)	(0.0070)	(0.0073)	(0.0071)	(0.0077)
Gender	0.1825**	-0.0240	0.0983	0.0719	-0.2554***
	(0.0793)	(0.0853)	(0.0796)	(0.0772)	(0.0929)
Age	0.0116	0.0386***	-0.0014	0.0171	0.0123
	(0.0135)	(0.0144)	(0.0117)	(0.0106)	(0.0139)
Age squared	-0.0002**	-0.0005***	-0.0000	-0.0002**	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Marital status	-0.0096	0.1767**	0.0752	-0.0017	0.0890
	(0.0836)	(0.0839)	(0.0791)	(0.0692)	(0.0932)
Ethnicity	0.7952***	0.1908**	0.2376***	0.2060***	-0.3476***
	(0.0973)	(0.0959)	(0.0786)	(0.0563)	(0.0826)
Education	0.0328***	0.0307***	0.0178***	0.0136**	-0.0017
	(0.0075)	(0.0100)	(0.0057)	(0.0054)	(0.0061)
Health status	-0.0579***	-0.0381**	-0.0099	-0.0285*	0.1564***
	(0.0199)	(0.0193)	(0.0177)	(0.0168)	(0.0196)
Household size	0.0506***	0.0842***	-0.0084	0.0300***	0.0621***
	(0.0133)	(0.0116)	(0.0113)	(0.0104)	(0.0125)
Asset 10,000USD-PPP	0.0009*	0.0190*	0.0003	-0.0005	-0.0002
	(0.0005)	(0.0114)	(0.0003)	(0.0003)	(0.0003)
Remittance 10,000USD-PPP	0.0031	0.0013	0.0356***	0.0408***	-0.0070
	(0.0071)	(0.0064)	(0.0075)	(0.0081)	(0.0056)
Member of social groups	0.0721***	0.0346**	0.0172	0.0666***	0.0659***
	(0.0145)	(0.0152)	(0.0134)	(0.0134)	(0.0146)
Wage-employee	0.0461**	0.0271	-0.0354**	0.0096	0.0579***
	(0.0213)	(0.0214)	(0.0168)	(0.0160)	(0.0192)
Natural shock	-0.1362***	-0.0024	-0.1650***	0.0781**	0.2634***
	(0.0400)	(0.0413)	(0.0382)	(0.0339)	(0.0420)
Social shock	-0.0948	-0.1522**	-0.1060*	0.0988	-0.0602
	(0.0671)	(0.0672)	(0.0599)	(0.0649)	(0.0717)
Economic shock	-0.0273	-0.0931**	-0.0921***	0.0345	0.2066***
	(0.0407)	(0.0402)	(0.0333)	(0.0358)	(0.0398)
Crime shock	0.0351	-0.0493	-0.1661***	0.0693	0.2146***
	(0.0621)	(0.0524)	(0.0496)	(0.0512)	(0.0562)
Wave (reference group: 2013)					
Wave 2016	-0.2578***	0.1606***	0.4182***	0.2236***	-0.1094**
	(0.0570)	(0.0420)	(0.0541)	(0.0448)	(0.0445)
Wave 2017	-0.0563	-0.1126**	-0.1075*	0.8140***	-0.0541
	(0.0672)	(0.0509)	(0.0554)	(0.0508)	(0.0521)
Constant	-2.4732***	-1.7393***	-0.8452***	-1.6671***	0.3102
	(0.3630)	(0.3832)	(0.3136)	(0.2861)	(0.3966)
Number of observations	5701	5701	5701	5701	5701
Number of clusters	110	110	110	110	110

Note: Robust standard errors are clustered by subdistrict and reported in parentheses. Significance levels: * < 10% ** < 5% *** < 1%.

of the four financial alternatives. These findings, however, may be biased due to the fact that univariate probit models do not account for unobserved heterogeneity. As with the univariate probit model, the multivariate probit model in Table 6 demonstrates that health insurance has statistically significant effects on savings, investments, and credit. However, unlike the univariate probit model, multivariate probit does not show an effect of health insurance on private insurance. This may be explained by examining the estimated correlations between paired choices of financial services. These correlations imply that unobserved factors jointly influence each pair of choices, but univariate probit models overlook these effects, resulting in a statistically significant effect of health insurance on private insurance.

