THE DYNAMICS OF RURAL HOUSEHOLDS DEBT IN THAILAND AND VIETNAM

Von der Wirtschaftswissenschaftlichen Fakultät

der Gottfried Wilhelm Leibniz Universität Hannover

zur Erlangung des Grades

DOKTORIN DER WIRTSCHAFTSWISSENSCHAFTEN

Dr. rer. pol.

genehmigte Dissertation

von

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geboren am 03.12.1984 in Addis Ababa, Ethiopia

2017

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Tag der Promotion: July 31, 2017

ACKNOWLEDGEMENTS

I have been able to complete this dissertation only with the immeasurable and valuable support I have received from my family, friends, colleagues and everyone at the faculty, either passively or actively.

My deepest gratitude goes to my supervisor, Professor Dr. Hermann Waibel for guiding me, standing by me, teaching me and most of all being patient with me all through the length of this project. I honestly could not have come this far without your esteemed support.

I would also like to thank Professor Dr. Ulrike Grote for opening the doors to me and supporting me during my MSc. studies, giving me a foundation to be able to complete this dissertation. Thank you also for agreeing to be the second referee of this work.

My parents, Dr. Beyene Chichaibelu and Mrs. Yalemshet Wolde Amanuel, I would not have come this far with this work and even in life without your great love, sacrifice and support. My siblings, Michael Beyene, Blen Beyene and Biruktawit Beyene, I am blessed to have you to call on and receive counsel and strength breeding words all through the project. To you all, I am most grateful for everything.

With humility and gratitude, I would like to thank Professor Dr. Wolfgang Pittroff, Professor Dr. Dieter-M. Hörmann, Professor Dr. Harmen Storck and Mrs. Evis Storck and the Lukas Community, for your inexhaustible support, guidance and providence all through this project.

Finally, I will thank my friends at the institute who have now become family. The past few years of knowing you all, I have been blessed with your bounty of kindness, graciousness, encouragement and support. I would not have wished for a different group of friends.

ZUSAMMENFASSUNG

Die Verschuldung von Haushalten hat in den meisten Teilen Asiens erheblich zugenommen und unlängst einen neuen Rekordstand erreicht. Teilweise spiegelt diese Entwicklung Fortschritte im Finanzsystem und ökonomisches Wachstum wieder, andererseits birgt die Haushaltsverschuldung ein erhöhtes Risiko makroökonomischer und finanzieller Instabilität. Auf Haushaltsebene ist die zunehmende Verschuldung vor allem unter den Armen in ländlichen Gebieten besorgniserregend. Die jüngsten Mikrofinanzkrisen in Entwicklungsländern haben gezeigt, wie eine exzessive Schuldenanhäufung Haushalte gegenüber Schocks verwundbar macht, die Ausfallrate erhöht und zu einer Tilgungskrise führen kann. In Anbetracht des anhaltenden Ausbaus der finanziellen Inklusion als Mittel zur Erlangung der neuen nachhaltigen Entwicklungsziele in Asien, ist es wesentlich die finanzielle Situation der armen und verletzlichen Bevölkerungsschichten zu bewerten, um letztlich die negativen Folgen solcher Interventionen abwenden zu können.

Zu diesem Zweck wird in dieser Arbeit die Verschuldung ländlicher Haushalte in Thailand und Vietnam analysiert mit einem besonderen Fokus auf jene Haushalte, deren Konsumniveau nahe der Armutsgrenze liegt. Die spezifischen Ziele dieser Arbeit sind: (i) das Ausmaß der Überschuldung und ihre Beständigkeit unter den ländlichen Haushalten in Thailand und Vietnam zu untersuchen und die Faktoren zu bestimmen, die zu dieser Überschuldung geführt haben, insbesondere verhaltensbezogene und soziale Faktoren; (ii) den Einfluss von mannigfachen Kreditzugängen auf das erhöhte Risiko der Überschuldung ländlicher Haushalte und deren Gefangensein in einer Schuldenfalle zu analysieren (iii) die beobachteten länderspezifischen Unterschiede in der Schuldenmarktbeteiligung, im Schuldenstand und in der Überschuldung zwischen den ländlichen Haushalten in Thailand

und Vietnam zu analysieren und die Faktoren zu bestimmen, die diese länderspezifischen Unterschiede erklären können.

Zur Bearbeitung dieser Zielstellungen nutzt diese Arbeit einem Paneldatensatz von ca. 4300 ländlichen Haushalten aus sechs Provinzen im Nordosten Thailands und der Nordzentralen Küste und dem zentralen Hochland Vietnams. Die Haushaltsdaten wurden 2007, 2008, 2010 und 2011 in jenen Provinzen erhoben, die einen hohen Anteil an ländlichen Haushalten haben, die in Armut leben oder dem Risiko ausgesetzt sind, in Armut zu fallen. Diese Arbeit identifiziert überschuldete Haushalte mithilfe von Indikatoren für den Kreditausfall und der Schuldendienstquote. Ein Haushalt gilt folglich als überschuldet, sofern der Kredit nicht zurückgezahlt werden kann oder die Tilgung 50% des jährlichen Haushaltseinkommens übersteigt.

Methodisch trägt diese Arbeit zum gegenwärtigen Forschungsstand in der Haushaltsüberschuldung und finanziellen Vulnerabilität auf verschiedene Weise bei. Erstens, mithilfe der Integration von drei ökonomischen Theoriemodellen, dem Lebenszyklus-, dem Verhaltens- und dem Sozialvergleichsmodell, identifiziert diese Arbeit Faktoren, die zur Überschuldung ländlicher Haushalte und ihrer Beständigkeit in Südostasien beitragen – eine Region, in der bisher wenig empirische Forschung zu diesem Thema stattgefunden hat. Dazu liefert ein Random Effects Dynamic Probit-Modell empirische Evidenz für die Beständigkeit des Überschuldungsproblems unter ländlichen Haushalten in Südostasien. Zweitens, basierend auf der Verhaltenstheorie und der Neuen Institutionenökonomik in der Mikrofinanzierung, wird die Hypothese der bidirektionalen Relation zwischen multipler Kreditaufnahme und Überschuldung mithilfe eines Dynamischen Random Effects Bivariaten Probit-Modells getestet. Dieses Modell erfasst die dynamische Interdependenz und die simultane Kausalität zwischen den beiden finanziellen Zielvariablen und kontrolliert dabei die unbeobachtete Haushaltsheterogenität in den Übergangswahrscheinlichkeiten. Drittens, die beobachteten länderspezifischen Unterschiede in der Schuldensituation ländlicher Haushalte werden zwischen zwei Ländern Südostasiens untersucht, in denen bisher die empirische Evidenz an Faktoren auf nationaler Ebene aufgrund mangelnder vergleichbarer Mikrodaten begrenzt war.

Die Ergebnisse dieser Arbeit liefern neue Erkenntnisse für Finanzinstitutionen, die den ländlichen Armen in entwickelnden und aufstrebenden Volkswirtschaften dienen. Die Ergebnisse zeigen, dass ein erheblicher Teil der ländlichen Haushalte in Thailand und Vietnam überschuldet sind. Die Schätzungen des wahren Zustandsabhängigkeitseffekts zeigen, dass das Problem der Überschuldung für ländliche Haushalte in Thailand ein dauerhaftes Problem ist, während es in Vietnam nur ein vorübergehendes Problem ist. Außerdem heben die Schätzergebnisse hervor, dass der Armutszustand ländlicher Haushalte im Sinne eines niedrigen Einkommensniveaus und Einkommensschocks das Risiko der Überschuldung beeinflussen. Ebenso scheinen Entscheidungsträger ländlicher Haushalte, die überoptimistisch ihre finanzielle Situation betrachten und ihre gesellschaftliche Stellung als gering einschätzen, ein erhöhtes Überschuldungsrisiko zu haben.

Ferner legen die Ergebnisse dar, dass sowohl ländliche Haushalte in Thailand als auch in Vietnam mehrfach Kredite von verschiedenen Kleinkreditgebern aufnehmen. In Thailand haben Anwender dieser Praxis der mehrfachen Kreditaufnahme ein höheres Überschuldungsrisiko. Die vorherrschende Meinung, dass eine mehrfache Kreditaufnahme ländlichen Haushalten erlaubt unbezahlbare Schulden zu refinanzieren und sie in einer

Schuldenfalle gefangen hält, wurde von den empirischen Ergebnissen allerdings nicht bestätigt.

Während die mehrfache Kreditaufnahme und die Überschuldung problematisch für ländliche Haushalte in beiden Ländern sind, gibt es erhebliche länderspezifische Unterschiede in ihrem Ausmaß und in ihrer Relation. Die Ergebnisse zeigen, dass sich das höhere Ausmaß an Schulden und Überschuldung in Thailand durch Unterschiede im kulturellen, institutionellen und ökonomischen Umfeld erklären lassen. Während die Ausstattung ländlicher Haushalte die beobachteten Unterschiede in der Überschuldung am unteren Ende der Schuldenverteilung erklärt, wird die höhere Verschuldung am oberen Ende eher durch das laxe wirtschaftliche Umfeld als durch Ausstattungseffekte in Thailand erklärt. Das wirtschaftliche Umfeld in Thailand kennzeichnet sich durch eine besondere Milde für ökonomisch benachteiligte Haushalte, die hoch verschuldet sind, im Vergleich zum vietnamesischen Pendant.

Daher wird in dieser Arbeit geschlussfolgert, dass, während die finanzielle Inklusion ein wichtiger Baustein der ländlichen Entwicklung bleibt, das ungehinderte Wachstum des Mikrofinanzmarktes die finanzielle Vulnerabilität und damit das Armutsrisiko ländlicher Haushalte durch Verschuldung erhöht, insofern nicht politische Entscheidungsträger eingreifen, um die Abwärtsrisiken von Mikrokrediten zu minimieren.

Stichworte: Mikrokredite, ländlicher Kreditmarkt, Haushaltsüberschuldung, mehrfache Kreditaufnahme, Thailand, Vietnam

ABSTRACT

Household debt has grown dramatically in most parts of Asia and recently reached a new peak. While this development partly reflects the progress in financial development and economic growth, rising household indebtedness has also been linked with increased risk of macroeconomic and financial instability. At the household level, the growing indebtedness among the rural poor is particularly worrying. The recent microfinance crises in developing countries have illustrated how such excessive accumulation of debt might make households more vulnerable to shocks, increase delinquency rates and lead to repayment crisis. Additionally, in light of the ongoing effort to promote financial inclusion as a means to achieve the new sustainable development goals in Asia, assessing financial situation of the poor and vulnerable segments of the population is vital to mitigate the adverse consequences of such interventions.

To this end, this thesis aims to examine rural household's indebtedness in Thailand and Vietnam particularly focusing on households whose consumption level is near the poverty line. The specific research objectives of the thesis are: (i) to examine the extent of over-indebtedness and its persistence among rural households' in Thailand and Vietnam and identify the factors that contribute to such financial outcomes among rural households, particularly focusing on the effect of behavioral and social factors; (ii) to examine whether access to credit from multiple microcredit agencies increases rural households' risk of falling into over-indebtedness and getting trapped in debt cycles; (iii) to analyze the observed cross-country differences in credit market participation, level of household debt holding and over-indebtedness between rural households in Thailand and Vietnam and examine factors that explain such country-level differences in rural household debt.

To do so, the thesis draws on a household panel survey data of around 4300 rural households from six provinces in Northeastern Thailand and the North Central Coast and Central Highlands of Vietnam. The household panel survey collected in 2007, 2008, 2010 and 2011 targeted provinces with a large share of rural households that are either living in poverty or are vulnerable to fall into poverty. Using this dataset, the thesis mainly identifies over-indebted households based on the default and debt-service ratio indicators. Hence, an over-indebted household is one that has either defaulted on a loan or whose annual debt repayment requires more than 50% of its annual income.

Methodologically, this thesis makes the following key contributions to current research on households' indebtedness and financial vulnerability. First, by integrating three economic theoretical models: the life cycle, behavioral and social comparison models, the thesis identifies factors that contribute to rural households' over-indebtedness and its persistency in Southeast Asia where there has been little empirical research. While the random effects dynamic probit model estimation provides an empirical evidence for the persistence of over-indebtedness problem among rural households in Southeast Asia. Second, drawing from behavioral and new institutional economic theories on microfinance, a hypothesis of bidirectional relationship between multiple borrowing and over-indebtedness is tested using a dynamic random-effect bivariate probit model. This model captures the dynamic interdependency and simultaneous causality between the two financial outcomes while controlling for unobserved household heterogeneity in transition probabilities. Third, the observed cross-country difference in rural household debt situation is examined between two countries in Southeast Asia where empirical evidence on country-level factors has been limited due to lack of comparable micro-level data.

The results presented in this thesis provide some novel insights to financial institutions that serve the rural poor in developing and emerging market economies. The results suggest that a considerable share of rural households both in Thailand and Vietnam are over-indebted. The estimates on the true state dependence effect of over-indebtedness show that Thai rural households face the problem of over-indebtedness persistently, while those in Vietnam face over-indebtedness transiently. The estimation results also highlight that rural household's poverty status in terms of low-level of income and income shocks influence their risk of falling into over-indebtedness. Rural household whose decision makers are overoptimistic about their financial situation in the future and those who consider themselves being of low social standing were also found to be more likely to be over-indebted.

Also, the results reveal that both rural households in Thailand and Vietnam take on multiple loans from several microcredit lenders. And those that adopt multiple borrowing practices face higher risk of over-indebtedness in Thailand. However, the widely held notion that multiple borrowing allows rural households to refinance unpayable debts and trap them in a debt cycles was not confirmed by the empirical results. While multiple borrowing and over-indebtedness are a problem for the rural poor in both countries, there is a considerable difference in the extent of these problems and their relationship across the two countries.

Furthermore, the results show that the higher prevalence of debt and over-indebtedness observed among Thai rural households is largely explained by differences in the cultural, institutional and economic environment that rural households of similar characteristics face in the two countries. While rural household's endowments explain to some extent the observed difference in indebtedness levels at the lower end of the debt distribution, the higher debt holding at the top of the debt distribution observed among rural households in Thailand is explained by lax economic environment than by endowment effects. The economic environment in Thailand is particularly more lenient to the economically disadvantaged rural households holding high amounts of debt as compared to what their counterparts face in Vietnam.

Hence, this thesis concludes that while financial inclusion remains an important ingredient in rural development, the unlimited growth of microcredit markets could make rural households more financially vulnerable and further impoverish them through debt, unless policy makers take proper steps to mitigate the downside risks of microcredit.

Keywords: Microcredit, Rural credit market, Houseold Over-indebtedness, Multiple borrowing, Thailand, Vietnam.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ADB	Asian Development Bank
APE	Average Partial Effect
ATM	Automated Teller Machine
BAAC	Bank for Agriculture and Agricultural Cooperatives
BWTP	Banking With the Poor Network
CGAP	Consultative Group to Assist the Poor
DAR	Debt to Asset Ratio
DFG	German Research Foundation
DIR	Debt to Income Ratio
DSR	Debt-Service Ratio
ECB	European Central Bank
FDC	Foundation for Development Cooperation
IFC	International Financial Corporation
IMF	International Monetary Fund
NCIC	National Credit Information Center
OECD	Organization for Economic Co-operation and Development
OXERA	Oxford Economic Research Associates
PPP	Purchasing Power Parity
PPR	Predicted Probability Ratio
RIF	Recentered Influence Function
SGP	Savings Groups for Production
THB	Thai Baht
VBARD	Vietnam Bank for Agriculture and Rural Development
VBSP	Vietnam Bank for Social Policy
VF	Village Fund

Chapter 1: Introduction

1.1 Background

The rural financial sectors in Thailand and Vietnam have witnessed extensive growth, of which coupled with governmental reforms has helped to expand financial services to rural households. While the governments of both countries have established several specialized financial institutions to mainly serve rural households, these formal financial institutions have also developed further and increased their outreach to agricultural and rural areas to provide credit products.

One effect of the development of the rural financial sector has been a growing household indebtedness in both countries. In Thailand, policy makers are especially concerned by the fact that the lowest income group bears the highest debt burden. There is also a scare that poorer households in these rural areas might be caught in a perpetual debt cycle, taking multiple loans from several lenders to refinance unpayable debts (ADB, 2013). However, assessing rural households' financial position has been a problem in both countries due to the absence of credit information on households' level of indebtedness and credit histories (ADB, 2015). In Thailand, the primary lenders of rural households, including the Bank for Agriculture and Agricultural Cooperatives (BAAC), the Village Fund (VF), agricultural and savings cooperatives, credit unions, farmers' groups, saving groups and informal lenders, are not members of the credit bureaus and therefore do not report credit information(ADB, 2013). In vietnam, the private credit bureaus collect credit information on households from financial institutions only voluntarily and the National Credit Information Center (NCIC) only collects information from regulated credit providers on large loans (International Financial Corporation (IFC), 2014). Hence, only little is known about the prevalence of over-indebtedness and multiple borrowing among rural household in Thailand and Vietnam.

Consequently, this thesis intends to fill this gap by examining rural households' indebtedness in Thailand and Vietnam to understand its extent, persistence, interrelationship with multiple borrowing practices, and country-level differences.

1.2 Research Objectives

The overall objective of this thesis is to assess rural households' financial vulnerability in the context of the broadening financial inclusion in Thailand and Vietnam, two emerging market economies in SoutheastAsia. There are four essays in which the overall objective shall be reached.

The **first essay** investigates the extent of over-indebtedness and its persistence among rural households' in Ubon Ratchathani in Thailand and Thua Thien-Hue in Vietnam. Following the insights from institutional economics, behavioral economics and social comparison theories, the essay identifies the factors that contribute to rural households' over-indebtedness and its persistency. It has five specific objectives:

1. To identify the extent of over-indebtedness;
2. To examine whether over-indebtedness is a persistent problem for rural households;
3. To identify the demographic and socio-economic factors that influence rural household's risk of over-indebtedness;
4. To examine whether overoptimistic and risk-taking behavior is associated with increased risk of over-indebtedness; and
5. To examine whether rural household's subjective wealth assessment and social relative standing are associated with increased risk of over-indebtedness.

The **second** and **third essays** focus on examining the relationship between multiple borrowing and over-indebtedness to determine to what extent rural households in Thailand and Vietnam become trapped in debt cycles. While the second essay investigets this relationship using the sample of rural households from Ubon Ratchathani in Thailand and Thua Thien-Hue in Vietnam, the third essay further examines the extent of the two financial outcomes and their relationship particularily focusing on Thai rural households from Ubon Ratchathani seeing that multiple borrowing is a major problem for the Thai rural households than those in Vietnam. Although the theoretical literature on financial intermediation suggests a bidirectional relationship between the two outcomes, previous studies focus primarily on the unidirectional effects of multiple borrowing on over-indebtedness and do not address the potential endogeneity between the two outcomes. Combining the insights from institutional and behavioral economics theories, we instead test the bidirectional relationship between multiple borrowing and over-indebtedness and address the following specific objectives:

1. To examine whether borrowing from multiple sources simultaneously increase rural households' risk of over-indebtedness; and
2. To examine whether over-indebted rural households refinance ultimately unpayable debt through multiple borrowing and become trapped in cyclical debt.

The **fourth essay** explores differences in credit market participation, level of household debt holding and over-indebtedness between rural households in Thailand and Vietnam. In this regard, the literature on household debt in developed countries decompose cross-country differences into a part that arises from differences in household structure and those that arise from differences in the economic environment (e.g., Christelis, Georgarakos, & Haliassos, 2013; Jappelli et al., 2013; Christelis et al. 2015; Bover et al., 2016). This essay contributes to the current literature by specifically focusing on rural households and analyzing cross-country differences in household debt in Southeast Asia. Focusing on rural households debt situation is particularily critical in Southeast Asia since the population is predominantly rural, informal lending still plays a crucial role and debt burden falls disproportionately on the rural poor (particularly in Thailand) (ADB, 2015). To do so, the following specific objectives are addressed:

1. To examine whether and to what extent the observed cross-country differences in rural household debt prevalence and over-indebtedness are explained by variation in household structure or the economic environment;
2. To examine whether and to what extent the observed cross-country differences in rural household's debt holding and level of indebtedness are explained by variation in household structure or the economic environment;
3. To investigate whether and to what extent the observed cross-country gap in rural household debt holding and indebtedness varies across the debt distribution; and
4. To investigate whether the factors underlying the observed cross-country gap in rural household debt holding and indebtedness varies across the debt distribution.

1.3. Methodology

To achieve the overall objective of the research, the thesis draws from several theoretical models and applies several empirical methodologies that are briefly explained below.

The **first essay** draws from three economic theoretical models to identify the factors that contribute to rural household's over-indebtedness and its persistency. In relation to household over-indebtedness, most analyses are grounded on the life-cycle-permanent-income theory of Modigliani (1966) and Friedman (1957). These models view household debt from a microeconomic perspective and construct a theory by examining a representative household who makes rational choices in response to changes in income to maximize life-time utility. These theories generally suggest that socio-economic and demographic characteristics such as age and education level of the household head, size and composition of the household, current and future income level of the household and adverse shocks to income and expense significantly influence rural households' risk of over-indebtedness. Alternatively, behavioral economic theories suggest that heuristics such as "bounded rationality" can increase households' likelihood of accumulating excessive amounts of debt compared to their earnings (Kilborn, 2005). In this regard, empirical literatures in behavioral economics have shown that such behavioral factors as overconfidence bias (Hyytinen and Putkuri, 2012) and risk preferences (Brown, Garino & Taylor, 2013) influence households risk of over-indebtedness. Finally, both theory and empirical evidence supports that household's risk of over-indebtedness is influenced by their perceived relative social standing (Shen, 2013). The empirical literature has found a considerable evidence that when household perceive their own social standing to be lower than their social reference group, they tend to overspend and accumulate debt relative to their income in an attempt to catch up with their peers (Georgarakos, Haliassos & Pasini, 2014). Taking the implication of these theories into consideration, rural household's probability of experiencing over-indebtedness, and its persistence is estimated using Heckman's random effects dynamic probit model (Heckman, 1981; Stewart, 2007; Stewart, 2006). The model allows the persistency of over-indebtedness to be tested while controlling for the effect of households' socioeconomic, demographic, behavioral characteristics and unobserved household heterogeneity.

In the **second and third essay,** two strands of economic theories underlie the hypothesis of a bidirectional relationship between multiple borrowing and over-indebtedness in Thailand and Vietnam. The first strand of theories in institutional economics view multiple borrowing as a principal agent problem that arises due to information asymmetry and leads to a moral hazard problem where borrowers take new loans hiding their other loan contracts from lenders. Such hidden information on borrower's level of indebtedness involves a negative externality since the hidden debt increase their level of indebtedness and reduces the probability that each loan gets repaid (McIntosh & Wydick, 2007). Additionally, multiple borrowing practices increase the problem of fungibility of money and allow households to take loans for consumption purposes. Loans used for consumption purposes increase households' debt burden since they do not generate additional income and improve their repayment capacity (Guha and Chowdhury, 2013). Even when loans are used for productive purposes, multiple borrowing can lead to over-indebtedness because simultaneously investing in various projects reduces the probability that all investments succeed given a borrower's limited time and capabilities (Casini, 2015). The second stands of theories in behavioral economics suggest that multiple borrowing allows over-indebted households to refinance unpayable debt and trap them in vicious debt cycle. According to these theories, households make such imprudent borrowing decisions that trap them in a cyclical debt due to their present-biased and time-inconsistent preferences (Arnold & Booker, 2013). To empirically test the bidirectional relationship conceptualized by the theories, we used a dynamic random-effect bivariate probit model in combination with Mundlak's (1978) approach that relaxes the strict exogeneity assumption for covariates (Devicienti and Poggi, 2010). The model allows us to estimate the persistency of multiple borrowing and over-indebtedness and the true cross-state dependence effects between the two outcomes while controlling for correlated unobserved heterogeneity and accounting for the initial conditions. This econometric approach captures the dynamic interdependency and simultaneous causality between multiple borrowing and over-indebtedness (Heckman, 2008).

The **fourth essay** aims to identify the factors that underlie the observed cross-country differences in credit market participation, level of household debt holding and over-indebtedness between rural households in Thailand and Vietnam established in the first and second essay. To do that, we follow the empirical literature from advance economies and decompose the cross-country difference in rural household's debt situation into a part that is driven by differences in cultural, institutional and economic environment and a part that is driven by differences in the distribution of the observed household characteristics using three counterfactual decomposition methods. First, a non-linear decomposition method (Fairlie, 1999 & 2005) is used to decompose the differences in the prevalence of debt, default and over-indebtedness between rural households in Thailand and Vietnam. Second, the Oaxaca-Blinder decomposition method (Blinder 1973; Oaxaca 1973) is used to compute the level of household debt and indebtedness gap and decompose the gaps into their separate underlying factors. Finally, the Recentered Influence Function Regression decomposition method (Firpo et al., 2009) is additionally used to decompose the level of household debt and indebtedness gap and identify the contribution of individual covariates and the economic environment at different quantiles of the unconditional distributions.

1.4 Data

This thesis is based on a unique household panel dataset collected from Thailand and Vietnam as part of the project "Vulnerability in Southeast Asia" – a long-term research project funded by the German Research Foundation (DFG). The initial survey was conducted in 2007 in six provinces in Northeastern Thailand and the North Central Coast and Central Highland of Vietnam. Since then, the survey has collected data annually until 2011 with exception of a one-year gap in 2009. In 2011, data was collected only from one province in each country. The six provinces; Buriram, Ubon Ratchathani and Nakhon Phanom from Thailand, Ha Tinh, Thua Thien Hue and Dac Lac from Vietnam, were purposively selected, targeting rural households that are either living in poverty or are vulnerable to fall into poverty, to achieve the overall goal of the project (Hardeweg, Klasen & Waibel, 2012).

The sample households were then selected from the six provinces using a three stage cluster sampling design. In the first stage, sub-districts in Thailand and communes in Vietnam were selected using a systematic random sampling based on a probability proportional to the size of the population. In the second stage, two villages were selected from the sampled sub-districts with a probability proportional to the size of the population. In the last stage, 10 households were selected from each sampled villages from a household lists ordered by household size using a systematic random sampling technique that gave each household an equal chance of being selected. In total, approximately 2200 households were sampled in each country at the end. The rate of attrition was low over the four waves that only 5.8% of the households covered in the first survey were not in the 2011 survey. Overall, the carefully sampled households are representative of rural households in northeastern Thailand and North Central Coast and Central Highland of Vietnam.

