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# Over-indebtedness and its persistence in rural households in Thailand and Vietnam

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ABSTRACT

This study analyzes the determinants of household over-indebtedness and its persistence for rural household borrowers in Thailand and Vietnam. A household is considered to be over-indebted if it is in default or arrears on a loan or if its ratio of debt service to income exceeds 50 percent. The persistence of over-indebtedness was tested using a Heckman random effects dynamic probit model controlling for the effect of household demographic, socioeconomic, and behavioral characteristics. For Thailand, but not for Vietnam, past experience of over-indebtedness increases the probability of being over-indebted in the present, controlling for other household characteristics. Village support systems in Vietnam may be more effective in delivering households out of over-indebtedness than in Thailand where heavy debt burdens are taken more for granted. Household characteristics that significantly increase the probability of over-indebtedness include poverty, household size, low education, overly optimistic forecasting of income, and a sense of being less well off than other villagers.



## 1. Introduction

Financial debt is a major problem for poor households in developing countries. Many countries, including Nicaragua, Morocco, Pakistan, and India, have experienced financial crises in connection with the rapid expansion of microfinance (Chen et al., 2010; Lascelles & Mendelson, 2012). These crises have been marked by widespread over-indebtedness, rapid growth in defaults, and in India, even default-related suicides (Bateman & Chang, 2012; Chen et al., 2010; Lützenkirchen & Weistroffer, 2012).

Research on micro-borrower over-indebtedness in Ghana (Schicks, 2013a, 2013b), Cambodia (Liv, 2013), Thailand (Siripanyawat, Sawangngoenyuang, & Thungkasemvathana, 2010), and Bangladesh (Khandker, Faruqee, & Samad, 2013) has shown that poor households often borrow large amounts relative to their incomes. For the poor, over-indebtedness usually co-exists with economic and social exclusion and a high incidence of poverty (Bateman & Chang, 2012; Schicks, 2013a, 2013b). Thus, understanding the factors that can lead to over-indebtedness is important for designing better micro-credit policies in developing countries.

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This study contributes in a number of ways to an understanding of rural household over-indebtedness in Thailand and Vietnam. First, we discuss the definition of over-indebtedness and identify two dummy variable indicators for use in this study. The "default" indicator takes on a value of one when a household experiences a default or an arrear on a loan commitment. The "debt service" indicator takes on a value of one when a household's ratio of debt service to income exceeds 50 percent. We measure the extent of household over-indebtedness in both countries based on these indicators. Second, we analyze the influence of demographic and economic characteristics on the probability of over-indebtedness. Third, we analyze behavioral biases that cause households to make suboptimal and unsustainable borrowing decisions. And fourth, exploiting the panel nature of our unique dataset, we analyze the persistence of over-indebtedness.

We make use of a balanced panel of nearly 1600 rural households from one province in Thailand (Ubon Ratchathani) and one in Vietnam (Thua Thien-Hue) for four survey waves in 2007, 2008, 2010, and 2011. We apply Heckman's random effects dynamic probit model (Stewart, 2007; Stewart, 2006) to estimate the probability of a household experiencing over-indebtedness as a function of household characteristics.

We find that for Thailand the evidence supports true state dependence for over-indebtedness such that being over-indebted in the current period is significantly related to being over-indebted in the previous period even when other observed and unobserved household characteristics are controlled for. This is not so for Vietnam, where the persistence of over-indebtedness is explained by observed and unobserved household heterogeneity without significant influence of prior over-indebtedness. Vietnamese households may be less prone than Thai households to becoming mired in over-indebtedness once they fall into such a state due to better community support systems that facilitate recovery from debt problems.

We further find that in both countries, over-indebtedness shows a strong negative association with income, households in the bottom quintile being more likely to exceed the 50 percent debt-service-to-income threshold than those in the top quintile by 37 percentage points in Thailand and 25 percentage points in Vietnam. Demographic factors associated with over-indebtedness in both countries include household size and the head of household being middle aged and poorly educated. Psychological factors associated with over-indebtedness include overly optimistic forecasting of income and a sense of being less well off than other villagers. A number of other factors are found to be significant only in one country or the other.

The remainder of the paper is organized as follows. Section 2 presents information on rural credit markets in Thailand and Vietnam. Section 3 discusses definition and measurement of over-indebtedness and reviews relevant theories of household borrowing behavior. Sections 4 and 5 discuss the data and present descriptive statistics on the incidence and extent of household over-indebtedness and its persistence. Section 6 lays out the econometric framework. Section 7 presents model results, while Section 8 contains robustness checks. Finally, Section 9 concludes.

## 2. Rural credit markets in Thailand and Vietnam

During the past two decades, Thailand and Vietnam have achieved high economic growth and impressive reductions in poverty. In part, this is attributable to the development of rural microcredit markets to facilitate investment in agriculture and small businesses. To provide the rural poor with access to affordable credit, both Thailand and Vietnam have established specialized financial institutions and credit programs. In Thailand, the most notable microfinance institutions are the Bank for Agriculture and Agricultural Cooperatives (BAAC) and the Village Fund (VF). In Vietnam, they are the Vietnam Bank for Social Policy (VBSP) and the Vietnam Bank for Agriculture and Rural Development (VBARD). Other semi-formal and informal microfinance institutions also exist, similar to those found in most developing countries (King, 2008; Menkhoff, Neuberger, & Rungruxsirivorn, 2012). Beyond this, governments in both countries have introduced state-run or government regulated financial institutions to facilitate growth of larger rural enterprises that are more sophisticated, innovation-driven, and technology intensive (Bateman, 2013; Bateman & Chang, 2012).

The financial systems of Thailand and Vietnam are similar in the level of government involvement and the enforcement of regulation. However, the countries differ in financial depth, credit outreach, and the range of credit programs introduced in rural areas. While the Thai government began to support homegrown non-bank financial institutions and develop the BAAC in the mid-1970s (Menkhoff & Rungruxsirivorn, 2011; Menkhoff & Suwanaporn, 2007), Vietnam's establishment of the VBARD and VBSP did not occur until the early 1990s (Dufhues, Heidhues, & Buchenrieder, 2004).

The Thai institutions have enhanced household access to financial services, especially in non-municipal areas. However, some argue that government facilitation of borrowing in Thailand has shifted the attitudes of poor households toward indebtedness. Siripanyawat et al. (2010) argue that some households have come to perceive being indebted as a norm and regard not paying back their loans on time as acceptable since the money came from the government. Consistent with this, Kaboski and Townsend (2011) found that instead of investing in income generating activities in response to the introduction of the "million baht village fund", households increased their borrowing and consumption almost equally. These authors further found that, compared to a direct transfer program, a large-scale microfinance program is less beneficial for some households due to the enduring burden of debt service.

Vietnam is a lower income country with a shorter history of rural credit development. It also differs from Thailand in being a country that has transitioned from socialism with strong rural community organization thus evolving from very different origins. Rural financial institutions rely heavily on customary norms and peer pressure in rural communities to encourage loan repayment. The whole village participates in social activities together and takes on a role in loan monitoring, which puts pressure on households to repay their debts on time in order to avoid economic and social sanctions (Okae, 2009). In view of these societal differences, one may expect household over-indebtedness to be a less persistent problem among Vietnamese than among Thai households.

## 3. Theory and literature review

### *3.1. Measures of over-indebtedness*

No commonly accepted definition exists of household over-indebtedness. Broadly, the approaches found in the literature can be distinguished between subjective and objective. Subjective measures are based on households judging their own financial situations. Schicks (2014) considers a household's struggle and sacrifice related to debt repayment, including reducing spending on food consumption, taking children out of school, working additional jobs, and increasing work hours. However, the drawback of such subjective measures is that they can be inconsistent as they depend on borrower attitude and degree of financial literacy (Betti, Dourmashkin, Rossi, & Yin, 2007; D'Alessio & Iezzi, 2013; Schicks & Rosenberg, 2011). For the purpose of comparing households between countries, subjective indicators are thus not very useful.

Objective measures of over-indebtedness include the debt to income ratio, debt service to income ratio, debt to asset ratio, default and arrears positions, net wealth, and number of loans (Betti et al., 2007; D'Alessio & Iezzi, 2013; Schicks, 2013a, 2013b). These measures have been used individually (Giarda, 2013; Haas, 2006; May & Tudela, 2005) or in concert (Anderloni, Bacchiocchi & Vandone, 2012; Brown, Garino & Taylor, 2008; Stamp, 2009), both by financial institutions and in academic studies. However, there are a couple of limitations to such objective measures. The first is that they may understate the burden of over-indebtedness as they fail to capture the sacrifices that households make in order to service their debts, such as foregoing basic needs or neglecting family life (Betti et al., 2007; Schicks & Rosenberg, 2011). The second limitation relates to the difficulty of determining critical levels of the indicators. As noted by Betti et al. (2007), it is difficult to define an optimal level of indebtedness, as household circumstances have a bearing on what they can manage. Despite these limitations, empirical studies of over-indebtedness have found that objective indicators involving debt ratios and default and arrears positions align fairly well with the subjective perceptions of households (D'Alessio & Iezzi, 2013; Keese, 2012; Rinaldi & Sanchis-Arellano, 2006).

Clearly, finding a single ideal measure of over-indebtedness is not possible (Betti et al., 2007; D'Alessio & Iezzi, 2013; Schicks & Rosenberg, 2011). Different measures capture different aspects of the problem (Gumy, 2007; D'Alessio & Iezzi, 2013; Disney, Bridges, & Gathergood, 2008). With this in mind, some analysts use a combination of subjective and objective indicators (Anioła & Gołaś, 2012; Gumy, 2007). The problem with using multiple indicators, however, is that many households will be considered over-indebted by at least one indicator and the most serious cases may not stand out. Hence, Disney et al. (2008) suggest that when using multiple indicators in combination, one should focus on those that best reflect the structural and life cycle conditions of the household.

### *3.2. Drivers of over-indebtedness*

Given the household nature of our data, we focus on the borrower side to understand the reasons for over-indebtedness. Three approaches to understanding borrower behavior have gained prominence.

The first of these approaches rests on the life cycle/permanent income model of Modigliani (1966) and Friedman (1957) that treats indebtedness as part of an optimization strategy within the life cycle of a household. The hypothesis holds that households borrow money to transfer consumption from periods of high income to periods of low income. At the early stage of a household's life cycle, borrowing can help to smooth consumption so as to maximize lifetime utility. The amount of borrowing will depend on the path of expected earnings over time. Therefore, a high level of indebtedness relative to current income or assets at an early stage of a household's life cycle does not necessarily suggest that the household is over-indebted (Betti et al., 2007). The life cycle model can be extended by incorporating uncertainty with respect to negative adverse shocks within a context of imperfect credit markets (Betti et al., 2007). This combination can result in over-indebtedness (Gumy, 2007). For example, Gonzalez (2008) found that unexpected adverse shocks played a major role in the Bolivian household over-indebtedness crisis of 1999 to 2002. Similarly, Schicks (2014) found that unexpected shocks significantly increased the likelihood of over-indebtedness of micro-borrowers in Ghana. Uncertainty can also contribute to over-indebtedness if households overestimate future income (Brown, Garino, Taylor, & Price, 2005). Brown et al. (2005) present a theoretical framework in which financial expectations determine the level of outstanding debt and the growth of debt. In their model, households maximize expected lifetime utility by smoothing consumption, relying on borrowing in anticipation of higher incomes in the future. Their empirical analysis using panel data from the UK confirms the importance of financial expectations in determining household debt (Brown et al., 2005; Brown et al., 2008).

A second approach to explaining household borrowing and over-indebtedness derives from behavioral theory. Behavioral "biases" and "heuristics" have been shown to distort household assessment of the probabilities of financial events. This can result in significant deviation from the optimal borrowing strategy that maximizes expected lifetime utility (Betti et al., 2007; Lea, Webley, & Walker, 1995; Livingstone & Lunt, 1992; Meier & Sprenger, 2010). "Bounds of rationality" can increase the likelihood of households accumulating excessive debt compared to their earnings (Kilborn, 2005). Using Finnish household panel data, Hyytinen and Putkuri (2012) show how overly optimistic perceptions with high forecast errors significantly increased the probability of household over-indebtedness. Further, two interconnected behavioral biases can affect borrowing behavior: risk taking (risk loving instead of risk aversion) and present-biasedness in time preference (Betti et al., 2007; Brown, Garino, & Taylor, 2013; Norum, 2008). Households that engage in risk taking behavior are more likely to be present biased in their time preferences, which makes their consumption and spending decisions unsustainable in the face of adverse events (Betti et al., 2007; Norum, 2008). Moreover, according to the life cycle hypothesis, households borrow to finance an increase in current consumption based on expected future earnings. Because future earnings are directly influenced by the risk taking behavior of households, the ability to repay debt is also subject to household risk preferences. Brown et al. (2013) explored this relationship using U. S. panel data. They found that households with lower risk aversion had higher levels of accumulated debt. However, Keese (2012) did not find a significant relationship between risk attitude and a subjective measure of over-indebtedness. The hypothesis, in any case, is that overly optimistic and risk taking households face a greater tendency toward over-indebtedness.

A third approach to understanding over-indebtedness involves subjective wealth assessment and social comparison theory. Households that compare themselves with wealthier households in their social circle and perceive their own social standing to be lower tend to overspend relative to their levels of income and thus borrow more in an attempt to catch up with their peers (Cynamon & Fazzari, 2008; Lea et al., 1995; Livingstone & Lunt, 1992). Using Dutch household data, Georgarakos, Haliassosa, and Pasini (2014) showed that perceived higher average income within a household's social circle led to greater borrowing and heavier debt burdens.

The foregoing approaches to understanding over-indebtedness pertain to its level in static terms. The persistence of over-indebtedness is also of interest for our purposes. A diverse array of studies examining debt repayment problems (Böheim & Taylor, 2000; May & Tudela, 2005), debt or financial difficulties (Stamp, 2009), financial hardship (Brown, Ghosh & Taylor, 2014), and financial distress (Giarda, 2013) have all found high degrees of persistence in over-indebtedness. Such persistence indicates that the conditional probability of a household being over-indebted is a function of its past experience with over-indebtedness. Observed persistence may emerge as a result of two distinct causal mechanisms, one involving true state dependence, the other deriving from household heterogeneity that disposes some households to be continuously over-indebted. In the case of true state dependence, past over-indebtedness directly affects household resources and behavior in such a way as to influence the propensity for over-indebtedness in the future. Alternatively, persistence may result from observed and unobserved household characteristics that themselves persist in causing over-indebtedness over time (Heckman, 1981a; Hsiao, 2003). A study of Italian households in financial distress found that true state dependence explained the greater part of persistence controlling for observed and unobserved household heterogeneity (Giarda, 2013).

## 4. Data description

We use data on rural households from the Thai province of Ubon Rathchathani and the Vietnamese province of Thua Thien Hue collected under the "Vulnerability in Southeast Asia" project funded by the German Research Foundation. The survey was conducted annually from 2007 to 2011 with a one-year gap in 2009. The two provinces were selected to target rural households that were poor or at risk of falling into poverty. Households were drawn from within the two provinces following a three stage stratified sampling design. First, 85 sub-districts were randomly selected with probability proportional to population density. Then two or so rural villages were randomly selected from each sub-district with probability proportional to size of population. Finally, ten households were randomly selected from each village with equal probability (Hardeweg, Klasen, & Waibel, 2012). In total, the sample comprised 1688 rural households from the two provinces.