The sign of the coefficients in the multivariate probit model indicates that enrolling in health insurance increases families' probability of saving and investing, but decreases their probability of gaining further credit. This is most likely because health insurance enables families to reduce out-of-pocket expenditures (Erlangga et al., 2019), allowing them to improve their financial status and therefore increase the possibility that they would save and invest a portion of their income while borrowing less. And, it can be inferred that health insurance helps households improve their financial well-being and should be regarded as a supplement to a family's overall financial strategy. The results imply that social security policies aimed at

Table 6
Multivariate probit coefficients.

	Health insurance (1)	Private insurance (2)	Savings (3)	Investments (4)	Credit (5)
Health insurance		0.2943	0.6481***	0.2191*	-0.6150***
		(0.2116)	(0.1231)	(0.1178)	(0.1760)
Coverage rate	2.6166***				
	(0.2086)				
Risk attitude	0.0262***	0.0558***	0.0336***	0.0182**	0.0202***
	(0.0092)	(0.0071)	(0.0074)	(0.0072)	(0.0075)
Gender	0.1801**	-0.0206	0.0785	0.0701	-0.2189**
	(0.0800)	(0.0875)	(0.0793)	(0.0770)	(0.0897)
Age	0.0122	0.0395***	-0.0034	0.0171	0.0135
	(0.0136)	(0.0146)	(0.0116)	(0.0105)	(0.0142)
Age squared	-0.0002**	-0.0005***	0.0000	-0.0002**	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Marital status	-0.0103	0.1799**	0.0721	-0.0034	0.0957
	(0.0838)	(0.0846)	(0.0785)	(0.0697)	(0.0886)
Ethnicity	0.7949***	0.2261	0.0914	0.1782**	-0.1150
	(0.0971)	(0.1434)	(0.0940)	(0.0784)	(0.1005)
Education	0.0328***	0.0311***	0.0162***	0.0136**	0.0009
	(0.0075)	(0.0098)	(0.0055)	(0.0053)	(0.0061)
Health status	-0.0578***	-0.0396**	-0.0017	-0.0270	0.1394***
	(0.0199)	(0.0188)	(0.0178)	(0.0170)	(0.0210)
Household size	0.0487***	0.0861***	-0.0151	0.0287***	0.0712***
	(0.0135)	(0.0119)	(0.0115)	(0.0109)	(0.0125)
Asset 10,000USD-PPP	0.0009**	0.0153	0.0002	-0.0005*	-0.0002
	(0.0005)	(0.0096)	(0.0003)	(0.0003)	(0.0003)
Remittance 10,000USD-PPP	0.0020	0.0014	0.0345***	0.0403***	-0.0055
	(0.0065)	(0.0064)	(0.0073)	(0.0080)	(0.0054)
Member of social groups	0.0726***	0.0357**	0.0102	0.0653***	0.0730***
	(0.0145)	(0.0159)	(0.0137)	(0.0133)	(0.0149)
Wage-employee	0.0435**	0.0280	-0.0424**	0.0081	0.0678***
	(0.0212)	(0.0216)	(0.0169)	(0.0159)	(0.0184)
Natural shock	-0.1376***	-0.0079	-0.1427***	0.0817**	0.2246***
	(0.0403)	(0.0404)	(0.0375)	(0.0345)	(0.0430)
Social shock	-0.0934	-0.1525**	-0.1035*	0.0998	-0.0636
	(0.0675)	(0.0669)	(0.0604)	(0.0646)	(0.0718)
Economic shock	-0.0274	-0.0922**	-0.0940***	0.0352	0.2023***
	(0.0409)	(0.0398)	(0.0344)	(0.0358)	(0.0399)
Crime shock	0.0339	-0.0528	-0.1602***	0.0700	0.1994***
	(0.0627)	(0.0523)	(0.0497)	(0.0510)	(0.0547)
Wave 2016	-0.2514***	0.1606***	0.4260***	0.2255***	-0.1380***
	(0.0565)	(0.0413)	(0.0547)	(0.0459)	(0.0454)
Wave 2017	-0.0572	-0.0959	-0.1571***	0.8044***	0.0236
	(0.0663)	(0.0630)	(0.0596)	(0.0540)	(0.0610)
Constant	-2.4688***	-1.7568***	-0.8046***	-1.6737***	0.2816
	(0.3655)	(0.3868)	(0.3110)	(0.2840)	(0.3971)
Number of observations	5701	5701	5701	5701	5701
Number of clusters	110	110	110	110	110
Number of draws	150	150	150	150	150

Note: Robust standard errors are clustered by subdistrict and reported in parentheses; significance levels: * < 10% ** < 5% *** < 1%.

expanding health insurance coverage have effects on family finances. These effects should not be overlooked when designing health insurance schemes.