In the **first and second essay,** we restricted our sample to 1582 households in the two province that were observed in each of the four waves, specifically 914 households from Ubon Ratchathani and 668 households from Thua Thien Hue, as the econometric models used in the essays require the panel to be balanced. In the **third essay**, we further restricted our sample to 914 households from Ubon Ratchathani in Thailand and focused on analyzing the over-indebtedness of rural households in Thailand and the role of multiple borrowing. We decided to refocus our analysis only on Thai rural households because the first two essays showed that there is a major cross-country difference in the prevalence of debt problems among rural households in the two countries and the relationship between multiple borrowing and over-indebtedness which could not be explained and addressed with the empirical analysis in the first and second essay. Instead in the **fourth essay,** we address this issue by identifying the factors that underlie these observed cross-country differences in credit market participation, level of household debt holding and over-indebtedness between rural households in Thailand and Vietnam. This essay used the 2008 cross-section data of around 4300 households from all six provinces in Thailand and Vietnam.

All four essays make use of the detailed information collected on households borrowing, loan defaults and arrears along with a full set of household level data such as households demographics, social and economic characteristics and special modules on risks and shocks. This rich information gathered by the survey facilitates the use of objective indicators of over-indebtedness and multiple borrowing. Throughout the thesis, four common objective indicators of over-indebtedness are used: default and arrear, debt-service ratio, debt to income ratio and debt to asset ratio. Based on the default indicator, a household is considered to be over-indebted when a household has reported at least one default or arrear on one of their loan commitments in the previous year (Disney, Bridges & Gathergood, 2008). The debt-service ratio indicator is calculated as the ratio of annual debt repayment obligation to annual household income. Based on the debt-service ratio indicator, a household is considered to be over-indebted when its debt repayment in relation to income surpasses a certain threshold, commonly set at 40% or 50% (Muthitacharoen et al., 2015; D'Alessio & Iezzi, 2013). The debt to income and debt to asset ratios measure household's level of indebtedness by linking household's total outstanding debt amount with the total annual household income or the total value of household asset including the house value, respectively. These indicators capture different aspect of over-indebtedness and financial vulnerability of households as established by literature (Disney et al., 2008; D'Alessio & Iezzi, 2013). To date, there is no consensus on which indicator best captures over-indebtedness. Hence, we follow the literature in using multiple indicators that best reflect the structural and life cycle conditions of a household (Disney et al., 2008; D'Alessio & Iezzi, 2013). As regards multiple borrowing, a household is identified as a multiple borrower when a household has multiple active loans outstanding simultaneously regardless of the source of the loan.

One of the strengths of this study is its reliance on this rich panel dataset from emerging market economies in Asia where the debt burden disproportionately falls on the rural poor. Given that very little is known about the prevalence of over-indebtedness among the rural poor in Asia, research that focuses on assessing their financial situation remains vital. In this regrade, using this micro data has facilitated a richer evaluation of the factors that contribute to rural household's over-indebtedness and its persistency.

However, there are certain limitations to the data that need to be kept in mind when interpreting the results. First, the data only records a short debt repayment and default history of households, which is used in the first three essays to estimate persistency of over-indebtedness and the dynamic interdependency between multiple borrowing and over-indebtedness. In a short panel data setting, it is difficult to consistently estimate the persistence of such intertemporal choices due to the correlation between the time-invariant unobserved household heterogeneity and the covariates of interest (Bartolucci & Pigini, 2017). To estimate consistent parameters that best capture inter-temporal choice behaviors, one needs to properly address the correlation between the unobserved household-specific effects and covariates using econometric approaches as the ones developed by Heckman (1981) (used in the first essay) and Wooldridge (2005) (used in the second and third essay). Second, given that we calculate the indicators of over-indebtedness using self-reported data, the extent of it among rural households in Thailand and Vietnam might be underestimated. Since households who face severe debt repayment problems might be reluctant to disclose sincerely and accurately, the extent of their indebtedness.

Thirdly, although the data has some information on the purpose of loans, however it is not very detailed. While the data possesses information on the three most important uses of each loan proceeds, however it is not sufficient to determine the amount of debt, households used for productive or unproductive purposes and their incentive for multiple borrowing. This has constrained the study from further looking into whether the purpose of loan determines the two financial outcomes and the relationship between them. Fourthly, the data does not indicate the nature of the loans obtained by the surveyed households. The loans recorded in our dataset were not differentiated into group liability loans or individual liability loans. In theory, the nature of the loans could determine the debt repayment outcome of households (Gine & Karlan, 2006). However, we could not address this in our analysis due to data limitations. Fifth, the data on arrears and default history of households lacks information on duration of arrears that could be used to assess if households are in arrears on structural bases. Finally, the quantification of the amount of debt repayment per year was difficult because respondents found the borrowing questions, such as the terms of loans, too complicated and in some cases could not quantify the amount of loan already repaid and the remaining outstanding debt. This was especially complicated for informal loans, since loans taken from family members usually do not have properly defined terms.

Notwithstanding the aforementioned limitations, the dataset presents a rich pool of information on households borrowing behavior coupled with a full set of household and village level data, which was sufficient to analyze the problem of over-indebtedness among rural households in Thailand and Vietnam, which have been previously overlooked in earlier studies.

1.5 Results

First, the results from the **first essay** show that a considerable share of rural households both in Thailand and Vietnam are over-indebted. Second, the estimates on the true state dependence effect of over-indebtedness indicate that over-indebtedness is a persistent problem for rural households in Thailand. This is however not the case for rural households in Vietnam, where the persistence of over-indebtedness is explained by unobserved household heterogeneity. Third, several of the household characteristics contribute to rural households' over-indebtedness and its persistency, as suggested by the life cycle theory. For instance, households with male, middle-aged, and higher-educated household heads are found to be more likely to experience over-indebtedness than those with female, younger and less-educated household heads in both countries. An interesting finding is also that the probability of over-indebtedness is positively associated with a household's poverty status in terms of low level of income as well as with experiencing adverse shocks to income and expenses. This implies that while microcredit is being supported as poverty reduction strategy, it might have an adverse impact on rural poor household's wellbeing, make them more vulnerable to shocks and push them further into poverty and debt trap. Furthermore, results show that rural households that have optimistic financial expectation face a higher risk of falling into over-indebtedness. Forth, in line with the behavioral theories, the results indicate that individual willingness to take risk and overoptimistic financial expectations contribute to rural households over-indebtedness in Thailand. Finally, our finding also confirm that rural households' subjective wealth assessment and relative social standing significantly influences their probability of experiencing over-indebtedness both in Thailand and Vietnam.

The results from the **second and third essay** indicate that rural households both in Thailand and Vietnam take multiple loans from several sources. The rural households adopt multiple borrowing practices in response to adverse shocks. Consistent with the new institutional economic theories, the rural households that adopted multiple borrowing practices in Thailand were found to be more likely to be over-indebted. However, the results do not confirm the revers effect that over-indebted households use multiple loans to refinance ultimately unpayable debt and become trapped in debt cycles, as suggested by behavioral economic theories. This finding is in line with the literature that views multiple borrowing as a financial management tool used by rural households, which still carries a higher risk of over-indebtedness (Wampfler et al., 2014; Guha & Chowdhury, 2013; Casini, 2015). In contrast to Thailand, adopting multiple borrowing practices did not lead Vietnamese rural households into over-indebtedness. In addition, the overall findings of the first and second essays reveal cross-country differences in the extent of over-indebtedness and multiple borrowing besides the relationship between them. We show in the fourth essay that these cross-country differences are mainly explained by differences in cultural, institutional and economic environments between the two countries.

The findings from **fourth essay** explain the observed cross-country difference in rural households borrowing behavior and the financial vulnerability they face. First, the results show higher prevalence of debt and over-indebtedness among rural households in Thailand than in Vietnam. Second, the Thai rural households that participate in the credit market also hold larger amounts of debt and face higher level of indebtedness than the Vietnamese rural households. Third, these observed differences arise mainly due to dissimilarity in the cultural, institutional and economic environment that rural households of similar characteristics face in the two countries. Fourth, the cultural, institutional and economic environment in Thailand is found to be particularly more lenient to the economically disadvantaged rural households holding high amounts of debt as compared to what their counterparts face in Vietnam. Finally, the differences in debt holding and level of indebtedness is more pronounced along the debt distribution, and the higher gap observed at the top of the debt distribution is largely explained by differences in the cultural, institutional and economic environment.

1.6 Conclusion and Policy Implications

The rural financial markets in Asia have developed substantially and played a key role in economic development and poverty reduction. However, the recently growing problem of rural household’s over-indebtedness in Asia is threatening this promising progress towards poverty alleviation. At the same time, while financial inclusion of the rural poor is being highly promoted in developing and emerging market economies to meet the new sustainable development goals, the deepening financial inclusion, particularly the credit outreach to the rural poor, might further exacerbate the problem of rural household’s over-indebtedness and poverty, unless steps are taken to mitigate the adverse impact of microcredit.

Within this context, this thesis explores rural households’ risk of over-indebtedness and financial vulnerability in Thailand and Vietnam. The empirical evidences presented in the thesis provide some novel insights and several policy implications for microcredit programs that serve the rural poor in developing and emerging market economies in this regard.

First, the persistence of over-indebtedness found among rural households in Thailand indicates that microcredit programs that are meant to improve the wellbeing of poor rural households can lead certain types of households into a “debt trap”. The rural poor that experience adverse income shocks especially seem to face higher risk of over-indebtedness. Hence, we recommend that highly and persistently indebted households should be rather served by specifically designed poverty reduction programs such as cash transfer programs. Furthermore, the governments of developing and emerging market economies need to effectively implement the client protection principles for microfinance to ensure microcredit products do not further impoverish the already poor clients through over-indebtedness. These principles include making sure that financial institutions: (i) appropriately design and deliver their microcredit products according to the client's needs, (ii) prevent over-indebtedness of clients by carefully screening the clients ability to repay debt without becoming over-indebted and sharing credit information on their clients, (iii) help clients to make an informed decision by clearly communicating information on pricing, terms and conditions of credit products, and (iv) set prices, terms and conditions of credit products in an affordable way to the clients (Forster, Lahaye & McKee, 2009).

Second, the significant association found between over-indebtedness and behavioral biases suggests that although financial literacy education is important, it is insufficient to solve the problem of over-indebtedness. Also, with the primary interest of credit agents being selling more microcredit products, they are unlikely to improve the decision making of borrowers. Hence our recommendation that government advisory services should integrate financial portfolios in their extension portfolio and offer independent advice in order to empower poor rural households for better financial decision making. This may serve as a first step to overcome the existing "culture of indebtedness".

Third, the existence of an intertemporal effect of multiple borrowing on rural household's risk of over-indebtedness strongly suggests that, regulatory agencies and public and private financial institutions should implement measures that make it more difficult for micro-borrowers to take multiple loans. Furthermore, the dynamic effect of multiple borrowing on over-indebtedness advocates that a major entry point to prevent over-indebtedness is to have better control of multiple borrowing. Such measures include, for example, increasing information sharing among lending institutions on the credit history and total credit obligations of borrowers, universal reporting to the national credit bureau, and improving the financial literacy of households.

Forth, the findings that multiple borrowing and over-indebtedness are often a result of various types of shocks that are largely beyond the control of rural households demands that more effective insurance mechanisms must be implemented in rural Thailand and Vietnam and countries with similar conditions.

Fifth, the findings show that the observed cross-country difference in borrowing behavior and over-indebtedness of rural household in Thailand and Vietnam is mainly explained by differences in the cultural, institutional and economic environment that rural households of similar characteristics face in the two countries. The higher debt holding observed among rural households in Thailand, especially at the top of the debt distribution is explained by lax economic environment than by endowment effects. Although the results show a strong link between the economic environment and accumulation of debt by rural households, the specific mechanisms through which the economic environment contributes to rural household's over-indebtedness are not investigated in this thesis. Furthermore, since the results are derived from counterfactual decomposition analysis that relies on associational inference, it does not provide a causal explanation of the observed difference between the two countries. Therefore, it is difficult to draw a specific policy conclusion.

In conclusion, while microcredit remains a central element of rural development policies, the unlimited growth of microcredit markets could make rural households more financially vulnerable.

1.7 Future Research

The theoretical and empirical analyses carried out in this thesis raise several issues in need of further research.

This thesis analyzed the problem of rural household’s over-indebtedness and financial vulnerability in Thailand and Vietnam mainly focused on the factors that determine such financial outcomes only from borrower’s perspective. All the supply side factors (Vogelgesang, 2003; Gonzalez, 2008; Schicks, 2013) that might contribute to rural household’s over-indebtedness were not analyzed in this thesis due to data limitations. Hence, this thesis is limited in providing specific recommendations to financial institution serving the rural poor. While the results of the thesis present several unique insights to financial institutions and policy makers on ways to protect the rural poor from further impoverishment through over-indebtedness, an in-depth analysis of the supply side factors is needed to determine the major policy entry points for preventing over-indebtedness and effectively implementing regulations for financial institutions that serve the rural poor. Further research on the supply side factors would need to consider the behavior of lenders, terms and conditions of loans from lenders, type of loan contracts, information asymmetry and competition in microcredit markets, type, structure and organization of the financial institutions, the incentive system of lenders for loan officers, and the governance structure for the financial institutions.

In addition, the results of this thesis show the ability of the new institutional economic theories, behavioral economic theories and social comparisons theories to serve as framework in analyzing the observed over-indebtedness problem among rural households in Thailand and Vietnam. Drawing insights from these theories, several behavioral and social factors that might lead rural households to fall into over-indebtedness have been tested. The results confirmed that behavioral biases and subjective social relative standing do play a role in rural household’s over-indebtedness. However, this thesis was not able to directly test other behavioral and social factors that potentially affect rural household's risk of over-indebtedness. In particular, time preference of households which is emphasized by both institutional and behavioral models on microfinance could not be tested due to data limitation. Both theories hypothesize that multiple borrowing and over-indebtedness occur due to present-biased and time-inconsistent preferences of households who hyperbolically discount the burden of debt repayment problems in the future (McIntosh and Wydick, 2007; Arnold and Booker, 2013). Other social factors such as the culture of indebtedness and households attitude towards debt which are expected to be associated with the risk of over-indebtedness in Thailand (Siripanyawat et al., 2010) could not also be covered in this thesis. Although the thesis could not reflect all of these factors in the analysis, it was able to take into account their consequence in the empirical analysis.

Furthermore, the cultural, institutional and economic environment in Thailand is found to be particularly more lenient to the economically disadvantaged rural households holding high amounts of debt as compared to what their counterparts face in Vietnam. However, these results need to be cautiously interpreted since the analysis is based on a cross-section data and a household survey data limited to certain regions in the two countries. Furthermore, the essay could not investigate the specific mechanisms through which the economic environment contributes to rural household's over-indebtedness since it is a two country study. To gain an insight into cross-country variation in rural household debt and explore country-level factors that explain this variation, future research should extend the analysis to a region-wide study in Asia wherein all the mechanisms that reflect the effect of the institutional and economic environment on rural household debt can be directly evaluated. To do so, future data collection also should focus on the additional important dimensions of the financial markets in rural areas, including accessibility of certain credit products, legal enforcement of contracts, the depth of information available about borrowers and credit conditions (Bover et al., 2016).

Finally, while the results of this thesis indicate the need for combining microcredit products with micro-insurance schemes to prevent rural households from taking on more loans as a shock coping strategy, the effectiveness of such interventions and their potential benefit is not well known. Hence, there is an urgent need for further research on the effect of additionally providing micro-insurance schemes with microcredit products on such financial outcomes.

1.8 Thesis Outline

This thesis is organized in five chapters, with each chapter presenting one essay with the exception of chapter 1, which provides an introduction and summary of the thesis. Table 1.1 below shows the histry of the four essays included in the thesis.

Chapter 2 presents the **first essay** “Over-indebtedness and Its Persistence among Rural Households in Thailand and Vietnam” that was submitted to the Journal of Asian Economics. A previous version of this essay has been presented at the International Conference of the Courant Research Centre "Poverty, Equity, and Growth in Developing and Transition Countries" and the Ibero-America Institute of Economic Research in 2014.

Chapter 3 presents the **second essay** “The Interrelated Dynamics of Multiple Borrowing and Over-indebtedness among Rural Households in Thailand and Vietnam” that was published as proceedings of the 29th Triennial Conference of the International Conference of Agricultural Economists in 2015 (ICAE-2015). A previous version of this essay has been presented at the PEGNet Conference in 2014.

Chapter 4 presents the **third essay** “Borrowing from “Pui” to pay “Pom”: Multiple borrowing and over-indebtedness in rural Thailand” that was published in the World Development journal. This paper was presented at the 9th International Conference of the Asian Society of Agricultural Economists in 2017.

Chapter 5 presents the **fourth essay** “Exploring Differences in Rural Household Debt between Thailand and Vietnam: Economic Environment versus Household Characteristics”.

This essay has been presented at the Thailand and Vietnam Socio-Economic Panel (TVSEP) data use workshop in 2017.

Table 1.1: Overview of Essays in this Thesis

	Title	Authors	Presented/ Submitted/ published
Chapter 2	Over-indebtedness and its Persistence among Rural Households in Thailand and Vietnam	B. B. Chichaibelu and H. Waibel	Submitted to: *Journal of Asian Economics 2017* Presented at : International Conference of the Courant Research Center "Poverty, Equity, and Growth in Developing and Transition Countries" and the Ibero-America Institute of Economic Research July 2 - 4, 2014, Göttingen, Germany
Chapter 3	The Interrelated Dynamics of Multiple Borrowing and Over-indebtedness among Rural Households in Thailand and Vietnam	B. B. Chichaibelu and H. Waibel	Published as a conference proceedings in the ICAE Conference 2015; August 9-14, Milan, Italy Previous version presented at: PEGNet Conference 2014; September 18-19, Lusaka, Zambia
Chapter 4	Borrowing from "Pui" to pay "Pom": Multiple Borrowing and Over-indebtedness in rural Thailand	B. B. Chichaibelu and H. Waibel	Published in: *World Development* 2017 Presented at : ASAE International Conference in 2017; January 11-13, Bangkok, Thailand
Chapter 5	Exploring Differences in Rural Household Debt between Thailand and Vietnam: Economic Environment versus Household Characteristics	B. B. Chichaibelu and H. Waibel	Presented at : TVSEP data use workshop 2017; March 15, Hannover, Germany

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CHAPTER 2: OVER-INDEBTEDNESS AND ITS PERSISTENCE AMONG RURAL HOUSEHOLDS IN THAILAND AND VIETNAM

This chapter is a paper submitted for publication to

Journal of Asian Economics, 2017

and presented at:

International Conference of the Courant Research Center "Poverty, Equity and Growth in Developing and Transition Countries" and the Ibero-American Institute of Economic Research. July 2 – 4, 2014, Göttingen, Germany.

Abstract

Using default and debt-service ratio indicators of over-indebtedness, this study analyzes the determinants of household over-indebtedness and its persistence in the context of micro-borrowers in emerging and developing countries' microcredit market. The persistence of over-indebtedness was tested by means of a Heckman random effects dynamic probit model controlling for the effect of households' socioeconomic, demographic and behavioral characteristics. The results for Thailand show that past experience of over-indebtedness increases the probability of experiencing the same conditions in the future. However this could not be confirmed for Vietnam. In addition, other factors significantly influence the probability of experiencing over-indebtedness in both countries. These include being poor and experiencing negative shocks, as well as behavioral variables, such as optimistic future financial expectations, overoptimistic financial forecast errors, risk attitude and social comparison.

Keywords: Microcredit, household over-indebtedness, persistence of over-indebtedness, random effects dynamic probit model, Thailand, Vietnam.

2.1 Introduction

Financial debt is a major problem of poor households in developing countries. Many countries, including Nicaragua, Morocco, Pakistan and India, have experienced financial crises, often as a consequence of the rapid expansion of the microfinance industry (Chen et al., 2010; Lascelles, & Mendelson, 2012). These repayment crises have been marked by massive client over-indebtedness, rapidly growing client defaults, and in India, default-related suicides (Chen et al., 2010; Lützenkirchen et al., 2012 and Bateman and Chang, 2012).

Research on micro-borrowers' over-indebtedness in Ghana (Schicks, 2013), Cambodia (Liv, 2013), Thailand (Siripanyawat, Sawangngoenyuang & Thungkasemvathana, 2010) and Bangladesh (Khandker, Faruqee & Samad, 2013) have shown that poor households often borrow high amounts relative to their income level. For the poor, over-indebtedness usually means economic and social exclusion and increased risk of poverty (Bateman & Chang, 2012; Schicks, 2013). Thus, understanding the factors that can lead to over-indebtedness is important to design better microcredit policies in developing countries.

This study contributes to the empirical analysis of over-indebtedness in rural microcredit markets in Thailand and Vietnam. We first discuss the definition of over-indebtedness. In this paper, we consider a household to be over-indebted if there is one default or arrear on a loan commitment, and we evaluate the extent of household over-indebtedness in both countries. Secondly, we analyze the influence of household-level characteristics, including demographic and economic household characteristics, on the probability of over-indebtedness. Thirdly, we analyze behavioral biases that cause households to make suboptimal and unsustainable borrowing decisions as a possible cause of over-indebtedness. Fourthly, exploiting the panel nature of our unique dataset, we contribute to the literature by analyzing the persistence of over-indebtedness, which, so far, has not been covered widely in related literature.

Using four waves of panel data from approximately 1600 rural households in two provinces in Thailand and Vietnam, namely, Ubon Ratchathani and Thua Thien-Hue, respectively, we estimate a household's probability of experiencing over-indebtedness using Heckman's random effects dynamic probit model (Stewart, 2007; Stewart, 2006).

Our main findings are as follows: First, there is evidence of a true state dependence of over-indebtedness both in terms of default and debt-service ratio indicators after controlling for observed and unobserved differences in household characteristics in Thai province. This is not the case in Vietnam, where the persistence of over-indebtedness is explained by unobserved household heterogeneity. In both countries, the probability of over-indebtedness was positively related to a household's poverty status in terms of low level of income, as well as adverse income shocks. Finally, household decision makers who are optimistic about their financial situation in the future and those who consider themselves being of low social standing were also more likely to be over-indebted.

The remainder of the paper is organized as follows: Section 2.2 briefly presents information about the rural credit market of Thailand and Vietnam, putting it within the context of more-advanced microcredit markets in other developing countries. Section 2.3 provides an introduction to the existing approaches in defining and measuring over-indebtedness and undertakes a review of relevant theories that can help explain households' borrowing behavior. Sections 2.4 and 2.5 discuss the data and present descriptive results on the incidence and extent of households' over-indebtedness and its persistence in both countries. Section 2.6 illustrates the econometric framework in further detail. Section 2.7 presents the model results, and section 2.8 concludes.

2.2 Rural Credit Markets in Thailand and Vietnam

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 Bank for Social Policy (VBSP) and the Vietnam Bank for Agriculture and Rural Development (VBARD). Similar to rural credit markets in developing countries, other semi-formal and informal microfinance institutions exist (King, 2008; Menkhoff, Neuberger & Rungruxsirivorn, 2012).

The microfinance and micro-lending institutions of Thailand and Vietnam have some notable features that distinguish them from the typical microfinance institutions of other South and Southeast Asian countries such as Bangladesh, India and Cambodia. During the past two decades, Thailand and Vietnam have shown high economic growth and have achieved impressive poverty reduction rates. In part, this is attributable to the development of the rural microcredit market, which has facilitated investment in agriculture and rural small-scale enterprises. In particular, the governments of both countries have introduced state-run or government regulated policy interventions along with the financial institutions to facilitate large growth-oriented enterprises that are relatively sophisticated, innovation-driven and technologically intensive (Bateman & Chang, 2012; Bateman, 2013).

The financial system and institutions of Thailand and Vietnam are quite similar, especially in the level of government involvement in the sector and enforcement of regulations. However, they differ in financial depth, credit outreach and the range of credit programs introduced in rural areas. While the Vietnamese government began to introduce and support formal financial intermediaries in rural areas such as VBARD and VBSP around the early 1990s (Dufhues, Heidhues, & Buchenrieder, 2004), the Thai government introduced such financial institutions as early as the mid-1970s by supporting homegrown non-bank financial institutions and promoting the BAAC into a rural development bank (Menkhoff & Suwanaporn, 2007; Menkhoff & Rungruxsirivorn, 2011). The institutions introduced by the Thai government have enhanced access to financial services, particularly for households in the non-municipal areas of Thailand. However, some argue that such government interventions in Thailand have shifted poor households' attitudes towards indebtedness. Siripanyawat et al. (2010) argue that some households have begun to perceive being indebted as a norm and deem not paying back their loan on time acceptable because it was funded by the government. This line of argument is also in conformity with results found in a recent study by Kaboski and Townsend (2011). They found that instead of investing in income generating activities in response to the introduction of a "million baht village fund", households increased their borrowing and consumption almost equally. They also found that, compared to a direct transfer program, a large-scale microfinance program is less beneficial for some households because they have to cover the interest cost. Defaulting households will face an even larger debt-service ratio because they will continue to have larger interest payments. In contrast, Vietnam's rural credit market shows better performance in terms of a high level of loan repayment. For instance, the ratio of loans in arrears to total outstanding loans to farmers was 0.98% for VBARD in Vietnam, while it was 13.5% for BAAC in Thailand in 2001 (Okae, 2009). The sound performance of Vietnam's rural financial institutions and the low level of default have been explained by the strong reliance of the financial institutions on the customary rules of behavior in rural communities. The fact that the whole rural community participates in social activities together and assumes the role of a loan monitoring system puts pressure on households to repay their debt on time in order to avoid economic and social sanctions from others (Okae, 2009). Therefore, one can expect household over-indebtedness to be a greater problem among Thai households than among Vietnamese households.

2.3 Theoretical Background and Literature Review

2.3.1 Defining and measuring household over-indebtedness

To date, there is no commonly accepted definition of household over-indebtedness. Generally, two major concepts of over-indebtedness can be specified in the literature, namely, subjective and objective (see table A1 in the appendix for the list of common indicators).