To obtain a balanced panel, we limit the sample to 1582 households – 914 in Thailand and 668 in Vietnam – for which data are available for all four years. Hence, we have a dataset comprising 6328 observations. The dataset contains detailed information on borrowing and on loan defaults and arrears, along with standard demographic, social, and economic characteristics. We follow Disney et al. (2008) in using loan defaults or arrears as one indicator of over-indebtedness – henceforth, the "default" indicator. Specifically, we define the default indicator as equal to one if a household reported at least one default or arrear on a loan commitment during the previous year. The survey posed the question: *'During the past twelve months, have you ever defaulted on or failed to pay back a loan on time?'* This indicator, however, tends to understate the extent of over-indebtedness because of the lengths to which households will go in order to avoid default. Some take out new loans to meet existing debt service obligations. Others sacrifice their basic needs and a healthy, sustainable lifestyle. The default indicator thus tends to conceal the problem of over-indebtedness until it reaches a breaking point (Schicks, 2014; Schicks & Rosenberg, 2011).

In light of this limitation, we take as a second indicator the ratio of debt service to income. This "debt service" indicator is defined as the proportion of annual gross income that a household devotes to servicing its debt obligations (ECB, 2013). A household is typically considered over-indebted when its annual debt repayment obligation relative to income surpasses a threshold of 40 or 50 percent (Banbula, Kotula, Przeworska, & Strzelecki, 2016; D'Alessio & Iezzi, 2013; Disney et al., 2008; Muthitacharoen, Nuntramas, & Chotewattanakul, 2015). Following precedent, we define a debt service indicator of over-indebtedness as equal to one for a household whose debt service ratio exceeds 50 percent.

## 5. Descriptive statistics

### 5.1. Indebtedness and over-indebtedness

The extent of indebtedness and over-indebtedness among our sample households is given by country, year, and indicator in Table 1. Over the four years, 80–89 percent of Thai households and 63–76 percent of Vietnamese households were indebted. The share of indebted households rose steadily over time in Vietnam whereas it fluctuated in Thailand. Indebted households had a median outstanding balance of US$2491 in Thailand and a much lower US$1033 in Vietnam where income is also lower (values in purchasing power parity terms, 2005 US dollars).

The default indicator of over-indebtedness generally shows a lower incidence than the debt service indicator, with the gap between the two measures much larger for Thailand than for Vietnam. Judging by the default indicator, on average across years, 8 percent of Thai households and 9 percent of Vietnamese households were over-indebted. Alternatively, judging by the debt service indicator, on average 34 percent of Thai households and 12 percent of Vietnamese households were over-indebted. Among indebted households in particular, the share defaulting is slightly higher in Vietnam than in Thailand even as the share incurring high debt service ratios is much lower in Vietnam. Hence Thai households seem better able than Vietnamese households to endure high debt service ratios without defaulting. These patterns are consistent with findings reported in the literature (D'Alessio & Iezzi, 2013; Disney et al., 2008).

The persistence of over-indebtedness is captured in Tables 2 and 3. Table 2 shows the share of households that were over-indebted for a given number of years up to the maximum possible four years. The default indicator shows the share of households that were over-indebted at some time during the four years at 22 percent for Thailand (78 percent never having been over-indebted) and 24 percent for Vietnam (76 percent never having been over-indebted). For the debt service ratio, the shares over-indebted at some point were 68 percent for Thailand and 34 percent for Vietnam. At the opposite extreme, for both countries less than half a percent of households registered as in default for all four years, although in Thailand 5.6 percent were over-indebted for all four years according to the debt service indicator. This suggests households enter in and out of over-indebtedness, with continuous over-indebtedness for multiple years being rare.

Table 3 presents a transition matrix showing probabilities of being over-indebted in a given year conditional on the status of over-indebtedness in the previous year. The conditional probability of remaining over-indebted from year to year reaches as high as 41.7 percent for Thailand with respect to the debt service indicator. For Vietnam by this indictor, the probability is a much lower 16.2 percent. The comparison is reversed between the two countries for the default indicator with 29.7 percent of the Vietnamese households expected to remain in default from year to year versus only 18.4 percent of the Thai households. By contrast, the probability of a household that is not in default in the previous year going into default is quite low at 2.6 percent for Thailand and 4.1 percent for Vietnam. The probability of crossing over the debt service threshold is higher at 11.3 percent for Thailand and 8.3 percent for Vietnam.

However, one must be cautions in the interpretation of these results. Conditional probabilities cannot be taken at face value because the tendency to remain over-indebted could be driven indirectly by household specific characteristics rather than by the prior state of over-indebtedness per se. While the descriptive probabilities of transition provide a superficial measure of the problem of persistence, they do not indicate causality between the state of over-indebtedness from one period to the next. To distinguish between true state dependence and heterogeneous effects of household characteristics, a dynamic modeling approach is needed.

### 5.2. Explanatory variables

Summary statistics for the explanatory variables of our model, for data pooled over the four years, are reported in Table 4 for Thailand and Table 5 for Vietnam. The tables also report statistical test results for differences in the values of each variable between over-indebted and not over-indebted households.

**Table 1**
Extent of household indebtedness and over-indebtedness.

| | | Number of households | Indebted households% | Over-indebtedness by indicator% of total households | | Over-indebtedness by indicator% of indebted households | |
|---|---|---|---|---|---|---|---|
| | | | | default | debt service | default | debt service |
| Thailand | 2007 | 914 | 86.3 | 13.0 | 39.6 | 15.1 | 45.9 |
| | 2008 | 914 | 89.5 | 9.8 | 48.4 | 10.9 | 54.0 |
| | 2010 | 914 | 78.6 | 2.6 | 17.7 | 3.3 | 22.6 |
| | 2011 | 914 | 84.1 | 4.8 | 29.5 | 5.7 | 35.1 |
| Vietnam | 2007 | 668 | 63.0 | 11.1 | 15.7 | 17.3 | 24.9 |
| | 2008 | 668 | 67.5 | 10.9 | 11.2 | 15.7 | 16.6 |
| | 2010 | 668 | 70.2 | 6.0 | 8.5 | 8.1 | 12.2 |
| | 2011 | 668 | 76.2 | 7.3 | 11.7 | 9.6 | 15.3 |

*Source*: Author calculation from survey data.

**Table 2**
Share of households persisting in over-indebtedness.

| Country | Number of Years | Default Indicator% | Debt Service Indicator% |
|---|---|---|---|
| Thailand | 0 | 77.8 | 31.8 |
| | 1 | 16.0 | 25.8 |
| | 2 | 4.7 | 23.2 |
| | 3 | 1.2 | 13.6 |
| | 4 | 0.3 | 5.6 |
| Vietnam | 0 | 75.8 | 66.0 |
| | 1 | 15.9 | 23.2 |
| | 2 | 6.1 | 8.5 |
| | 3 | 1.8 | 2.1 |
| | 4 | 0.4 | 0.2 |

*Source:* Author calculation from survey data.

**Table 3**
Probability of over-indebtedness in current year conditional on status in previous year.

| Indicator | Year *t*-1 | Year *t* | |
|---|---|---|---|
| | | Thailand% | Vietnam% |
| Default | No | 2.6 | 4.1 |
| | Yes | 18.4 | 29.7 |
| Debt service | No | 11.3 | 8.3 |
| | Yes | 41.7 | 16.2 |

*Note*: The gap between observations is two years in the 2008–2010 instance.*Source*: Author calculation from survey data.

A first category of variables captures socio-economic and demographic characteristics following the life cycle theory of borrowing (Brown et al., 2014; Vandone, 2009) and following existing literature (Anderloni & Vandone, 2008; Brown & Taylor, 2008; Brown et al., 2014; D'Alessio & Iezzi, 2013; Disney et al., 2008; Schicks, 2014). Hereby the two most important variables are number of children and household size. For the default indicator, over-indebted households show statistically higher headcounts for both variables than households that are not over-indebted. For the debt service indicator, however, no conclusive pattern emerges. A number of variables in the demographic and socio-economic category pertain to the household head: gender (female or male); marital status (married or single); age (under 35, 35–44, 45–54, 55–64, or 65 and above); education (primary or less, secondary, or higher education); and main occupation (agricultural, off-farm employed, self-employed, and inactive). Statistical differences in these variables between over-indebted and not over-indebted households register inconsistently by country and debt indicator. For Vietnam, there is also an ethnicity indicator (Kinh or non-Kinh), with households exceeding the debt service threshold more likely to be of the non-Kinh ethnicity.

Other economic variables apply to the household as a whole: land rental status (renter or non-renter); savings status (savings or no savings); and income quintile. For both countries and both indicators, to a statistically significant degree, over-indebted households are more likely to be in lower income quintiles than households that are not over-indebted. Differences for over-indebted households relative to others are not consistent across country or indicators for land rental or savings status.

Three dummy variables capture shocks experienced by the household: unexpected shock to expenses; expected shock to expenses; and unexpected shock to income. Unexpected shocks to both expenses and income register as statistically significant for over-indebted households versus their non-over-indebted counterparts in both countries. The pattern for expected shocks to expenses is more mixed by country and indicator.

A second category of variables pertains to household risk attitudes and expectations about the future. The risk attitude variable is based on a response of zero, *"unwilling to take risk"*, to 10, *"fully prepared to take risk"*, on a Likert scale for the survey question *"Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?"* In light of their responses, we grouped households into three categories of risk averse, risk neutral, and risk taker. The variable on expected future income derives from the survey question: *"Do you think your household will be better off next year?"* Household responses were grouped into categories of better, same, or worse. Finally, we constructed a variable for the household forecast error in predicting future income by taking the difference between its expectation for period $t$ and the subsequent realization at period $t + 1$. In addition to the question about whether a household expected to be better off in the next year, another question asked for a retrospective assessment: *"Do you think your household is better off than last year?"* The response categories for both questions were *"much better off"*, *"better off"*, *"same"*, *"worse off"*, and *"much worse off"*. Household responses to these two questions were matched to quantify the forecast errors with households then grouped accordingly following Hyytinen and Putkuri (2012). The four categories for the resulting forecast error variable are: pessimistic forecast error; no forecast error; prudentially optimistic forecast error; and non-prudentially optimistic forecast error. Households that made a pessimistic forecast error expected to become worse off but actually did not become worse off. Households that made a prudentially optimistic forecast error expected to become better and did not, although they did not become worse off

**Table 4**
Descriptive statistics, Thailand.

| Variable | | Number of observations (3656) | All Households | Default Indicator | | | Debt Service Indicator | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Over-indebted | Not over-indebted | | Over-indebted | Not over-indebted | |
| Numerical Variables | | | mean | mean | mean | t-test | mean | mean | t-test |
| Number of children | | 3656 | 1.41 | 1.68 | 1.39 | 4.07*** | 1.44 | 1.39 | 1.29* |
| Household size | | 3656 | 5.32 | 5.77 | 5.29 | 3.45*** | 5.24 | 5.37 | -1.68** |
| Categorical Variables | | | % | % | % | $Chi^2$ test | % | % | $Chi^2$ test |
| Head gender | female | 1152 | 31.5 | 31.4 | 31.5 | 0.001 | 29.0 | 32.8 | 5.60** |
| | male | 2504 | 68.5 | 68.6 | 68.5 | | 71.0 | 67.2 | |
| Head marital status | married | 2883 | 78.9 | 78.0 | 78.9 | 0.13 | 81.2 | 77.7 | 5.88** |
| | single | 773 | 21.1 | 22.0 | 21.1 | | 18.9 | 22.3 | |
| Head age | <35 | 102 | 2.8 | 3.6 | 2.7 | 13.00** | 3.3 | 2.5 | 32.01*** |
| | 35–44 | 621 | 17.0 | 17.7 | 16.9 | | 18.9 | 16.0 | |
| | 45–54 | 1001 | 27.4 | 34.3 | 26.8 | | 29.7 | 26.2 | |
| | 55–64 | 975 | 26.7 | 26.0 | 26.7 | | 27.4 | 26.3 | |
| | >64 | 957 | 26.2 | 18.4 | 26.8 | | 20.6 | 29.0 | |
| Head education | primary or less | 3192 | 87.3 | 84.8 | 87.5 | 1.73 | 85.6 | 88.2 | 11.87** |
| | secondary | 372 | 10.2 | 11.9 | 10.0 | | 10.7 | 9.9 | |
| | tertiary | 92 | 2.5 | 3.3 | 2.5 | | 3.7 | 1.9 | |
| Head occupation | agricultural | 2084 | 57.0 | 54.5 | 57.2 | 2.26 | 60.8 | 55.1 | 14.72*** |
| | self-employed | 369 | 10.1 | 11.2 | 10.0 | | 9.8 | 10.3 | |
| | off-farm | 666 | 18.2 | 20.9 | 18.0 | | 17.5 | 18.6 | |
| | inactive | 537 | 14.7 | 13.4 | 14.8 | | 12.0 | 16.1 | |
| Land rental | renter | 860 | 23.5 | 28.5 | 23.1 | 4.15** | 26.1 | 22.2 | 7.06** |
| | non-renter | 2796 | 76.5 | 71.5 | 76.9 | | 73.9 | 77.8 | |
| Savings | yes | 3042 | 83.2 | 83.0 | 83.2 | 0.006 | 87.8 | 80.9 | 27.99*** |
| | no | 614 | 16.8 | 17.0 | 16.8 | | 12.2 | 19.1 | |
| Income quintile | 1 | 732 | 20 | 23.5 | 19.7 | 17.65*** | 32.1 | 13.8 | 257.30*** |
| | 2 | 731 | 20 | 27.1 | 19.4 | | 23.9 | 18.0 | |
| | 3 | 731 | 20 | 19.5 | 20.0 | | 19.1 | 20.5 | |
| | 4 | 731 | 20 | 16.6 | 20.3 | | 12.5 | 23.8 | |
| | 5 | 731 | 20 | 13.4 | 20.5 | | 12.5 | 23.8 | |
| Shock to expenses, unexpected | yes | 1612 | 44.1 | 51.6 | 43.5 | 6.89** | 47.1 | 42.6 | 6.79** |
| | no | | | | | | | | |
| | no | 2044 | 55.9 | 48.4 | 56.5 | | 52.9 | 57.4 | |
| Shock to expenses, expected | yes | 329 | 9 | 13.4 | 8.6 | 6.95** | 10.0 | 8.5 | 2.06 |
| | no | | | | | | | | |
| | no | 3327 | 91 | 86.6 | 91.4 | | 90.1 | 91.5 | |
| Shock to income, unexpected | yes | 1794 | 49.1 | 54.9 | 48.6 | 4.03** | 53.4 | 46.9 | 13.99*** |
| | no | | | | | | | | |
| | no | 1862 | 50.9 | 45.1 | 51.4 | | 46.6 | 53.1 | |
| Expected future income | better | 2153 | 59.1 | 56.8 | 61.3 | 4.35 | 60.8 | 61.0 | 2.99 |
| | same | 945 | 25.9 | 27.1 | 26.7 | | 25.7 | 27.3 | |
| | worse | 434 | 11.9 | 16.2 | 12.0 | | 13.5 | 11.7 | |
| Risk attitude | risk averse | 1297 | 35.6 | 36.4 | 35.5 | 0.12 | 32.0 | 37.4 | 11.28** |
| | risk neutral | 1426 | 39.1 | 38.2 | 39.2 | | 40.5 | 38.4 | |
| | risk taker | 923 | 25.3 | 25.5 | 25.3 | | 27.5 | 24.2 | |
| Forecast error | pessimistic | 786 | 21.5 | 19.1 | 21.7 | 1.98 | 21.2 | 21.7 | 0.11 |
| | no forecast error | 1442 | 39.4 | 33.6 | 39.9 | | 39.6 | 39.4 | |
| | prudentially optimistic | 839 | 22.9 | 25.3 | 22.8 | | 23.0 | 22.9 | |
| | non-prudentially optimistic | 589 | 16.1 | 22.0 | 15.6 | | 16.3 | 16.0 | |
| Subjective well-being vs other villagers | Better off | 543 | 14.9 | 6.5 | 15.6 | 88.69*** | 12.0 | 16.4 | 13.53*** |
| | Same | 2469 | 67.7 | 56.2 | 68.7 | | 69.1 | 67.1 | |
| | Worse off | 632 | 17.4 | 37.3 | 15.7 | | 18.9 | 16.5 | |

*** 1%, ** 5%, * 10% levels of significance.
*Note*: The *t*-test tests whether the mean of over-indebted households exceeds the mean of not over-indebted households. The $chi^2$ test tests for a difference in the frequency distribution of a categorical variable between over-indebted households and not over-indebted households.