4.3. Correlations between the error terms

Auxiliary results of a multivariate probit model are the correlation coefficients (ρ) between error terms, which reflect the influence of unobserved confounders. Hence, it is necessary to concentrate on correlation coefficients in Table 7 to understand the effect of unobserved variables on health insurance and four financial service choices in detail. The values of $\chi^2 = 253.929$ and p $=$ 0.0000 allow for the rejection of the hypothesis that the correlations between the error terms of equations are zero; hence, it is more appropriate to jointly estimate the likelihood of each financial choice using a set of equations rather than individual equations. A majority of the correlation coefficients are statistically significant. This may reflect a pattern of household financial service choices. To be specific, positive correlations exist between error terms of financial service equations such as private insurance and savings, private insurance and investments, savings and investments, and investments and credit. Such correlations reveal a degree of supplementary between these financial services. Error terms

Table 7
Correlation between error terms in multivariate probit regressions.

	Health insurance	Private insurance	Savings	Investments
Private insurance	0.0551 (0.1299)			
Savings	-0.2255*** (0.0703)	0.1337*** (0.0337)		
Investments	-0.414 (0.0727)	0.1408*** (0.0243)	0.0860*** (0.0263)	
Credit	0.3472*** (0.1092)	0.0510 (0.0329)	-0.2846*** (0.0257)	0.0518* (0.0303)

Note: $\chi^2(10\ \text{df}) = 253.929$; Prob $> \chi^2 = 0.0000$; standard errors are reported in parentheses; significance levels: *< 10% **< 5% ***< 1%.

Table 8
IV random-effects two-stage least-squares regressions.

	Private insurance (1)	Savings (2)	Investments (3)	Credit (4)
Health insurance	-0.0200 (0.0529)	0.1014* (0.0544)	0.4245*** (0.0580)	-0.1500*** (0.0526)
Risk attitude	0.0153*** (0.0021)	0.0127*** (0.0027)	0.0066** (0.0028)	0.0032 (0.0022)
Gender	0.0015 (0.0287)	0.0383 (0.0296)	0.0122 (0.0277)	-0.0546* (0.0283)
Age	0.0128*** (0.0045)	-0.0011 (0.0040)	0.0109*** (0.0038)	0.0073* (0.0043)
Age squared	-0.0002*** (0.0000)	-0.0000 (0.0000)	-0.0001*** (0.0000)	-0.0001*** (0.0000)
Marital status	0.0725*** (0.0275)	0.0163 (0.0288)	-0.0076 (0.0273)	0.0244 (0.0281)
Ethnicity	0.1461*** (0.0441)	0.1086*** (0.0355)	-0.1015*** (0.0351)	-0.0611** (0.0286)
Education	0.0107*** (0.0033)	0.0068*** (0.0023)	0.0032 (0.0021)	0.0007 (0.0021)
Health status	-0.0135** (0.0064)	0.0002 (0.0064)	0.0049 (0.0067)	0.0313*** (0.0050)
Household size	0.0348*** (0.0036)	0.0092** (0.0039)	-0.0119*** (0.0041)	0.0179*** (0.0033)
Asset 10,000USD-PPP	0.0001** (0.0000)	0.0001 (0.0001)	-0.0002***(0.0001)	0.0000 (0.0001)
Remittance 10,000USD-PPP	0.0005 (0.0017)	0.0086*** (0.0024)	0.0133*** (0.0047)	-0.0015 (0.0014)
Member of social groups	0.0098** (0.0048)	-0.0017 (0.0051)	0.0169*** (0.0053)	0.0252*** (0.0043)
Wage-employee	0.0129** (0.0065)	-0.0120* (0.0063)	0.0078 (0.0061)	0.0170*** (0.0054)
Natural shock	-0.0012 (0.0131)	-0.0502*** (0.0140)	0.0272** (0.0131)	0.0595*** (0.0126)
Social shock	-0.0251 (0.0219)	-0.0268 (0.0222)	0.0131 (0.0246)	-0.0203 (0.0201)
Economic shock	-0.0245** (0.0118)	-0.0200 (0.0123)	-0.0078 (0.0132)	0.0554*** (0.0114)
Crime shock	-0.0092 (0.0161)	-0.0217 (0.0179)	0.0282 (0.0196)	0.0395*** (0.0144)
Constant	-0.0735 (0.1259)	0.1702 (0.1063)	-0.0828 (0.1030)	0.5726*** (0.1143)
Number of observations	5701	5701	5701	5701
Number of clusters	110	110	110	110