Subjective definitions of over-indebtedness are based on the notion that households are able to judge their financial situation. Schicks (2014) considers a household's struggle and sacrifice related to repaying debt, including reducing spending on food consumption, taking children out of school, taking additional jobs and increasing working hours. However, the limitation of using such subjective measures is that they can be biased, as they depend on the decision maker's attitude, such as optimism or pessimism, in addition to the problem of insufficient financial literacy (Betti et al., 2007; Schicks & Rosenberg, 2011; Keese, 2012; D'Alessio & Iezzi, 2013). Hence, for the purpose of comparing households between countries, subjective indicators are not useful.

Objective definitions of over-indebtedness include financial measures such as debt-to-income ratio, debt-service ratio, debt-to-asset ratio, default and arrears, net wealth and number of loans (Betti et al., 2007; Schicks, 2013; D'Alessio & Iezzi, 2013). These measures have been used individually (May & Tudela, 2005; Haas, 2006; Giarda, 2013) or as multiple indicators simultaneously (Brown, Garino & Taylor, 2008; Stamp, 2009; Anderloni, Bacchiocchi & Vandone, 2012), both by formal financial institutions and in scientific studies. However, there are some limitations as well. The first limitation of the objective indicators is that they can underestimate the problem of over-indebtedness, as they only look at the actual non-repayment of debt and do not consider households that sacrifice their basic needs for debt repayment, which is not uncommon for borrowers in developing countries (Betti et al., 2007; Schicks & Rosenburg, 2011). The second limitation relates to the difficulty of determining the critical level of indebtedness. As noted by Betti et al. (2007), it is difficult to define an optimal level of indebtedness, as it varies depending on the household's characteristics, especially its demographic status. Despite these difficulties, empirical studies on over-indebtedness have found that debt-ratio-based objective indicators can generally explain the debt burden as subjectively perceived by the household as well as default and arrears (Rinaldi & Sanchis-Arellano, 2006; Keese, 2012; D'Alessio & Iezzi, 2013).

Considering the limitations of the indicators discussed above, it becomes clear that finding a single optimal measure that captures every aspect of over-indebtedness is not possible (Betti et al., 2007; Schicks & Rosenburg, 2011; D'Alessio & Iezzi, 2013). However, each indicator taken separately can capture different aspects of over-indebtedness (Gumy, 2007; Disney, Bridges & Gathergood, 2008; D'Alessio & Iezzi, 2013). Therefore, some studies use a combination of subjective and objective indicators (Gumy, 2007; Anioła & Gołaś, 2012). The problem, however, in using several indicators is that the genuinely over-indebted households may not be identified, as most households will be considered over-indebted by at least one of the indicators. Hence, Disney et al. (2008) suggest that when using objective and subjective indicators, one should choose those that best reflect the structural and life cycle conditions of a household.

2.3.2 Identifying the drivers of over-indebtedness

While outcome indicators of over-indebtedness are an empirical issue and cannot easily be defined from a theoretical perspective, there are theoretical explanations identifying the factors that cause households to get into over-indebtedness. While there are supply and demand side factors in this study, we focus on the borrowers' side.

From the borrowers' perspective, there are three models:

The first is the life-cycle-permanent-income model of Modigliani (1966) and Friedman (1957) that considers indebtedness to be an optimization strategy subject to the household's life cycle. The hypothesis is that households borrow money to transfer consumption from periods of high income to periods of low income. Usually, at the early stage of a household's life cycle, consumption smoothing is undertaken as a means 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 income or assets at early stages 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 as a result of negative adverse shocks due to market imperfection and uncertainty (Betti et al., 2007). Uncertainty can thus lead to over-indebtedness (Gumy, 2007). For example, Gonzalez (2008) found that unexpected adverse shocks played a major role in the Bolivian household over-indebtedness crisis that occurred during the period 1999 to 2002. Similarly, Schicks (2014) found that unexpected shocks significantly increased the likelihood of over-indebtedness of micro-borrowers in Ghana. Another form of uncertainty is households optimistic expectation of future income, which can lead to over-indebtedness, as spending and borrowing decisions can be based on misguided expectations (Brown et al. 2005). Brown et al. (2005) present a theoretical framework where optimistic financial expectation positively determines the amount of outstanding debt and the growth of debt. In their model, households maximize expected lifetime utility by smoothing consumption through borrowing in anticipation of better income in the future. Evidence from their empirical analysis that used a panel data set from the UK also suggests that financial expectations are important determinants of household debt (Brown et al., 2005; Brown et al., 2008).

The second model that can explain over-indebtedness is derived from behavioral theory. It can be shown that behavioral "biases" and "heuristics" can lead to a distortion of a household's assessment of the probabilities of financial events. Consequently, there is a significant deviation from the optimal strategy that maximizes expected lifetime utility (Livingstone & Lunt, 1992; Lea, Webley & Walker, 1995; Betti et al., 2007; Meier & Sprenger, 2010). Heuristics such as "bounds" of rationality can increase households' likelihood of accumulating excessive amounts of debt compared to their earnings (Kilborn, 2005). An example from Finland illustrates this. Using Finnish household panel survey data for the period 1994 to 2009, Hyytinen and Putkuri (2012) show how overoptimistic behavior of households with high forecast errors significantly increased the probability of over-indebtedness. Additionally, two interconnected behavioral factors can affect borrowing behavior: risk-taking (risk loving instead of risk aversion) and present-biasedness in time preference (Betti et al., 2007; Norum, 2008; Brown, Garino & Taylor, 2013). Firstly, 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). Secondly, according to the life cycle hypothesis, households borrow to finance their increase in current consumption based on repayment from future earnings. Because future earnings are directly influenced by the risk-taking behavior of households, their ability to repay their debt is also subject to households' risk preferences. Brown et al. (2013) explored this relationship using the U.S. household-level panel survey of income dynamics from 1984 to 2007. He found that households with a lower degree of risk aversion had higher levels of accumulated debt. Hence, following these behavioral theories, overoptimistic and risk-taking households are expected to face higher risk of over-indebtedness.

The third model that can explain over-indebtedness comprises 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 level of income and thus borrow more in an attempt to catch up with their peers (Livingstone & Lunt, 1992; Lea et al., 1995; Cynamon & Fazzari, 2008). A recent empirical study using the Dutch population-wide survey showed that perceived higher average income in a social circle not only drives households to borrow more but also leads to a financial debt burden after controlling for common household debt-determining factors such as demographics, wealth, region and time fixed effects. This effect of perceived social relative standing was actually found to be stronger for households that perceive their income to be below the average income of their social circle (Georgarakos, Haliassos & Pasini, 2014).

Finally, though not explored in the context of microcredit markets of developing countries, empirical studies that examine different types of financial problems, such as housing payment problems (Böheim & Rene, 2000; May & Tudela, 2005), debt problems or financial difficulties (Stamp, 2009), financial hardship (Brown, Ghosh & Taylor, 2014) and financial distress (Giarda, 2013), have found household over-indebtedness to be highly persistent. The persistence of over-indebtedness indicates that the conditional probability of a household experiencing over-indebtedness in the future is a function of its past experience of over-indebtedness. This persistence may, however, emerge due to two potential explanations, either from true state dependence or from observed and unobserved household heterogeneity. In the case of true state dependence, current experience of over-indebtedness directly affects the household's resources and as well as its preferences and behavior, and therefore, it increases households' propensity to experience it in the future. Alternatively, persistence may arise from household heterogeneity in their propensities to experience over-indebtedness in all periods (Heckman, 1981a; Hsiao, 2003). An empirical study of Italian households in financial distress showed that true state dependence explains the greater part of households' probability of experiencing financial distress in the future after controlling for both observed and unobserved household heterogeneity (Giarda, 2013).

2.4 Data Description

We use data on 1582 rural households in Thailand and Vietnam from the "Vulnerability in Southeast Asia" project funded by the German Research Foundation (DFG) for the period 2007 to 2011. The survey has been conducted annually with the exception of a one-year gap in 2009. The survey has collected data from 2200 rural households from three provinces in Northeastern Thailand and another 2200 rural households from three provinces in the North Central Coast and Central Highland of Vietnam (Hardeweg, Klasen & Waibel, 2012). To meet the general objective of the project, the six provinces—Buriram, Ubon Ratchathani and Nakhon Phanom from Thailand and Ha Tinh, Thua Thien Hue and Dac Lac from Vietnam—were selected to target rural households that are either poor or are at risk of falling into poverty. After selecting the provinces, approximately 220 villages were selected using a systematic random sampling based on a probability proportional to the size of the population. Finally, 10 households were sampled in each village by again using a systematic random sample with equal probability from household lists ordered by household size.

For the aim of our analysis, we selected two provinces, Ubon Ratchathani in Thailand and Thua Thien Hue in Vietnam. In these two provinces, we have four survey waves: 2007, 2008, 2010 and 2011. We restrict our sample to the 1582 households that were observed in each of the four waves, as the econometric model used in this study requires the panel to be balanced. This allows us to better evaluate the persistence of over-indebtedness. Hence, we have a data set with a total sample size of 6328 observations in two countries. Our data set contains detailed information on households' borrowing, loan defaults and arrears, along with a full set of household-level data such as demographics and social and economic characteristics, as is common in standard household surveys. These detailed data on the financial situation of the households in our data facilitate the use of objective indicators of over-indebtedness. Based on the data available from the survey, we follow Disney et al. (2008) in using the default and arrear indicators (henceforth referred to as default), as discussed in section 2.2. Hence, we define those households as over-indebted that report at least one default or arrear on one of their loan commitments in 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?'*

However, the default indicator is limited in that it underestimates the extent of rural households' over-indebtedness. Because rural households borrow from multiple sources as a way of managing their debt and go to great lengths to avoid debt repayment problems by significantly sacrificing on their basic needs, the default indicator conceals the problem of over-indebtedness until it reaches a critical level and materializes as a default or arrear (Schicks & Rosenberg, 2011; Schicks, 2014).

Therefore, we additionally use the debt-service ratio (DSR) indicator as an outcome variable. The DSR indicator is defined as the proportion of annual gross income that a household must devote to service its annual debt obligation (ECB, 2013). Based on the DSR indicator, a household is considered over-indebted when its annual debt repayment obligation in relation to income surpasses a certain threshold, commonly set at 40% or 50% (Disney et al., 2008 & D'Alessio & Iezzi, 2013; Muthitacharoen, Nuntramas & Chotewattanakul, 2015; Banbula, Kotula, Przeworska, & Strzelecki, 2016). We follow these recent studies and identify a household whose annual debt repayment requires more than 50% of its annual income as over-indebted. Hence, a household whose annual debt repayment requires more than 50% of its annual income is identified as over-indebted.

2.5 Descriptive Results

In this section, we show the degree of over-indebtedness of our sample households using different indicators. Table 2.1 presents the distribution of indebted and over-indebted households in Ubon Ratchathani and Thua Thien Hue over the four-year period. Between 80 and 89% of the Thai households and 63 to 76% of the Vietnamese households had taken at least one loan. In Thailand, indebted households had a median outstanding debt of approximately 2,491 US$ and 1033 US$ (both values in PPP (2005)) in Vietnam. While we find a steadily increasing proportion of indebted households in Vietnam, the share of indebted households in Thailand fluctuates over the years.

The extent of over-indebtedness among both Thai and Vietnamese households over the four-year period is different when taking the indicators "default" and "debt-service ratio". For the default indicator, on average, approximately 8% of the Thai households and 9% of the Vietnamese households were over-indebted. For the DSR indicator, on average, approximately 34% of Thai households and 12% of Vietnamese households were over-indebted. In terms of the DSR indicator, in both countries, over-indebtedness increased initially from 2007 to 2008 and declined in 2010 from a relatively higher incidence in the previous periods, followed by an increase in 2011. On the other hand, based on the default indicator, over-indebtedness declined in both countries but then rose slightly in 2011. Overall, we find a slightly higher default rate among Vietnamese households than the Thai households, while it is opposite for the DSR indicator. This contrasting result is not surprising when compared to findings in the literature (e.g., Disney et al., 2008; D'Alessio & Iezzi, 2013).

Table 2.1: The Extent of Households' Indebtedness and Over-Indebtedness in Thailand and Vietnam

Country and Wave ID		Number of households	Indebted households	Over-indebted households according to different indicators (Percentage of total households)		Over-indebted households according to different indicators (Percentage of indebted households)	
				Default	DSR	Default	DSR
Thailand	2007	914	86	13	40	15	46
	2008	914	89	10	48	11	54
	2010	914	79	03	18	03	23
	2011	914	84	05	30	06	35
Vietnam	2007	668	63	11	16	17	25
	2008	668	68	11	11	16	17
	2010	668	70	06	09	08	12
	2011	668	76	07	12	10	15

Source: Own calculation based on household survey 2007 to 2011

Using the 2011 data, table 2.2 and table 2.3 summarize some basic statistical parameters (mean or percentage) of variables that, based on theoretical considerations (section 2.4), may influence over-indebtedness for Thailand and Vietnam, respectively. In addition, the characteristics of over-indebted and non-over-indebted households are tested for significant differences using both default payment and the debt-service ratio. Table 2.2 shows results for Thailand. It can be seen that the variables where significant differences are found differ by indicator except for the savings variable. For some variables, e.g., education, the expected differences are found. In Vietnam (table 2.3), basically the same pattern can be observed. The only congruence with regard to significant differences between the two over-indebtedness indicators is the 3rd income quintile. Again, some of the differences between the two groups of households are significant, as expected, such as household size, savings, age, occupation of household head and unexpected shocks to income, as well as behavioral variables, such as a household's forecast error on future income and risk attitude. Also, the social comparison is significantly different between the two groups depending on the over-indebtedness indicator chosen.

Table 2.2: Descriptive Statistics of the Thai Sample using the Latest Data (2011)

Variable		N	Mean or percent	Default		Chi^2 or t-test	DSR		Chi^2 or t-test
				Over-indebted	Not over-indebted		Over-indebted	Not over-indebted	
Female HHH		288	32	5	95	0.08	27	73	1.59
Marital status		721	79	5	95	0.80	30	70	0.51
Number of children		692	1.41	1.72	1.39	-1.91**	1.44	1.39	-0.64
Household size		-	5.61	6.02	5.58	-1.20	5.57	5.62	0.30
Land tenure status		157	17	6	94	0.33	69	31	0.09
Savings (dummy)		735	82	4	96	8.64***	31	69	7.67**
Age of HHH group	Below 35	10	1	20	80	21.72***	20	80	2.74
	35 - 44	137	15	3	97		29	71	
	45 - 54	250	27	8	92		29	71	
	55 - 64	261	29	6	94		33	67	
	65 and above	256	28	1	99		27	73	
Education of HHH Group	Illiterate and primary education	787	86	4	96	3.09	28	72	9.65**
	Secondary education	98	11	8	92		31	69	
	Higher Education	29	3	7	93		55	45	
Occupation of HHH	In-active	140	15	3	97	1.56	25	75	2.29
	Agricultural	506	56	5	95		31	69	
	Off-farm	93	10	5	95		30	70	
	Self-employed	175	19	6	94		28	72	
Income quintile	Quintile 1	131	14	6	94	1.99	45	56	41.5***
	Quintile 2	166	18	6	94		38	62	
	Quintile 3	180	20	5	95		36	64	
	Quintile 4	209	23	4	96		20	80	
	Quintile 5	228	25	3	96		20	80	
Shocks	Unexpected shock to expenses	504	55	6	94	3.17*	30	70	0.20
	Expected shocks to expenses	122	13	6	94	0.26	30	70	0.0001

	Unexpected Shocks to income	633	69	6	94	2.29	32	68	5.56**
Future expectation of income (five years)	Better	590	66	5	95		32	68	
	Same	186	21	6	94	1.00	23	77	6.21**
	Worse	115	13	3	96		27	73	
Risk attitude (based on 0 to 10 Likert scale)	Risk averse	330	36	5	95		25	75	
	Risk neutral	306	34	4	96	1.73	31	69	7.25**
	Risk taker	274	30	6	94		34	66	
Over-optimism (Forecast errors)	Pessimistic	208	23	5	95		26	74	
	No forecast error	385	42	3	97		33	67	
	prudentially optimistic	189	21	7	93	3.94	31	69	6.21
	non-prudentially optimistic	132	14	6	94		77	23	
Subjective wellbeing compared to the villagers	Better off	131	14	2	98		34	66	
	Same	635	70	4	96		30	70	
	Worse off	143	16	10	90	9.93**	25	75	2.36

Source: Own calculation based on household survey 2011.

Table 2.3: Descriptive Statistics of the Vietnamese sample using the latest data (2011)

Variable		N	Mean or percent	Default		Chi^2 or t-test	DSR		Chi^2 or t-test
				Over-indebted	Not over-indebted		Over-indebted	Not over-indebted	
Female HHH		138	21	5	95	1.31	9	91	0.86
Ethnicity (Non-Kinh)		163	24	9	91	1.05	14	86	1.19
Marital status		547	82	8	92	4.30**	12	88	1.08
Number of children		524	1.77	2.20	1.73	-2.29**	1.79	1.76	-0.153
Household size		-	5.62	6.16	5.58	-1.68**	5.76	5.60	-0.58
Land tenure status		151	23	11	89	4.02**	13	87	0.15
Savings (dummy)			68	6	94	4.22**	11	89	0.10
Age of HHH group	Below 35	59	9	5	95		8	92	
	35 - 44	167	25	12	88		13	87	
	45 - 54	193	29	8	92	10.63***	12	88	4.26
	55 - 64	110	16	5	95		15	85	
	65 and above	139	21	3	97		7	92	
Education of HHH Group	Illiterate and primary education	406	61	8	92		12	88	
	Secondary education	234	35	7	93	2.39	12	88	0.59
	Higher Education	28	4	0	100		7	93	
Occupation of HHH	In-active	44	7	2	98		11	89	
	Agricultural	402	60	9	91	7.33*	13	87	2.19
	Off-farm	68	10	1	99		12	88	
	Self-employed	154	23	6	98		8	92	
Income quintile	Quintile 1	91	14	2	98		25	75	
	Quintile 2	112	17	13	87		21	79	
	Quintile 3	123	18	8	92	20.09***	10	89	39.1***
	Quintile 4	147	22	12	88		8	92	
	Quintile 5	195	29	3	97		4	96	
Shocks	Unexpected shock to expenses	367	55	8	92	0.10	13	87	1.5
	Expected shocks to expenses	60	9	5	95	0.52	7	93	1.60
	Unexpected Shocks to income	439	66	10	90	11.40***	13	87	1.45
Future expectation of income (five years)	Better	400	62	7	93		12	88	
	Same	167	26	10	90	2.66	10	90	1.07
	Worse	75	12	4	96		13	87	
Risk attitude (based on 0 to 10 Likert scale)	Risk averse	250	38	9	91		12	98	
	Risk neutral	159	24	11	89	7.75**	11	99	0.043
	Risk taker	255	38	4	96		12	98	
Over-optimism (Forecast errors)	Pessimistic	138	21	12	88		9	91	
	No forecast error	265	40	7	93	7.48*	12	88	2.43

	prudentially optimistic	128	19	4	96		15	85	
	non-prudentially optimistic	137	20	7	93		12	88	
Subjective wellbeing compared to the villagers	Better off	128	19	4	96		9	91	
	Same	306	46	5	95	16.5***	10	90	4.39
	Worse off	230	35	13	87		15	85	

Source: Own calculation based on household survey 2011.

To illustrate the dynamics of over-indebtedness and the transition probabilities, in tables 2.4 and 2.5, we exploit the panel dimension of our dataset. Table 2.4 and table 2.5 provide information on the persistency of over-indebtedness and the aggregate state dependence effect in Thailand and Vietnam using the two indicators. In conformity with the literature, the percentage of households in both countries that experience over-indebtedness in at least one year over the four waves is higher than the cross-sectional incidence of over-indebtedness. In particular, for the default indicator, 22% of Thai households and 24% of Vietnamese households were over-indebted in at least one year as compared to an average of 8% and 9% over the four years. Moreover, the DSR indicator shows that 68% of the Thai households and 34% of the Vietnamese households had been over-indebted at least once over the four waves. Considering all four waves, approximately 6% of the households in Thailand were always over-indebted based on the DSR indicator. This suggests that there is a steady entry in and out of over-indebtedness, which means a low probability that a household faces over-indebtedness continuously.

Table 2.4: Number of Years in Over-Indebtedness Based on Default and Arrears and Debt-Service Ratio

Country	Number of Years	Default	DSR
Thailand	0	78	32
	1	16	26
	2	5	23
	3	1	13
	4	0	6
Vietnam	0	76	66
	1	16	23
	2	6	9
	3	2	2
	4	0	0

Source: Own calculation based on household survey 2007 to 2011.

Nevertheless, households that experienced over-indebtedness in the past are more likely to be over-indebted in the next period. Table 2.5 presents the transition matrix of over-indebtedness and shows that between 18% and 42% of the Thai households and 16% to 30% of the households in Vietnam persisted in being over-indebted based on the two indicators. Approximately 2% and 4% of Thai and Vietnamese households that were not over-indebted in the previous periods became over-indebted the next period, while 81% and 70% of the over-indebted households in the previous period got out of it in the next period. This pattern suggests that the chance of escaping over-indebtedness is higher than the probability of getting into it. However, persistency of over-indebtedness is higher for Thai households for the DSR indicator, while it is the opposite for the default indicator, although the difference on the latter is small.

Table 2.5: Probability of Experiencing Over-Indebtedness in Current Year, Conditional on Households' Past Experience of Over-Indebtedness

		Year t			
Over-indebtedness indicators	Year t-1	Thailand		Vietnam	
		No	Yes	No	Yes
Default	No	97.36	2.64	95.87	4.13
Default	Yes	81.63	18.37	70.27	29.73
Debt-service ratio	No	88.72	11.28	91.71	8.29
Debt-service ratio	Yes	58.33	41.67	83.78	16.22

Source: Own calculation based on household survey 2007 to 2011.

However, one must be cautions in the interpretation of these results. Conditional probabilities cannot be taken at face value, because the results could be driven either by the observed or unobserved heterogeneity of households, and these are not controlled for in the transition matrix. While the description of the over-indebtedness situation provides a first entry to the problem, the tables and tests do not show any causal relationship. To distinguish between these two effects, a dynamic modeling approach is needed, which will be explained in the next section.

2.6 An Econometric Model of Over-Indebtedness Transitions

To model over-indebtedness transitions between two consecutive years $t-1$ and t and identify factors that influence a household's probability of becoming over-indebted, 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 $t-1$ (to account for the initial conditions problem), and the correlation of unobserved heterogeneity influencing these processes. Together, these three components characterize the determinants of over-indebtedness persistence and over-indebtedness entry rates.

In practice, separating these three components is not straightforward, as it requires the treatment of the (endogenous) initial conditions problem and unobserved persistent household heterogeneity (Heckman, 1981a; Chay & Hyslop, 2014). The random effects dynamic probit model solves both problems and allows the average effect of the true state dependence to be estimated. The endogeneity of initial conditions is solved by following several approaches, such as Orme's (2001) two steps procedure, Wooldrige's (2005) conditional maximum likelihood estimator, or the most popular approach proposed by Heckman (1981b), which involves specifying a reduced-form linear approximation for the first-year households' over-indebtedness status. The model also controls for the persistent unobserved household heterogeneity in transition probabilities by introducing the household time-invariant effect. We adapt Stewart's (2005) dynamic model specification for unemployment, which follows the approach proposed by Heckman, and we formulate our dynamic model for household over-indebtedness as follows.

2.6.1 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.

$$y_{it}^* = 1(x_{it}'\beta + y_{it-1}\gamma + \varepsilon_i + u_{it} > 0) \qquad (i = 1, \ldots, N; t = 2, \ldots, T) \qquad (1)$$

In equation (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 households in the previous period. The residual u_{it} is an unobservable time and household-varying error term assumed to follow

$N(0, \sigma_u^2)$. The scalar ε_i is the (unobserved) household-specific time-invariant effect, which determines households' 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, $i = 1 \dots N$ in period t, $t = 1 \dots T$, is related to the latent variable y_{it}^* in equation (1) by the following relationship:

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

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

$$\rho = corr(\varepsilon_{it}, \varepsilon_{is}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_u^2} \qquad t, s = 1, \dots, T; t \neq s \tag{3}$$

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 (ε_i) and the observed household characteristics (x_{it}) by assuming that

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

where α_i is distributed as $N(0, \sigma_u^2)$ 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, α_i , left at the end are not correlated with observed household characteristics. Adding that to equation 1, we can rewrite our model as:

$$y_{it}^* = 1(x_{it}'\beta + y_{it-1}\gamma + \overline{x}_i'a + \alpha_i + u_{it} > 0) \qquad (i = 1, \dots, N; t = 2, \dots, T) \qquad (5)$$

To consistently estimate such a model, we need to make additional assumptions concerning the relationship of the initial observations, y_{i1}, and the unobserved time-invariant household effect. We could assume that the initial conditions are either exogenous or are correlated with the unobserved household-specific effect, α_i. The exogeneity assumption 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 up the likelihood into two factors and maximizing the joint probability for $t = 2, \dots, T$ without taking the first year into account. However, here the process of household over-indebtedness is most likely not to be observed for each household from the beginning, and hence, the initial conditions are most likely to be correlated with α_i. Therefore, the estimation of simple models such as the standard random effects probit model will overestimate the state dependence.

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

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

Where z_{i1} includes x_{i1}, exogenous pre-sample variables and the vector of exogenous factors' means, and η_i is assumed to be distributed as standard normal and correlated with α_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 α_i and satisfies the $N(0, \sigma_u^2)$ assumption as for $t \geq 2$. Moreover, the potential differences between the error variance of the initial period and the following periods will be captured by θ. Thus, combining equations (5) and (6), the linearized reduced form for the latent variable for the first period can be written as:

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

The correlation of the household-specific effect presented in equations (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, α_i, using Heckman's approach is (see Stewart, 2007 and 2006):

$$p_{it}(\alpha^*) = \begin{cases} \Phi[(y_{it-1}\gamma + x_{it}'\beta + \sigma_\alpha\alpha^*)(2y_{it} - 1)] \; for \; t \geq 2 \\ \Phi[(z_{i1}'\pi + \theta\sigma_\alpha \alpha^*)(2y_{i1} - 1)] \; for \; t \geq 1 \end{cases} \tag{9}$$

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

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

Where F is the distribution function of $\alpha^* = \sqrt{\lambda/(1-\lambda)}$ and can be integrated out using Gauss-Hermite quadrature (Stewart, 2006). The model can be estimated using Mark Stewart's program module redprob in Stata.