**Table 5**
Descriptive statistics, Vietnam.

| Variable | | Number of observations (2672) | | Default Indicator | | | Debt Service Indicator | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Over-indebted | Not over-indebted | | Over-indebted | Not over-indebted | |
| Numerical Variables | | | mean | mean | mean | t-test | mean | mean | *t*-test |
| Number of children | | 2672 | 1.77 | 2.01 | 1.75 | 2.82** | 1.75 | 1.78 | −0.32 |
| Household size | | 2672 | 5.34 | 5.78 | 5.29 | 3.37*** | 5.37 | 5.33 | 0.34 |
| Categorical Variables | | | % | % | % | $Chi^2$ test | % | % | $Chi^2$ test |
| Head gender | female | 552 | 20.7 | 15.3 | 21.2 | 4.61** | 17.8 | 21 | 1.8 |
| | male | 2120 | 79.3 | 84.8 | 78.8 | | 82.2 | 79 | |
| Head ethnicity | non-Kinh | 652 | 24.4 | 25.4 | 24.3 | 0.14 | 29.5 | 23.7 | 5.07** |
| | Kinh | 2020 | 75.6 | 74.6 | 75.7 | | 70.5 | 76.3 | |
| Head marital status | married | 2215 | 82.9 | 87.7 | 82.4 | 4.23** | 84.8 | 82.7 | 0.87 |
| | single | 457 | 17.1 | 12.3 | 17.6 | | 15.2 | 17.4 | |
| Head age | <35 | 355 | 13.3 | 12.7 | 13.3 | 6.87 | 14.9 | 13.1 | 19.43*** |
| | 35–44 | 719 | 26.9 | 32.2 | 26.4 | | 28.6 | 26.7 | |
| | 45–54 | 704 | 26.3 | 28 | 26.2 | | 25.1 | 26.5 | |
| | 55–64 | 396 | 14.8 | 13.6 | 14.9 | | 20.3 | 14.1 | |
| | >64 | 498 | 18.6 | 13.6 | 19.1 | | 11.1 | 19.6 | |
| Head education | primary or less | 1633 | 61.1 | 61.9 | 61 | 7.32** | 61.3 | 61.1 | 0 |
| | secondary | 928 | 34.7 | 37.3 | 34.5 | | 34.6 | 34.8 | |
| | tertiary | 111 | 4.2 | 0.9 | 4.5 | | 4.1 | 4.2 | |
| Head occupation | agricultural | 1634 | 61.2 | 68.6 | 60.4 | 11.11** | 66.7 | 60.4 | 5.21 |
| | self-employed | 277 | 10.4 | 4.7 | 10.9 | | 9.8 | 10.4 | |
| | off-farm | 594 | 22.2 | 21.6 | 22.3 | | 17.8 | 22.8 | |
| | inactive | 167 | 6.3 | 5.1 | 6.6 | | 5.7 | 6.3 | |
| Land rental | renter | 437 | 16.4 | 15.7 | 16.4 | 0.08 | 17.1 | 16.2 | 0.16 |
| | non-renter | 2235 | 83.6 | 84.3 | 83.6 | | 82.9 | 83.8 | |
| Savings | yes | 1022 | 38.2 | 27.5 | 39.3 | 12.56*** | 35.2 | 38.7 | 1.37 |
| | no | 1650 | 61.8 | 72.5 | 60.7 | | 64.8 | 61.4 | |
| Income quintile | 1 | 535 | 20 | 20.8 | 20 | 30.89*** | 45.7 | 16.6 | 179.11*** |
| | 2 | 534 | 20 | 28 | 19.2 | | 24.1 | 19.4 | |
| | 3 | 535 | 20 | 24.6 | 19.6 | | 14.3 | 20.8 | |
| | 4 | 534 | 20 | 19.1 | 20.1 | | 9.2 | 21.4 | |
| | 5 | 534 | 20 | 7.6 | 21.2 | | 6.7 | 21.8 | |
| Shock to expenses, unexpected | yes | 1156 | 43.3 | 50 | 42.6 | 4.78** | 48.9 | 42.5 | 4.60** |
| | no | | | | | | | | |
| | no | 1516 | 56.7 | 50 | 57.4 | | 51.1 | 57.5 | |
| Shock to expenses, expected | yes | 208 | 7.8 | 7.2 | 7.8 | 0.12 | 8.9 | 7.6 | 0.6 |
| | no | | | | | | | | |
| | no | 2464 | 82.2 | 92.8 | 92.2 | | 91.1 | 92.4 | |
| Shock to income, unexpected | yes | 1703 | 63.7 | 78 | 62.4 | 22.68*** | 69.5 | 63 | 5.17** |
| | no | | | | | | | | |
| | no | 969 | 36.3 | 22 | 37.6 | | 30.5 | 37 | |
| Expected future income | better | 1611 | 60.7 | 61.4 | 63.4 | 0.66 | 65.2 | 63 | 0.9 |
| | same | 716 | 27 | 30.5 | 27.9 | | 27.4 | 28.2 | |
| | worse | 220 | 8.3 | 8.2 | 8.7 | | 7.4 | 8.8 | |
| Risk attitude | risk averse | 1067 | 40.2 | 49.4 | 39.4 | 8.94** | 42.2 | 40 | 0.87 |
| | risk neutral | 539 | 20.3 | 17.5 | 20.6 | | 20.8 | 20.3 | |
| | risk taker | 1046 | 39.4 | 33.2 | 40.1 | | 37.1 | 39.8 | |
| Forecast error | pessimistic | 438 | 16.4 | 19.1 | 16.1 | 1.98 | 14.9 | 16.6 | 4.26 |
| | no forecast error | 1001 | 37.5 | 35.2 | 37.7 | | 33.7 | 38 | |
| | prudentially optimistic | 633 | 23.7 | 22 | 23.9 | | 27.3 | 23.2 | |
| | non-prudentially optimistic | 600 | 22.5 | 23.7 | 22.3 | | 24.1 | 22.2 | |
| Subjective well-being vs other villagers | Better off | 446 | 16.7 | 6.8 | 17.7 | 35.27*** | 11.5 | 17.5 | 7.43** |
| | Same | 1223 | 45.9 | 39.8 | 46.2 | | 47.5 | 45.7 | |
| | Worse off | 995 | 37.3 | 53.4 | 35.8 | | 41.1 | 36.9 | |

*** 1%, ** 5%, * 10% levels of significance.
Note: The *t*-test tests whether the mean of over-indebted households exceeds the mean of not over-indebted households. The $chi^2$ test tests for a difference in the frequency distribution of a categorical variable between over-indebted households and not over-indebted households.

either. Households that made a non-prudentially optimistic forecast error expected not to become worse off and yet did become worse off. Differences for these variables between over-indebted and not over-indebted households register with only spotty statistical significance.

Finally, a variable of a psychological nature reflects a household's subjective sense of well-being relative to others in the same village (better off, same, or worse off). The hypothesis is that households that perceive themselves to be less well off than others in their village will be more inclined to live beyond their means and fall into over-indebtedness. Indeed, over-indebted households are far more likely to perceive themselves as worse off than do households that are not over-indebted for both countries and both indicators.

## 6. An econometric model of over-indebtedness

To model household over-indebtedness and the transition between two consecutive years, $t$ and $t$-1, we used a random effects dynamic probit model. There are three parts to this dynamic model: the determination of over-indebtedness status in period $t$; the determination of over-indebtedness status in period $t-1$; and an accounting for correlation of unobserved heterogeneity influencing these processes. Together, these three components characterize the determinants of over-indebtedness entry rates and persistence.

In practice, separating these three components is not straightforward, as it requires the handling of endogenous initial conditions and unobserved persistent household heterogeneity (Heckman, 1981a; Chay & Hyslop, 2014). The random effects dynamic probit model solves both problems and allows the effect of true state dependence to be estimated. Several approaches have been proposed to deal with the endogeneity of initial conditions, including Orme's (2001) two step procedure, Wooldridge's (2005) conditional maximum likelihood estimator, and the most popular approach proposed by Heckman (1981b), which involves specifying a reduced-form linear approximation for the first-year status of a variable. The Heckman model also controls for persistent unobserved household heterogeneity in estimating transition probabilities by including a household time-invariant effect. We adapt Stewart's (2007) dynamic model specification, as applied to analyzing unemployment, which is based on the approach proposed by Heckman.

### 6.1. Random effects dynamic probit model

For a household $i$, the propensity to be over-indebted at time $t$ is expressed in terms of latent variable $y^*_{it}$ as follows:

$$y^*_{it} = 1(x'_{it}\beta + y_{it-1}\gamma + \varepsilon_i + u_{it} > 0), \quad \text{where, } i = 1, \ldots, N; t = 2, \ldots T \tag{1}$$

In Eq. (1), $x_{it}$ is a vector of explanatory variables and $y_{it-1}$ is the lagged dependent variable, which stands for the over-indebtedness status of the household in the previous period. The residual $u_{it}$ is an unobservable time and household-varying error term assumed to follow a distribution $N(0, \sigma^2_u)$. The scalar $\varepsilon_i$ is the (unobserved) household-specific time-invariant effect, which determines the household's tendency to be over-indebted. It accounts for household characteristics such as debt perception, time preference, and the like that are not observed in our data. The observed binary variable $y_{it}$, which indicates the over-indebtedness status of household $i$ in period $t$, is related to the latent variable $y^*_{it}$ in Eq. (1) by the following relationship:

$$y_{it} = \begin{cases} 1 if y^*_{it} \geq 0 \\ 0 if y^*_{it} < 0 \end{cases}. \tag{2}$$

Further, because the composite error term, $v_{it} = \varepsilon_i + u_{it}$, will be serially correlated even if $u_{it}$ is not, we adopt the household-specific random effects notion that the pairwise correlations between the composite errors of any two different periods are equal:

$$\rho = corr(\varepsilon_{it}, \varepsilon_{is}) = \frac{\sigma^2_\alpha}{\sigma^2_\alpha + \sigma^2_u}, \quad \text{where } t, s = 1, \ldots, T; t \neq s. \tag{3}$$

In contrast to the standard uncorrelated random effects model, we follow Stewart (2006) and the mainstream literature in adopting Mundlak (1978) and Chamberlain (1984) to allow for possible correlation between the unobserved household characteristics ($\varepsilon_i$) and the observed household characteristics ($x_{it}$) by assuming that:

$$\varepsilon_i = \overline{x}'_i a + \alpha_i, \tag{4}$$

where $\alpha_i$ is distributed as $N(0, \sigma^2_u)$ and is assumed to be independent of $x_{it}$ and $u_{it}$ for all households and time periods. Here, $\overline{x}'_i$ is the mean of each household characteristic within the vector $x_{it}$ over the time period, which in terms of estimation implies that we add time average variables to the vector of the explanatory variables. This method ensures that the household specific differences, $\alpha_i$, that remain are not correlated with observed household characteristics. Adding that to Eq. (1), we can rewrite our model as:

$$y^*_{it} = 1\text{if}(x'_{it}\beta + y_{it-1}\gamma + \overline{x}'_i a + \alpha_i + u_{it} > 0)(i = 1, \ldots, N; t = 2, \ldots T) \tag{5}$$

To consistently estimate this model, we need to make additional assumptions concerning the relationship between the initial observations, $y_{i1}$, and the unobserved time-invariant household effect. We could assume either that the initial conditions are exogenous or that they are correlated with the unobserved household specific effect, $\alpha_i$. The assumption of exogeinty is valid only if the stochastic process that generates the outcome is serially independent and if a truly new process is observed at the beginning of the sample (Hsiao, 2003). In that case, the standard random effects probit model can be used by splitting the likelihood into two factors and maximizing the joint probability for $t = 2, \ldots, T$, without taking the first year into account. However, here the process of household over-indebtedness is not observed for each household from an original state, and hence, the initial conditions are likely to be correlated with $\alpha_i$. Therefore, the estimation of simple models such as the standard random effects probit model will overestimate the state dependence.

As discussed above, although other methods have been developed to handle the endogeneity problem of the initial conditions, such as Orme (2001) and Wooldridge (2005), we follow the approach proposed by Heckman (1981b) and solve the initial conditions problem by specifying a reduced-form linear approximation for the first year as:

$$y_{i1} = 1(z_{i1}^{'}\pi + \eta_i > 0). \tag{6}$$

where $z_{i1}$ includes $x_{i1}$, exogenous pre-sample variables and the vector of exogenous factor means, and $\eta_i$ is assumed to be distributed as standard normal and correlated with $\alpha_i$ but uncorrelated with $u_{it}$ for $t \geq 2$. As described by Stewart (2006), using an orthogonal projection, such correlation can be rewritten as:

$$\eta_i = \theta\alpha_i + u_{i1}, \tag{7}$$

where $u_{i1}$ is independent of $\alpha_i$ and satisfies the $N(0, \sigma_u^2)$ assumption for $t \geq 2$. Moreover, the potential differences between the error variance of the initial period and the following periods will be captured by $\theta$. Thus, combining Eqs. (5) and (6), the linearized reduced form for the latent variable for the first period can be written as:

$$y_{i1}^{*} = z_{i1}^{'}\pi + \theta\alpha_i + u_{i1} \quad (i = 1, \ldots, N). \tag{8}$$

The correlation of the household-specific effect presented in Eqs. (6) and (7) suggests that to consistently estimate the model parameters, we need a joint probability modeling approach for the initial period equation and the structural equation. Therefore, with the variance of the residual $u_{it}$ normalized to be one, the joint probability of being over-indebted for household $i$, given the unobserved household-specific time-invariant effect, $\alpha_i$, using Heckman's approach is (see Stewart, 2006, 2007):

$$p_{it}(\alpha^*) = \begin{cases} \Phi\left[\left(y_{it-1}\gamma + x_{it}^{'}\beta + \sigma_\alpha\alpha^*\right)(2y_{it} - 1)\right] fort \geq 2 \\ \Phi\left[\left(z_{i1}^{'}\pi + \theta\sigma_\alpha\alpha^*\right)(2y_{i1} - 1)\right] fort \geq 1 \end{cases}. \tag{9}$$

The model parameters are therefore estimated by maximizing the following likelihood function:

$$\Pi_i \int \alpha * \left\{\Phi = \left[\left(z_{i1}^{'}\pi + \theta\sigma_\alpha\alpha^*\right)(2y_{i1} - 1)\right] \Pi_{t=2}^{T} \Phi\left[\left(y_{it-1}\gamma + x_{it}^{'}\beta + \sigma_\alpha\alpha^*\right)(2y_{it} - 1)\right]\right\} dF(\alpha*), \tag{10}$$

where $F$ is the distribution function of$\alpha^* = \sqrt{\lambda/(1-\lambda)}$ and can be integrated out using Gauss-Hermite quadrature (Stewart, 2006).[1]

Finally, the models are estimated using a balanced panel dataset as these estimators were derived for balanced panel data where all cross-sectional units are observed in all time periods. One may thus worry about the potential attrition and sample selection bias that can arise as a consequence of extracting a balanced panel from an unbalanced one. However, as argued in the literature, Wooldridge's (2005) random effects dynamic probit model which we use as a check for such biases has an advantage in handling attrition and selection problems (Devicienti & Poggi, 2010). Wooldridge's estimator allows attrition and selection to depend on the initial conditions arbitrarily. Households with different initial over-indebtedness status are allowed to have different probabilities for missing data in the later time periods. Hence, the estimator addresses such biases implicitly without directly modeling them as a function of the initial conditions. Nevertheless, attrition bias is not much of a concern in our dataset because the attrition over the four waves of sampling was just 6.28 percent.