Note: Robust standard errors are clustered by subdistrict and reported in parentheses; significance levels: *< 10% **< 5% *** < 1%.

in savings and credit equations have a negative correlation, meaning that the two are considered to be substitutes to some degree.

The first column in Table 7 depicts the correlations between error terms in health insurance and those in the other four equations. We see a positive correlation between the residuals in the health insurance and credit equations. This correlation, however, does not represent the positive relationship between health insurance and credit (Filippini et al., 2018); rather, it implies the presence of unobserved factors impacting both health insurance and credit in the same direction. Such a correlation is subsumed into the coefficient α_4 (-0.6150) in column 5 of Table 6. There is a strong and negative correlation between residuals in health insurance and savings equations. Similarly, this is not an indicator concluding that health insurance has a negative effect on savings, but rather one showing that an unobserved variable has an opposing effect on the two choices.

5. Robustness checks

In this part, we will test the robustness of the multivariate probit model's coefficients using two distinct methodologies. In the first, two-stage least-squares random-effects regressions are done, treating the dataset as a panel dataset. As aforementioned, we utilize the coverage rate of government insurance in a district as an IV for health insurance status to account for endogeneity caused by unobserved heterogeneity. Table 8 summarizes the findings from the IV two-stage least-squares random-effects regressions. As can be seen, the two-stage least-squares random-effects technique replicates the multivariate probit model's findings regarding the impact of health insurance on financial service choices. In the second, recursive bivariate probit regressions are used for pairings of health insurance and each of the four financial options. The findings are described in Table 9. Similar to the multivariate probit approach, the recursive bivariate probit method shows that health insurance has a positive impact on savings and investments but a negative impact on credit. It could hence be said that multivariate probit findings are robust to alternative econometric techniques.

Table 9
Bivariate probit models.