2.6.2 Measuring the Persistence of Household Over-Indebtedness

To measure the persistence of household over-indebtedness, the transition probabilities and 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 (2005), 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-indebtedness status at $t-1$ as fixed at 0 and fixed at 1 and then averaging each probability over all households as follows:

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

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

2.6.3 Model Specification

As discussed earlier, we identify over-indebted households using two indicator variables that take on the value one to indicate the state of being over-indebted in a given year t, specifically using default and DSR indicators. Based on the two indicators, we run four different specifications of the random effects dynamic probit model for each country separately. Except for the ethnic minority dummy variable included in the regression for Vietnam, we use the same sets of explanatory variables for both countries in each model, including the lag dependent variable. Year dummies are included in each specification to control for time trend.

In the initial period of each model, we additionally include pre-sample dummy variables such as whether the previous location of a household head was rural or urban and whether the household head was educated in a rural or urban area.

In the first model specification, using each indicator for Thailand and Vietnam, we regress the basic set of household-level variables, including age (household head aged below 35, 35 - 44, 45 - 54, 55 - 64, 65 and above), gender, household head level of education (primary, secondary and higher education), marital status, number of children, household size, land rental status, main occupation of household head (inactive, agricultural, off-farm employed and self-employed), income quintiles and type of shock households experienced (unexpected shock to expenses, expected shocks to expenses and unexpected shocks to income) in the first specification along with the status of over-indebtedness in the previous period. These groups of variables generally capture the socio-economic and demographic characteristics of the household and their effect on over-indebtedness.

In the second specification, we add dummy variables for the future financial expectation of households (better, same and worse) and their risk attitudes (risk averse, risk neutral, risk takers). Household's future financial expectation dummy variables were constructed using the question *"Do you think your household will be better off next year?"* The risk attitude of the household was based on a Likert scale response of 0 *"unwilling to take risk"* to 10 *"fully prepared to take risk"* for a question *"Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?"* Then, based on the Likert scale, we grouped the households into the three categories and omitted the risk takers as the comparison group.

In the third specification, instead of the future financial expectation of the households, we included the overoptimistic future financial expectation or household forecast error to determine whether over-indebtedness is influenced by the actual positive financial expectation or by the overoptimistic forecast error instead. The future financial forecast error dummy variables were quantified using the difference between a household's financial expectation for period t and the subsequent realization at period $t+1$ following the method of Hyytinen and Putkuri (2012). Specifically, it was based on the questions *"Do you think your household is better off than last year?"* and *"Do you think your household will be better off next year?"* The response categories for both questions were *"Much better off"*, *"Better off"*, *"Same"*, *"Worse off"* and *"Much worse off"*. Household's responses to these two questions were then matched to quantify the forecast errors and to group the households accordingly. Following Hyytinen and Putkuri (2012), we grouped the households into four groups: pessimistic forecast error, no forecast error, prudentially optimistic forecast error and non-prudentially optimistic forecast error. Households that made a prudentially optimistic forecast error are those that performed financially worse than they expected in the previous year but whose financial situation still did not actually worsen, whereas households that made a non-prudentially optimistic forecast error are those that actually performed worse financially in addition to facing negative surprise compared to what they expected.

In the fourth specification, we added households' future financial expectation and forecast error together with households' subjective relative standing in the social circle (subjective perception of households' wellbeing in comparison to villagers: better, same and worse) to examine the effect of all of these behavioral factors on over-indebtedness. Specifically, after controlling for all other household characteristics, if significant, the effect of the subjective perception of households' wellbeing in comparison to their villagers on over-indebtedness captures the social comparison effect, where households that perceive their wellbeing to be lower than that of other households in their village will borrow more and accumulate a higher level of debt to seek social status, thereby over-indebting themselves.

In this study, the reference category was selected in such a way that it represents the situation of rural households with the oldest higher-educated and single household male head whose main income source is self-employment in a small-scale enterprise earning high income and having less risk aversion and a non-prudentially overoptimistic financial expectation.

2.7 Model results

2.7.1 Persistence of households' over-indebtedness in Thailand and Vietnam

The results of Heckman's random effects dynamic probit model are reported for Thailand in table 2.6 and for Vietnam in table 2.7.[1] As discussed above, these tables present four specifications of the empirical model of equation (5) for each indicator, namely, the default and DSR indicators. The evidence presented in table 2.6 confirms our prior expectation that the past experience of over-indebtedness positively increases the likelihood of experiencing over-indebtedness in the future for Thai households, regardless of the indicator used. After controlling for unobserved household heterogeneity, the true state dependence effect is statistically significant for Thai households in all model specifications, as indicated by a statistically significant positive coefficient on the lagged dummy variable of over-indebtedness.[2]

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[1] Several robustness checks were performed to check for the robustness of the true state dependence effect. We first estimated the random effects dynamic probit mode following Orme's (2001) two step procedure and Wooldrige's (2005) conditional maximum likelihood approaches. Then, we estimated a random effects dynamic probit model with autocorrelated errors using Stewart's (2006) Stata command redpace to check for serial correlation.

[2] The result from the robustness checks showed very similar results, with slight differences from the estimated coefficients. For instance, for the fourth model's specification of the default indicator, the estimated coefficients of the true state dependence effect were 0.628 for Wooldrige's model, 0.651 for Orme's model and 0.649 for Heckman's model. The result from the model with autocorrelated errors also confirmed that our result is robust to serial correlation.

According to the APE reported under the fourth specification in table 2.6, Thai households that default on a loan at $t-1$ face a default risk that is approximately 10 percentage points higher than the risk of households that do not default on a loan at $t-1$. Given their observed and unobserved sets of characteristics, households that did not default on a loan at $t-1$ would be 3 times more likely to default on a loan in period t had they defaulted on a loan at $t-1$, according to the predicted probability ratio. Similarly for the DSR indicator, Thai households that were over-indebted at $t-1$ face a risk of over-indebtedness that is approximately 8 percentage points higher than that of households that were not over-indebted at $t-1$. In terms of the DSR indicator, households would be 1.4 times as likely to be over-indebted had they been over-indebted at $t-1$ (see the fourth specification in table 2.6). Furthermore, the average partial effect of the true state dependence effect based on these two indicators reveals that the degree of persistence of defaulting on a loan is higher compared to the degree of persistence of a household's debt service burden in Thailand.

Table 2.6: Random Effects Dynamic Probit Estimation for Thai Household's Probability of Over-Indebtedness (Heckman's Estimator)

variables	Structural equation							
	Default				DSR			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
Over-indebted last year (lagged status of default or DSR indicators)	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)
Age of HH head below 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)
Age of HH head 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)
Age of HH head 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)
Age of HH head 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)
Female HH head	-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)
No of Children (0-14)	-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)
Married HH head	-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)
Illiterate and primary education	-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)
Secondary education	-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)
Land rental status	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)
HH that have 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)
Agricultural HH	-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)
Off-farm employed HH	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)
Inactive HH	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)
Unexpected shocks to expenses	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)
Expected shocks to expenses	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)
Unexpected shocks to income	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)
Future exception of income (Same)		-0.0397		-0.0223		-0.158*		-0.142
		(-0.33)		(-0.18)		(-1.80)		(-1.53)
Future exception of income (Worse)		-0.119		-0.115		-0.0441		-0.0202
		(-0.76)		(-0.69)		(-0.39)		(-0.17)
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)
Pessimistic forecast error			-0.245*	-0.200			-0.120	-0.158
			(-1.70)	(-1.24)			(-1.05)	(-1.26)
No forecast error			-0.305**	-0.260*			-0.0758	-0.100
			(-2.28)	(-1.81)			(-0.72)	(-0.91)
Prudentially optimistic forecast error			-0.177	-0.113			-0.0676	-0.118
			(-1.21)	(-0.71)			(-0.58)	(-0.95)
Subjective wellbeing in comparison to villagers (Better)				-0.719**				0.110
				(-3.86)				(0.81)
Subjective wellbeing in comparison to villagers (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**
	(-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)
ρ	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)
θ	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	-1629.439	-1853.764	-1607.985
LR test: rho=0 chi2(1)	12.49***	140.9***	12.51***	108.6***	347.88***	429.9***	116.16***	455.24***
Wald test	95.46***	83.60***	95.99***	141.2***	120.07***	311.7***	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
AEP: $\hat{p}_1 - \hat{p}_0$	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. Initial condition equation estimates excluded for brevity.
3. $\hat{p}_0$, $\hat{p}_1$: predicted probabilities of households' over-indebtedness at t given over-indebtedness status at $t-1$, respectively.
4. APE: average partial effect; PPR: predicted probability ratio.

Source: Own calculation based on household survey 2007 to 2011.

Additionally, the estimate of the unobserved individual effects (ρ) confirms the unobserved household's heterogeneity effects on the likelihood of experiencing over-indebtedness, with the log likelihood ratio test of 455.24 at a significance level of 0.1% (see the estimates based on the DSR indicator in the fourth column of table 2.6). This estimate implies that approximately 37% of the composite variance of households' over-indebtedness is explained by unobserved household-specific characteristics. The magnitude of this parameter further indicates the importance of the unobserved household heterogeneity in the analysis of households' over-indebtedness, and it stresses the suitability of panel data in such studies.

The significant estimate of θ indicates that the exogeneity assumption of the initial condition can be rejected in this case. Compared with the random effects estimator, which considers the initial conditions to be exogenous, Heckman's estimator reduces the true state dependence effect of over-indebtedness by approximately a half and nearly doubles the estimate of ρ, as it controls for the endogeneity of the initial conditions. After scaling the coefficient of the true state dependence effect of the over-indebtedness estimate by multiplying it with $\sqrt{(1-\rho)}$, the standard random effects probit model results in a coefficient of 0.54, while the Heckman estimator results in 0.228 (see the first model specification in table 2.6 under the DSR indicator). The coefficient further increases to 0.906 for the pooled probit estimator, even though we do not present these results in the paper, for of brevity. On the other hand, it should be noted that the exogeneity of the initial conditions is not rejected in the model specifications for the default indicator.

In contrast to the findings for Thailand, the estimates of the corresponding random effects dynamic probit model for Vietnamese households reveal that the conditional probability of experiencing over-indebtedness in the future does not depend on the probability of having experienced over-indebtedness in the previous periods (see table 2.7). Instead, approximately 20 to 40% of the composite variance of household's over-indebtedness is explained by unobserved household heterogeneity after controlling for the endogeneity of the initial conditions. However, the results of the random effects probit models, which assume exogenous initial conditions, overestimated the true state dependence effect, suggesting that the Vietnamese households experience over-indebtedness persistently. The results also estimated a lower unobserved household heterogeneity effect.

Table 2.7: Random effects dynamic probit estimation for Vietnamese households' probability of over-indebtedness (Heckman's estimator)

variables	Structural equation							
	Default				DSR			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
Over-indebted last year (lagged status of default or DSR indicators)	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)
Age of HH head below 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)
Age of HH head 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)
Age of HH head 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)
Age of HH head 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)
Female HH head	-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)
No of Children (0-14)	-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)
Married HH head	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)
Ethnic minorities (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)
Illiterate HH	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)
Primary education	-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)
Land rental status	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)
HH that have 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)
Agricultural HH	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)
Off-farm employed HH	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)
Inactive HH	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)
Unexpected shocks to expenses	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)
Expected shocks to expenses	-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)
Unexpected shocks to income	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)
Future exception of income (Same)		-0.0534		-0.120		-0.169		-0.137

		(-0.36)		(-0.78)		(-1.35)		(-1.04)
Future exception of income (Worse)		-0.0105		-0.248		-0.449**		-0.427*
		(-0.04)		(-0.96)		(-2.08)		(-1.86)
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)
Pessimistic forecast error			0.253	0.392**			-0.0650	0.0527
			(1.54)	(1.99)			(-0.42)	(0.31)
No forecast error			-0.0600	-0.0153			-0.0448	-0.0957
			(-0.42)	(-0.09)			(-0.35)	(-0.70)
Prudentially optimistic forecast error			-0.116	0.0247			0.229	0.137
			(-0.69)	(0.13)			(1.62)	(0.87)
Subjective wellbeing in comparison to villagers (Better)				-0.415*				-0.0554
				(-1.89)				(-0.29)
Subjective wellbeing in comparison to villagers (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
	(-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)
ρ	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)
θ	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: rho=0 chi2(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
AEP: . $\hat{p}_1 - \hat{p}_0$	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. Initial condition equation estimates excluded for brevity
3. $\hat{p}_0$, $\hat{p}_1$: predicted probabilities of households' over-indebtedness at t given over-indebtedness status at $t-1$, respectively.
4. APE: average partial effect; PPR: predicted probability ratio.

Source: Own calculation based on household survey 2007 to 2011.

Overall, we find that Vietnamese households experience periods of temporary over-indebtedness both in terms of default and DSR, whereas for Thai households, the problem of being over-indebted persists over time. Although it is surprising to find such differing results in terms of the persistency of household's over-indebtedness for these two countries, which follow a fairly similar financial system, the results are in line with the existing literature, which suggests a very low level of default and late repayment in Vietnam's rural credit market (Okae, 2009). According to Okae (2009), the rural credit institutions in Vietnam have been successful in terms of a high level of loan repayment due to community relationship and social ties. Specifically, the author suggests that the direct monitoring mechanisms of the rural communities that are enacted by the members and the potential economic and social sanctions on defaulting households from others enforces repayment and therefore results in a low level of over-indebtedness among rural communities of Vietnam.

2.7.2 Determinants of households' over-indebtedness in Thailand and Vietnam

The marginal effect of covariates is presented in table 2.8 for Thailand and in table 2.9 for Vietnam based on Orme's random effects dynamic probit model. Among the demographic household characteristics, Thai households headed by middle-aged members are more likely to be over-indebted compared to those headed by older household heads for all indicators of over-indebtedness (see table 2.8). Reducing the age of the household head from the 65 and above group to the 45 to 54 group increases the likelihood of experiencing over-indebtedness by approximately 4 percentage points (pp) in terms of default and 7 pp in terms of DSR. While marital status and the number of children does not matter for Thai households, being a male-headed household and having a larger household size significantly increases the likelihood of experiencing over-indebtedness, depending on the model specification. According to the marginal effects in table 2.8, being a female-headed household reduces the likelihood of defaulting on a loan by approximately 2 pp, while it reduces the likelihood of being over-indebted by approximately 4 pp in terms of the DSR indicator.

Table 2.8: Over-Indebtedness Transition Probabilities for Thai Households (Orme's Estimator)

variables	Default				DSR			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
Over-indebted last year (lagged status of default or DSR indicators)	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)
Age of HH head below 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)
Age of HH head 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)
Age of HH head 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)
Age of HH head 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)
Female HH 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)
No of Children (0-14)	-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)
Married HH head	-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)
Illiterate and primary education	-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)
Secondary education	-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)
Land rental status	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)
HH that have 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)
Agricultural HH	-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)
Off-farm employed HH	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)
Inactive HH	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)
Unexpected shocks to expenses	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)
Expected shocks to expenses	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)
Unexpected shocks to income	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)
Future exception of income (Same)		-0.00174		-0.00329		-0.0414*		-0.0420*
		(-0.17)		(-0.30)		(-1.87)		(-1.88)
Future exception of income (Worse)		-0.00841		-0.0162		-0.0145		-0.0162
		(-0.62)		(-1.13)		(-0.51)		(-0.57)
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)
Pessimistic forecast error			-0.0245*	-0.0164			0.00268	-0.00435
			(-1.90)	(-1.18)			(0.10)	(-0.15)
No forecast error			-0.0263**	-0.0215*			0.0135	0.00827
			(-2.35)	(-1.77)			(0.54)	(0.31)
Prudentially optimistic forecast error			-0.0334**	-0.0352**			0.0532**	0.0460
			(-2.65)	(-2.41)			(2.02)	(1.60)
Subjective wellbeing in comparison to villagers (Better)				-0.0593**				0.0232
				(-3.33)				(0.68)
Subjective wellbeing in comparison to villagers (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)
u_{i1}	0.0254**				0.139**			
	(3.67)				(8.90)			
u_{i2}		0.0249**				0.129**		

	Default Model (1)	Default Model (2)	Default Model (3)	Default Model (4)	DSR Model (1)	DSR Model (2)	DSR Model (3)	DSR Model (4)
		(3.37)				(7.82)		
u_{i3}			0.0251**				0.140**	
			(3.60)				(8.91)	
u_{i4}				0.0187**				0.127**
				(2.40)				(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.
Source: Own calculation based on household survey 2007 to 2011.

Similarly, Vietnamese households headed by a household member in the 55 to 64 age group have a 6 pp higher chance of becoming over-indebted in terms of DSR, whereas the probability of default is unrelated to the age of the household head (see table 2.9). Table 2.9 also shows that a larger household size significantly increases the probability of being over-indebted. Thus, an increase in household size by one member increases the probability of experiencing over-indebtedness by approximately 1 pp in terms of both default and the DSR indicator. However, among the Vietnamese households, we do not find any significance difference between female- or male-headed households. Such household characteristics as ethnicity, marital status and the number of children in a household do not significantly influence the probability of experiencing over-indebtedness.

Table 2.9: Over-Indebtedness Transition Probabilities for Vietnamese Households (Orme's Estimator)

variables	Default				DSR			
	Model (1)	Model (2)	Model (3)	Model (4)	Model (1)	Model (2)	Model (3)	Model (4)
Over-indebted last year (lagged status of default or DSR indicators)	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)
Age of HH head below 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)
Age of HH head 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)
Age of HH head 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)
Age of HH head 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)
Female HH head	-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)
No of Children (0-14)	-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)
Married HH head	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)
Ethnic minorities (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)
Illiterate HH	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)
Primary education	-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)

Land rental status	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)
HH that have 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)
Agricultural HH	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)
Off-farm employed HH	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)
Inactive HH	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)
Unexpected shocks to expenses	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)
Expected shocks to expenses	-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)
Unexpected shocks to income	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)
Future exception of income (Same)		-0.00183		-0.00222		-0.0265*		-0.0262*
		(-0.16)		(-0.19)		(-1.68)		(-1.66)
Future exception of income (Worse)		-0.00109		-0.00825		-0.0556**		-0.0560**
		(-0.06)		(-0.41)		(-2.09)		(-2.07)
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)
Pessimistic forecast error			0.00386	-0.000720			-0.00323	-0.00739
			(0.25)	(-0.04)			(-0.16)	(-0.35)
No forecast error			-0.00890	-0.00934			0.00647	0.00507
			(-0.69)	(-0.69)			(0.40)	(0.30)
Prudentially optimistic forecast error			-0.00952	-0.00449			-0.00969	-0.0181
			(-0.70)	(-0.31)			(-0.55)	(-0.94)
Subjective wellbeing in comparison to villagers (Better)				-0.0447**				-0.00338
				(-2.31)				(-0.15)
Subjective wellbeing in comparison to villagers (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)
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 .331	0.314	0.283	0.166	0.176	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.

Source: Own calculation based on household survey 2007 to 2011.

In both countries, a lower level of education significantly reduces the likelihood of experiencing over-indebtedness. Regardless of the indicator used, the probability of becoming over-indebted is positively related to the education level of the household head. A Thai household with a lower-educated household head has a 32 pp less chance of accumulating a high level of debt relative to its income and a 5 pp less chance of defaulting as compared to households with a higher-educated head. For Vietnamese households, this effect is significant only when the DSR indicator is used. Thus, families with lower-educated household heads are less likely to be over-indebted by approximately 5 pp compared to those with higher-educated household heads. This may be contrary to expectations. However, households with lower education levels face more-severe credit constraints and, therefore, have less opportunity to over-borrow. For instance, in Thailand, Siripanyawat et al. (2010) found that households with an undergraduate degree or higher education had the tendency to accumulate higher amounts of debt due to greater access to the formal sources of loans. Nonetheless, the fact that the effect of education becomes mainly insignificant in the case of the default model suggests that households with higher education are more likely to accumulate higher amounts of debt given their prospects of earning more income in the future, but not to extent that they would be defaulting.

We also find that in Thailand, a household head's major occupation does not significantly affect the probability of being over-indebted. This is the case for both indicators. In Vietnam, households with small-scale enterprises are more likely to be over-indebted, albeit only in terms of the debt-service-ratio indicator. These suggests that while there is no difference between the occupation groups in terms of default indicator, which can be considered a more severe threat to household welfare, households with self-employment are more vulnerable to adverse economic shocks, which increase their debt burden.

Consistent with many literatures, in both countries, income strongly impacts the probability of becoming over-indebted. For Thailand's default indicator, the first and second income quintiles are significant, i.e., the likelihood of becoming over-indebted increases by approximately 3 pp for both quintiles. In Vietnam, the income effect is significant throughout the quintiles for the full model (see table 2.9), with 4.9, 5.3, 4.5 and 4.4 pp from the first to fourth quintiles, respectively. Level of income is indeed the main factor responsible for loan defaults as well as for the DSR indicator, where the effect is even stronger. For instance, being in the poorest income group in Thailand increases the probability by 37 pp and in Vietnam by 25 pp.

Furthermore, while household savings is positively related to over-indebtedness in terms of the DSR indicator in both countries, the effect becomes insignificant and takes on a negative sign when we consider the probability of default, perhaps because households keep some precautionary savings as self-insurance against shocks. Households only draw from their savings when the default materializes. Alternatively, it is also not unusual for micro-lenders in microcredit markets of developing countries to require micro-borrowers to open a savings account to obtain a loan. For defaulting households, savings are depleted, which is in line with existing literature (Anderloni & Vandone, 2008).

Concerning adverse economic shocks, we find that both unexpected shocks to income and expenses have a significant positive effect on households' over-indebtedness. However, the effect of both types of shocks and their significance depends on the indicator used and the model specification. For the default indicator, an unexpected shock that leads to higher household expenses increases the likelihood of default by approximately 1 pp for Thai households, while these effects are not significant in Vietnam. These effects also become insignificant for Thai households when we control for all the behavioral factors and for households' subjective relative social standing. For Thai households, we find that unexpected shocks to income increase the likelihood of being over-indebted by approximately 1.5 and 3.8 pp in terms of default and DSR indicators, respectively. In Vietnam, it significantly increases the likelihood of default by approximately 2.7 pp.

As hypothesized, we also find that in both countries, future financial expectation significantly influences the probability of being over-indebted in terms of the DSR indicator after controlling for overoptimistic financial forecast errors and other household characteristics. Households with an optimistic financial expectation were more likely to be over-indebted compared to those that expect their financial situation either to stay the same or change for the worse, even after controlling for the accuracy of their expectation. For instance, in Vietnam, households with a pessimistic financial expectation were less likely to be over-indebted by approximately 5 pp, and Thai households that expected the same future financial situation in five years were less likely to be over-indebted by approximately 4 pp. In fact, households' financial forecast error is not significantly related to over-indebtedness in terms of the DSR indictor. In line with existing literature, this result suggests that a household's optimistic future financial expectation itself, not its accuracy, is what makes it more likely to be over-indebted (Brown et al., 2005).

In contrast, we find that a Thai household's probability of defaulting on a loan is significantly related to making financial forecast errors instead of their future financial expectations. As presented in table 2.8, households with non-prudently overoptimistic financial forecast errors are more likely to default on a loan compared to those who make pessimistic, no or prudently overoptimistic forecast errors. For instance, compared to the reference group, those that make pessimistic financial forecast errors are less likely to default on a loan by approximately 2.4 pp, while those that make no forecast error and prudently overoptimistic forecast errors are 2.6 pp (3.3 pp) less likely to default. In sum, the results support the notion that an overoptimistic future financial expectation co-varies positively with the probability of default in Thailand, while for Vietnam, financial forecast error is not at all significantly related to over-indebtedness, regardless of the indicator used.

We also find that, in line with earlier findings, the household head's attitude towards risk significantly influences the probability of experiencing over-indebtedness for Thai households in terms of the DSR ratio. In Thailand, households that revealed a higher level of risk aversion were less likely to be over-indebted than those that revealed a higher level of risk tolerance. On the other hand, we find no significant reduction in the likelihood of experiencing over-indebtedness for the risk-averse households in Vietnam across all model specifications and indicators (see table 2.9). Furthermore, in terms of default, we also do not find any significant effect of the household head's attitudes towards risk on over-indebtedness. Nonetheless, our results for Thai households in terms of the DSR indicator confirm the results of Brown et al. (2013), who also found an inverse relationship between the amount of debt households accumulate and their attitude towards risk. On the other hand, the insignificance of the relationship between the household head's risk attitude and the likelihood of defaulting in Thailand suggests that risk attitude can only explain the accumulation of debt to a certain degree. Risk can lead to a higher debt service burden, but it cannot explain such extreme situation where households ultimately default on their debt. This argument is also supported by the results in the aforementioned study, which finds that the influence of the risk attitude of households in the U.S. diminishes as their debt burden increases. This paper states that the effect of risk attitude is clearly less explanatory and insignificant, especially for the group of households that accumulated the highest level of unsecured debt. Finally, the magnitude of this effect remained the same and was significant for all the specifications, including the model where we include all of the household behavioral factors.

Likewise, the results presented in tables 2.8 and 2.9 further confirm that subjective relative social standing significantly influences households' probability of experiencing over-indebtedness in terms of the default indicator both for Thai and Vietnamese households. Specifically, households that perceive their subjective relative social standing to be worse than that of other households in their village were more likely to default or reschedule payment on a loan. Households that perceived their relative subjective wellbeing to be either better or the same as other villagers were less likely to default on a loan by approximately 6 and 4 pp among the Thai households and by approximately 4.5 and 4 pp among the Vietnamese households. It should also be noted that this effect is robust to the inclusion of the household's future financial expectation and their forecast error. Georgarakos et al. (2014), who have found similar results in the context of developed countries, explain that social comparison can affect the borrowing decision of households through different channels. First, households can obtain financial information, such as the possibility of and procedure for getting a loan through direct consultation with those they consider to be in a better financial position than them. Second, households can be introduced to the culture of indebtedness, looking at the borrowing decision of their well-to-do peers. Third, such households tend to spend more trying to keep up with the living standard of the other villagers. Finally, these households could spend more than what is optimal if they expect to borrow directly from their peers in case of an adverse shock.