### *6.2. Measuring the persistence of household over-indebtedness*

To measure the persistence of household over-indebtedness, the transition probabilities along with the associated average partial effect (APE) and predicted probability ratio (PPR) are calculated by conditioning on the over-indebtedness status at $t - 1$. First, following the method by Stewart (2007), the persistence rate and entry rate of over-indebtedness are calculated for each household in the sample based on estimates of counterfactual outcome probabilities, taking the over-

[1] The model can be estimated using Mark Stewart's program module "redprob" in Stata.

**Table 6**
Random effects dynamic probit estimates for probability of over-indebtedness, Thailand.

| | Default Indicator | | | | Debt Service Indicator | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| **Structural Equation** | | | | | | | | |
| Over-indebtedness lag | 0.524** | 0.547** | 0.504** | 0.649** | 0.228** | 0.293** | 0.232** | 0.302** |
| | (2.97) | (2.89) | (2.83) | (3.62) | (2.43) | (2.99) | (2.47) | (3.06) |
| Number of children | −0.00636 | 0.0108 | −0.000455 | 0.0231 | −0.0472 | −0.0437 | −0.0494 | −0.0413 |
| | (−0.12) | (0.18) | (−0.01) | (0.39) | (−0.93) | (−0.85) | (−0.97) | (−0.80) |
| Household size | 0.0652** | 0.0454 | 0.0654** | 0.0405 | 0.0535** | 0.0434 | 0.0509** | 0.0380 |
| | (2.49) | (1.47) | (2.43) | (1.34) | (2.10) | (1.64) | (1.99) | (1.42) |
| Head female | −0.157 | −0.171 | −0.185 | −0.220* | −0.191* | −0.137 | −0.182* | −0.153 |
| | (−1.36) | (−1.32) | (−1.55) | (−1.74) | (−1.81) | (−1.29) | (−1.73) | (−1.43) |
| Head married | −0.130 | −0.142 | −0.159 | −0.138 | 0.00776 | −0.00238 | 0.0119 | −0.00362 |
| | (−0.95) | (−0.95) | (−1.13) | (−0.95) | (0.06) | (−0.02) | (0.10) | (−0.03) |
| Head age <35 | 0.483* | 0.387 | 0.506* | 0.425 | 0.0911 | 0.131 | 0.0529 | 0.127 |
| | (1.69) | (1.29) | (1.73) | (1.47) | (0.34) | (0.49) | (0.20) | (0.47) |
| Head age 35–44 | 0.153 | −0.0196 | 0.157 | −0.0344 | 0.356** | 0.282* | 0.303** | 0.279* |
| | (0.82) | (−0.09) | (0.82) | (−0.17) | (2.45) | (1.89) | (2.08) | (1.86) |
| Head age 45–54 | 0.514** | 0.451** | 0.531** | 0.440** | 0.307** | 0.283** | 0.271** | 0.290** |
| | (3.46) | (2.81) | (3.46) | (2.81) | (2.53) | (2.27) | (2.23) | (2.32) |
| Head age 55–64 | 0.386** | 0.327** | 0.408** | 0.303** | 0.282** | 0.234** | 0.256** | 0.261** |
| | (2.66) | (2.09) | (2.73) | (1.96) | (2.44) | (1.98) | (2.21) | (2.20) |
| Head education primary or less | −0.267 | −0.279 | −0.283 | −0.361 | −0.951** | −0.880** | −0.937** | −0.905** |
| | (−0.94) | (−0.93) | (−0.97) | (−1.26) | (−3.66) | (−3.39) | (−3.62) | (−3.48) |
| Head education secondary | −0.430 | −0.507* | −0.459* | −0.651** | −1.326** | −1.197** | −1.307** | −1.220** |
| | (−1.61) | (−1.80) | (−1.68) | (−2.39) | (−5.43) | (−4.89) | (−5.36) | (−4.95) |
| Head agricultural | −0.0381 | 0.0576 | −0.0334 | −0.00199 | 0.0692 | 0.00704 | 0.0697 | −0.00331 |
| | (−0.24) | (0.33) | (−0.20) | (−0.01) | (0.54) | (0.05) | (0.54) | (−0.03) |
| Head off-farm employed | 0.0993 | 0.141 | 0.102 | 0.0657 | −0.0547 | −0.0657 | −0.0417 | −0.0828 |
| | (0.56) | (0.73) | (0.57) | (0.35) | (−0.38) | (−0.45) | (−0.29) | (−0.57) |
| Head inactive | 0.0248 | 0.0813 | 0.0246 | −0.0177 | 0.0847 | 0.0606 | 0.0785 | 0.0684 |
| | (0.12) | (0.36) | (0.12) | (−0.08) | (0.51) | (0.36) | (0.47) | (0.40) |
| Land rental | 0.116 | 0.0543 | 0.120 | 0.0548 | 0.0580 | 0.0422 | 0.0627 | 0.0717 |
| | (1.12) | (0.47) | (1.14) | (0.48) | (0.69) | (0.49) | (0.74) | (0.82) |
| Savings | −0.256** | −0.192 | −0.243** | −0.118 | 0.240** | 0.167* | 0.248** | 0.137 |
| | (−2.29) | (−1.55) | (−2.13) | (−0.95) | (2.54) | (1.70) | (2.62) | (1.38) |
| Income quintile 1 | 0.308** | 0.279* | 0.288* | 0.137 | 1.548** | 1.446** | 1.565** | 1.465** |
| | (2.00) | (1.68) | (1.83) | (0.82) | (10.91) | (10.03) | (10.94) | (9.97) |
| Income quintile 2 | 0.298** | 0.239 | 0.301* | 0.112 | 1.039** | 0.946** | 1.056** | 0.957** |
| | (1.96) | (1.47) | (1.95) | (0.69) | (8.14) | (7.26) | (8.21) | (7.26) |
| Income quintile 3 | 0.108 | 0.0240 | 0.116 | −0.0423 | 0.784** | 0.772** | 0.805** | 0.758** |
| | (0.69) | (0.14) | (0.73) | (−0.25) | (6.39) | (6.09) | (6.52) | (5.94) |
| Income quintile 4 | 0.155 | 0.0358 | 0.151 | −0.000327 | 0.161 | 0.120 | 0.168 | 0.118 |
| | (1.03) | (0.22) | (0.99) | (−0.00) | (1.39) | (1.02) | (1.44) | (0.99) |
| Shock to expenses, unexpected | 0.155* | 0.154 | 0.159* | 0.147 | −0.0310 | −0.0126 | −0.0273 | −0.00357 |
| | (1.68) | (1.53) | (1.69) | (1.49) | (−0.44) | (−0.17) | (−0.39) | (−0.05) |
| Shock to expenses, expected | 0.166 | 0.195 | 0.170 | 0.155 | 0.115 | 0.0826 | 0.114 | 0.0972 |
| | (1.26) | (1.37) | (1.27) | (1.09) | (1.02) | (0.71) | (1.02) | (0.83) |
| Shock to income, unexpected | 0.172* | 0.140 | 0.177* | 0.158 | 0.122* | 0.132* | 0.121 | 0.127* |
| | (1.77) | (1.33) | (1.78) | (1.51) | (1.66) | (1.74) | (1.64) | (1.66) |
| Risk averse | | 0.0278 | 0.0447 | 0.00342 | | −0.262** | −0.279** | −0.264** |
| | | (0.23) | (0.38) | (0.03) | | (−2.88) | (−3.17) | (−2.87) |
| Risk neutral | | −0.148 | −0.106 | −0.158 | | −0.0863 | −0.118 | −0.0930 |
| | | (−1.19) | (−0.91) | (−1.28) | | (−0.98) | (−1.38) | (−1.05) |
| Expected future income same | | −0.0397 | | −0.0223 | | −0.158* | | −0.142 |
| | | (−0.33) | | (−0.18) | | (−1.80) | | (−1.53) |
| Expected future income worse | | −0.119 | | −0.115 | | −0.0441 | | −0.0202 |
| | | (−0.76) | | (−0.69) | | (−0.39) | | (−0.17) |
| Forecast error pessimistic | | | −0.245* | −0.200 | | | −0.120 | −0.158 |
| | | | (−1.70) | (−1.24) | | | (−1.05) | (−1.26) |
| Forecast error none | | | −0.305** | −0.260* | | | −0.0758 | −0.100 |
| | | | (−2.28) | (−1.81) | | | (−0.72) | (−0.91) |
| Forecast error prudentially optimistic | | | −0.177 | −0.113 | | | −0.0676 | −0.118 |
| | | | (−1.21) | (−0.71) | | | (−0.58) | (−0.95) |
| Subjective well-being better off | | | | −0.719** | | | | 0.110 |
| | | | | (−3.86) | | | | (0.81) |
| Subjective well-being same | | | | −0.489** | | | | 0.208* |
| | | | | (−3.95) | | | | (1.93) |
| 2010 | −0.659** | −0.696** | −0.676** | −0.652** | −1.116** | −1.071** | −1.141** | −1.078** |
| | (−4.91) | (−4.77) | (−5.00) | (−4.66) | (−12.92) | (−11.79) | (−13.07) | (−11.72) |
| 2011 | −0.340** | −0.396** | −0.367** | −0.379** | −0.505** | −0.476** | −0.523** | −0.472** |

**Table 6** (*Continued*)

| | Default Indicator | | | | Debt Service Indicator | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| | (−2.83) | (−2.97) | (−3.00) | (−2.94) | (−6.12) | (−5.47) | (−6.28) | (−5.40) |
| Constant | −1.817** | −1.563** | −1.574** | −0.682 | −0.397 | −0.152 | −0.171 | −0.144 |
| | (−4.76) | (−3.76) | (−3.85) | (−1.56) | (−1.19) | (−0.44) | (−0.49) | (−0.39) |
| **Initial Condition Equation** | | | | | | | | |
| Number of children | 0.221 | 0.147 | 0.175 | 0.190 | 0.0143 | -0.0526 | 0.00775 | -0.0413 |
| | (0.46) | (1.01) | (0.98) | (0.62) | (0.20) | (−0.65) | (0.11) | (−0.50) |
| Household size | 0.123 | 0.115 | 0.0917 | 0.118 | 0.107** | 0.150** | 0.105** | 0.142** |
| | (0.46) | (1.21) | (0.97) | (0.63) | (2.64) | (3.09) | (2.59) | (2.88) |
| Head female | 0.178 | −0.0876 | 0.152 | −0.154 | −0.160 | −0.0782 | −0.147 | −0.0875 |
| | (0.36) | (−0.34) | (0.55) | (−0.42) | (−0.98) | (−0.44) | (−0.91) | (−0.48) |
| Head married | −0.622 | −0.483 | −0.452 | −0.418 | −0.0255 | 0.0532 | −0.00758 | 0.0593 |
| | (−0.46) | (−1.12) | (−0.96) | (−0.59) | (−0.13) | (0.25) | (−0.04) | (0.28) |
| Head age <35 | −0.169 | −0.132 | −0.188 | −0.123 | 0.691** | 0.690* | 0.639* | 0.715* |
| | (−0.20) | (−0.23) | (−0.31) | (−0.19) | (2.04) | (1.87) | (1.89) | (1.91) |
| Head age 35–44 | 0.804 | 0.784 | 0.562 | 0.634 | 0.462** | 0.464* | 0.388* | 0.440* |
| | (0.46) | (1.29) | (0.98) | (0.62) | (2.04) | (1.82) | (1.70) | (1.71) |
| Head age 45–54 | 0.537 | 0.510 | 0.386 | 0.582 | 0.417** | 0.356 | 0.376* | 0.338 |
| | (0.45) | (1.14) | (0.88) | (0.63) | (2.12) | (1.64) | (1.92) | (1.54) |
| Head age 55–64 | 0.00961 | 0.0461 | −0.0330 | 0.0584 | 0.361* | 0.305 | 0.303 | 0.317 |
| | (0.02) | (0.14) | (−0.10) | (0.16) | (1.92) | (1.44) | (1.60) | (1.49) |
| Head education primary or less | −0.501 | −0.412 | −0.461 | −0.649 | −0.0616 | −0.127 | −0.0260 | −0.175 |
| | (−0.35) | (−0.54) | (−0.54) | (−0.52) | (−0.13) | (−0.25) | (−0.05) | (−0.34) |
| Head education secondary | −0.825 | −0.741 | −0.697 | −1.193 | −0.279 | −0.386 | −0.247 | −0.466 |
| | (−0.42) | (−0.88) | (−0.75) | (−0.62) | (−0.60) | (−0.76) | (−0.53) | (−0.90) |
| Head agricultural | −0.395 | −0.288 | −0.308 | −0.392 | 0.0151 | −0.0538 | 0.0257 | −0.0985 |
| | (−0.43) | (−0.77) | (−0.75) | (−0.57) | (0.07) | (−0.23) | (0.12) | (−0.41) |
| Head off-farm employed | −0.415 | −0.448 | −0.325 | −0.608 | 0.00442 | −0.114 | 0.00423 | −0.153 |
| | (−0.42) | (−0.95) | (−0.71) | (−0.61) | (0.02) | (−0.43) | (0.02) | (−0.56) |
| Head inactive | −0.208 | −0.0120 | −0.172 | 0.0336 | −0.0248 | −0.298 | −0.0341 | −0.301 |
| | (−0.29) | (−0.03) | (−0.38) | (0.07) | (−0.09) | (−0.98) | (−0.13) | (−0.98) |
| Land rental | 0.0434 | 0.0426 | 0.0323 | −0.0773 | −0.0881 | −0.0889 | −0.0897 | −0.110 |
| | (0.14) | (0.19) | (0.14) | (−0.27) | (−0.60) | (−0.55) | (−0.61) | (−0.67) |
| Savings | 1.059 | 0.868 | 0.828 | 1.096 | 0.720** | 0.667** | 0.724** | 0.721** |
| | (0.47) | (1.31) | (1.10) | (0.65) | (3.63) | (3.05) | (3.65) | (3.21) |
| Income quintile 1 | 0.512 | 0.264 | 0.422 | 0.130 | 2.538** | 2.723** | 2.526** | 2.682** |
| | (0.44) | (0.67) | (0.86) | (0.29) | (8.41) | (7.33) | (8.43) | (7.11) |
| Income quintile 2 | 1.036 | 0.726 | 0.815 | 0.674 | 1.528** | 1.743** | 1.506** | 1.700** |
| | (0.47) | (1.28) | (1.11) | (0.63) | (6.17) | (5.89) | (6.13) | (5.64) |
| Income quintile 3 | 0.916 | 0.686 | 0.725 | 0.712 | 1.189** | 1.308** | 1.176** | 1.260** |
| | (0.47) | (1.24) | (1.07) | (0.63) | (4.92) | (4.64) | (4.88) | (4.40) |
| Income quintile 4 | 0.458 | 0.309 | 0.345 | 0.248 | 0.561** | 0.568** | 0.543** | 0.541** |
| | (0.43) | (0.74) | (0.74) | (0.44) | (2.44) | (2.19) | (2.37) | (2.06) |
| Shock to expenses, unexpected | 0.251 | 0.287 | 0.239 | 0.358 | 0.222* | 0.323** | 0.237* | 0.331** |
| | (0.43) | (1.07) | (0.86) | (0.62) | (1.76) | (2.30) | (1.87) | (2.32) |
| Shock to expenses, expected | 0.903 | 0.482 | 0.722 | 0.575 | 0.307 | 0.419 | 0.304 | 0.419 |
| | (0.46) | (0.98) | (1.05) | (0.60) | (1.17) | (1.48) | (1.17) | (1.47) |
| Shock to income, unexpected | 0.170 | 0.150 | 0.132 | 0.149 | 0.0545 | 0.0357 | 0.0533 | 0.00109 |
| | (0.39) | (0.68) | (0.58) | (0.47) | (0.44) | (0.26) | (0.43) | (0.01) |
| Risk averse | | −0.144 | −0.0319 | −0.300 | | −0.252 | −0.243 | −0.256 |
| | | (−0.52) | (−0.12) | (−0.56) | | (−1.39) | (−1.47) | (−1.39) |
| Risk neutral | | 0.0955 | 0.137 | −0.0199 | | −0.0512 | −0.0164 | −0.0693 |
| | | (0.37) | (0.49) | (−0.07) | | (−0.29) | (−0.10) | (−0.39) |
| Expected future income same | | −0.0851 | | 0.246 | | −0.0733 | | 0.00526 |
| | | (−0.38) | | (0.51) | | (−0.49) | | (0.03) |
| Expected future income worse | | 0.728 | | 1.703 | | 0.414* | | 0.610** |
| | | (1.35) | | (0.67) | | (1.83) | | (2.13) |
| Forecast error pessimistic | | | −0.120 | −1.275 | | | −0.0802 | −0.206 |
| | | | (−0.35) | (−0.66) | | | (−0.41) | (−0.85) |
| Forecast error none | | | −0.00255 | −0.290 | | | −0.0613 | 0.0234 |
| | | | (−0.01) | (−0.56) | | | (−0.37) | (0.13) |
| Forecast error prudentially optimistic | | | 0.175 | 0.385 | | | −0.0800 | 0.118 |
| | | | (0.55) | (0.57) | | | (−0.47) | (0.54) |
| Subjective well-being better off | | | | −0.661 | | | | −0.179 |
| | | | | (−0.60) | | | | (−0.55) |
| Subjective well-being same | | | | −0.889 | | | | −0.0953 |
| | | | | (−0.67) | | | | (−0.58) |
| Previous location rural | −0.378 | −0.436 | −0.306 | −0.419 | −0.731** | −0.732** | −0.731** | −0.725** |
| | (−0.37) | (−0.78) | (−0.54) | (−0.51) | (−2.32) | (−2.15) | (−2.33) | (−2.10) |