	Health insurance (1)	Private insurance (2)	Savings (3)	Investments (4)	Credit (5)
Health insurance		0.2917	0.6779***	0.2483**	-0.6698***
		(0.2374)	(0.1271)	(0.1216)	(0.1876)
Coverage rate	2.6251***				
	(0.2105)				
Risk attitude	0.0270***	0.0560***	0.0333***	0.0177**	0.0201***
	(0.0092)	(0.0071)	(0.0074)	(0.0072)	(0.0074)
Gender	0.1803**	-0.0197	0.0774	0.0669	-0.2169**
	(0.0793)	(0.0874)	(0.0788)	(0.0766)	(0.0902)
Age	0.0112	0.0390***	-0.0033	0.0166	0.0143
	(0.0135)	(0.0145)	(0.0116)	(0.0106)	(0.0142)
Age squared	-0.0002**	-0.0005***	0.0000	-0.0002**	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Marital status	-0.0124	0.1781**	0.0686	-0.0030	0.0965
	(0.0835)	(0.0839)	(0.0779)	(0.0694)	(0.0890)
Ethnicity	0.7921***	0.2268	0.0816	0.1671**	-0.0961
	(0.0978)	(0.1502)	(0.0944)	(0.0810)	(0.1034)
Education	0.0334***	0.0311***	0.0157***	0.0131**	0.0010
	(0.0076)	(0.0099)	(0.0056)	(0.0053)	(0.0061)
Health status	-0.0584***	-0.0401**	-0.0010	-0.0264	0.1373***
	(0.0200)	(0.0188)	(0.0178)	(0.0170)	(0.0215)
Household size	0.0500***	0.0859***	-0.0159	0.0281***	0.0721***
	(0.0134)	(0.0121)	(0.0115)	(0.0109)	(0.0125)
Asset 10,000USD-PPP	0.0009*	0.0192*	0.0002	-0.0005	-0.0001
	(0.0005)	(0.0114)	(0.0003)	(0.0003)	(0.0003)
Remittance 10,000USD-PPP	0.0030	0.0014	0.0347***	0.0406***	-0.0059
	(0.0070)	(0.0064)	(0.0075)	(0.0080)	(0.0055)
Member of social groups	0.0728***	0.0363**	0.0099	0.0647***	0.0742***
	(0.0145)	(0.0161)	(0.0138)	(0.0135)	(0.0149)
Wage-employee	0.0462**	0.0289	-0.0431***	0.0075	0.0687***
	(0.0214)	(0.0217)	(0.0167)	(0.0159)	(0.0186)
Natural shock	-0.1358***	-0.0073	-0.1412***	0.0833**	0.2202***
	(0.0404)	(0.0406)	(0.0374)	(0.0344)	(0.0436)
Social shock	-0.0926	-0.1527**	-0.1013*	0.0993	-0.0601
	(0.0670)	(0.0674)	(0.0602)	(0.0648)	(0.0712)
Economic shock	-0.0272	-0.0929**	-0.0923***	0.0340	0.2013***
	(0.0408)	(0.0400)	(0.0343)	(0.0357)	(0.0396)
Crime shock	0.0366	-0.0499	-0.1606***	0.0702	0.2023***
	(0.0625)	(0.0525)	(0.0498)	(0.0510)	(0.0544)
Wave (reference group: 2013)					
Wave 2016	-0.2571***	0.1565***	0.4283***	0.2273***	-0.1334***
	(0.0567)	(0.0413)	(0.0546)	(0.0460)	(0.0454)
Wave 2017	-0.0568	-0.0992	-0.1632***	0.7990***	0.0383
	(0.0670)	(0.0666)	(0.0599)	(0.0540)	(0.0621)
Constant	-2.4576***	-1.7450***	-0.8050***	-1.6582***	0.2629
	(0.3614)	(0.3849)	(0.3117)	(0.2848)	(0.3987)
Number of observations	5701	5701	5701	5701	5701
Number of clusters	110	110	110	110	110
ρ		0.0565	-0.2453***	-0.0610	0.3819***
		(0.1470)	(0.0792)	(0.0742)	(0.1169)

Note: The estimates in column (1) are based on bivariate probit regression of health insurance and savings. Robust standard errors are clustered by subdistrict and reported in parentheses. Significance levels: * < 10% ** < 5% *** < 1%.

6. Conclusion

While the impact of health insurance has been widely discussed, little is known about the impact on households' financial service choices. Using the TVSEP dataset waves 2013, 2016, and 2017, this paper fills a gap in the literature by investigating the impacts of health insurance on households' financial service choices. Unlike previous research, which has ignored the interdependence of financial service choices, this study uses multivariate probit regressions to jointly estimate correlated outcomes, resulting in more efficient results.

The results indicate that while health insurance has no influence on private insurance, it has a positive effect on savings and investments and a negative effect on credit, and these results are robust to different econometric specifications. The effects demonstrate that health insurance plays a role in enhancing the financial well-being of families. Additionally, the pattern of residual correlations in financial service equations shows that, to some degree, the linkages between financial services might be regarded as substitutes or supplements for families. Despite a fresh attempt to examine the influence of health insurance on financial services use in Vietnam, further impact research of this kind in LMICs is needed to provide conclusive evidence.

Funding

This research is funded by the Vietnam National Foundation for Science and Technology Development (NAFOSTED) under grant number NE/S003061/1.

Availability of data

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflict of Interest

The authors declare that they have no conflict of interest.

Acknowledgements

The authors would like to thank TVSEP team in Hannover, Germany for supplying data without which this study could not be finished.

References

Aaker, D.A., Keller, K.L., 1990. Consumer evaluations of brand extensions. J. Market. 54 (1), 27. doi:10.2307/1252171.