2.8 Summary and Conclusion

Based on a unique panel dataset for the period 2007 to 2011 from Thailand and Vietnam, this paper provides empirical evidence about the factors that can lead households into over-indebtedness. Using three theoretical models, i.e., the standard life cycle model, a behavioral model and a social comparison model, we estimated the probability of a household experiencing over-indebtedness, and its persistence.

Our results suggest that a clear association exists between experiencing over-indebtedness and several of the household characteristics included in the life cycle model. In both countries, the probability of experiencing over-indebtedness is higher for larger households with male, middle-aged and higher-educated household heads. Furthermore, low income levels, income shocks and optimistic financial expectations of household heads are significant factors contributing to over-indebtedness. However, factors such as ethnicity (Vietnam), number of children, marital status and occupation of household heads (Thailand) are not statistically significant.

The behavioral model confirms for Thailand that individual willingness to take risk and overoptimistic financial expectations can lead to over-indebtedness, while these coefficients are insignificant in the Vietnam model.

In the social comparison model, we find that households that consider their wellbeing to be below that of other households in the village have a higher likelihood of being over-indebted. Furthermore, in all three models (Thailand), we find that a household's history of over-indebtedness is a significant factor in explaining current over-indebtedness. Generally, our findings are in line with the results of the few empirical studies conducted so far in a range of countries.

Our results have several policy implications for microcredit programs for the rural poor.
First, microcredit programs that are meant to improve the wellbeing of poor rural households can lead certain types of households into a "debt trap". Hence, governments should effectively implement regulations that force financial institutions to better tailor their microcredit products to the needs of their clients. This should include improving the practice of sharing information among lending institutions on borrowers' credit history by regularly reporting to the National Credit Bureau.

Second, because of the close association we found between over-indebtedness and poverty, we recommend that highly and persistently indebted households should be served by specifically designed poverty reduction programs such as cash transfer programs.

Third, the significant effect of negative shocks as a cause of over-indebtedness in both countries suggests that microcredit institutions should combine microcredit products with insurance schemes in order to reduce the need to take on more loans as a shock coping strategy.

Finally, the significant association between over-indebtedness and behavioral biases tells us that although financial literacy education is important, it is insufficient to solve the problem of over-indebtedness. Also, credit agents are unlikely to improve the decision making of borrowers, as their main interest is selling microcredit products. Therefore, we recommend that government advisory services should integrate financial portfolios in their extension portfolio and offer independent advice in order to empower poor rural households in financial decision making. This may serve as a first step to overcome the existing "culture of indebtedness".

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Appendix

Table A1: List of common indicators of over-indebtedness

	Indicator	Source
Subjective (qualitative)	Perception of debt burden	Disney et al., 2008; Keese, 2012; D'Alessio & Iezzi, 2013
	Struggle and sacrifice related to repaying debt	Schicks, 2014
	Financial difficulty	Betti et al., 2007
Objective (quantitative)	Debt-service ratio	D'Alessio & Iezzi, 2013; Khandker et al., 2013
	Debt to income ratio	Betti et al., 2007
	Debt to asset ratio	Betti et al., 2007; Khandker et al., 2013
	Default	Betti et al., 2007
	Arrear	Disney et al., 2008; D'Alessio & Iezzi, 2013
	Net wealth	Giarda, 2013
	Number of credit commitments >4	D'Alessio & Iezzi, 2013

CHAPTER 3: INTERRELATED DYNAMICS OF MULTIPLE BORROWING AND OVER-INDEBTEDNESS AMONG RURAL HOUSEHOLDS IN THAILAND AND VIETNAM

This chapter is a paper published as a conference proceeding of

ICAE Conference 2015; August 9-14, Milan, Italy.

and presented at:

PEGNet Conference 2014; September 18-19, Lusaka, Zambia

Abstract

Does multiple borrowing lead micro-borrowers into over-indebtedness? Do over-indebted micro-borrowers take loans to refinance existing loans that are ultimately unpayable and get trapped in a vicious circle of debt? Using a longitudinal household survey data, this study addresses such questions by examining the dynamic interdependency between over-indebtedness and multiple borrowing in the context of micro-borrowers in Thailand and Vietnam. Specifically, the trues state dependence and cross-state dependence effects of over-indebtedness and multiple borrowing are tested using the dynamic random effect bivariate probit model while controlling for observed and unobserved household heterogeneity. Results suggest that taking multiple borrowing simultaneously does positively influence household's risk of becoming over-indebted in Thailand, while in Vietnam it has no significant influence on household's risk of over-indebtedness. Additionally, though households reported of taking multiple loans to repay back old debts both in Thailand and Vietnam, the empirical results do not show a significant cross-state dependence effect of over-indebtedness on multiple borrowing.

Keywords: Microcredit, Multiple Borrowing, Household Over-indebtedness, Dynamic Random Effect Bivariate Probit Model, Thailand, Vietnam

3.1 Introduction

In the last three decades, the microfinance industry has witnessed a substantial growth accompanied by a high incidence of multiple borrowing among its clients in developing and emerging market economies. On one hand, multiple borrowing, simply defined as taking multiple loans from multiple sources simultaneously, is considered to be a common and optimal cash flow management strategy of low-income households in developing countries. Low-income households take multiple loans from multiple sources to (1) smoothen their cash flow on regular bases (2) acquire larger loans than a micro-lender offers when creditworthy, (3) manage inflexible loan repayment schedules of microfinance institutions when faced with unexpected adverse shocks (Chen et al., 2010; Schicks & Rosenberg, 2011; Guérin, 2012; Wampfler et. al., 2014). On the other hand, multiple borrowing is becoming increasingly perceived as a symptom of household's over-indebtedness. Through multiple borrowing, households can (1) increase the amount of loan that they can borrow and accumulate more debt than they can repay, (2) simply refinance or turn-over existing loans that are ultimately unpayable and enter into a vicious circle of debt and dependency, (3) easily default on a loan from one micro-lender while still keeping their borrowing relationship with other micro-lenders and meeting their financial needs elsewhere (Chen et al., 2010; Schicks & Rosenberg, 2011).

The empirical evidence on the relationship between multiple borrowing and over-indebtedness has also been conflicting. Some studies find a positive correlation between multiple borrowing and over-indebtedness (Vogelgesang, 2003; Mpogole et al., 2012), while others do not observe any relation (Krishnaswamy, 2007; Gonzalez, 2008; Schicks, 2014).

Furthermore, as most of the studies are exploratory research based on cross-section and qualitative data, they have merely established an evidence of the correlation between multiple borrowing and over-indebtedness than an unambiguous causal relationship. Though cross-section data is useful for many purposes, such data is insufficient to analyze the dynamics of over-indebtedness and its dynamic interdependency with multiple borrowing, as the latter is likely to be an endogenous factor of over-indebtedness.

Therefore, this research aims at understanding the dynamic interdependency between multiple borrowing and households' over-indebtedness in the context of developing countries microcredit market by posing the following key questions: Do households who previously take multiple loans become over-indebted in the future? Do over-indebted households take on more loans to repay back other debts? Is the positive correlation between over-indebtedness and multiple borrowing found in the exploratory research due to genuine interdependence or due to spurious correlation?

Using a four wave panel data for around 1600 rural households from two provinces in Thailand and Vietnam, we analyze the dynamic interdependency between multiple borrowing and household's over-indebtedness using the dynamic bivariate probit model which controls for unobserved household heterogeneity and the endogeneity of initial conditions. Results suggest that, in overheated microcredit markets such as Thailand, taking multiple loans from several sources does increase households' likelihood of experiencing over-indebtedness in the future. Hence, policy makers and industry stakeholders should give more attention to multiple borrowing and also take stapes to protect microcredit borrowers from taking on multiple loans and accumulating more debt than they can repay.

3.2 Literature Review

The increasing incidence of multiple borrowing and over-indebtedness among microcredit borrowers of developing countries has attracted a growing interest among academics and come to be a major concern for industry stakeholders. Unfortunately, however, empirical literature that looks to assess the actual impact of multiple borrowing from the perspective of borrowers and literature covering the theoretical framework for multiple borrowing and over-indebtedness remain very limited. Most of the academic literature has mainly focused on assessing the impact of microcredit on borrowers' wellbeing (Morvant-Roux et al., 2014) leaving the subject of multiple borrowing and its impact on over-indebtedness nearly untouched and limited to a few case studies (Vogelgesang, 2003; McIntosh et al., 2005; Krishnaswamy, 2007; Chen et al., 2010; Schicks & Rosenberg, 2011; Khandker et al., 2013). In what follows, we review the theoretical literature on the impact of competition among microfinance institutions on repayment performance and default in the context of microcredit markets of developing countries to indirectly infer the effect of multiple borrowing on over-indebtedness and motivate our study theoretically.

A growing theoretical literature on microfinance competition shows that competition among micro-lenders leads to an increase in borrowers' over-indebtedness and default. One mechanism through which competition increases over-indebtedness and the default risk of borrowers is through multiple borrowing (Vogelgesang, 2003; McIntosh & Wydick, 2005; Casini, 2010; Guha & Chowdhury, 2013). In competitive microcredit markets where there is a problem of information asymmetry, borrowers can easily take multiple loans concealing their actual level of indebtedness. This makes proper risk assessment and pricing of uncollateralized lending difficult for lenders and ultimately lead to borrowers over-indebtedness and default (Casini, 2010; Guha & Chowdhury, 2013).

In microcredit markets where the poor are provided with uncollateralized loans, information asymmetry over borrowers' credit history is an important factor which influences enforcement costs, reputation effects, multiple borrowing and repayment performance (Hoff & Stiglitz, 1997; McIntosh et al., 2005). Lenders overcome the problem of asymmetric information, simply defined as a situation where lenders lack both *positive* (information on total indebtedness of borrowers including whether borrowers have debts from other sources) and *negative* (information on defaulters) information on borrowers (McIntosh et al., 2005), and its effect on repayment performance by relying on inside reputation mechanisms (Vogelgesang, 2003) and dynamic incentives (McIntosh & Wydick, 2005) emanating from a reciprocal borrower-lender relationships (Casini, 2010; Chen et al., 2010). On the borrower's side, the expected future benefit of a continued access to credit from a lender creates a dynamic incentive and makes them repay their loan even when it is collateral-free (Hoff & Stiglitz, 1997). This also creates an inside reputation mechanism where borrowers who repay on time and keep a long-term relationship with a lender get a better condition for their loans. At the same time, lenders also depend on borrowers' timely repayment to avoid losses. This mutual interdependent borrower-lender relationship that ensures both parties discipline in the markets can, however, be gradually undermined as the levels of multiple borrowing increases in a competitive and crowded market (Casini, 2010; Chen et al., 2010). Such instances allow borrowers to increase their level of indebtedness and also default on a loan with one micro-lender while still keeping their borrowing relationship with other micro-lenders and meeting their financial needs elsewhere (Chen et al., 2010).

Hoff and Stiglitz (1998) highlight this limitation of the reputation effect in their theoretical model. Borrowers' incentive to default on a loan increases with increasing number of lenders in a market as one lender's reputation effect alone does not generate dynamic repayment incentives when borrowers have the choice to switch from one lender to another in a market where there is no negative borrower information sharing. In general, their results suggest that a system of negative borrower information sharing should be in place to strengthen the dynamic incentives effect and prevent multiple borrowing. However, a system of negative borrower information sharing alone is not enough to strengthen dynamic incentives and reduce the incentives for multiple borrowing and default. The strength of the dynamic incentive effect on repayment and multiple borrowing is also influenced by borrowers' present value of the continued future access to credit form a lender and positive borrower information asymmetry (McIntosh & Wydick, 2005).

According to the theoretical model of McIntosh and Wydick (2005), dynamic incentives or in other words borrowers' present value of the continued access to credit form a lender in the future are negatively related to borrowers' rate of time preference. Impatient borrowers with high rate of time preference take multiple loans to get a larger loan size. They increase their loan size by borrowing multiple loans from different sources while lowering their overall borrowing cost by taking smaller loans separately and creating a false impression for lenders that they are borrowing only a fraction of their actual total borrowings (McIntosh & Wydick, 2005). Since in this case money is fungible, multiple loans could be used for a more risky investment (Casini, 2010) or a consumption purpose (Guha & Chowdhury, 2013) without lenders awareness. In general, when there is an information asymmetry over borrowers' indebtedness among competing lenders, such instances of multiple borrowing lead to an increase in total borrowing and indebtedness and ultimately raise borrowers expected default rate for the following reasons. Firstly, since multiple borrowing reduces overall borrowing costs of borrowers, total borrowing and indebtedness increases. Secondly, borrowers' risk of default on a loan increases because the true probability of repayment no longer depends only on one lender's own lending but also on other unknown amount of loan borrowed from elsewhere (McIntosh & Wydick, 2005). An important implication of their result is the need for a central system of information sharing for both positive and negative borrowers' credit history.

Contrary to the theoretical reductive conceptualization of multiple borrowing as problem that results in over-indebtedness due to information asymmetry in microcredit markets, a recent theoretical study by Guha and Chowdhury (2014) shows that multiple borrowing does not necessarily reflect increased indebtedness and identified a positive aspect of multiple borrowing. Households take multiple borrowing for various reasons that are not related to over-indebtedness. For instance, households may take multiple loans to access a range of complementary credit products (Chen et al., 2010; Guérin, 2012; Wampfler et. al., 2014), to expand and diversify their social networks and reduce dependency on one credit source while maintaining creditworthiness with several credit sources (Guérin, 2012) or to cover expenses when faced with unexpected shocks (Schicks & Rosenberg, 2011). Guha and Chowdhury's (2014) theoretical framework shows this complex reality of poor households financial management strategy using an example where poor borrowers take multiple loans from different sources without increasing overall borrowers indebtedness. Additionally, their results shows the potential positive effect of multiple borrowing where due to scarce fund available to micro-lenders leads them to coordinate and provide complementary credit products that are conditional on having a credit contract with another lender to fill in the large capital needed for a technological intensive project of the poor. In this case, with the presence of multiple borrowing, competition among micro-lenders will have a positive effect on borrower targeting and encourage lending to the poor.

Empirical studies which have looked at multiple borrowing and its effect on over-indebtedness also find evidences for both of the alternative views reflected in the theoretical literature. Though the endogeneity problem of multiple borrowing is not addressed in these empirical studies, few of them have found a positive correlation between multiple borrowing and over-indebtedness. For instance, a qualitative exploratory study of the incidence of multiple borrowing in Bangladesh by Chaudhury and Matin, (2002) found a high level of multiple borrowing affecting all income groups equally while in terms of repayment performance households in the low income group were doing worse than the high income groups. This study also found that multiple borrowing was mainly distress driven even if some households also took loans in response to opportunities to invest in businesses. This indicates that the additional loans which are not used for productive purposes can potentially result in repayment problems. By the same token, a study by Vogelgesang (2003) which analyzes the effect of rapidly growing supply of microcredit and increasing competition in Bolivia affirmed that higher levels of indebtedness where many micro-borrowers simultaneously take multiple loans from several sources, corresponds with increasing competition and supply. Borrowers that took multiple loans from several sources at the same time were also found to be more likely to default than others. Moreover, late payments on a previous loan or on a prior instalment of a current loan were found to be highly significant predictors of defaulting on a loan in the future.

Supporting the alternative view of multiple borrowing, other empirical studies have found that multiple borrowing does not necessarily reflect households' struggle with debt repayment or over-indebtedness. For instance, an empirical study by Gonzalez (2008) on households' over-indebtedness in the portfolios of microfinance institutions found that over-indebtedness in Bolivia was not associated with multiple borrowing and that households can become over-indebted just with one loan. Similarly, a study of micro-borrowers in Ghana showed that a high level of over-indebtedness occurred in an environment with a low level of multiple borrowing contradicting the notion of preventing over-indebtedness by reducing multiple borrowing and using credit bureaus (Schicks, 2014). Finally, using a longitudinal household survey data from Bangladesh, Khandker et al. (2013) found that while multiple borrowing increased over-indebtedness in the short run, it reduced over-indebtedness in the long run by influencing the debt to asset ratio favorably. This reflects that multiple borrowing helped borrowers in Bangladesh to increase their assets more than their debt in the long run.

In sum, this study aims at illuminating this ambiguity surrounding the effect of multiple borrowing on households' over-indebtedness by empirically testing the assumption that taking multiple loans from several sources simultaneously leads households to accumulate excessive amount of debt and eventually become over-indebted.

3.3 Data Description and Indicators

As already discussed, we use data on 1582 rural households in Thailand and Vietnam from the "Vulnerability in Southeast Asia" - project funded by the German Research Foundation (DFG) for the period 2007 to 2011. The survey has been conducted annually with the exception of one-year gap between 2008 and 2010. The survey has collected data from 2200 rural households from three provinces in Northeastern Thailand and another 2200 rural households from three provinces in the North Central Coast and Central Highland of Vietnam (Hardeweg, et al., 2012). The six provinces, namely Buriram, Ubon Ratchathani and Nakhon Phanom from Thailand, Ha Tinh, Thua Thien Hue and Dac Lac from Vietnam, were purposively selected targeting rural households either poor or those who are at risk of falling into poverty to meet the general objective of the project. After selecting the provinces, around 220 villages were selected using a systematic random sampling based on a probability proportional to the size of the population. Finally, 10 households were sampled in each village by using again a systematic random sample with equal probability from household lists ordered by household size. Over the four waves, the attrition rate was very low that 4,205 households were interviewed in 2010 in the six provinces and 1588 households were interviewed in 2011 taking two provinces from the two countries.

For the aim of our analysis, we focus on the two provinces, Ubon Ratchathani in Thailand and Thua Thien Hue in Vietnam, which were surveyed over the four waves, as it gives us longer observation to evaluate the dynamic interdependence of multiple borrowing and over-indebtedness. Furthermore, we restrict our sample to the 1582 households which were observed in each of the four waves, specifically 914 households from Ubon Ratchathani and 668 households from Thua Thien Hue, as the econometric model used in this study requires the panel to be balanced. Hence, we have data set with a total sample size of 6328 observation in two countries. In particular, our data contains detailed information on households borrowing, loan defaults and arrears along with a full set of household level data such as households demographics, social and economic characteristics that is common in standard household surveys. This detailed data on financial situation of households allows us to quantify most of the common objective indicators of over-indebtedness used in the existing literature and indicators of multiple borrowing discussed below.

Multiple borrowing can be defined as the practice of borrowing from different sources simultaneously (CGAP, 2012). However, that is a narrow definition of multiple borrowing as multiple borrowing can also take other several forms. According to Wampfler et. al. (2014), households take multiple loans from one financial institution, several financial institutions or both formal and informal credit sources simultaneously. Though it is not the usual type of multiple borrowing, households could take different microcredit products such as investment loans, education loans, working capital loans and the like from the same financial institution. Alternatively, they may take a loan from one lender to repay other outstanding loan from a different lender which inevitably leads to a debt build up, impoverishment and greater vulnerability. Finally, households may also take multiple loans from both formal and informal credit sources either as a substitution strategy for expensive sources, to overcome limitations of the formal credit supply or to serve different needs of households, for example using informal sources for household expenditure while using the formal sources for investment purposes (Chen et al., 2010; Wampfler et. al., 2014). Taking all of these forms into account, *a household is identified as a multiple borrower if the household has multiple active loans outstanding simultaneously regardless of the source of the loan.*

Though a growing attention has been recently devoted to households' over-indebtedness in the microfinance and household finance literature, defining over-indebtedness is still not an easy task since there is no commonly accepted definition of household over-indebtedness yet. This lack of conceptual consensus on what constitutes over-indebtedness and how it ought to be measured is evident from the number of expressions, definitions and indicators that the academic literature uses to describe and measure it. For instance, May and Tudela (2005), who use financial difficulty to refer to over-indebtedness define it as a situation where "*households' flow of income is insufficient to meet their mortgage payments without placing excessive burden on the household*". Another study by Haas (2006), which emphasizes the link between poverty and over-indebtedness, interprets over-indebtedness as a situation where insufficient income makes household unable to repay back their debt in spite of reducing their living standard to pay back their debts. Del Rio and Young (2008), who instead use the subjective perception of households to define over-indebtedness, identify households who consider their unsecured debt to be a burden as over-indebted. Alternatively, a study by Disney et al., (2008) which uses households current arrear as an indicator, classify households as over-indebted *"when they fall into arrears on at least one credit commitment"*. Using another quantitative indicator, a recent study in Italy identified those households who have negative or slightly positive net wealth to be over-indebted (Giarda, 2013). The study by Schicks (2014), which focuses on over-indebtedness of microfinance clients' from a customer protection point of view and takes borrowers experience into account, defines over-indebtedness as a situation where a household "*is continuously struggling to meet repayment* *deadlines and structurally has to make unduly high sacrifices related to his/her loan obligations*".

Apparently, there is also a lack of distinction between the actual definition and indicator of over-indebtedness. At times, the studies explain the indicator used to measure over-indebtedness as a definition and end up inaccurately classifying households into the over-indebted and non-over-indebted groups (Schicks, 2010). Nevertheless, the indicators used to measure over-indebtedness both in developed and developing country context can be categorized into three models: the administrative model, the objective model and the subjective model (Betti et al., 2007). The administrative model considers legally bankrupt households as over-indebted relying on official or legal procedures of bankruptcy that is specific to a country. The objective indicators such as debt-to-income ratio, debt-service-cost ratio and debt-to-asset ratio which are based on quantitative data (Schicks, 2010; D'Alessio & Iezzi, 2013) compare either the stock or flow of debt to household income or assets and classify households whose ratio is above a threshold as over-indebted. Finally, the subjective indicators classify households as over-indebted based on subjective data which reflects the household perception of either their debt situation or as in the study by Schicks, (2014) the struggle and sacrifice related to their debt commitments.

However, all of the over-indebtedness indicators mentioned above have certain limitations. The administrative indicators are limited by the fact that they only consider households who actually go through bankruptcy and default but not those who face sever debt burden and still manage to pay their debt by taking extreme measures. Additionally, its dependency on the judicial system of each country limits its usefulness for comparative studies such us ours. The objective indicators, especially the debt-ratio indicators' major limitation relates to the difficulty of determining the critical level or threshold of indebtedness above which a household will be identified as over-indebted. The difficulty arises due to the fact that the optimal level of indebtedness varies based on the household's stage of the life cycle and household specific characteristics. As a result, there can be no single optimal level of indebtedness and, therefore, a threshold which can be used to identify households over-indebtedness. Finally, as the subjective indicators are based on subjective data their limitation relates to the fact that what each household perceives as being excessive and burdensome may be affected by their subjective biases (Betti et al., 2007; Schicks & Rosenberg, 2011; D'Alessio & Iezzi, 2013). Hence, their usefulness in the context of comparing household over-indebtedness in between countries is limited.

Considering these limitations of the indicators mentioned above, finding a single optimal measure that captures every aspect of over-indebtedness is difficult (for a detailed discussion on limitations of the over-indebtedness indicators, see Betti et al., 2007; Schicks & Rosenburg, 2011; D'Alessio & Iezzi, 2013). Though all agree that there is no single optimal measure that captures true over-indebtedness, recent studies of over-indebtedness have tended to converge on a common set of indicators (D'Alessio & Iezzi, 2013). One of these common set of indicators of over-indebtedness is the debt-servicing-cost. The debt-service-cost indicator identifies households with high level of debt burden as over-indebted by setting a critical level or a threshold on debt repayments relative to income above which are thought to represent a high debt burden for households (D'Alessio & Iezzi, 2013). We also apply the debt-service-cost indicator with a 50 percent threshold commonly used in several studies (Disney et al., 2008; D'Alessio & Iezzi, 2013). Hence, *a household whose debt repayment per year takes more than 50 percent of income is identified as over-indebted*. Though not yet used in a developing country context, these indicator has been applied in several studies that focus on developed consumer credit markets (Disney et al., 2008; Anioła & Gołaś, 2012; Keese, 2012; D'Alessio & Iezzi, 2013).

3.4 The Relationship between Multiple Borrowing and Over-indebtedness in Thailand and Vietnam: Descriptive Results

Based on the indicators discussed above, table 3.1 presents the distribution of multiple borrowing and over-indebted households in Ubon Ratchathani in Thailand and Thua Thien Hue in Vietnam over the five years period. The table reveals a high level of incidence of indebtedness in both countries, whereby 80 to 89 percent of the Thai households and 63 to 76 percent of the Vietnamese households had at least taken one loan in our sample over the four waves. From the indebted households, 76% of the Thai households and 42% of the Vietnamese households had multiple borrowing while around 40% of the Thai households and 17% of the Vietnamese households were over-indebted on average over the period of 2007 to 2011. Taking both formal and informal sources of loan into consideration, around 62% of the Thai households and 32% of the Vietnamese households were cross-indebted among the indebted households. Over the five years period, the trends of both multiple borrowing and over-indebtedness initially increase and decline in 2010 from a relatively higher incidence in the previous periods and then again increase to a higher level in 2011 in Thailand, while in Vietnam the incidence of over-indebtedness declined and multiple borrowing increased more steadily and reached to a highest level in 2011. Comparing the extent of multiple borrowing and over-indebtedness between Thailand and Vietnam, table 3.1 suggests a higher level of over-indebtedness and multiple borrowing among Thai households than Vietnamese households respectively.