**Table 6** (*Continued*)

| | Default Indicator | | | | Debt Service Indicator | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| Education location rural | −0.116 | 0.0318 | −0.0826 | −0.0919 | 0.385 | 0.420 | 0.366 | 0.404 |
| | (−0.21) | (0.08) | (−0.21) | (−0.20) | (1.59) | (1.59) | (1.52) | (1.50) |
| Constant | −4.171 | −3.111 | −3.270 | −2.323 | −3.012** | −2.982** | −2.835** | −2.818** |
| | (−0.47) | (−1.42) | (−1.16) | (−0.64) | (−4.72) | (−4.16) | (−4.41) | (−3.73) |
| $\rho$ | 0.094 | 0.131 | 0.121 | 0.059 | 0.432*** | 0.371*** | 0.429*** | 0.366*** |
| | (0.111) | (0.118) | (0.107) | (0.099) | (0.050) | (0.057) | (0.050) | (0.057) |
| $\theta$ | 6.479 | 3.417 | 4.035 | 5.843 | 1.166*** | 1.368*** | 1.151*** | 1.386*** |
| | (20.398) | (4.800) | (6.341) | (17.156) | (0.219) | (0.321) | (0.218) | (0.332) |
| Log-likelihood | −830.347 | −725.907 | −825.49 | −695.821 | −1861.396 | −1629.4395 | −1853.764 | −1607.985 |
| LR test: ρ=0 chi2(1) | 12.49*** | 140.92*** | 12.51*** | 108.60*** | 347.88*** | 429.93*** | 116.16*** | 455.24*** |
| Wald test | 95.46*** | 83.60*** | 95.99*** | 141.20*** | 120.07*** | 311.68*** | 352.34*** | 312.57*** |
| Predicted prob. $\hat{p}_0$ | 0.055 | 0.045 | 0.050 | 0.053 | 0.217 | 0.229 | 0.218 | 0.236 |
| Predicted prob. $\hat{p}_1$ | 0.137 | 0.123 | 0.125 | 0.154 | 0.284 | 0.319 | 0.285 | 0.329 |
| APE: $\hat{p}_1 - \hat{p}_0$ | 0.082 | 0.078 | 0.075 | 0.101 | 0.067 | 0.090 | 0.067 | 0.093 |
| PPR: $\hat{p}_1/\hat{p}_0$ | 2.51 | 2.73 | 2.50 | 2.90 | 1.30 | 1.39 | 1.30 | 1.39 |
| Number of observations | 3646 | 3646 | 3646 | 3646 | 3646 | 3646 | 3646 | 3646 |

***1%, ** 5%, * 10% levels of significance

*Notes*:

1. Robust standard errors in parentheses.
2. $\hat{p}_0$, $\hat{p}_1$: predicted probabilities of households' over-indebtedness at $t$ given over-indebtedness status at $t-1$, respectively.
3. APE: average partial effect; PPR: predicted probability ratio.

indebtedness status at $t-1$ as fixed at 0 and fixed at 1 and then averaging each probability over all households as follows:

$$\hat{p}_1 = \frac{1}{N}\sum_{i=1}^{N}\Phi\left\{\left(\overline{x}'\hat{\beta} + \hat{\gamma}_j + \overline{x}_i'\hat{a}\right)\left(1-\hat{\lambda}\right)^{\frac{1}{2}}\right\}, \hat{p}_0 = \frac{1}{N}\sum_{i=1}^{N}\Phi\left\{\left(\overline{x}'\hat{\beta} + \overline{x}_i'\hat{a}\right)\left(1-\hat{\lambda}\right)^{\frac{1}{2}}\right\}. \quad (11)$$

Second, the associated average partial effect is calculated by taking the difference between these two probabilities $APE = \hat{p}_1 - \hat{p}_0$, while the predicted probability ratio is calculated by taking their ratio, $PPR = \hat{p}_1/\hat{p}_0$.

### *6.3. Model specifications*

We identify over-indebted households using the default and debt service indicator variables which take on a value of one if the household is over-indebted in a given year *t*, and a value of zero otherwise. For each of these indicators and each country, we run four different specifications of the random effects dynamic probit model. For both countries, the same sets of explanatory variables are used in each model, with the addition for Vietnam of an ethnic dummy variable. All models include the lagged value of the dependent variable as well as year dummies to control for time effects. The initial condition estimation for each model further includes pre-sample dummy variables for whether a household head's previous location was rural or urban and whether the head was educated in a rural or urban area.

Model 1 includes only basic household socio-economic and demographic variables as motivated by the life cycle theory. Model 2 includes additionally the variables for risk attitude and future expectations. Model 3 substitutes the forecast error variable for the future expectations variable. Finally, Model 4 incorporates both the future expectations variable and the forecast error variable, and brings in as well the variable for subjective well-being relative to other villagers. Model 4 thus encompasses all our explanatory variables.

Estimation results for the categorical variables take as reference a household whose head exhibits the following characteristics: male; single; age 65 or older; educated at post-secondary level; and self-employed. The reference household as a whole is characterized by: not renting land; no savings; income quintile 5; no shocks to expenses or income; risk taker; expected future income better; forecast error non-prudentially optimistic; and subjective well-being worse off relative to other villagers.

## 7. Estimation results

### *7.1. Persistence of household over-indebtedness in Thailand and Vietnam*

Estimation results for Heckman's random effects dynamic probit model, as expressed in Eq. (5), are reported for Thailand in Table 6 and for Vietnam in Table 7. For each country, the table presents results for four model specifications for each of the two over-indebtedness indicators taken as the dependent variable. For Thailand, the lagged over-indebtedness variable is statistically significance for both indicators and all four models. This confirms our prior expectation that past over-

**Table 7**
Random effects dynamic probit estimates for probability of over-indebtedness, Vietnam.

| | Default Indicator | | | | Debt Service Indicator | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| **Structural Equation** | | | | | | | | |
| Over-indebtedness lag | 0.191 | 0.177 | 0.208 | 0.264 | 0.0805 | 0.108 | 0.0989 | 0.103 |
| | (0.92) | (0.77) | (1.01) | (1.14) | (0.51) | (0.62) | (0.62) | (0.58) |
| Number of children | −0.0276 | −0.0385 | −0.0315 | −0.0500 | −0.0694 | −0.100* | −0.0731 | −0.101* |
| | (−0.46) | (−0.53) | (−0.52) | (−0.72) | (−1.26) | (−1.70) | (−1.32) | (−1.68) |
| Household size | 0.103** | 0.125** | 0.107** | 0.123** | 0.0782** | 0.107** | 0.0788** | 0.107** |
| | (2.66) | (2.77) | (2.79) | (2.83) | (2.38) | (3.09) | (2.39) | (3.08) |
| Head female | −0.0762 | −0.0344 | −0.0977 | −0.0739 | −0.0260 | −0.0179 | −0.0127 | −0.0163 |
| | (−0.34) | (−0.13) | (−0.44) | (−0.30) | (−0.14) | (−0.09) | (−0.07) | (−0.08) |
| Head married | 0.189 | 0.239 | 0.176 | 0.255 | 0.326 | 0.281 | 0.327 | 0.282 |
| | (0.78) | (0.85) | (0.73) | (0.93) | (1.57) | (1.27) | (1.58) | (1.27) |
| Head age <35 | 0.0267 | 0.0669 | −0.0157 | −0.0206 | 0.121 | 0.0511 | 0.112 | 0.0459 |
| | (0.10) | (0.21) | (−0.06) | (−0.07) | (0.54) | (0.21) | (0.49) | (0.19) |
| Head age 35–44 | 0.164 | 0.217 | 0.181 | 0.156 | 0.406** | 0.327 | 0.399** | 0.329 |
| | (0.75) | (0.80) | (0.83) | (0.60) | (2.08) | (1.53) | (2.03) | (1.52) |
| Head age 45–54 | 0.0250 | 0.111 | 0.0432 | 0.111 | 0.291 | 0.185 | 0.289 | 0.201 |
| | (0.12) | (0.45) | (0.21) | (0.46) | (1.58) | (0.94) | (1.56) | (1.01) |
| Head age 55–64 | −0.0379 | 0.109 | −0.0305 | 0.132 | 0.533** | 0.417** | 0.528** | 0.407** |
| | (−0.17) | (0.43) | (−0.14) | (0.53) | (2.78) | (2.06) | (2.75) | (1.99) |
| Head illiterate | 0.179 | 0.210 | 0.132 | 0.117 | −0.384** | −0.333* | −0.378** | −0.336* |
| | (0.96) | (0.95) | (0.71) | (0.55) | (−2.15) | (−1.74) | (−2.10) | (−1.74) |
| Head education primary | −0.0830 | −0.0949 | −0.126 | −0.116 | −0.0678 | −0.0408 | −0.0613 | −0.0464 |
| | (−0.59) | (−0.57) | (−0.89) | (−0.73) | (−0.57) | (−0.32) | (−0.52) | (−0.36) |
| Head agricultural | 0.264 | 0.181 | 0.290 | 0.177 | −0.394** | −0.412** | −0.423** | −0.438** |
| | (1.07) | (0.64) | (1.17) | (0.64) | (−2.20) | (−2.09) | (−2.35) | (−2.19) |
| Head off-farm employed | 0.264 | 0.224 | 0.268 | 0.170 | −0.346* | −0.274 | −0.359* | −0.304 |
| | (1.01) | (0.74) | (1.02) | (0.58) | (−1.82) | (−1.33) | (−1.88) | (−1.44) |
| Head inactive | 0.217 | 0.0352 | 0.250 | 0.0791 | −0.121 | 0.0228 | −0.122 | −0.00296 |
| | (0.63) | (0.08) | (0.72) | (0.19) | (−0.45) | (0.08) | (−0.45) | (−0.01) |
| Head ethnicity non-Kinh | −0.133 | −0.229 | −0.150 | −0.275 | −0.0939 | −0.0993 | −0.0642 | −0.0939 |
| | (−0.85) | (−1.19) | (−0.95) | (−1.47) | (−0.70) | (−0.69) | (−0.48) | (−0.64) |
| Land rental | 0.0504 | −0.0241 | 0.0615 | −0.0318 | 0.186 | 0.137 | 0.192 | 0.141 |
| | (0.33) | (−0.13) | (0.40) | (−0.18) | (1.42) | (0.97) | (1.46) | (0.99) |
| Savings | −0.0816 | 0.0380 | −0.0328 | 0.111 | 0.176 | 0.204 | 0.171 | 0.214 |
| | (−0.58) | (0.23) | (−0.23) | (0.68) | (1.49) | (1.58) | (1.42) | (1.62) |
| Income quintile 1 | 0.773** | 0.765** | 0.725** | 0.649** | 1.850** | 1.836** | 1.851** | 1.834** |
| | (3.34) | (2.90) | (3.11) | (2.43) | (8.54) | (7.91) | (8.49) | (7.75) |
| Income quintile 2 | 0.802** | 0.841** | 0.777** | 0.707** | 1.168** | 1.250** | 1.145** | 1.222** |
| | (3.65) | (3.40) | (3.51) | (2.83) | (6.16) | (6.24) | (6.02) | (5.99) |
| Income quintile 3 | 0.624** | 0.617** | 0.603** | 0.563** | 0.678** | 0.583** | 0.684** | 0.559** |
| | (3.02) | (2.67) | (2.91) | (2.44) | (3.75) | (3.07) | (3.76) | (2.91) |
| Income quintile 4 | 0.538** | 0.600** | 0.538** | 0.546** | 0.260 | 0.299 | 0.246 | 0.274 |
| | (2.67) | (2.68) | (2.65) | (2.42) | (1.47) | (1.62) | (1.38) | (1.47) |
| Shock to expenses, unexpected | 0.130 | 0.244* | 0.129 | 0.203 | 0.155 | 0.140 | 0.155 | 0.141 |
| | (1.15) | (1.84) | (1.14) | (1.57) | (1.57) | (1.30) | (1.57) | (1.30) |
| Shock to expenses, expected | −0.309 | −0.220 | −0.313 | −0.252 | 0.219 | 0.0914 | 0.209 | 0.0878 |
| | (−1.35) | (−0.89) | (−1.39) | (−1.04) | (1.37) | (0.52) | (1.29) | (0.50) |
| Shock to income, unexpected | 0.314** | 0.371** | 0.318** | 0.364** | −0.0353 | −0.0381 | −0.0360 | −0.0462 |
| | (2.35) | (2.39) | (2.37) | (2.39) | (−0.32) | (−0.32) | (−0.32) | (−0.38) |
| Risk averse | | 0.157 | 0.152 | 0.0845 | | 0.0716 | 0.0472 | 0.0827 |
| | | (1.04) | (1.19) | (0.56) | | (0.57) | (0.41) | (0.64) |
| Risk neutral | | −0.0927 | −0.109 | −0.131 | | 0.0911 | 0.149 | 0.0934 |
| | | (−0.53) | (−0.70) | (−0.74) | | (0.66) | (1.14) | (0.67) |
| Expected future income same | | −0.0534 | | −0.120 | | −0.169 | | −0.137 |
| | | (−0.36) | | (−0.78) | | (−1.35) | | (−1.04) |
| Expected future income worse | | −0.0105 | | −0.248 | | −0.449** | | −0.427* |
| | | (−0.04) | | (−0.96) | | (−2.08) | | (−1.86) |
| Forecast error pessimistic | | | 0.253 | 0.392** | | | −0.0650 | 0.0527 |
| | | | (1.54) | (1.99) | | | (−0.42) | (0.31) |
| Forecast error none | | | −0.0600 | −0.0153 | | | −0.0448 | −0.0957 |
| | | | (−0.42) | (−0.09) | | | (−0.35) | (−0.70) |
| Forecast error prudentially optimistic | | | −0.116 | 0.0247 | | | 0.229 | 0.137 |
| | | | (−0.69) | (0.13) | | | (1.62) | (0.87) |
| Subjective well-being better off | | | | −0.415* | | | | −0.0554 |
| | | | | (−1.89) | | | | (−0.29) |
| Subjective well-being same | | | | −0.466** | | | | 0.0580 |
| | | | | (−3.12) | | | | (0.45) |
| 2010 | −0.405** | −0.508** | −0.421** | −0.515** | 0.0844 | 0.0910 | 0.0889 | 0.0898 |