Allison, P.D., 2009. Fixed Effects Regression Methods for Longitudinal Data Using SAS. SAS institute, Cary (N.C.) 2005.

Belderbos, R., Carree, M., Diederen, B., Lokshin, B., Veugelers, R., 2004. Heterogeneity in R&D cooperation strategies. Int. J. Ind Organiz. 22 (8–9), 1237–1263. doi:10.1016/j.ijindorg.2004.08.001.

Bendig, M., Giesbert, L., Steiner, S., 2009. Savings, credit, and insurance: household demand for formal financial services in rural ghana. African Affairs.

Bollen, K.A., Brand, J.E., 2010. A General panel model with random and fixed effects: a structural equations approach. Soc. Forces 89 (1), 1–34. doi:10.1353/sof.2010.0072.

Bornstein, G., Indarte, S., 2020. *The Impact of Social Insurance on Household Debt* (Working paper).

Cappellari, L., Jenkins, S.P., 2003. Multivariate probit regression using simulated maximum likelihood. Stata J. 3 (3), 278–294. doi:10.1177/1536867x0300300305.

Chen, G., Liu, G.G., Xu, F., 2014. The impact of the urban resident basic medical insurance on health services utilisation in China. Pharmacoeconomics 32 (3), 277–292. doi:10.1007/s40273-013-0097-7.

Chib, S., Greenberg, E., 2007. Semiparametric modeling and estimation of instrumental variable models. J. Comput. Graph. Statist. 16 (1), 86–114. doi:10.1198/106186007X180723.

Clark, T.S., Linzer, D.A., 2015. Should I use fixed or random effects? Polit. Sci. Res. Methods 3 (2), 399–408. doi:10.1017/psrm.2014.32.

Docrat, S., Besada, D., Cleary, S., Lund, C., 2020. The impact of social, national and community-based health insurance on health care utilization for mental, neurological and substance-use disorders in low- and middle-income countries: a systematic review. Health Econ. Rev. 10 (1). doi:10.1186/s13561-020-00268-x.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: Measurement, determinants, and behavioral consequences. J. Eur. Econ. Assoc. 9 (3), 522–550. doi:10.1111/j.1542-4774.2011.01015.x.

Doiron, D., Jones, G., Savage, E., 2008. Healthy, wealthy and insured? The role of self-assessed health in the demand for private health insurance. Health Econ. 17 (3), 317–334. doi:10.1002/hec.1267.

Erlangga, D., Suhrcke, M., Ali, S., Bloor, K., 2019. The impact of public health insurance on health care utilisation, financial protection and health status in low: The middle-income countries: a systematic review. (PLoS ONE (2019)14:8 (e0219731) DOI: 10.1371/journal.pone.0219731). PLoS One 14 (11), 1–20. doi:10.1371/journal.pone.0225237.

Escobar, M.L., Griffin, C.C., Paul Shaw, R., 2010. The impact of health insurance in low- and middle-income countries. The Impact of Health Insurance in Low- And Middle-Income Countries doi:10.1080/17441692.2012.660975.

Farrell, L., Fry, T.R.L., Risse, L., 2016. The significance of financial self-efficacy in explaining women's personal finance behaviour. J. Econ. Psychol. 54, 85–99. doi:10.1016/j.joep.2015.07.001.

Filippini, M., Greene, W.H., Kumar, N., Martinez-Cruz, A.L., 2018. A note on the different interpretation of the correlation parameters in the bivariate probit and the recursive bivariate probit. Econ. Lett. 167, 104–107. doi:10.1016/j.econlet.2018.03.018.

Gallagher, E.A., Gopalan, R., Grinstein-Weiss, M., Sabat, J., 2020. Medicaid and household savings behavior: new evidence from tax refunds. J. Financ. Econ. 136 (2), 523–546. doi:10.1016/j.jfineco.2019.10.008.

Giesbert, L., Steiner, S., Bendig, M., 2011. Participation in micro life insurance and the use of other financial services in Ghana. J. Risk Insur. 78 (1), 7–35. doi:10.1111/j.1539-6975.2010.01405.x.

Giné, X., Townsend, R., Vickery, J., 2008. Patterns of rainfall insurance participation in rural India. World Bank Econ. Rev. 22 (3), 539–566. doi:10.1093/wber/lhn015.