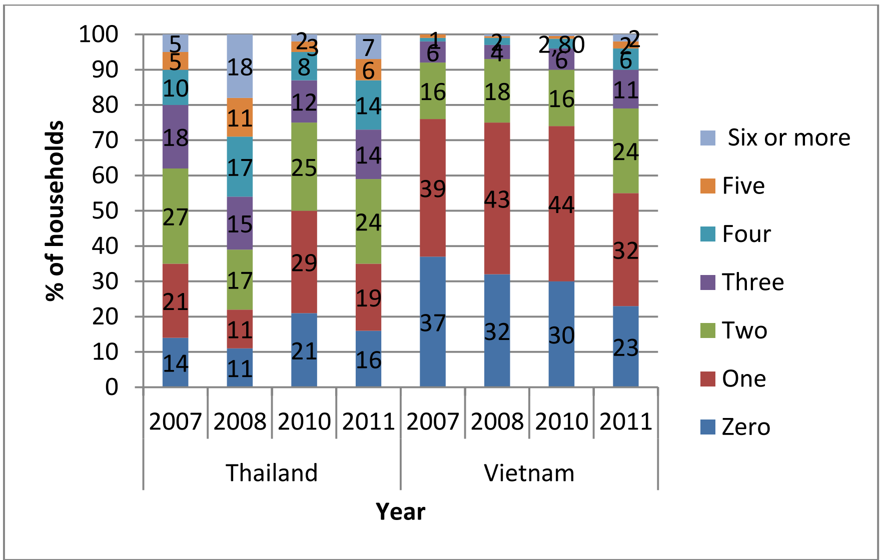
Table 3.1: The Extent of Indebtedness, Over-Indebtedness and Multiple Borrowing among Households in Thailand and Vietnam from 2007 to 2011

Country and Wave ID		Indebted households (percent)	Over-indebted, multiple borrowing and cross-indebted households (Percentage to total households)			Over-indebted multiple borrowing and cross-indebted household (Percentage to indebted households)		
			Over-indebted	Multiple borrowing	Cross-indebted	Over-indebted	Multiple borrowing	Cross-indebted
Thailand (914 HH)	2007	86	40	65	59	46	75	69
	2008	89	48	79	65	54	88	72
	2010	79	18	50	40	23	64	50
	2011	84	30	65	49	35	78	58
Vietnam (668 HH)	2007	63	16	24	19	25	38	29
	2008	68	11	25	20	17	37	29
	2010	70	09	26	19	12	37	28
	2011	76	12	44	33	15	58	43

Source: Own calculation based on household survey 2007 to 2011.

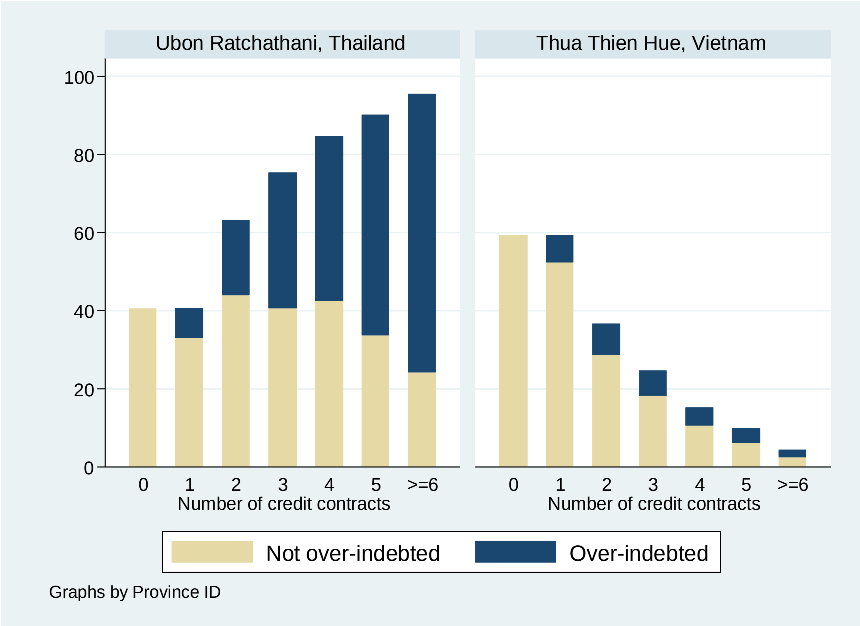
Focusing on the degree of multiple borrowing, we found that households had parallel credit contracts ranging from 2 to 14 in Thailand and 2 to 9 in Vietnam. On average, indebted households were repaying on 2.94 and 1.68 credit contracts in Thailand and Vietnam respectively. Furthermore, having more than 3 credit contracts was very common that around 42% of the households in Thailand and 11% of the households in Vietnam had 3 or more active loans on average over the four waves (see figure 3.1). As can be seen from figure 3.2, it is also evident that the problem of over-indebtedness is more frequent among multiple borrowing households. The percentage of over-indebted households increases with higher number of loans. For instance, among Thai households with a single loan, only 19% are over-indebted compared to 74% of those who have six or more loans. Similarly, out of the Vietnamese households with a single loan, only 12% are over-indebted compared to 43% of those who have six or more loans. Such results have lead few recent studies to suggest using multiple borrowing as a proxy or an objective indicator for over-indebtedness (Disney et al., 2008; D'Alessio & Iezzi, 2013; Schicks, 2014).

Figure 3.1: Multiple Borrowings: Percentage of Households by the Number of Credit Contracts in Thailand and Vietnam, from 2007 to 2011



Source: Own calculation based on household survey 2007 to 2011.

Figure 3.2: Multiple Borrowing and Over-Indebtedness in Thailand and Vietnam



Source: Own calculation based on household survey 2007 to 2011.

However, as can be seen in table 3.2, we find that the degree of overlap between multiple borrowing and over-indebtedness is quite imperfect both in Thailand and Vietnam over the period of 2007 to 2011. Out of the total households who had multiple borrowing, only 46% and 24% of them were over-indebted in Thailand and Vietnam. And from the over-indebted households, 89% and 61% of them had multiple borrowing in Thailand and Vietnam. This finding is however not surprising since households could also be over-indebted with a single loan or since taking multiple loans could be a perfectly manageable cash flow management strategy of households (Schicks & Rosenburg, 2011). Nevertheless, it is important to disprove the notion that multiple borrowing is just another way of measuring over-indebtedness before we begin to investigate their interdependency.

Table 3.2: The Degree of Overlap Between Over-Indebtedness and Multiple Borrowing Over the Period of Five Years (2007 to 2011)

Country			Multiple borrowing		Over-indebtedness	
			No	Yes	No	Yes
Thailand	Over-indebtedness	No	89	54	-	-
		Yes	11	46	-	-
	Multiple borrowing	No	-	-	48	11
		Yes	-	-	52	89

Vietnam	Over-indebtedness	No	93	76	-	-
		Yes	7	24	-	-
	Multiple borrowing	No	-	-	75	39
		Yes	-	-	25	61

Source: Own calculation based on household survey 2007 to 2011.

According to Devicienti and Poggi (2010), one way of doing that is to use a nonlinear Wald proportionality test on the coefficients of two separate probit models, one for over-indebtedness using the debt-service-cost indicator and the other for multiple borrowing. If the two indicators are measuring the same underlying concept, then the coefficients of the two models will be the scaled versions of each other. Following Devicienti and Poggi (2010), we run two separate static probit models for multiple borrowing and over-indebtedness for each year and each country and carried out a nonlinear Wald test. The models included such explanatory variables as gender, age, education and marital status of the household head, household size, income quintile groups, type of occupation and shocks. In each case, the nonlinear Wald test rejected the null hypothesis that multiple borrowing is an alternative way of measuring over-indebtedness at least at the 5% level of statistical significance.

Having disproved the notion that multiple borrowing and over-indebtedness are simply alternative ways of measuring the same underlying concept, one important question that remains to be answered is whether the probability of experiencing over-indebtedness in period t positively correlates with the probability of experiencing over-indebtedness in period $t + 1$ and having multiple borrowing $t + 1$? To answer such questions and examine households' dynamic experience of over-indebtedness and multiple borrowing and the transition and cross-transitions probabilities from the two states, we shift our emphasis to the panel dimension of our dataset. Using the indicators discussed in the previous section, table 3.3 and 3.4, provide information on the persistency of over-indebtedness and multiple borrowing in the Thailand and Vietnam. In conformity with the literature, the percentage of households in both countries who experience over-indebtedness and have multiple borrowing in at least one year over the four waves are higher than the cross-sectional incidence of over-indebtedness and multiple borrowing. In particular, 78% of Thai households and 34% of Vietnamese households in our sample were over-indebted in at least one year as compared to an average of 40% and 17% over the four years. And in the case of multiple borrowing, around 86% of Thai households and 60% of Vietnamese households in our sample had taken multiple loans simultaneously in at least one year as compared to an average of 62% and 32% over the four years. Considering all of the four waves, while around 6% and 39% of the Thai households were always over-indebted and had multiple borrowing respectively, only one household was always over-indebted and around 5% of the Vietnamese households had multiple borrowing over the four periods. These results suggest that over-indebtedness and multiple borrowing are more persistent for the Thai households than for the Vietnamese households. Nevertheless, it is evident that there is a steady entry into and out of the state of over-indebtedness and multiple borrowing so that the same households do not face over-indebtedness and multiple borrowing continuously in both countries.

Table 3.3: Number of Years in Over-Indebtedness and Multiple Borrowing

Country	Number of Years	Over-indebted	Multiple borrowing
Thailand	0	32	14
	1	26	11
	2	23	16
	3	13	20
	4	6	39
Vietnam	0	66	40
	1	23	25
	2	9	17
	3	2	13
	4	0	5

Source: Own calculation based on household survey 2007 to 2011.

Though households do not face over-indebtedness and multiple borrowing continuously over the four periods, households who experience over-indebtedness or have multiple borrowing in the past seem to be more likely of experiencing over-indebtedness in the next period both in Thailand and Vietnam. As can be seen in table 3.4 under columns 4 and 6, the conditional probability of being over-indebted in the current period for a Thai household given that the household was not over-indebted in the previous period is 23% as compared to a 48%

conditional probability of being over-indebted in the current period given that the household was over-indebted in the previous period. Similarly, for a Vietnamese household the conditional probability of being over-indebted in the current year is 9% if the household was not over-indebted in the previous period, but the conditional probability will increase to 22% for those who were over-indebted in the previous period. The conditional probability of having multiple borrowing also shows a possible state dependence for both Thai and Vietnamese households with a higher jump (from 36% to 80% for Thailand and from 22% to 61% for Vietnam) in the probability of having multiple borrowing for the households who had multiple borrowing in the previous period.

Table 3.4: Probability of Experiencing Over-Indebtedness in Current Year, Conditional on Household's Past Experience of Over-Indebtedness and Multiple Borrowing Status

Indicators	Year $t-1$	Year t Thailand No	Yes	Vietnam No	Yes
Over-indebted (Over-indebted $t-1$)	No	77	23	91	9
	Yes	52	48	78	22
Multiple borrowing (Multiple borrowing $t-1$)	No	67	36	78	22
	Yes	20	80	39	61
Over-indebted (Multiple borrowing $t-1$)	No	83	17	92	8
	Yes	60	40	81	19
Multiple borrowing (Over-indebted $t-1$)	No	43	57	71	29
	Yes	22	78	52	48

Source: Own calculation based on household survey 2007 to 2011.

In terms of the cross-state dependence between over-indebtedness and multiple borrowing, table 3.4 also shows a positive relationship between the previous states of multiple borrowing and over-indebtedness and the current state of the other. Specifically, while the probability of being over-indebted in the current year is 17% for the Thai households who did not have multiple borrowing in the previous period, it increases to 40% for those who had multiple borrowing in the previous period. For the Vietnamese households it follows the same pattern in that the conditional probability of being over-indebted is as twice as likely for the households who had multiple borrowing in the previous period. Likewise, the conditional probability of having multiple borrowing simultaneously in the current year is higher for households who were over-indebted in the previous period compared to those who were not for both Thai and Vietnamese households. These results suggest that there is likely to be a positive cross-state dependence effect between multiple borrowing and over-indebtedness.

However, the observed persistence of over-indebtedness showed in table 3.5 could be to some degree or even entirely due to household heterogeneity. For instance, the fourth row in table 3.6 shows that the (unconditional) probability of being over-indebted is higher for those with a younger, male, married and more educated household heads and who are among the poorest income quintile groups in Thailand. Similarly, the (unconditional) probability of being over-indebted is higher for Vietnamese households with a younger, male and married household heads and for those who are among the poorest income quintile groups. Therefore, even if over-indebtedness is truly not structurally persistent for both of the Thai and Vietnamese households in our sample, these observed heterogeneities would cause the group of households that were over-indebted in the previous period to have a higher aggregate probability of being over-indebted at the current period than those who were not over-indebted.

Table 3.5: Unconditional and Conditional Probabilities of Over-Indebtedness for Thai Households, from 2008 to 2011

		Households (percent)	Unconditional	Not over-indebted at $t-1$	Over-indebted at $t-1$	Not a multiple borrower at $t-1$	Multiple borrower at $t-1$
All		100	31.87	23.20	47.83	16.77	40.17
Age of HH head group	Below 35	1	37.29	20.59	60	20.83	48.57
	35 - 45	15	34.89	25.72	50	15.63	42.77
	45 - 55	27	34.75	25.66	48.66	18.14	40.91
	55 - 65	29	33.02	22.93	50.36	19.55	40.55
	Above 65	28	25.47	20.22	39.70	14	35.82
Female headed HH (%)	Male	78	33.12	24.98	47.30	19.10	40.08
	Female	32	29.17	19.55	49.11	12.61	40.39
Married HH head	Single	21	28.18	18.05	50.27	12.24	39.76
	Married	79	32.87	24.69	47.25	18.29	40.27
Education of HH head groups	Illiterate and primary education	86	30.90	21.99	47.48	15.94	39.52
	Secondary education	11	33.92	27.32	45.63	18.67	39.34
	Higher Education	3	56.34	50	65.52	40	65.22
Occupation of HHH	In-active	15	33.59	24.74	48.30	16.96	41.46
	Agricultural	56	31.37	20.69	50.52	13.58	38.95
	Off-farm	10	31.46	23.03	47.93	19.05	39.03
	Self-employed	19	26.11	19.73	42.86	15.34	35.48
Income quintile	Quintile 1	14	49.61	37.04	70.83	23.94	67.66
	Quintile 2	18	38.77	30.51	53.16	18.13	50.91
	Quintile 3	20	31.50	25.17	42.19	13.30	41.06
	Quintile 4	23	20.07	12.34	36.41	9.84	25.26
	Quintile 5	25	22.01	13.76	37.02	17.84	23.94

Source: Own calculation based on household survey 2007 to 2011.

Table 3.6: Unconditional and Conditional Probabilities of Over-Indebtedness for Vietnamese Households, from 2008 to 2011

		Households (percent)	Unconditional	Not over-indebted at $t-1$	Over-indebted at $t-1$	Not a multiple borrower at $t-1$	Multiple borrower at $t-1$
All		100	10.48	8.94	21.94	7.70	18.91
Age of HH head group	Below 35	9	10.46	8.78	20.59	7.43	27.03
	35 - 45	25	11.95	9.85	25.71	7.92	21.12
	45 - 55	29	9.56	8.15	22.64	7.35	14.72
	55 - 65	16	14.57	12.30	26	9.95	27.16
	Above 65	21	6.63	6.63	6.67	6.53	7.27
Female headed HH (%)	Male	79	10.75	9.24	21.65	7.81	18.82
	Female	21	9.42	7.82	23.26	7.31	19.44
Married HH head	Single	17	8.96	7.74	19.44	6.60	20.69
	Married	83	10.80	9.20	22.39	7.96	18.68
Education of HH head groups	Illiterate	18	7.89	6.21	24.24	15.94	39.52
	Primary education	43	11.81	10.41	21.90	18.67	39.34
	Secondary and Higher education	39	10.19	8.60	21.21	40	65.22
Occupation of HHH	In-active	7	11.08	9.52	21.79	8.43	19.21
	Agricultural	60	12	8.99	36.36	7.19	22.95
	Off-farm	10	8.57	7.60	17.02	5.31	18.10
	Self-employed	23	9.02	8.18	16.64	9.62	5.56
Income quintile	Quintile 1	14	23.40	20.34	46.15	18.91	46.30
	Quintile 2	17	14.29	12.58	23.73	9.76	27.55
	Quintile 3	18	8.31	6.94	18.37	5.03	19.78
	Quintile 4	22	5.63	4.72	13.33	3.62	10.66
	Quintile 5	29	4.40	3.66	11.11	2.79	8.33

Source: Own calculation based on household survey 2007 to 2011.

Furthermore, taking the various characteristics of households into consideration, table 3.5 and 3.6 present the over-indebtedness probabilities, both unconditional and conditional on being over-indebted and having multiple borrowing in the previous period for Thai and Vietnamese households in our sample. Comparing the conditional probabilities in column 5 and 6 of table 3.5 and 3.6 revel that there is a difference between the probabilities of being over-indebted conditional on the status of over-indebtedness in the previous period within all subgroups. For instance, the conditional probability of being over-indebted for both Thai and Vietnamese households that were over-indebted in the previous period are as twice as likely to be over-indebted compared to the those who were not over-indebted in the previous period (70% as compared to 37% for Thai households and 46% as compared to 20% for Vietnam households). Likewise, the aggregate cross-persistency that we saw in table 3.4 is also confirmed for all of the subgroups of households in Thailand and Vietnam where each subgroup is at least twice as likely to be over-indebted if they had a multiple borrowing in the previous period compared to those who did not have multiple borrowing previously.

Conditional probabilities, however, cannot be taken at face value because the observed persistency of over-indebtedness and multiple borrowing in both countries could also be driven by the unobserved heterogeneity of households which are not controlled for in the conditional probability matrixes instead of a genuine state dependence effect. Therefore, we use the dynamic random effects bivariate probit model, which will be explained in the following section, to distinguish between these two effects by including a number of explanatory variables to control for households heterogeneity.

3.5 An Econometric Model for the Interdependent Dynamics of Multiple Borrowing and Over-Indebtedness

To study the described relationship between multiple borrowing and being over-indebted among Thai and Vietnamese households, we use a dynamic random-effect bivariate probit model that allows a spillover effect between the two states. This model was selected because it allows us to test whether each of the states have a true influence on future values of the outcomes — e.g. being a multiple borrower in the past having an effect on current over-indebtedness. As a first-order Markov chain model, it allows the state dependence of multiple borrowing and over-indebtedness and the cross-state dependence effects between the two states while allowing for correlated unobserved heterogeneity and accounting for the initial conditions.

In the next subsection, we first focus on the model specification. Most of the discussion on the model follows Devicienti and Poggi (2010), Alessie et al. (2004) and Stewart (2007). We adopt Devicienti and Poggi's (2010) model specification for poverty and social exclusion which follows the approach proposed by Wooldridge (2005) in treating the initial conditions problem and formulate our dynamic random effect bivariate probit model for interrelated dynamics of multiple borrowing and over-indebtedness as follows.

3.5.1 Dynamic random-effect bivariate probit model

For a household i, the propensity to be over-indebted at time t is expressed in terms of latent variable y_{1it}^* as specified in equation (1), while the propensity to have multiple borrowing at time t is expressed in terms of latent variable y_{2it}^* as specified in equation (2).

$$y_{1it}^* = x_{1it}'\beta_1 + y_{1it-1}\gamma_{11} + y_{2it-1}\gamma_{12} + c_{1i} + u_{1it} \tag{1}$$

$$y_{2it}^* = x_{2it}'\beta_2 + y_{1it-1}\gamma_{21} + y_{2it-1}\gamma_{22} + c_{2i} + u_{2it} \tag{2}$$

$$y_{jit} = 1\left[y_{jit}^* > 0\right] j = 1,2\ t = 2, \ldots, T \tag{3}$$

The two binary dependent variables indicate a specific state a household is at, y_{1it} equal to one if the household is over-indebted in t, and zero otherwise; y_{2it} equal to one if household i has multiple borrowing in t, and zero otherwise. In equation (1) and (2), the vector x includes the observed explanatory variables such as household's socio-demographic and economic characteristics that are assumed to be strictly exogenous and are kept the same in both equations. The vectors β_1 and β_2 are the analogous parameters to be estimated showing for instance how economic factors such as households level of income and shocks influence the probability of becoming over-indebted or taking multiple loans. We assume here that, the error terms u_{1it} and u_{2it} are serially independent and follow a bivariate normal distribution, with zero means, unit variances and cross-equation covariance ρ. c_{1i} and c_{2i} represent the unobserved time-invariant household specific random effects which are assumed also to be bivariate normal with variances σ_{c1}^2 and σ_{c2}^2 and covariance $\sigma_{c1}\sigma_{c2}\rho_c$. c_{1i} and c_{2i} capture unobserved households characteristics that remain constant over time, like financial literacy, debt perception, time preference or household's ability. We also assume that (c_{1i}, c_{2i}), $(u_{1it}, u_{2it}; t = 1, \ldots, T)$ and $(x_{it}; t = 1, \ldots, T)$ are independent (implying that x_{it} is strictly exogenous).

An important aspect of the dynamic random effects bivariate probit model is that it explicitly accounts for the effect of being at a specific state in year $t-1$ and the dependence of each state on the previous outcome of the other state, specifically the state dependence and cross-state dependence effects, by including the lag of the dependent variables, y_{1it-1} and y_{2it-1}, as specified in equation (1) and (2). Hence, the model allows us to establish the casual effect of having multiple borrowing in the past on current multiple borrowings and over-indebtedness of households and vice versa after accounting for the effect of household's unobserved heterogeneity using the bivariate model specified above. If the unobserved households' heterogeneity is not controlled for, the true state dependence would be overestimated due to the spurious state dependence effect.

To account for the cross-state dependence effect between borrowing from multiple sources and over-indebtedness, the model includes cross-lagged variables among the explanatory variables: lagged multiple borrowing y_{2it-1} is included in the over-indebtedness equation and lagged over-indebtedness y_{1it-1} is included in the multiple borrowing equation. This allows as to determine whether the observed correlation between borrowing from multiple sources and being over-indebted is due to spurious state dependence, i.e. correlated unobserved heterogeneity ($\rho_c \neq 0$), or a true cross-state dependence where γ_{12} and γ_{21} are not equal to zero given the unobserved heterogeneity.

However, there are special cases where one would not need the bivariate models specified above to identify the interdependency between the two outcomes (Alessie et al., 2004; Stewart, 2007). If $\gamma_{12} = 0$, equation (1) for household's over-indebtedness would exclude the lagged dummy for multiple borrowing. Then, equation (1) can be considered by itself and the rest of the parameters can be estimated consistently using the standard univariate random-effect dynamic probit model (Stewart, 2007; Devicienti & Poggi, 2010). Another special case where equation (1) can be considered by itself is when $\gamma_{12} \neq 0$, but the error terms and the random effects of equation (1) and (2) are independent ($\rho = \rho_c = 0$). In which case, the standard univariate random-effect dynamic probit model can again estimate the parameters consistently treating y_{2it-1} as a weakly exogenous regressor (Stewart, 2007; Devicienti & Poggi, 2010). With the exception of such special cases, the joint estimation of the first three models is necessary to get consistent estimates of the parameters.

3.5.2 Initial conditions and estimation

One important issue in estimating the dynamic random effect bivariate probit model which is well established in the literature is the treatment of the initial conditions. The problem of the initial conditions arises because the beginning of the observation period does not usually coincide with the period where households begin to experience the outcome, in this case multiple borrowing and over-indebtedness (Heckman, 1981a). Therefore, to consistently estimate such a model, we need to make additional assumptions concerning the relationship of the initial observations, y_{1i1} and y_{2i1}, and the unobserved time-invariant household effect. We could either assume that the initial conditions are exogenous or correlated with unobserved household-specific effect, c_{1i} and c_{2i}. The exogeneity assumption is valid only if the stochastic process that generates the outcomes 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 bivariate probit model can be used by splitting up the likelihood into four factors and maximizing the joint probability for t=2,…,T without taking the first year into account. However, here the process of household over-indebtedness and multiple borrowing are most likely not observed for each household from the beginning. Therefore, the initial observations y_{1i1} and y_{2i1} are more likely to be endogenous and correlated with the unobserved time-invariant household effects, c_{1i} and c_{2i}. Hence, the estimation of simple models such as the standard random effects bivariate probit model will overestimate the state dependence.

To address the problem of initial conditions and estimate the model, we adopt the strategy suggested by Devicienti and Poggi (2010) which extends the simple approach proposed by

Wooldridge (2005) to the bivariate case. That is, a Conditional Maximum Likelihood (CLM) estimator which consider the distribution conditional on the initial values and the observed history of strictly exogenous explanatory variables (Wooldrige, 2005). In the case of the bivariate probit model, Devicienti and Poggi (2010) specify the individual specific effects c_{1i} and c_{2i} given the initial conditions, which in our case are the over-indebtedness initial condition y_{1i1} and the multiple borrowing initial condition y_{2i1}, and the time-constant explanatory variables $\overline{x}_i$, as follows:

$$c_{1i} = a_{10} + a_{11}y_{1i1} + a_{12}y_{2i1} + \overline{x}_i a_{13} + \alpha_{1i} \quad (4)$$

$$c_{2i} = a_{20} + a_{21}y_{2i1} + a_{22}y_{2i1} + \overline{x}_i a_{23} + \alpha_{2i} \quad (5)$$

where a_{j0}, a_{j1}, a_{j2} and a_{j3} $(j = 1, 2)$ are parameters to be estimated, $(\alpha_{1i}, \alpha_{2i})$ are normally distributed with covariance matrix Σ_α:

$$\Sigma_\alpha = \begin{pmatrix} \sigma_{\alpha 1}^2 & \sigma_{\alpha 1}^2 \sigma_{\alpha 2}^2 \rho_c \\ . & \sigma_{\alpha 2}^2 \end{pmatrix}$$

Inserting equation (4) and (5) in model (1) and (2) gives us:

$$y_{1it}^* = x_{1it}'\beta_1 + y_{1it-1}\gamma_{11} + y_{2it-1}\gamma_{12} + a_{10} + a_{11}y_{1i1} + a_{12}y_{2i1} + \overline{x}_i a_{13} + \alpha_{1i} + u_{1it} \quad (6)$$

$$y_{2it}^* = x_{2it}'\beta_2 + y_{1it-1}\gamma_{21} + y_{2it-1}\gamma_{22} + a_{20} + a_{21}y_{2i1} + a_{22}y_{2i1} + \overline{x}_i a_{23} + \alpha_{2i} + u_{2it} \quad (7)$$

Following Devicienti and Poggi (2010), the model parameters are consistently estimated using Conditional Maximum Simulated Likelihood methods where a household i 's contribution to the likelihood can be specified as follows:

$$L^w = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \prod_{t=1}^{T} \Phi_2\big(\tilde{y}_{1it}\mu_{1it}, \tilde{y}_{2it}\mu_{2it}, \tilde{y}_{1it}\, \tilde{y}_{2it}\, \rho \big| y_{1t-1}, y_{2t-1} \dots x_{it,}\overline{x}_i\big)\, \mathrm{g}(\alpha_1, \alpha_2, \Sigma_\alpha) d\alpha_{1i} d\alpha_{2i} \quad (8)$$

Where μ_{1it} and μ_{2it} are the right hand side of equations (6) and (7) without the error terms u_{1it} and u_{2it}, $\tilde{y}_{jit} = 2y_{jit} - 1$ for $j = 1,2$ and $\mathrm{g}(.)$ represents the bivariate normal density.