**Table 7** (*Continued*)

| | Default Indicator | | | | Debt Service Indicator | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| | (−3.09) | (−3.30) | (−3.15) | (−3.34) | (0.65) | (0.64) | (0.68) | (0.62) |
| 2011 | −0.253* | −0.346** | −0.289* | −0.408** | −0.109 | −0.0851 | −0.129 | −0.0890 |
| | (−1.69) | (−1.96) | (−1.91) | (−2.31) | (−0.93) | (−0.66) | (−1.07) | (−0.69) |
| Constant | −3.334** | −3.698** | −3.352** | −3.179** | −2.925** | −2.872** | −2.971** | −2.874** |
| | (−6.95) | (−6.37) | (−6.75) | (−5.30) | (−7.69) | (−6.93) | (−7.38) | (−6.33) |
| **Initial condition equation** | | | | | | | | |
| Number of children | 0.0500 | 0.0719 | 0.0477 | 0.0704 | −0.114 | −0.0797 | −0.101 | −0.101 |
| | (0.59) | (0.72) | (0.55) | (0.72) | (−1.10) | (−0.77) | (−0.99) | (−0.91) |
| Household size | −0.00689 | −0.0248 | −0.0195 | −0.0153 | 0.0884 | 0.0907 | 0.0874 | 0.108 |
| | (−0.11) | (−0.34) | (−0.30) | (−0.21) | (1.22) | (1.23) | (1.21) | (1.37) |
| Head female | −0.255 | −0.00615 | −0.191 | −0.0494 | −0.418 | −0.425 | −0.430 | −0.446 |
| | (−0.78) | (−0.02) | (−0.57) | (−0.13) | (−1.23) | (−1.18) | (−1.27) | (−1.19) |
| Head married | −0.0170 | −0.109 | −0.0596 | −0.128 | −0.193 | −0.478 | −0.243 | −0.560 |
| | (−0.05) | (−0.26) | (−0.16) | (−0.30) | (−0.54) | (−1.23) | (−0.68) | (−1.37) |
| Head age <35 | 0.162 | 0.0296 | 0.295 | 0.0470 | 0.704 | 0.396 | 0.678 | 0.496 |
| | (0.43) | (0.06) | (0.75) | (0.10) | (1.62) | (0.93) | (1.57) | (1.11) |
| Head age 35–44 | 0.310 | 0.403 | 0.431 | 0.359 | 0.962** | 0.837* | 0.908** | 0.869* |
| | (0.92) | (0.96) | (1.20) | (0.88) | (2.12) | (1.84) | (2.03) | (1.85) |
| Head age 45–54 | 0.546 | 0.631 | 0.676* | 0.648 | 1.071** | 0.830* | 1.031** | 0.809* |
| | (1.61) | (1.51) | (1.86) | (1.58) | (2.30) | (1.86) | (2.24) | (1.77) |
| Head age 55–64 | 0.413 | 0.565 | 0.510 | 0.577 | 1.066** | 0.837* | 1.042** | 0.848* |
| | (1.15) | (1.31) | (1.35) | (1.35) | (2.34) | (1.89) | (2.33) | (1.87) |
| Head illiterate | −0.172 | −0.189 | −0.264 | −0.255 | −0.303 | −0.102 | −0.302 | −0.0514 |
| | (−0.62) | (−0.57) | (−0.92) | (−0.78) | (−0.91) | (−0.30) | (−0.90) | (−0.15) |
| Head education primary | −0.192 | −0.202 | −0.191 | −0.262 | −0.0185 | 0.0204 | −0.0189 | 0.0342 |
| | (−0.90) | (−0.79) | (−0.87) | (−1.03) | (−0.07) | (0.08) | (−0.08) | (0.13) |
| Head agricultural | 0.353 | 0.228 | 0.345 | 0.151 | 0.125 | 0.164 | 0.139 | 0.237 |
| | (0.99) | (0.56) | (0.93) | (0.38) | (0.31) | (0.39) | (0.34) | (0.51) |
| Head off-farm employed | 0.336 | 0.120 | 0.358 | 0.0805 | 0.0603 | 0.0636 | 0.0847 | 0.144 |
| | (0.90) | (0.28) | (0.93) | (0.19) | (0.14) | (0.14) | (0.20) | (0.30) |
| Head inactive | 0.458 | −0.109 | 0.208 | −0.251 | 0.516 | 0.537 | 0.522 | 0.578 |
| | (0.90) | (−0.17) | (0.38) | (−0.39) | (0.95) | (0.94) | (0.96) | (0.95) |
| Head ethnicity non-Kinh | −0.113 | −0.319 | −0.218 | −0.331 | −0.215 | −0.0469 | −0.159 | −0.0519 |
| | (−0.48) | (−1.05) | (−0.89) | (−1.12) | (−0.84) | (−0.17) | (−0.60) | (−0.18) |
| Land rental | −0.122 | −0.170 | −0.160 | −0.240 | 0.0774 | 0.0489 | 0.102 | 0.0531 |
| | (−0.49) | (−0.58) | (−0.62) | (−0.83) | (0.28) | (0.17) | (0.37) | (0.18) |
| Savings | −0.0883 | 0.103 | −0.125 | 0.0872 | 0.0556 | −0.0183 | 0.0252 | −0.0373 |
| | (−0.45) | (0.45) | (−0.61) | (0.38) | (0.25) | (−0.08) | (0.11) | (−0.15) |
| Income quintile 1 | 0.0932 | 0.266 | 0.0933 | 0.175 | 3.423** | 3.186** | 3.389** | 3.185** |
| | (0.25) | (0.59) | (0.24) | (0.38) | (3.18) | (3.04) | (3.16) | (2.92) |
| Income quintile 2 | 0.580 | 0.589 | 0.530 | 0.493 | 2.302** | 2.136** | 2.305** | 2.156** |
| | (1.64) | (1.34) | (1.43) | (1.09) | (2.58) | (2.42) | (2.57) | (2.35) |
| Income quintile 3 | 0.475 | 0.664 | 0.528 | 0.573 | 1.548** | 1.485* | 1.532* | 1.380* |
| | (1.34) | (1.55) | (1.41) | (1.30) | (1.96) | (1.90) | (1.93) | (1.72) |
| Income quintile 4 | 0.122 | 0.235 | 0.120 | 0.104 | 1.078 | 1.067 | 1.045 | 1.009 |
| | (0.32) | (0.53) | (0.31) | (0.23) | (1.40) | (1.39) | (1.36) | (1.30) |
| Shock to expenses, unexpected | 0.380** | 0.627** | 0.345* | 0.569** | 0.418* | 0.449* | 0.428* | 0.425* |
| | (2.14) | (2.72) | (1.88) | (2.52) | (1.87) | (1.90) | (1.91) | (1.76) |
| Shock to expenses, expected | 0.171 | 0.259 | 0.255 | 0.284 | −0.461 | −0.453 | −0.488 | −0.391 |
| | (0.52) | (0.67) | (0.76) | (0.75) | (−1.02) | (−0.95) | (−1.08) | (−0.80) |
| Shock to income, unexpected | 0.649** | 0.866** | 0.686** | 0.791** | −0.0856 | −0.109 | −0.0884 | −0.0958 |
| | (2.77) | (2.87) | (2.81) | (2.72) | (−0.35) | (−0.43) | (−0.37) | (−0.37) |
| Risk averse | | 0.347 | 0.273 | 0.303 | | −0.112 | −0.152 | −0.0815 |
| | | (1.50) | (1.33) | (1.30) | | (−0.48) | (−0.67) | (−0.33) |
| Risk neutral | | −0.0635 | 0.154 | −0.0819 | | −0.0957 | −0.148 | −0.0376 |
| | | (−0.20) | (0.59) | (−0.27) | | (−0.35) | (−0.55) | (−0.13) |
| Expected future income same | | −0.431* | | −0.375 | | −0.167 | | −0.0998 |
| | | (−1.69) | | (−1.29) | | (−0.72) | | (−0.34) |
| Expected future income worse | | −0.554 | | −0.265 | | −0.269 | | −0.250 |
| | | (−1.32) | | (−0.49) | | (−0.70) | | (−0.46) |
| Forecast error pessimistic | | | −0.700** | −0.477 | | | −0.186 | −0.213 |
| | | | (−2.05) | (−1.07) | | | (−0.59) | (−0.52) |
| Forecast error none | | | 0.00111 | 0.0183 | | | −0.0602 | −0.0498 |
| | | | (0.00) | (0.07) | | | (−0.23) | (−0.17) |
| Forecast error prudentially optimistic | | | −0.0385 | −0.166 | | | −0.0353 | −0.0226 |
| | | | (−0.16) | (−0.55) | | | (−0.13) | (−0.07) |
| Subjective well-being better off | | | | −0.515 | | | | 0.106 |
| | | | | (−1.22) | | | | (0.25) |

**Table 7** (*Continued*)

| | Default Indicator | | | | Debt Service Indicator | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| Subjective well-being same | | | | 0.0102 | | | | 0.286 |
| | | | | (0.04) | | | | (1.13) |
| Previous location rural | −0.0768 | −0.0559 | −0.0990 | 0.104 | −0.235 | −0.394 | −0.243 | −0.442 |
| | (−0.14) | (−0.09) | (−0.18) | (0.16) | (−0.40) | (−0.61) | (−0.42) | (−0.65) |
| Education location rural | 0.154 | 0.279 | 0.151 | 0.241 | 0.810** | 0.883** | 0.791** | 0.869** |
| | (0.56) | (0.86) | (0.54) | (0.75) | (2.23) | (2.27) | (2.20) | (2.15) |
| Constant | −2.981** | −3.337** | −2.999** | −2.843** | −4.952** | −4.286** | −4.711** | −4.502** |
| | (−4.15) | (−3.69) | (−3.85) | (−3.07) | (−3.39) | (−3.09) | (−3.26) | (−2.95) |
| $\rho$ | 0.355*** | 0.407*** | 0.341*** | 0.349*** | 0.261*** | 0.227** | 0.258*** | 0.234** |
| | (0.107) | (0.113) | (0.108) | (0.123) | (0.090) | (0.101) | (0.091) | (0.103) |
| $\theta$ | 1.042** | 1.069** | 1.105** | 1.082** | 1.874* | 1.846 | 1.838* | 1.864 |
| | (0.107) | (0.441) | (0.459) | (0.512) | (1.061) | (1.230) | (1.047) | (1.248) |
| Log-likelihood | −685.400 | −541.639 | −669.488 | −530.629 | −788.536 | −666.009 | −782.430 | −659.904 |
| LR test: ρ=0 $chi^2(1)$ | 41.61*** | 236.84*** | 50.41*** | 227.16*** | 35.03*** | 189.17*** | 36.05*** | 189.40*** |
| Wald test | 58.06*** | 52.88*** | 66.59*** | 67.01*** | 116.44*** | 103.72*** | 119.25*** | 104.77*** |
| Predicted prob. $\hat{p}_0$ | 0.023 | 0.016 | 0.025 | 0.023 | 0.058 | 0.061 | 0.060 | 0.061 |
| Predicted prob. $\hat{p}_1$ | 0.037 | 0.025 | 0.041 | 0.042 | 0.067 | 0.074 | 0.071 | 0.073 |
| APE:. $\hat{p}_1 - \hat{p}_0$ | 0.014 | 0.009 | 0.016 | 0.019 | 0.009 | 0.013 | 0.011 | 0.012 |
| PPR:$\hat{p}_1/\hat{p}_0$ | 1.60 | 1.56 | 1.64 | 1.82 | 1.15 | 1.21 | 1.18 | 1.19 |
| Number of observations | 2655 | 2655 | 2655 | 2655 | 2655 | 2655 | 2655 | 2655 |

*** 1%, ** 5%, * 10% levels of significance.

*Notes*:

1. Robust standard errors in parentheses.
2. $\hat{p}_0$, $\hat{p}_1$: predicted probabilities of households' over-indebtedness at $t$ given over-indebtedness status at $t-1$, respectively.
3. APE: average partial effect; PPR: predicted probability ratio.

indebtedness increases the likelihood of over-indebtedness in the present. With both observed and unobserved household heterogeneity controlled for, this result implies true state dependence for over-indebtedness in Thailand.

Estimates for the average partial effect (APE) and the predicted probability ratio (PPR) reported at the bottom of Table 6 quantify the link between present and past over-indebtedness. Consider the results for the most encompassing model, Model 4. With respect to the default indicator, the APE value implies that households in default at $t-1$ face a risk of being in default at $t$ that is 10.1 percentage points higher than for households not in default at $t-1$, controlling for all household characteristics. Put in ratio terms, the PPR value indicates that households in default at $t-1$ are 2.9 times more likely to be in default at $t$ than households not in default at $t-1$, controlling for all household characteristics. With respect to the debt service indicator, the APE value indicates that households that were over-indebted at $t-1$ face a risk of over-indebtedness at $t$ that is 9.3 percentage points higher than for households that were not over-indebted at $t-1$. The PPR value indicates that households that were over-indebted in terms of debt service at $t-1$ are 1.39 times as likely to be over-indebted at $t$ than households not over-indebted at $t-1$. Comparing APE values for the two different over-indebtedness indicators shows that the persistence of default is more serious than the persistence of debt service over-indebtedness.

The estimate of the unobserved individual effects, $\rho$, captures the impact of unobserved household heterogeneity on the likelihood of experiencing over-indebtedness. For the debt service indicator under Model 4, 36.6 percent of the composite variance of household over-indebtedness is explained by unobserved household characteristics, with statistical significance at the one percent level. More generally, the magnitude of the $\rho$ estimates across models suggests the importance of unobserved household heterogeneity in the analysis, and stresses the desirability of panel data for this study.

The statistical significance of the estimate of $\theta$ indicates that the exogeneity assumption of the initial condition must be rejected for the debt service indicator (although not for the default indicator). This validates the applicability of Heckman's estimate for true state dependence as opposed to a random effects estimator which treats the initial conditions as exogenous.