Gloede, O., Menkhoff, L., Waibel, H., 2015. Shocks, individual risk attitude, and vulnerability to poverty among rural households in Thailand and Vietnam. World Dev. 71, 54–78. doi:10.1016/j.worlddev.2013.11.005.

Greene, W.H., 2012. Econometric Analysis.

Hill, T.D., Davis, A.P., Roos, J.M., French, M.T., 2020. Limitations of fixed-effects models for panel data. Sociol. Perspect. 63 (3), 357–369. doi:10.1177/0731121419863785.

Jorgensen, S.L., Siegel, P.B., 2019. Social protection in an era of increasing uncertainty and disruption. Social Protection in an Era of Increasing Uncertainty and Disruption (Issue 1930). World Bank, Washington, DC doi:10.1596/31812.

Kirdruang, P., Glewwe, P., 2018. The impact of universal health coverage on households' consumption and savings in Thailand. J. Asia Pac. Econ. 23 (1), 78–98. doi:10.1080/13547860.2017.1359893.

Kumar, A., 2019. Investigating household choice for health and life insurance. Appl. Econ. Lett. 26 (4), 267–273. doi:10.1080/13504851.2018.1467543.

Kutzin, J., 2012. Anything goes on the path to universal health coverage? No. Bull. World Health Organ. 90 (11), 867–868. doi:10.2471/BLT.12.113654.

Lagomarsino, G., Garabrant, A., Adyas, A., Muga, R., Otoo, N., 2012. Moving towards universal health coverage: Health insurance reforms in nine developing countries in Africa and Asia. Lancet North Am. Ed. 380 (9845), 933–943. doi:10.1016/S0140-6736(12)61147-7.
Liebenehm, S., Degener, N., Strobl, E., 2018. Rainfall Shocks and Risk Aversion: Evidence from Southeast Asia.
Maddala, G.S., 1983. Limited-Dependent and Qualitative Variables in Econometrics. Cambridge University Press, Cambridge.
Nguyen, D.L., Grote, U., Nguyen, T.T., 2019. Migration, crop production and non-farm labor diversification in rural Vietnam. Econ. Anal. Policy 63, 175–187. doi:10.1016/j.eap.2019.06.003.
Priebe, J., Rink, U., Stemmler, H., 2017. Health shocks and risk aversion: Panel and experimental evidence from Vietnam. Courant Research Centre 'Poverty, Equity and Growth in Developing and Transition Countries: Statistical Methods and Analysis Empirical' 267 (August), 0–34.
Stanciole, A.E., 2008. Health insurance and lifestyle choices: Identifying ex ante moral hazard in the US market. Geneva Pap. Risk Insur. 33 (4), 627–644. doi:10.1057/gpp.2008.27.
The National Assembly of Vietnam, 2008. Law on Health Insurance (Luật Bảo hiểm y tế. Số 25/2008/QH12).
Treiman, D.J., 2009. Quantitative Data Analysis: Doing Social Research to Test Ideas. Jossey-Bass.
Vaisey, S., Miles, A., 2017. What you can—and can't—do with three-wave panel data. Sociol. Methods Res. 46 (1), 44–67. doi:10.1177/0049124114547769.
Van Minh, H., Kim Phuong, N.T., Saksena, P., James, C.D., Xu, K., 2013. Financial burden of household out-of pocket health expenditure in Viet Nam: Findings from the National Living Standard Survey 2002-2010. Soc. Sci. Med. 96, 258–263. doi:10.1016/j.socscimed.2012.11.028.
Viganò, L., Castellani, D., 2020. Financial decisions and risk management of low-income households in disaster-prone areas: Evidence from the portfolios of Ethiopian farmers. Int. J. Disast. Risk Reduct. 45 (January). doi:10.1016/j.ijdrr.2020.101475.
Wilde, J., 2000. Identification of multiple equation probit models with endogenous dummy regressors. Econ. Lett. 69 (3), 309–312. doi:10.1016/S0165-1765(00)00320-7.
Zhang, C., Fu, C., Song, Y., Feng, R., Wu, X., Li, Y., 2020. Utilization of public health care by people with private health insurance: A systematic review and meta-analysis. BMC Public Health 20 (1), 1–12. doi:10.1186/s12889-020-08861-9.