Lastly, as the model of Devicienti's and Poggi's (2010) treatment of the initial conditions follows the approach proposed by Wooldridge (2005), their bivariate model also needs to be estimated using a balanced panel data. This usually raises the question of potentially increasing the attrition and sample selection bias in the data. However, Devicienti and Poggi (2010) argue that the approach of Wooldridge (2005) rather has an advantage in handling attrition and selection problems. Specifically, Wooldridge's approach allows attrition and selection to depend on the initial conditions. Hence, households with different initial over-indebtedness and multiple borrowing statuses are allowed to have different probabilities for missing data. Accordingly, their model also accounts for selection and attrition problem without directly modeling them as a function of the initial conditions. In any case, attrition bias is not much of a concern in our dataset as the attrition over the four waves was 1.1 percent.

3.6 Empirical Results

In table 3.7, we present the estimation results of the dynamic random effects bivariate probit model for the dynamic interdependency between over-indebtedness and multiple borrowing which controls for both observed and unobserved household heterogeneity both for Thai and Vietnamese households. Using the indicator of multiple borrowing and over-indebtedness discussed in section 3.3, we run separate models for Thailand and Vietnam including the same set of explanatory variables for both countries in each model in addition to the previous period and initial period status of the two dependent variables. The explanatory variables include basic set of household level variables including age (household head aged below 34, 34 - 44, 44 - 54, 54 - 65, 65 and above), gender, household head level of education (primary, secondary and higher education), marital status, number of children, household size, main occupation of household head (inactive, agricultural, off-farm employed and self-employed), income quintiles and type of shock experienced households experienced (unexpected shock to expenses, expected shocks to expenses and unexpected shocks to income). Longitudinal averages are also included in the model to allow for the correlation between household specific effects and the time-varying variables, specifically number of children and household size (See table 3.1 for descriptive statistics on the explanatory variables). Additionally, year dummies are included in each equation to control for macro-economic shocks and time trends. While there are other factors that drive household over-indebtedness and multiple borrowing, we only control for these set of explanatory variables in order to not further complicate the model estimation which is already computationally demanding. Furthermore, the focus of the study mainly lies on the interrelated dynamics of multiple borrowing and over-indebtedness and not on the explanatory variables included in the model. Nevertheless, as the model controls for both correlated and uncorrelated household heterogeneity, omitted variable bias will not be an issue in the estimation (Devicienti & Poggi, 2010).

In the next section, we first present the results of the true state dependence and cross-state dependences effects of multiple borrowing and over-indebtedness which are indicated by the estimates of the lagged indicators of over-indebtedness and multiple borrowing. The discussion on the cross-state dependence effect between multiple borrowing and over-indebtedness will provide an evidence for whether multiple borrowing enables households to accumulate excessive amount of debt and lead them to over-indebtedness in the future or whether over-indebted households take additional loan to repay back old debts and fall into debt trap. Finally, we will briefly discuss the results of the unobserved household heterogeneity and its correlations.

3.6.1 Over-indebtedness

Columns (1) and (5) in table 3.7 present results of the over-indebtedness equations. As expected, the results reveal that taking multiple borrowing in the past is strongly associated with the risk of becoming over-indebted in the future for Thai households as indicated by the positive significant effect of the cross lagged multiple borrowing status at $t-1$ after controlling for (correlated) unobserved heterogeneity. Similarly, being over-indebted in the previous period positively increases household’s likelihood of becoming over-indebted in the future for Thai households as indicated by the positive significant effect of over-indebtedness status at $t-1$. To assess the magnitude of these effects, the transition probabilities of household's over-indebtedness and the associated average partial effect (APE) and predicted probability ratio (PPR) have been calculated for over-indebtedness by conditioning on the multiple borrowing status at $t-1$ and the over-indebtedness status at $t-1$ for both estimations presented in table 3.7. First, the transition probabilities of over-indebtedness were calculated for each household in the sample based on estimates of counterfactual outcome probabilities taking the multiple borrowing status at $t-1$ and the over-indebtedness status at $t-1$ as fixed at 0 and fixed at 1 and then averaging each probability over all households. Secondly, the associated average partial effect was calculated by taking the difference between these two probabilities ($\text{APE} = \hat{p}_1 - \hat{p}_0$), while the predicted probability ratio was calculated by taking their ratio ($PPR = \hat{p}_1/\hat{p}_0$) (Stewart, 2007).

Table 3.7: Dynamic Random Effects Bivariate Probit Model for Thai and Vietnamese Households Probability of Being Over-Indebted and Having Multiple Borrowing (Wooldrige's Estimator)

	Thailand				Vietnam			
	Over-indebtedness		Multiple borrowing		Over-indebtedness		Multiple borrowing	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Multiple borrowing at $(t-1)$	0.507**	0.111	0.944**	0.083	0.151	0.104	0.521**	0.0976
Over-indebted at $(t-1)$	0.147*	0.092	0.0244	0.096	0.0653	0.127	-0.0098	0.113
Multiple borrowing status initial year (t = 1)	0.472**	0.106	0.963**	0.083	0.367**	0.106	0.495**	0.0977
Over-indebted status initial year (t = 1)	0.577**	0.091	0.219**	0.075	0.448**	0.116	0.339**	0.107
Age of HH head below 35	-0.145	0.234	-0.646**	0.226	-0.229	0.181	-0.206	0.158
Age of HH head 45-54	-0.0968	0.118	-0.262**	0.113	-0.0889	0.164	0.0852	0.135
age of HH head 55-64	-0.0223	0.098	-0.440**	0.089	0.146	0.153	-0.0453	0.124
age of HH head above 65	-0.196	0.094	-0.631**	0.085	-0.299	0.158	-0.382**	0.132
Female HH head	-0.180*	0.083	-0.223**	0.075	0.0729	0.152	-0.00815	0.127
married HH head	-0.0212	0.099	-0.207**	0.088	0.413**	0.170	0.312*	0.144
No of Children (0-14)	-0.00703	0.090	0.0359	0.089	0.150	0.116	0.0102	0.089
Household size	0.0304	0.074	0.0264	0.071	-0.0557	0.078	0.0162	0.056
Ilitrate and primary education	-1.329**	0.198	0.339	0.186	-0.510**	0.222	-0.286	0.188
Secondary education	-1.041**	0.209	0.412*	0.202	-0.432*	0.217	-0.380*	0.183
Agricultural HH	0.0940	0.109	0.119	0.104	-0.379**	0.150	0.105	0.127
Off-farm employed HH	0.00569	0.123	-0.0569	0.117	-0.397**	0.161	0.135	0.135
Inactive HH	0.136	0.142	0.0951	0.132	-0.102	0.231	0.00423	0.204
Income quintile 1	1.336**	0.119	-0.197*	0.100	1.686**	0.160	-0.226	0.130

Income quintile 2	0.845**	0.107	0.00529	0.097	1.078**	0.154	0.0766	0.116
Income quintile 3	0.599**	0.103	0.110	0.094	1.078**	0.153	-0.00220	0.108
Income quintile 4	0.0688	0.100	0.0664	0.091	0.651**	0.154	0.104	0.102
Unexpected shocks to expenses	0.0151	0.063	-0.00805	0.061	0.100	0.086	0.0861	0.071
Expected shocks to expenses	0.0540	0.101	-0.166	0.101	0.174	0.143	0.312**	0.118
Unexpected shocks to income	0.0990	0.066	0.185**	0.064	-0.0516	0.095	0.108	0.077
Longitudinal average of children (0-14)	0.0136	0.103	-0.0443	0.101	0.146	0.127	0.0715	0.099
Longitudinal average of household size	-0.127	0.079	0.0419	0.075	-0.217	0.085	-0.0183	0.063
2008	0.486**	0.086	0.573**	0.087	-0.221*	0.112	-0.712**	0.093
2010	-0.708**	0.086	-0.939**	0.085	-0.254**	0.105	-0.675**	0.083
Constant	-0.911**	0.270	2.00	0.247	-2.227**	0.339	-0.41	0.284
ρ	0.502**	0.073			0.462**	0.073		
σ_{c1}	0.694**	0.096			0.499**	0.114		
σ_{c2}	0.533**	0.118			0.684**	0.083		
ρ_c	0.762**	2.323			1.544*	0.222		
Log likelihood	-2454.22				-1528.74			
APE of multiple borrowing at $(t-1)$: $\hat{p}_1 - \hat{p}_0$	14		28		1.51		20	
PPR multiple borrowing at $(t-1)$: $\hat{p}_1/\hat{p}_0$	1.86		1.53		1.40		2.16	
APE of over-indebtedness at $(t-1)$: $\hat{p}_1 - \hat{p}_0$	4		0.55		0.64		-0.32	
PPR over-indebtedness at $(t-1)$: $\hat{p}_1/\hat{p}_0$	1.18		1.01		1.15		0.98	
No. of Observations	2742		2742		2004		2004	

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

Notes:

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

Source: Own calculation based on household survey 2007 to 2011.

According to the APE of having multiple borrowing at $t-1$, Thai households that had multiple borrowing at $t-1$ face a risk of becoming over-indebted in the future by around 14 percentage points higher than the households that did not have multiple borrowing at $t-1$. Evidently, controlling for observed and unobserved household heterogeneity in the estimation reduced the conditional probabilities of experiencing over-indebtedness by about a half compared to the raw probabilities reported in the descriptive section for Thai households. According to the PPRs, Thai households that did not take multiple borrowings at $t-1$ would be around 2 times more likely to be over-indebted at t had they taken multiple loans from several sources at the same time at $t-1$ according to the predicted probability ratio. This positive dynamic spillover effect of multiple borrowing suggests that regardless of the purpose of taking a multiple loan, be it in response to a distress or opportunity, having multiple borrowings at the same time makes households more likely to face the risk of over-indebtedness. Similarly, the state dependence effect of over-indebtedness explains an increase in the over-indebtedness risk of 4 percentage points for Thai households. Given their observed and unobserved set of characteristics, Thai households that were not over-indebted at $t-1$ would be 1.2 times more likely to be over-indebted in period t had they been over-indebted at $t-1$ given their observed and unobserved set of characteristics.

In contrast to the findings for Thailand, estimates of the corresponding dynamic random-effects bivariate probit model for Vietnamese households' reveals that having multiple borrowing at $t-1$ or being over-indebted at $t-1$ does not significantly affect households' probability of becoming over-indebted in the future. This result is, however, not so surprising as these two countries differ on the level of financial depth, credit outreach and the number of credit programs introduced in rural areas. While the Vietnamese government began to introduce and support formal financial intermediaries in rural areas such as Vietnam Bank for Agriculture and Rural Development (VBARD) and Vietnam Bank for Social Policy (VBSP) around the early 1990s (Dufhues et al., 2004), the Thai government introduced such financial institutions as early as mid-1970s by supporting homegrown non-bank financial institutions and promoting the Bank for Agriculture and Agricultural Cooperatives (BAAC) into rural development bank (Menkhoff & Suwanaporn, 2007; Menkhoff & Rungruxsirivorn, 2011). The institutions introduced by Thai government have enhanced access to financial services particularly for households in the non-municipal areas of Thailand. Some argue that such government interventions in Thailand have shifted poor households' attitudes towards indebtedness. For instance, Siripanyawat et al. (2010) reports that some households have begun to perceive being indebted as a norm and deem not paying back their loan on time acceptable as it was funded by the government. In contrast, Vietnam's rural credit market shows a better performance in terms of high level of loan repayment. For instance, the ratio of loans in arrears to total outstanding loans to farmers was 0.98 percent for VBARD in Vietnam, while it was 13.5 percent for BAAC in Thailand in 2001 (Okae, 2009). The sound performance of the Vietnam's rural financial institutions and the low level of default have been explained by the strong reliance of the financial institutions on the customary rules of behavior in rural communities. Especially, the fact that the whole rural community participates in social activities together and assume the role of a loan monitoring system, puts pressure on households to repay their debt on time in order to avoid economic and social sanctions from others (Okae, 2009). Therefore, one can expect household over-indebtedness and multiple borrowing to be a bigger problem among Thai households than among Vietnamese households.

Finally, as for the control variables, we find that for Thai households having a male and higher educated household head and belonging to lower income groups influences their propensity to become over-indebted. While in Vietnam, the risk of facing over-indebtedness is influenced by marital and educational status of household head, major source of income and households level of income.

3.6.2 Multiple Borrowing

As can be seen, from the results of the multiple borrowing equations presented in Columns (2) and (6) in table 3.7, we find a positive significant true state dependence effect of multiple borrowing for both Thai and Vietnamese households as expected. In terms of the APE estimated by the model as explained in the previous section, both Thai and Vietnamese households who had taken multiple loans at $t-1$ were more likely to take multiple loans in the future by around 28 and 20 percentage points, respectively, than those households that did not have multiple borrowing at $t-1$. Households that did not take multiple borrowing would be around 2 times more likely to take multiple borrowing in period t had they had multiple borrowing at $t-1$ in both Thailand and Vietnam. This could mean that certain households in

Thailand and Vietnam are either persistently engaged in juggling debt from several sources as a way of managing their finances or are cote up in cyclical debt trap where they are simply refinancing or turning-over existing loans that are ultimately unpayable.

Regarding the cross-state dependence effect of over-indebtedness on multiple borrowing, we find that being over-indebted in the previous period does not influences households probability of taking multiple loans simultaneously in both Thailand and Vietnam. While households both in Thailand and Vietnam report of taking additional loans to pay back old debts, the result suggests no significant spillover effect from multiple borrowing to over-indebtedness. This reflects micro-lenders ability to effectively screen risky borrowers in terms of repayment capacity and level of indebtedness both in Thailand and Vietnam which prevents over-indebted borrowers from taking on additional borrowing once they pass the point where they can meet debt service payments without serious difficulty.

As for the control variables, we find that for Thai households having a male, middle aged and higher educated household head and belonging to the higher income groups and facing unexpected shocks to income influences their propensity to take multiple borrowing. While in Vietnam, household's probability of taking multiple borrowing is influenced by the age and marital status of household head and household's level of income and facing expected shocks to expenses.

To sum up, the results so far suggest that both multiple borrowing and over-indebtedness to be persistent and dynamically interrelated for Thai households but not for Vietnamese households. Furthermore, the estimates of the state dependence and cross-state dependence effect of both outcomes from the dynamic random effect bivariate model have shown that observed raw conditional probabilities and positive correlations between over-indebtedness and multiple borrowing is not entirely explained by a true state dependence effect after controlling observed and unobserved households heterogeneity. The next step is to look at the persistency of over-indebtedness and multiple borrowing that is unexplained by observed households characteristics and true state dependence effect.

3.6.3 Spurious state dependence effect on the persistency of multiple borrowing and over-indebtedness

The estimated standard deviations of time-invariant household specific random effects and the correlations between the time-invariant household specific effects and the error terms of the two outcome equations are presented at the bottom of table 3.7. Confirming the significance of controlling for unobserved household heterogeneity in our analysis, we find that the standard deviations of the household specific random effects are statistically significant at a 5 percent significance level in both models for Thailand and Vietnam. For both Thai and Vietnamese households, we find that variance of household's unobserved heterogeneity significantly explains both household's probability of becoming over-indebted and household's propensity to take multiple loans simultaneously. This shows that such unobserved households characteristics as financial literacy, debt perception or time preference might influences either household's propensity to become over-indebted or take multiple loans at the same time and therefore should be controlled for.

Furthermore, we find that these unobserved factors that drive multiple borrowing and over-indebtedness and the error terms are significantly correlated. Unobserved factors that drive multiple borrowing are positively associated with those that drive over-indebtedness in both Thailand and Vietnam. Similarly, the error terms of the two equations are positively significantly correlated with an estimated coefficient of about 0.5 for Thailand and 0.46 for Vietnam. As discussed in section 3.5, the significance of these correlations implies that multiple borrowing and over-indebtedness should be jointly estimated. Regarding the exogeneity of the initial conditions, the results indicate that the initial conditions of both over-indebtedness and multiple borrowing are positively correlated with the unobserved heterogeneity and therefore, the exogeneity assumptions of the initial conditions can be rejected for both outcomes in both countries' models.

3.7 Summary and Conclusion

This paper studies the dynamics of rural household's over-indebtedness and the role that multiple borrowing plays using data from the Vulnerability in Southeast Asia project in Thailand and Vietnam for the period 2007 to 2011. To uncover the true dynamic interdependency between multiple borrowing and over-indebtedness, the dynamic random effect bivariate probit model that controls for unobserved heterogeneity and initial conditions is estimated considering the potential endogeneity of multiple borrowing and over-indebtedness by allowing for spillover effects and correlation of random effects across multiple borrowing and over-indebtedness.

Results indicate that taking multiple borrowing concurrently increases household's likelihood of facing the risk of over-indebtedness by about 14 percentage points for Thai households. Given their observed and unobserved set of characteristics, Thai households that did not take multiple borrowings previously would be around 2 times more likely to be over-indebted had they taken multiple loans concurrently. By contrast, we find that this effect is not significant for Vietnamese households in our sample. Moreover, we do not find a significant dynamic spillover effect of over-indebtedness on multiple borrowing in both Thailand and Vietnam. This suggests that while multiple borrowing households face a higher risk of over-indebtedness because multiple borrowing enables them to accumulate excessive amounts of debt beyond the point which they would face a serious difficulty in meeting debt service payments, over-indebtedness does not lead households to refinance or recycle ultimately unpayable debts. The findings also suggest over-indebtedness and multiple borrowing to be more of a persistent problem for both households in Thailand and Vietnam which are explained in part by true state dependence effects. Finally, unobserved household heterogeneity was also found to be empirically significant, explaining about half of the unsystematic variation in the model and signifying that it should be controlled for. The significant positive correlation between the unobserved factors driving multiple borrowing and over-indebtedness further showed the need for the joint estimation of the two processes.

Turning to the main policy implication of the study, the result on the spillover effect of multiple borrowing on household's risk of over-indebtedness in Thailand suggests that industry stakeholders and policy makers should give more emphasis to the problem of multiple borrowing and take measures to protect micro-borrowers from taking multiple loans and ultimately becoming over-indebted. To this end, potential measures include cautiously lending to households with multiple borrowing, increasing information sharing among financial institutions on credit history and repayment performance of borrowers, improving financial education of households and financial advice to borrowers of the potential risk of multiple borrowing and over-indebtedness. Furthermore, the dynamic spillover effect of multiple borrowing on household's risk of over-indebtedness also reflects that preventive measures that focus on reducing multiple borrowing among micro-borrowers can reduce the problem of over-indebtedness in the future. Finally, the finding that households take multiple borrowing in response to distress (as a response to shocks to income and expenses) in Thailand and Vietnam suggests that providing households with alternative risk coping mechanisms such as micro-insurance may protect households from taking multiple loans and ultimately becoming over-indebted.

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CHAPTER 4: BORROWING FROM “PUI” TO PAY “POM”: MULTIPLE BORROWING AND OVER INDEBTEDNESS IN RURAL THAILAND

This chapter is a paper published as

Chichaibelu, B. B. and Waibel, H. (2017). "Borrowing from “Pui” to pay “Pom”: Multiple Borrowing and Over-indebtedness in rural Thailand", *World Development*, *98, 338-350*

and presented at:

ASAE International Conference. January 11-13, 2017, Bangkok, Thailand.

This article is available online at

https://doi.org/10.1016/j.worlddev.2017.04.032

CHAPTER 5: EXPLORING DIFFERENCES IN RURAL HOUSEHOLDS DEBT BETWEEN THAILAND AND VIETNAM: ECONOMIC ENVIRONMENT VERSUS HOUSEHOLD CHARACTERISTICS

This chapter is a paper presented at

TVSEP data use workshop 2017; March 15, Hannover, Germany

Abstract

Household debt in most parts of Asia has grown rapidly and reached unprecedented levels in recent years. Although indebtedness levels of most countries in Asia are still well below those in more advanced economies, there are significant cross-country variations. Rising indebtedness levels among low-income groups and rural households has also emerged as a concern for policy makers in the region. This study aims to explore cross-country differences in rural household's credit market participation, level of debt holding and over-indebtedness between Thailand and Vietnam. Using a unique rural household survey data from "Vulnerability in Southeast Asia" project, it first identifies socio-economic determinants of such market outcomes for rural households in Thailand and Vietnam. It then decomposes the observed differences into a part that arise due to configuration of household characteristics or a part that arise due to differences in economic environments using three decomposition methods. Significant differences are observed in credit market participation rates and level of debt holding and indebtedness between rural households in Thailand and Vietnam. Rural households in Thailand tend to participate more in the credit market and face higher risk of over-indebtedness. And those that participate in the credit market hold higher amounts of debt and face higher indebtedness levels in Thailand than rural households in Vietnam. These observed differences arise mainly due to dissimilarity in the economic environment that rural households of similar characteristics face. Particularly, the economically disadvantaged rural households in Thailand are more likely to participate in the credit market and face higher level of indebtedness mainly because the economic environment in Thailand is lenient to such households holding high amounts of debt as compared to their counterparts in Vietnam. Finally, difference in debt holding and indebtedness increases when going along the debt distribution and the higher gap observed at the top of the debt distribution is predominantly explained by differences in the economic environment.

Keywords: Rural households, Microcredit, Household debt, Household Indebtedness, Decomposition Analysis, Thailand, Vietnam

5.1 Introduction

Financial inclusion has been a major strategy used to achieve inclusive growth and development particularly in Asia where a significant progress has been achieved in the last decade (Asian Development Bank (ADB), 2014). However, one of the effects of the development of the financial sector has been the rapid growth of household debt that reached a record high recently in most parts of Asia. For instance in 2014, the ratio of household debt to household disposable income reached 141% in Malaysia and 126% in Thailand exceeding the levels before the financial crisis and above that of United States. Particularly in Thailand, between 2007 and 2014 the ratio of household debt to disposable income increased dramatically by 56 percentage points (ADB, 2015; Organization for Economic Co-operation and Development (OECD), 2016) growing much faster than it did in Korea or the United States (International Monetary Fund (IMF), 2016).

While household debt growth is a region-wide phenomenon in Asia, significant cross-country variations exist in the prevalence of debt, amount of debt holding and indebtedness levels in the region (ADB, 2015; OECD, 2016). Besides differences in aggregate indebtedness levels, the types of households that are disposed to high levels of indebtedness might also vary across countries in the region. For instance, one concern over household debt in Thailand has been that household debt falls disproportionately on agricultural and low-income rural households (Muthitacharoen, Nuntramas & Chotewattanakul, 2015; Tambunlertchai, 2015; IMF, 2016). High level of indebtedness is particularly considered a problem in northeastern Thailand where higher share of the rural population are indebted compared with urban population (ADB, 2013; Tambunlertchai, 2015). High debt burden is also more common among households in the lowest income quintile that spend 50% of their income to service debt. Similarly, indebtedness level among agricultural households tends to be higher compared with those of other occupations (IMF, 2016).

However, cross-country comparison of the prevalence and amount of debt holding in Asia has been either impossible due to lack of comparable micro-level data (Aminudin & Tissot, 2015) or complicated since such comparisons refer to households that are different in terms of socio-economic characteristics and economic environment they face depending on their country of residence (Christelis, Ehrmann, & Georgarakos, 2015). The measurement of household debt in Asia has been in itself a problem given low banking penetration and significant informal lending sector outside the banks (ADB, 2015). Hence, little is known about the prevalence, the amount of debt holding and the indebtedness levels across countries in the region. Although the need for greater use of micro data to assess households' indebtedness and financial stability has been emphasized by industry stakeholders, the assessment of household indebtedness in Asia has been mostly on aggregate level using macro data (e.g., Nakornthab, 2010; ADB, 2015; OECD, 2016). Aggregate level household indebtedness indicators, however, hide debt problems and vulnerabilities especially of low-income households (Aminudin & Tissot, 2015) and conceal households response to changes in the economic environment (Brown & Tayler, 2008). Hence, to assess the vulnerabilities and risk from the rapid growth of household debt in Asia and explore heterogeneity hidden behind aggregate level indicators, the analysis of micro data is necessary.

Previous research on household debt in advanced economies decompose the observed cross-country differences into a part that arises from differences in configuration of household characteristics such as age, education, income, assets and savings and those arising from differences in the economic environment (e.g., Christelis, Georgarakos, & Haliassos, 2013; Jappelli et al., 2013; Coletta et al., 2014; Wu, Fasianos and Kinsella, 2015; Christelis et al. 2015; Loschiavo, 2016; Bover et al., 2016). According to Christelis et al. (2015), the underlying factors behind cross-country differences in economic environment are differences in (1) market characteristics such as the accessibility of certain debt products, (2) legal conditions such as legal enforcement of contracts indicated by the time needed to repossess collateral, taxation of debt, regulatory loan-to-value ratios at origination and depth of information about borrowers (Bover et al., 2016), (3) cultural factors such as social acceptance of indebtedness or (4) policies such as macro-prudential or monetary policies.

In this paper, we add to the literature on household finance by specifically focusing on rural households and analyzing cross-country differences in credit market participation, level of debt holding and indebtedness in Thailand and Vietnam. Focusing on rural households debt situation is particularily critical in these two countries since the population is predominantly rural, informal lending still plays an important role and debt burden falls disproportionately on the rural poor (particularly in Thailand) (ADB, 2015). We use household survey data of the project “Vulnerability in Southeast Asia”, a harmonized rural household survey data in Thailand and Vietnam containing detailed information on household debt, loan defaults and late payments along with a full set of household level data such as households demographics, social and economic characteristics.