The findings for Vietnam with respect to true state dependence contrast with those for Thailand, as seen in Table 7. The coefficient estimates for the lagged value of the dependent variable are not statistically significant for Vietnam for either over-indebtedness indicator under any model. Thus controlling for household characteristics, in Vietnam current over-indebtedness is not found to depend on over-indebtedness in the previous period. Rather, as captured by $\rho$, roughly 20 to 40 percent of the composite variance of household over-indebtedness is explained by unobserved household heterogeneity after controlling for the endogeneity of the initial conditions.

While the simple transition matrix of Table 3 shows that for Vietnam, default in particular tends to be highly persistent over time, and much more so for Thailand, our econometric analysis traces this to household characteristics that predispose some to remain in default. Thus for Vietnamese households, over-indebtedness does not exhibit true state dependence as it does in Thailand. Households are able to transition out of over-indebtedness in Vietnam in association with their underlying circumstances whereas even if underlying circumstances change, Thai households will tend to remain over-indebted.

### 7.2. Determinants of household over-indebtedness in Thailand and Vietnam

Estimates of the marginal effects of covariates, based on Orme's random effects dynamic probit model, are presented in Table 8 for Thailand and Table 9 for Vietnam. Orme's estimator is used rather than Heckman's due to the relative simplicity of the interpretation of the estimates. Among the demographic variables, household size is positively related to over-indebtedness and statistically significant across most models and both indicators for both countries, even as number of children is not. The two explanatory variables are presumably highly correlated with household size absorbing more of the effect. Female head is negatively associated with over-indebtedness for all models and both indicators for both countries, although only for a few models for Thailand are the estimates statistically significant. Households with a middle aged head show statistically greater likelihood of over-indebtedness relative to the benchmark households headed by the elderly for both indicators in Thailand although only for the debt service indicator in Vietnam.

In both countries, a lower level of education is statistically associated with lower incidence of over-indebtedness, particularly with respect to the debt service indicator. In quantitative terms the effect is especially pronounced in Thailand where households whose heads have a primary or below level of education show more than a 30 percentage point lower incidence of exceeding the debt service threshold than those with education above the secondary level, and this applies across all four models. This result may seem contrary to expectations. However, households with lower education levels face more severe credit constraints, and therefore have less opportunity to over-borrow. For the case of Thailand, Siripanyawat et al. (2010) found that households headed by someone with a college degree tended to accumulate more debt due to easier access to formal credit. Nonetheless, the fact that the effect of education is generally insignificant for the default indicator suggests that while households with higher levels of education more often exceed our threshold for debt service over-indebtedness, this does not dispose them to higher rates of default.

In Thailand, the occupation of the household head is not significantly related to over-indebtedness. In Vietnam, however, households with heads engaged in agricultural and off-farm employment show lower rates of over-indebtedness than those in the benchmark group whose household heads are self-employed, albeit this holds only with respect to the debt service indicator. This suggests that while households with self-employed heads are no more prone to default, which would pose a more severe threat to household welfare, they do depend more on borrowing to pursue their livelihoods. Land rental is not associated with over-indebtedness in either country.

Households that have savings register in some models as less prone to default, but more prone to exceeding debt service threshold, with the pattern stronger in Thailand. This suggests that savings act as a buffer against default and will tend to be depleted before households default on their commitments. With respect to the positive relationship between savings and high debt service ratios, we note that it is common for lenders in microcredit markets of developing countries to require borrowers to open a savings account to obtain a loan. These findings regarding savings and over-indebtedness are in line with existing literature (Anderloni & Vandone, 2008; Brown et al., 2014).

Not surprisingly, lower incomes are associated with higher probabilities of over-indebtedness in both countries and for both indicators. Households in the bottom quintile are more likely to exceed the debt service threshold by 37 percentage points in Thailand and 24 percentage points in Vietnam than those in the top quintile, with findings consistent across models. The likelihood of over-indebtedness declines steadily across income quintiles. Nevertheless, the likelihood of default does not show such a regular and consistent pattern across quintiles. Indeed, for Vietnam, relative to the top quintile, the four lower quintiles show increased likelihoods of default that lie within a narrow range of 4.5 to 5.3 percentage points.

Shocks to expenses and income for the most part do not show a significant relationship with over-indebtedness with one exception. That exception is unexpected shocks to income increasing the likelihood of default in Vietnam by around 2.5 percentage points across all models. Similarly for risk attitude, an effect emerges that is narrowly focused but consistent across models. Risk averse households in Vietnam are less likely to be over-indebted by the debt service indicator to a degree of nearly seven percentage points relative to risk taking households. This latter result is in accord with Brown et al. (2013) who found for U.S. households an inverse relationship between the amount of debt households accumulate and their attitude toward risk. The Brown study further found, however, that the influence of risk attitude diminishes as household debt burdens increase such that even risk taking households become more cautious as they become more indebted. This is consistent with our result for Vietnam that despite risk attitude being related to over-indebtedness by the debt service standard, it is not reflected in the propensity for default.

With regard to future expectations, we hypothesize over-indebtedness to be negatively related to the expectation of lower future income but with the relationship further affected by whether expectations were proved right or wrong. Relative to the benchmark group of households that expected future income to be better, households who expected it to be the same or worse all show lower likelihoods of over-indebtedness across all models and both indicators, although the statistical significance of the estimates is more narrowly concentrated. The most clearly statistically supported relationship is for Vietnamese households with respect to the debt service indicator. Relative to households that expected future income to be higher, households that expected it to be the same were 2.6 percentage points less likely to be over-indebted and those who expected it to be worse 5.6 percentages points less likely to be over-indebted. The forecast error variables in the Vietnam case are not significant for any model or indicator. In the Thailand case, the statistical significance of the estimators is sensitive to model and indicator with the strongest pattern emerging for the default indicator. The benchmark group represents households that expected not to become worse off but did become worse off (prudentially optimistic forecast error). We hypothesize these households to be more prone to over-indebtedness and others to be less so by comparison, which indeed is

**Table 8**
Predicted marginal probabilities, Thailand.

| | Default Indicator | | | | Debt Service Indicator | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| Over-indebtedness lag | 0.0459** | 0.0479** | 0.0503** | 0.0621** | 0.0690** | 0.0845** | 0.0671** | 0.0849** |
| | (2.37) | (2.35) | (2.54) | (2.91) | (2.87) | (3.30) | (2.80) | (3.31) |
| Number of children | −0.000324 | −0.000346 | −0.000674 | 0.000649 | −0.0112 | −0.0104 | −0.0107 | −0.00880 |
| | (−0.07) | (−0.07) | (−0.14) | (0.12) | (−0.94) | (−0.86) | (−0.90) | (−0.71) |
| Household size | 0.00549** | 0.00457* | 0.00582** | 0.00432 | 0.0120** | 0.0116* | 0.0116* | 0.0101 |
| | (2.31) | (1.68) | (2.44) | (1.54) | (1.99) | (1.81) | (1.91) | (1.58) |
| Female head | −0.0130 | −0.0154 | −0.0154 | −0.0191* | −0.0463* | −0.0370 | −0.0431* | −0.0415 |
| | (−1.26) | (−1.39) | (−1.47) | (−1.66) | (−1.88) | (−1.47) | (−1.75) | (−1.64) |
| Head married | −0.00889 | −0.0111 | −0.0116 | −0.00979 | −0.000162 | 0.000435 | −0.000795 | −0.00275 |
| | (−0.73) | (−0.87) | (−0.93) | (−0.73) | (−0.01) | (0.01) | (−0.03) | (−0.09) |
| Head age <35 | 0.0402 | 0.0372 | 0.0463* | 0.0430 | 0.0158 | 0.0166 | 0.00702 | 0.0100 |
| | (1.56) | (1.41) | (1.77) | (1.59) | (0.24) | (0.25) | (0.11) | (0.15) |
| Head age 35–44 | 0.00911 | 0.00289 | 0.0134 | 0.000525 | 0.0786** | 0.0646* | 0.0704** | 0.0599* |
| | (0.55) | (0.16) | (0.80) | (0.03) | (2.28) | (1.79) | (2.02) | (1.66) |
| Head age 45–54 | 0.0431** | 0.0405** | 0.0468** | 0.0416** | 0.0741** | 0.0728** | 0.0662** | 0.0719** |
| | (3.24) | (2.90) | (3.44) | (2.88) | (2.55) | (2.41) | (2.27) | (2.37) |
| Head age 55–64 | 0.0332** | 0.0280** | 0.0349** | 0.0261* | 0.0686** | 0.0640** | 0.0641** | 0.0691** |
| | (2.54) | (2.05) | (2.63) | (1.84) | (2.47) | (2.22) | (2.30) | (2.39) |
| Head education primary or less | −0.0370 | −0.0405 | −0.0381 | −0.0505** | −0.322** | −0.317** | −0.333** | −0.322** |
| | (−1.53) | (−1.64) | (−1.56) | (−1.97) | (−5.77) | (−5.48) | (−5.91) | (−5.57) |
| Head education secondary | −0.0228 | −0.0231 | −0.0229 | −0.0274 | −0.227** | −0.230** | −0.243** | −0.238** |
| | (−0.89) | (−0.89) | (−0.88) | (−1.02) | (−3.76) | (−3.69) | (−4.00) | (−3.83) |
| Head agricultural | −0.00359 | 0.00377 | −0.00142 | 0.000606 | 0.0154 | 0.00614 | 0.0168 | 0.00268 |
| | (−0.25) | (0.25) | (−0.10) | (0.04) | (0.49) | (0.19) | (0.53) | (0.08) |
| Head off-farm employed | 0.0100 | 0.0171 | 0.00921 | 0.0132 | −0.0154 | −0.0200 | −0.0129 | −0.0250 |
| | (0.63) | (1.03) | (0.58) | (0.77) | (−0.43) | (−0.55) | (−0.36) | (−0.69) |
| Head inactive | 0.000883 | 0.00752 | 0.00418 | 0.00255 | 0.0202 | 0.0195 | 0.0186 | 0.0184 |
| | (0.05) | (0.38) | (0.22) | (0.12) | (0.49) | (0.46) | (0.45) | (0.43) |
| Land rental | 0.0135 | 0.00379 | 0.0111 | 0.00430 | 0.0151 | 0.0126 | 0.0140 | 0.0179 |
| | (1.44) | (0.38) | (1.17) | (0.41) | (0.72) | (0.58) | (0.67) | (0.82) |
| Savings | −0.0240** | −0.0175 | −0.0212** | −0.0121 | 0.0700** | 0.0499** | 0.0652** | 0.0418* |
| | (−2.39) | (−1.62) | (−2.09) | (−1.06) | (2.99) | (2.02) | (2.78) | (1.67) |
| Income quintile 1 | 0.0286** | 0.0246* | 0.0239* | 0.0134 | 0.370** | 0.367** | 0.378** | 0.371** |
| | (1.99) | (1.66) | (1.66) | (0.86) | (12.59) | (12.02) | (12.80) | (11.95) |
| Income quintile 2 | 0.0280** | 0.0229 | 0.0240* | 0.0128 | 0.247** | 0.237** | 0.250** | 0.238** |
| | (2.00) | (1.58) | (1.70) | (0.84) | (8.52) | (7.84) | (8.62) | (7.80) |
| Income quintile 3 | 0.00965 | 0.00196 | 0.00775 | −0.00525 | 0.185** | 0.188** | 0.191** | 0.186** |
| | (0.68) | (0.13) | (0.54) | (−0.34) | (6.45) | (6.26) | (6.65) | (6.16) |
| Income quintile 4 | 0.0139 | 0.00573 | 0.0141 | 0.00352 | 0.0340 | 0.0248 | 0.0349 | 0.0228 |
| | (1.01) | (0.41) | (1.02) | (0.24) | (1.19) | (0.83) | (1.22) | (0.77) |
| Shock to expenses, unexpected | 0.0156* | 0.0148* | 0.0112 | 0.0123 | −0.00364 | −0.00291 | −0.00314 | −0.000725 |
| | (1.84) | (1.67) | (1.32) | (1.32) | (−0.21) | (−0.16) | (−0.18) | (−0.04) |
| Shock to expenses, expected | 0.0151 | 0.0141 | 0.0123 | 0.00740 | 0.0307 | 0.0273 | 0.0292 | 0.0336 |
| | (1.28) | (1.15) | (1.03) | (0.56) | (1.09) | (0.94) | (1.04) | (1.15) |
| Shock to income, unexpected | 0.0159* | 0.0129 | 0.0135 | 0.0136 | 0.0332* | 0.0384** | 0.0300 | 0.0375* |
| | (1.80) | (1.40) | (1.50) | (1.41) | (1.82) | (2.01) | (1.64) | (1.95) |
| Risk averse | | 0.00276 | 0.00115 | −0.00132 | | −0.0676** | −0.0688** | −0.0692** |
| | | (0.26) | (0.11) | (−0.12) | | (−2.97) | (−3.18) | (−3.03) |
| Risk neutral | | −0.0106 | −0.0108 | −0.0136 | | −0.0252 | −0.0306 | −0.0287 |
| | | (−0.98) | (−1.03) | (−1.19) | | (−1.14) | (−1.45) | (−1.30) |
| Expected future income same | | −0.00174 | | −0.00329 | | −0.0414* | | −0.0420* |
| | | (−0.17) | | (−0.30) | | (−1.87) | | (−1.88) |
| Expected future income worse | | −0.00841 | | −0.0162 | | −0.0145 | | −0.0162 |
| | | (−0.62) | | (−1.13) | | (−0.51) | | (−0.57) |
| Forecast error pessimistic | | | −0.0245* | −0.0164 | | | 0.00268 | −0.00435 |
| | | | (−1.90) | (−1.18) | | | (0.10) | (−0.15) |
| Forecast error none | | | −0.0263** | −0.0215* | | | 0.0135 | 0.00827 |
| | | | (−2.35) | (−1.77) | | | (0.54) | (0.31) |
| Forecast error prudentially optimistic | | | −0.0334** | −0.0352** | | | 0.0532** | 0.0460 |
| | | | (−2.65) | (−2.41) | | | (2.02) | (1.60) |
| Subjective well-being better off | | | | −0.0593** | | | | 0.0232 |
| | | | | (−3.33) | | | | (0.68) |
| Subjective well-being same | | | | −0.0379** | | | | 0.0485* |
| | | | | (−3.26) | | | | (1.80) |
| 2010 | −0.0584** | −0.0611** | −0.0592** | −0.0614** | −0.279** | −0.275** | −0.279** | −0.273** |
| | (−5.12) | (−4.96) | (−5.05) | (−4.80) | (−14.84) | (−13.73) | (−14.62) | (−13.44) |
| 2011 | −0.0320** | −0.0317** | −0.0301** | −0.0296** | −0.127** | −0.124** | −0.125** | −0.122** |
| | (−3.19) | (−2.99) | (−2.95) | (−2.65) | (−6.47) | (−5.87) | (−6.27) | (−5.74) |

**Table 8** (*Continued*)

| | Default Indicator | | | | Debt Service Indicator | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| $u_{i1}$ | 0.0254** (3.67) | | | | 0.139** (8.90) | | | |
| $u_{i2}$ | | 0.0249** (3.37) | | | | 0.129** (7.82) | | |
| $u_{i3}$ | | | 0.0251** (3.60) | | | | 0.140** (8.91) | |
| $u_{i4}$ | | | | 0.0187** (2.40) | | | | 0.127** (7.75) |
| ρ | 0.068 | 0.087 | 0.041 | 0.011 | 0.339 | 0.285 | 0.341 | 0.280 |
| Log-likelihood | −506.45 | −450.32 | −494.44 | −438.40 | −1354.64 | −1202.01 | −1341.81 | −1188.39 |
| Wald test | 145.61 | 128.15 | 155.02 | 151.74 | 389.49 | 365.18 | 391.41 | 365.43 |
| Number of observation | 2742 | 2441 | 2731 | 2420 | 2742 | 2441 | 2731 | 2420 |

*** 1%, ** 5%, * 10% levels of significance.

what we find. Such a relationship is not confirmed by Brown et al. (2005) who find rather that a household's optimistic future financial expectation itself, not its accuracy, is associated with over-indebtedness.

Finally, with regard to subjective sense of well-being relative to other villagers, our hypothesis is that those who feel themselves to be the same as or better off than others are less likely to be over-indebted than those who feel themselves to be worse off. This hypothesis is confirmed for both countries with respect to the default indicator although not for the debt service indicator. Compared to households that perceived themselves to be worse off, households that perceived themselves to be the same as or better off than others were less likely to default by four to six percentage points in both countries. Georgarakos et al. (2014), who have found similar results in the context of developed countries, explain that social comparison can affect the decision of households to borrow when they are trying to keep up with local living standards and when they observe their better off neighbors borrowing even if they are themselves less equipped to take on debt repayment.

## 8. Robustness check

A major econometric issue in estimating the persistence of household over-indebtedness involves unobserved heterogeneity and initial conditions. We address this issue using several alternative estimators to assess the robustness of the results. First the random effects dynamic probit mode is estimated following Orme's (2001) two step procedure and Wooldridge's (2005) conditional maximum likelihood approach. Further, a random effects dynamic probit model with auto-correlated errors is estimated implementing Stewart's (2006) technique. The results from all approaches are consistent qualitatively, with slight differences in coefficient estimates. Additionally, applying Heckman's approach with auto-correlated errors also confirmed the robustness of the results.[2]

## 9. Summary and conclusion

This study analyzes over-indebtedness of rural households in Thailand and Vietnam. A unique panel dataset, involving four survey waves between 2007 and 2011, affords insight into the nature and causes of persistence in over-indebtedness at household level. The superficial observation that households that become over-indebted tend to remain so does not reveal whether such persistence is due to true state dependence – implying that an over-indebted state is inherently difficult to escape – or to persistence in the underlying household characteristics that tend to cause over-indebtedness. By controlling for both observed and unobserved household characteristics, we are able to distinguish between these two sources of persistence.

We make use of two dichotomous indicators of over-indebtedness: one is positive if the household is in default or arrears on a loan, the other if the ratio of debt service to income exceeds 50 percent. For both indicators, we find that over-indebtedness in Thailand exhibits true state dependence while in Vietnam it does not, with this result robust across a variety of model specifications. This result may seem surprising since for both countries we are looking at rural communities where households rely on micro-credit institutions for loans. The share of indebted households in default is similar between the two countries, albeit with much variation from year to year, although the share of households for which the ratio of debt service to income exceeds our threshold is much higher in Thailand than in Vietnam (Table 1).

An explanation for the difference in true state dependence between the two countries must be a matter of conjecture. Simple conditional probabilities (Table 3) show that for Vietnam, the probability of remaining in default for a household previously in default is much higher than for Thailand. Conversely, for Thailand, the probability of remaining over the debt

[2] Results are available from the authors on request.

**Table 9**
Predicted marginal probabilities, Vietnam.

| | Default Indicator | | | | Debt Service Indicator | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| Over-indebtedness lag | 0.0147 | 0.0223 | 0.0146 | 0.0304 | 0.0236 | 0.0167 | 0.0215 | 0.0165 |
| | (0.75) | (1.10) | (0.74) | (1.38) | (1.07) | (0.72) | (0.98) | (0.71) |
| Number of children | −0.00291 | −0.00527 | −0.00303 | −0.00665 | −0.00972 | −0.0111 | −0.00995 | −0.0109 |
| | (−0.55) | (−0.97) | (−0.56) | (−1.17) | (−1.41) | (−1.55) | (−1.42) | (−1.51) |
| Household size | 0.00879** | 0.0105** | 0.00924** | 0.0110** | 0.0102** | 0.0125** | 0.0104** | 0.0127** |
| | (2.49) | (2.89) | (2.56) | (2.97) | (2.42) | (2.88) | (2.45) | (2.90) |
| Head female | −0.00686 | −0.00702 | −0.00626 | −0.00948 | −0.00233 | −0.00573 | −0.00390 | −0.00627 |
| | (−0.35) | (−0.36) | (−0.32) | (−0.47) | (−0.10) | (−0.24) | (−0.16) | (−0.26) |
| Head married | 0.0172 | 0.0177 | 0.0190 | 0.0224 | 0.0374 | 0.0290 | 0.0406 | 0.0282 |
| | (0.80) | (0.82) | (0.87) | (0.99) | (1.42) | (1.08) | (1.53) | (1.04) |
| Head age <35 | 0.00686 | 0.00924 | 0.00283 | 0.00480 | 0.0136 | 0.00361 | 0.0184 | 0.00602 |
| | (0.30) | (0.39) | (0.12) | (0.19) | (0.47) | (0.12) | (0.64) | (0.20) |
| Head age 35–44 | 0.0162 | 0.0214 | 0.0184 | 0.0191 | 0.0542** | 0.0427 | 0.0566** | 0.0447* |
| | (0.83) | (1.05) | (0.93) | (0.90) | (2.18) | (1.63) | (2.26) | (1.70) |
| Head age 45–54 | 0.00505 | 0.0115 | 0.00553 | 0.0114 | 0.0412* | 0.0306 | 0.0404* | 0.0328 |
| | (0.28) | (0.62) | (0.31) | (0.59) | (1.77) | (1.27) | (1.73) | (1.36) |
| Head age 55–64 | −0.00342 | 0.00617 | −0.00369 | 0.00795 | 0.0711** | 0.0575** | 0.0680** | 0.0585** |
| | (−0.18) | (0.31) | (−0.19) | (0.39) | (2.96) | (2.31) | (2.81) | (2.34) |
| Head illiterate | 0.0163 | 0.0130 | 0.0123 | 0.00688 | −0.0476** | −0.0455* | −0.0509** | −0.0466** |
| | (1.01) | (0.80) | (0.75) | (0.41) | (−2.13) | (−1.95) | (−2.25) | (−1.99) |
| Head education primary | −0.00523 | −0.00508 | −0.00910 | −0.00738 | −0.0119 | −0.00897 | −0.0116 | −0.0101 |
| | (−0.42) | (−0.41) | (−0.72) | (−0.57) | (−0.79) | (−0.58) | (−0.77) | (−0.65) |
| Head agricultural | 0.0266 | 0.0279 | 0.0284 | 0.0270 | −0.0545** | −0.0615** | −0.0501** | −0.0631** |
| | (1.21) | (1.25) | (1.27) | (1.17) | (−2.39) | (−2.61) | (−2.17) | (−2.66) |
| Head off-farm employed | 0.0293 | 0.0285 | 0.0309 | 0.0248 | −0.0481** | −0.0455* | −0.0428* | −0.0466* |
| | (1.28) | (1.21) | (1.33) | (1.01) | (−1.98) | (−1.82) | (−1.75) | (−1.85) |
| Head inactive | 0.0206 | 0.0392 | 0.0264 | 0.0394 | −0.0185 | −0.0100 | −0.0134 | −0.0134 |
| | (0.67) | (1.25) | (0.85) | (1.20) | (−0.53) | (−0.28) | (−0.39) | (−0.37) |
| Head ethnicity non-Kinh | −0.0145 | −0.0147 | −0.0120 | −0.0178 | −0.00778 | −0.0125 | −0.0108 | −0.0112 |
| | (−1.05) | (−1.01) | (−0.85) | (−1.17) | (−0.47) | (−0.70) | (−0.64) | (−0.63) |
| Land rental | 0.00513 | 0.000268 | 0.00626 | 0.000770 | 0.0240 | 0.0191 | 0.0222 | 0.0182 |
| | (0.38) | (0.02) | (0.46) | (0.05) | (1.40) | (1.08) | (1.30) | (1.03) |
| Savings | −0.00605 | 0.00242 | −0.00319 | 0.00927 | 0.0253 | 0.0283* | 0.0233 | 0.0297* |
| | (−0.48) | (0.19) | (−0.25) | (0.68) | (1.63) | (1.74) | (1.49) | (1.78) |
| Income quintile 1 | 0.0674** | 0.0609** | 0.0641** | 0.0498** | 0.235* * | 0.245** | 0.239** | 0.245** |
| | (3.07) | (2.81) | (2.91) | (2.24) | (9.06) | (8.87) | (9.06) | (8.64) |
| Income quintile 2 | 0.0733** | 0.0611** | 0.0726** | 0.0533** | 0.152** | 0.164** | 0.152** | 0.163** |
| | (3.57) | (3.09) | (3.53) | (2.63) | (6.34) | (6.52) | (6.31) | (6.36) |
| Income quintile 3 | 0.0576** | 0.0493** | 0.0569** | 0.0458** | 0.0890** | 0.0805** | 0.0876** | 0.0790** |
| | (3.02) | (2.68) | (2.96) | (2.41) | (3.88) | (3.41) | (3.82) | (3.31) |
| Income quintile 4 | 0.0505** | 0.0464** | 0.0529** | 0.0445** | 0.0395* | 0.0405* | 0.0361 | 0.0399* |
| | (2.73) | (2.59) | (2.81) | (2.37) | (1.73) | (1.75) | (1.59) | (1.70) |
| Shock to expenses, unexpected | 0.0116 | 0.0164 | 0.0122 | 0.0143 | 0.0184 | 0.0199 | 0.0183 | 0.0198 |
| | (1.15) | (1.58) | (1.18) | (1.31) | (1.44) | (1.48) | (1.42) | (1.45) |
| Shock to expenses, expected | −0.0280 | −0.0229 | −0.0305 | −0.0279 | 0.0267 | 0.0136 | 0.0279 | 0.0125 |
| | (−1.36) | (−1.15) | (−1.46) | (−1.31) | (1.27) | (0.61) | (1.34) | (0.57) |
| Shock to income, unexpected | 0.0259** | 0.0277** | 0.0254** | 0.0277** | −0.000322 | −0.00572 | −0.00452 | −0.00603 |
| | (2.16) | (2.25) | (2.09) | (2.17) | (−0.02) | (−0.38) | (−0.32) | (−0.40) |
| Risk averse | | 0.0154 | 0.0118 | 0.00933 | | 0.00385 | 0.00148 | 0.00511 |
| | | (1.30) | (1.01) | (0.75) | | (0.24) | (0.10) | (0.32) |
| Risk neutral | | −0.00710 | −0.0114 | −0.0118 | | 0.0131 | 0.0159 | 0.0132 |
| | | (−0.52) | (−0.83) | (−0.80) | | (0.76) | (0.96) | (0.76) |
| Expected future income same | | −0.00183 | | −0.00222 | | −0.0265* | | −0.0262* |
| | | (−0.16) | | (−0.19) | | (−1.68) | | (−1.66) |
| Expected future income worse | | −0.00109 | | −0.00825 | | −0.0556** | | −0.0560** |
| | | (−0.06) | | (−0.41) | | (−2.09) | | (−2.07) |
| Forecast error pessimistic | | | 0.00386 | −0.000720 | | | −0.00323 | −0.00739 |
| | | | (0.25) | (−0.04) | | | (−0.16) | (−0.35) |
| Forecast error none | | | −0.00890 | −0.00934 | | | 0.00647 | 0.00507 |
| | | | (−0.69) | (−0.69) | | | (0.40) | (0.30) |
| Forecast error prudentially optimistic | | | −0.00952 | −0.00449 | | | −0.00969 | −0.0181 |
| | | (−0.70) | (−0.31) | | | (−0.55) | | (−0.94) |
| Subjective well-being better off | | | | −0.0447** | | | | −0.00338 |
| | | | | (−2.31) | | | | (−0.15) |
| Subjective wellbeing same | | | | −0.0401** | | | | 0.00708 |
| | | | | (−2.96) | | | | (0.45) |
| 2010 | −0.0345** | −0.0463** | −0.0383** | −0.0513** | −0.0176 | −0.00658 | −0.0165 | −0.00779 |
| | (−2.93) | (−3.50) | (−3.12) | (−3.70) | (−1.15) | (−0.41) | (−1.06) | (−0.48) |

**Table 9** (*Continued*)

| | Default Indicator | | | | Debt Service Indicator | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 1 | Model 2 | Model 3 | Model 4 |
| 2011 | −0.0212* | −0.0295** | −0.0221* | −0.0361** | 0.00557 | 0.0144 | 0.0106 | 0.0140 |
| | (−1.66) | (−2.20) | (−1.68) | (−2.52) | (0.33) | (0.80) | (0.62) | (0.78) |
| $u_{i1}$ | 0.0396** | | | | 0.0465** | | | |
| | (4.47) | | | | (4.33) | | | |
| $u_{i2}$ | | 0.0361** | | | | 0.0436** | | |
| | | (3.93) | | | | (3.90) | | |
| $u_{i3}$ | | | 0.0406** | | | | 0.0467** | |
| | | | (4.52) | | | | (4.33) | |
| $u_{i4}$ | | | | 0.0333** | | | | 0.0428** |
| | | | | (3.50) | | | | (3.79) |
| ρ | 0.316 | 0 0.331 | 0.314 | 0.283 | 0.166 | 0.176 | 0 0.195 | 0.190 |
| Log-likelihood | −486.95 | −411.65 | −479.12 | −405.10 | −571.68 | −494.23 | −560.85 | −492.89 |
| Wald test | 82.86 | 82.65 | 86.39 | 94.88 | 130.73 | 121.11 | 128.78 | 119.07 |
| Number of observations | 2004 | 1784 | 1976 | 1777 | 2004 | 1784 | 1976 | 1777 |

*** 1%, ** 5%, * 10% levels of significance.

service threshold for a household previously over the threshold is much higher than for Vietnam. Rather than persevering under high debt service burdens, Vietnamese households appear more ready to hold to default or arrears. Perhaps this behavior leads to debt forgiveness or renegotiation so as to return troubled households to financial viability.

Further, the community may play a bigger role in household borrowing affairs in Vietnam. According to Okae (2009), rural credit institutions in Vietnam have been successful in achieving a high level of loan repayment due to community relationships and social ties. Okae suggests that monitoring mechanisms are enacted by community members such that economic and social sanctions enforce repayment and restrain households from borrowing excessively. Thus while a household's circumstances may thrust it into over-indebtedness in either country, in Vietnam the household need not remain in such a state. Unexpected shocks to income and expenses are seen to be important factors in over-indebtedness in both countries, but whether the effects are transitory or lead to a debt spiral may well depend on community support of a sort that is more on offer in Vietnam with its legacy socialist structures.

Explanatory variables in our econometric model draw from three strains of theory: the life cycle theory of saving which emphasizes demographic and socio-economic variables; behavioral theory which points to the importance of attitudes and expectations; and social comparison theory which invokes subjective perceptions of relative well-being. Our results find the strongest and most consistent factor in over-indebtedness is low income. Among demographic factors, larger households with male, middle-aged, and higher-educated heads show some association with over-indebtedness. Ethnicity in Vietnam is not significant in explaining over-indebtedness. This is interesting since many studies point to differences in economic conditions between the Kinh majority and ethnic minority groups (e.g., Imai et al., 2011), and ethnic minorities are often maligned as having a "self-reinforcing culture of poverty" (Van de Walle & Gunewardena, 2001).

The behavioral variables of willingness to take risk and overly optimistic expectations are confirmed for Thailand as related to over-indebtedness, but not for Vietnam. Again, the social pressure in Vietnam's more tightly monitored village societies as contrasted with the more individualistic societies of Thailand could be a reason for this difference. Finally, social comparison theory is supported to some extent for both countries in that households that perceive themselves to be worse off are more likely to be over-indebted.

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