We decompose the difference in credit market participation, level of household debt holding and over-indebtedness using three counterfactual decomposition methods that compare the debt situation of rural households in Thailand to those in Vietnam. First, an extension of the Oaxaca-Blinder decomposition method for non-linear models is used to calculate differences in prevalence of debt and over-indebtedness. Second, the Oaxaca-Blinder decomposition method (Blinder 1973; Oaxaca 1973) is used to calculate the average differences in conditional amount of debt holding and indebtedness. Finally, the RIF-regression method proposed by Firpo, Fortin and Lemieux (2009) is additionally used to decompose the conditional amount of debt holding and indebtedness gap across the two countries and identify the contribution of individual covariates at different quantiles of the unconditional distributions.

Our results show that there are significant differences in observed credit market participation rates and level of debt holding and indebtedness between rural households in Thailand and Vietnam. Higher prevalence of debt and over-indebtedness is found among rural households in Thailand and those who participate in the credit market also hold relatively larger amounts of debt and face higher debt burden. These observed differences arise mainly due to dissimilarity in the economic environment that rural households of similar characteristics face. The economic environment in Thailand seems to be much more conducive for rural households to participate in the credit market and become over-indebted than in Vietnam. Particularly for the economically disadvantaged rural households, the economic environment in Thailand is more lenient to having high amounts of debt as compared to what their counterparts face in Vietnam. Additionally, differences in household structure can also explain to some extent the higher level of debt holding observed among rural households in Thailand. Finally, the findings from the RIF-regression decomposition analysis reveal that the differences in level of debt holdings and indebtedness increases when going along the debt distribution. While differences in household characteristics such as income and wealth predominantly explain the higher debt holding observed at bottom of the debt distribution among rural households in Thailand, differences in the economic environment explain larger portion of the difference especially at the upper tail of the debt distribution.

The remainder of the paper is organized as follows: Section 5.2 briefly discusses the data we use. Section 5.3 present descriptive results on the prevalence of debt and over-indebtedness and the conditional amount of debt holding and level of indebtedness. Section 5.4 presents the decomposition methods used. Section 5.5 and 5.6 outlines the results and provides concluding remarks.

5.2 Data

We use the 2008 data of rural household in Thailand and Vietnam collected by the project "Vulnerability in Southeast Asia" – a long-term research project funded by the German Research Foundation (DFG). The survey collected data from around 4200 rural households from six provinces in Northeastern Thailand and the North Central Coast and Central Highland of Vietnam. The six provinces, namely Buriram, Ubon Ratchathani and Nakhon Phanom from Thailand, Ha Tinh, Thua Thien Hue and Dac Lac from Vietnam, were first purposively selected targeting rural households that are either poor or face risk of falling into poverty to meet the general objective of the project (Hardeweg, Klasen & Waibel, 2012). Then, three stage cluster sampling design was implemented to select the sample of households. Firstly, sub-districts were randomly selected from strata with probability that is proportional to the population density in each province. After selecting the sub-districts, two villages were again selected randomly with probability proportional to size. Finally, 10 households were sampled in each village from a household list ordered by household size using a systematic random sampling technique that gave each household equal chance of being selected. Hence, the households in our sample are representative of rural households in Northeastern Thailand and the North Central Coast and Central Highland of Vietnam.

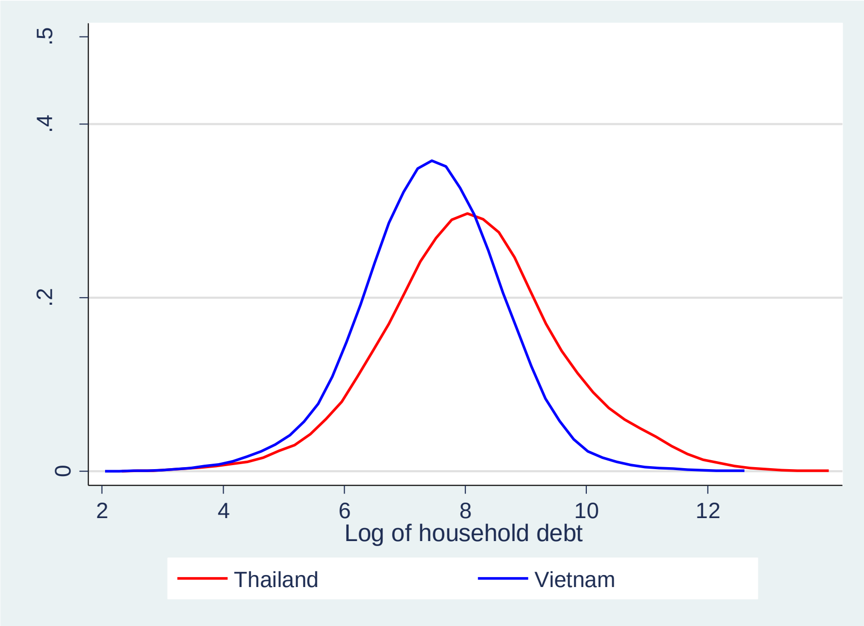
The data contain detailed information on households borrowing, loan defaults and arrears along with a full set of household level data such as households demographics, social and economic characteristics and special modules on risks and shocks. This detailed data on financial situation of households allows us to examine rural households borrowing behavior in in the two countries and decompose the differences into their separate underlying factors. In total, we compare 2148 rural households in Vietnam with 2136 rural households in Thailand.

5.3. Descriptive Statistics

5.3.1 Rural households' debt in Thailand and Vietnam

Next, we briefly describe the differences in rural households' credit market participation, level of debt holding and indebtedness between the two countries salient in our dataset. Figure 5.1, presents the raw log of debt distribution by country in 2008. As can be seen, the debt distribution for rural households in Vietnam is located to the left of that for rural households in Thailand and is thicker at the lower tail, indicating that a higher proportion of rural households in Vietnam hold a lower amount of debt compared to rural households in Thailand. In contrast, the debt distribution of rural households in Thailand lies to the right of those in Vietnam and is thicker in the upper tail, indicating higher level of debt holding among rural households in Thailand compared to those in Vietnam at all quintiles.

Figure 5.1: Raw Distribution of Rural Households' Debt in Thailand and Vietnam in 2008



Source: Own calculation based on household survey 2008.

Table 5.1 shows a comparison of the prevalence of debt and conditional debt amounts (which are scaled into PPP 2005 U.S. dollars) of rural households in Thailand and Vietnam. As can be seen, the proportion of rural households that have outstanding debt differs across the two countries both in 2008 and 2010. The prevalence of outstanding debt among rural households in Thailand is considerably larger than those in Vietnam especially in 2008, where more than 80% of the Thai rural households had debt in contrast to around 66% for Vietnamese rural households. Looking at the amount of outstanding debt held conditional on participation at the 10^{th}, 50^{th} and 90^{th} percentile, it is also apparent that Thai rural households hold higher amounts of debt than Vietnamese rural households along the whole debt distribution. At the 50^{th} and 90^{th} percentiles, Thai rural households held debt about twice and four times of the Vietnamese rural households' in 2008. However, it is clear that in Thailand rural household's debt has declined slightly along the whole distribution following the financial crisis in 2008. According to a recent study by World Bank, household indebtedness declined because households increased their debt repayment in 2009 in response to the crisis with the additional support of a stimulus introduced by the government (Khandker, Koolwal, Haughton & Jitsuchon, 2012). After this period, however, household debt grew rapidly and exceeded the levels before the financial crisis and above that of United States in 2014 (ADB, 2015; OECD, 2016). In contrast, the outstanding debt of rural households in Vietnam has increased between 2008 and 2010 slightly reducing the gap in debt distribution across the two countries.

Using four common indicators of over-indebtedness, table 5.1 further illustrates how the prevalence of over-indebtedness and level of debt burden vary among rural households across the two countries. The first indicator, the debt-service ratio (DSR), gauges the burden imposed by debt repayment and is the share of annual gross income that a household must devote to service its annual debt repayment (ECB, 2013). The DSR includes both the annual interest payment and principal repayment as a debt servicing cost while annual gross income includes household's earnings from all income-generating activities such as crop and livestock production, self-employment, off-farm employment, and return on assets (ECB, 2013). A high debt-service ratio reflects that households can spend less of their income on other things than repaying their debt; hence domestic demand will be constrained and the risk of default will rise, making access to credit in turn more difficult (Aminudin & Tissot, 2015).

Table 4.1: Summary Statistics for Debt Holdings, Debt-Service Ratio, Debt to Income Ratio, Debt to Asset Ratio and Default in 2008 and 2010

		Thailand		Vietnam	
		2008	2010	2008	2010
Outstanding Debt	Prevalence	0.82	0.74	0.66	0.69
	10th percentile	617	580	471	568
	50th percentile	3205	2926	1812	2270
	90th percentile	20294	16389	6196	8614
Debt-Service Ratio	Prevalence>40%	0.43	0.14	0.11	0.10
	10th percentile	0.00	0.00	0.00	0.00
	50th percentile	0.31	0.00	0.02	0.01
	90th percentile	1.63	0.54	0.46	0.40
Debt to Income Ratio	10th percentile	0.05	0.06	0.00	0.05
	50th percentile	0.71	0.41	0.37	0.48
	90th percentile	4.59	2.50	1.83	2.42
Debt to Asset Ratio	10th percentile	0.01	0.01	0.00	0.01
	50th percentile	0.08	0.07	0.07	0.08
	90th percentile	0.50	0.40	0.28	0.33
Default	Prevalence	0.11	0.05	0.05	0.07

Source: Own calculation based on household survey 2008 and 2010.

Based on the DSR indicator, a household is considered to be over-indebted when its annual debt repayment obligation in relation to income surpasses certain threshold, commonly set at 40% or 50% (OXERA, 2004; Disney, Bridges, & Gathergood, 2008; Bryan, Taylor, & Veliziotis, 2010; D'Alessio & Iezzi, 2013; Muthitacharoen et al., 2015; Banbula, Kotula, Przeworska, & Strzelecki, 2016). In this study, we use the DSR indicator with a 40 percent threshold to identify over-indebted households in Thailand and Vietnam. From the whole sample in 2008, about 43% of the rural households in Thailand were over-indebted where as 11% of those in Vietnam were over-indebted. According to the DSR, the top 10% of rural households that had highest DSR in Thailand spent nearly 2 times of their annual income for debt service payment, while in Vietnam they spent about half of their annual income. Moreover, the debt burden gap between rural households in Thailand and Vietnam increases significantly when going along the DSR distribution.

The other two indictors we use, debt to income and debt to asset ratios (DIR and DAR), on the other hand link the total outstanding debt amount with the total annual household income or the total value of household asset including the house value, respectively. While the DIR reflects the resources that households can use to pay back their debt in the short run, the DAR reflects their debt repayment capacity in the long run without taking the flow of income into account (Sierminska, 2014). Hence, high DIR and DAR levels indicate that households would not be able to pay back their loans even when they use all their income or liquidate all their assets. Pointing in the same direction as the DSR indicator, these indicators also show that the level of debt burden among rural household in Thailand is higher compared to those in Vietnam and the gap increases when going further along the DIR and DAR distributions (see table 5.1). Finally the fourth indicator, default, identifies those households who report default or late payment on a loan as over-indebted. According to this indicator, the prevalence of over-indebtedness was also higher among rural households in Thailand than those in Vietnam in 2008.

5.3.2 Explanatory Variables

This section discusses the explanatory variables that are included in the decomposition analysis. The explanatory variables include various socio-economic and demographic characteristics that determine household's participation in the credit market and their level of indebtedness. The choice of the explanatory variables is largely based on the existing literature dealing with households indebtedness in both developing and developed countries, including Disney et al. (2008), Brown and Taylor (2008), D'Alessio and Iezzi (2013), Schicks (2014), Wu et al. (2015) and Christelis et al. (2015).

In the decomposition analysis, we control for observed households characteristics such as age (household head aged below 39, 40 - 49, 50 - 59, 60 and above; taking 60 and above as the case category), gender (female or male household head; taking female as the base category), level of education of the household head (illiterate, primary, secondary and higher education; taking illiterate as the base category), marital status (married or single; taking single as the base category), household size, main occupation of household head (inactive, agricultural, off-farm employed and self-employed; taking inactive as the base category), household income and wealth quintiles (dummy variables that group households into quintiles according to households' income and wealth quintile distributions in Thailand; taking the first quintile as the base category), type of shock households experienced (unexpected shock to expenses, expected shocks to expenses and unexpected shocks to income), future financial expectation of households (better, same and worst; taking worst as the base category) and their risk attitudes (risk averse, risk neutral, risk takers; taking risk takers as the base category). Household's future financial expectation dummy variables were constructed using the question "Do you think your household will be better off next year?" The risk attitude of the households is based on a Likert scale response of 0 "unwilling to take risk" to 10 "fully prepared to take risk" for a question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?". Then, based on the Likert scale, we grouped the households into the three categories.

Table 5.2 shows a comparison of average characteristics of rural households in Thailand and Vietnam. On average, there are more Thai households in the top income, financial and real wealth quintiles than the Vietnamese households reflecting that Thai households have higher capacity to shoulder more debt than the Vietnamese households. On the contrary, rural households in Vietnam are younger and more educated and hence have higher earning capacity in the future which might explain a higher willingness to borrow and hold large amount of debt. However, Vietnamese rural households are also on average more risk averse than the Thai households and hence maybe less willing to hold large amount of debt.

Table 5.2: Average Household Characteristics by Country in 2008 and 2010

	Vietnam	Thailand
Age of HH head below 39	0.214	0.067
	(0.411)	(0.252)
Age of HH head 40-49	0.306	0.241
	(0.461)	(0.428)
Age of HH head 50-59	0.235	0.268
	(0.424)	(0.443)
Age of HH head 60 and above	0.245	0.424
	(0.430)	(0.490)
Female HH head	0.209	0.335
	(0.407)	(0.472)
Married HH head	0.852	0.782
	(0.355)	(0.413)
Household size	5.276	5.490
	(1.946)	(2.210)
Illiterate	0.113	0.045
	(0.32)	(0.210)
Primary education	0.317	0.843
	(0.465)	(0.364)
Secondary education	0.513	0.0936
	(0.500)	(0.292)
Higher education	0.057	0.0184
	(0.232)	(0.135)
Agricultural HH	0.665	0.606
	(0.472)	(0.489)
Self-employed HH	0.0751	0.082
	(0.264)	(0.274)
Off-farm employed HH	0.209	0.184
	(0.407)	(0.387)
Inactive HH	0.0509	0.128
	(0.220)	(0.330)
Income quintile 1	0.307	0.200
	(0.460)	(0.400)
Income quintile 2	0.234	0.200
	(0.423)	(0.400)
Income quintile 3	0.183	0.200
	(0.387)	(0.400)
Income quintile 4	0.169	0.200
	(0.375)	(0.400)
Income quintile 5	0.107	0.200
	(0.309)	(0.400)
Financial wealth quintile 1	0.663	0.215
	(0.47)	(0.410)
Financial wealth quintile 2	0.015	0.185
	(0.123)	(0.388)
Financial wealth quintile 3	0.0687	0.199
	(0.253)	(0.399)
Financial wealth quintile 4	0.0993	0.201
	(0.299)	(0.401)
Financial wealth quintile 5	0.154	0.200
	(0.361)	(0.400)
Real wealth quintile 1	0.286	0.200
	(0.450)	(0.400)
Real wealth quintile 2	0.287	0.200
	(0.452)	(0.401)
Real wealth quintile 3	0.180	0.200
	(0.384)	(0.400)
Real wealth quintile 4	0.119	0.200
	(0.323)	(0.400)

Real wealth quintile 5	0.128	0.200
	(0.334)	(0.400)
Income fluctuation (t-1)	0.613	0.681
	(0.487)	(0.466)
Unexpected shocks to expense	0.454	0.372
	(0.498)	(0.483)
Expected shocks to expense	0.119	0.0966
	(0.324)	(0.295)
Unexpected shocks to income	0.616	0.406
	(0.486)	(0.491)
Better future financial expectation	0.506	0.513
	(0.500)	(0.500)
Same future financial expectation	0.421	0.375
	(0.494)	(0.484)
Worst future financial expectation	0.073	0.112
	(0.260)	(0.320)
Risk averse	0.523	0.352
	(0.500)	(0.478)
Risk neutral	0.197	0.416
	(0.398)	(0.493)
Risk taker	0.28	0.232
	(0.450)	(0.420)
Observations	2024	2091

Source: Own calculation based on household survey 2008 and 2010.

5.4. Empirical Methodology

This section outlines the methods we used to decompose the observed difference in debt prevalence, debt holdings and over-indebtedness among rural households in Thailand and Vietnam, and proceeds in four parts. First, we begin with a discussion on the identification strategy and the parameters of interest using the observed log of debt distribution as an example to simplify the discussion. We then explain the three decomposition methods used to model differences in debt situation at a point in time, namely the non-linear Oaxaca-Blinder decomposition method (Fairlie 1999), the mean based Oaxaca-Blinder decomposition method (Blinder 1973; Oaxaca 1973) and the RIF-regression decomposition method (Firpo et al., 2009). These methods allow the observed differences to be decomposed into a part attributable to differences in the configuration of household characteristics (composition or endowment effect) and a part attributable to differences in the influence of a given set of characteristics due to cross-country differences in cultural, institutional and economic environment (coefficients or structural effect). The discussion on the decomposition methods is heavily based on Fortin, Leimieux, and Fripo (2011).

5.4.1. Identification Strategy

All three decomposition methods are based on estimating unconditional counterfactual distributions of the dependent variables. For the mutually exclusive groups of Thai rural households (T) and Vietnamese rural households (V), we for example observe the log of debt for each group (Y_T and Y_V respectively). The unconditional counterfactual distribution is then constructed to simulate how the log of debt distribution of rural households in Vietnam would be if they had the same configuration of characteristics and faced the same economic environment as rural households in Thailand, or conversely, what the log of debt distribution of rural households in Thailand would have been if they had the same configuration of characteristics and faced the same economic environment as rural households in Vietnam. In other words, the observed household debt distribution of Thai rural households provides a counterfactual for Vietnamese households, and vice versa. To establish these counterfactual distributions, the decomposition methods first examine the relationship between debt outcome variables such as log of debt and a set of observed and unobserved household characteristics.

$$Y_c = \theta_c(X_c, \varepsilon_c),\ c \in \{T, V\} \quad \varepsilon_c \tag{1}$$

$$\Delta_Y = Y_V - Y_T = [\theta_V(X_V, \varepsilon_V)] - [\theta_T(X_T, \varepsilon_T)] \tag{2}$$

where X_V and X_T are vectors of observable characteristics, θ_V and θ_T are the functional forms of the log of debt equation and ε_V and ε_T are vectors of unobservable characteristics for the Vietnamese and Thai rural household groups respectively.

The unconditional counterfactual distribution of the log of debt can then be constructed by integrating the conditional distribution of log of debt given a set of observable characteristics of Vietnamese rural household over the marginal distribution of observable characteristics of the Thai rural household. If the unconditional distribution of log of debt of rural households in each country is given by:

$$F_{Y_c}(Y) = \int F_{Y_c|X}(Y|X = x) \,.\, dF_{X_c}(X), c \in \{T, V\} \tag{3}$$

where $F_{Y_c|X}(Y|X=x)$ is the conditional distribution of log of debt and $F_{X_c}(X)$ is the marginal distribution of X, the unconditional counterfactual distribution of log of debt can be constructed by either replacing the conditional distribution of Vietnamese rural households with the corresponding conditional distribution of the Thai rural households or by substituting marginal distribution of the observed characteristics. In this study, we use rural households in Thailand as the reference group and construct a counterfactual distribution of log of debt, $F^C_{Y_V}$, by replacing $F_{Y_V|X}(Y|X=x)$ with $F_{Y_T|X}(Y|X=x)$ in equation (2) when $c = V$:

$$F^C_{Y_V}(Y) = \int F_{Y_T|X}(Y|X=x)\,.\,dF_{X_V}(X) \tag{4}$$

The unconditional counterfactual distribution $F^C_{Y_V}(Y)$ constitutes the distribution of log of debt that would have prevailed among the Vietnamese rural household if the distribution of characteristics were similar to the Thai rural household.

Following equation (1), the total difference in log of debt between rural households in the two countries can be written as:

$$\Delta_Y = \Delta_\theta + \Delta_X + \Delta_\varepsilon \tag{5}$$

where Δ_θ represents cross-country differences in the θ functions determined by institutional and economic environment in the two countries (i), Δ_X represents differences in the distribution of observable characteristics of rural households in the two countries (ii), and Δ_ε represents cross-country differences in the distribution of unobservable characteristics (iii). In constructing the unconditional counterfactual distribution of $F^C_{Y_V}$, replacing the conditional distribution of log of debt of the Vietnamese rural households with that of the Thai rural households group replaces both θ and the conditional distribution of ε. Therefore, cross-country difference in θ will be confounded by cross-country differences in the distribution of ε. In order to separate the cross-country differences in ε from the cross-country differences in

θ $(and\ X)$, the following two identification restrictions need to be imposed on the distribution of ε (see Fortin et. al, 2011 for detailed discussion of these assumptions).

i. First the overlapping support assumption is imposed to ensure that no single characteristic can identify to which group the rural households belong to (Fortin et al., 2011). This assumption rule out cases where observable and unobservable characteristics in the debt structural model are different for Thai and Vietnamese rural households.

ii. Second the conditional independence/ignorability assumption is imposed to ensure that the conditional distribution of ε given X is the same for rural households in both countries and is independent of their country membership ($\theta \perp \varepsilon | X, c = T, V$).

Under the overlapping support and conditional independence assumptions, the total difference in log of debt between rural households in Thailand and Vietnam, Δ_Y^v (where v represents a distributional statistics of log of debt such as the mean or quantiles), can be separated and identified in an aggregate decomposition as:

$$\Delta_Y^v = \Delta_\theta^v + \Delta_X^v \tag{6}$$

where $\Delta_\theta^v = v(F_{Y_V} - F_{Y_V}^c)$ captures the part driven by group differences in the log of debt structure (structural or coefficient effect) and $\Delta_X^v = v(F_{Y_V}^c - F_{Y_T})$ captures the part driven by group differences in the distribution of the observed characteristics (composition or endowment effect). The coefficient and covariate effects can further be decomposed into contributions attributable to each characteristic. To perform the detailed decomposition and identify the contributions of each characteristic, further assumptions are required. Since these assumptions are specific to the decomposition methods, they will be discussed further with each estimation procedure explained in the following sub-section.

5.4.2 Estimation Procedures

5.4.2.1 Non-linear Decomposition Method

To assess the difference in the prevalence of debt, default and over-indebtedness between rural households in Thailand and Vietnam, we apply an extension of the Oaxaca-Blinder decomposition method for non-linear models elaborated by Fairlie (1999, 2005). This method is especially suitable for calculating gaps for binary variables. This decomposition method computes the difference in the probability of holding debt, defaulting on a loan or becoming over-indebted between the two countries and quantifies the contribution of group differences in the configuration of characteristics and cultural, institutional and economic environment to the outcome differential.

First, a logit model is estimated for the probability of holding debt, defaulting on a loan and being over-indebted, Y:

$$p_c(Y) = F(X\beta), c \in \{T, V\} \tag{7}$$

Following Fairlie (1999) the gap in the prevalence rate of debt, default and over-indebtedness between rural households in Vietnam and our reference country Thailand can be expressed as:

$$\bar{Y}^T - \bar{Y}^V = \left[\sum_{i=1}^{N^T} \frac{F(X_i^T \hat{\beta}^V)}{N^T} - \sum_{i=1}^{N^V} \frac{F(X_i^V \hat{\beta}^V)}{N^V}\right] + \left[\sum_{i=1}^{N^V} \frac{F(X_i^T \hat{\beta}^T)}{N^T} - \sum_{i=1}^{N^V} \frac{F(X_i^T \hat{\beta}^V)}{N^T}\right] \tag{8}$$

where $\bar{Y}^c$ is the average probability of holding debt, default and over-indebtedness in country c , X^c is a set of average values of the household characteristics in country $c, \hat{\beta}^c$ is the coefficient estimates for country c, F is the cumulative distribution function from a logistic distribution and N^c refers to the sample size in each country. The first expression in the bracket represents the part of the cross-country debt prevalence gap which is driven by differences in the covariate effect (explained part), i.e. by differences in the distribution of X between Vietnam and Thailand. The second term captures the part of the cross-country debt prevalence gap that is driven by the coefficient effect (unexplained part), i.e. to differences in the group processes determining for instance the decision to participate in the credit market in Thailand and Vietnam. This unexplained gap can arise due to differences in cultural differences, institutional differences and other unobservable differences in economic environment between Thailand and Vietnam. Going forward, we will refer to this effect as the "coefficient effect".

The covariate effect is the estimate of the total contribution of the whole vector of household characteristics to the cross-country gap in prevalence of debt, default and over-indebtedness. Using coefficient estimates from a logit regression for a pooled sample, $\hat{\beta}^*$ to avoid the familiar index problem in decomposition methods, the independent contribution of individual covariates can be calculated as follows. For example, the independent contribution of real wealth, X_{RW}, and financial expectation, X_{FE}, to the debt prevalence gap can be expressed as:

$$\frac{1}{N^V}\sum_{i=1}^{N^V} F\left(\hat{\alpha}^* + X_{RWi}^T\hat{\beta}_{RW}^* + X_{FEi}^T\hat{\beta}_{FE}^*\right) - F\left(\hat{\alpha}^* + X_{RWi}^V\hat{\beta}_{RW}^* + X_{FEi}^T\hat{\beta}_{FE}^*\right) \quad (9)$$

$$\frac{1}{N^V}\sum_{i=1}^{N^V} F\left(\hat{\alpha}^* + X_{RWi}^V\hat{\beta}_{RW}^* + X_{FEi}^T\hat{\beta}_{FE}^*\right) - F\left(\hat{\alpha}^* + X_{RWi}^V\hat{\beta}_{RW}^* + X_{FEi}^V\hat{\beta}_{FE}^*\right) \quad (10)$$

Hence, the contribution of each of these variables to the debt prevalence gap is equal to the change in the average predicted probability from replacing the Vietnamese households' distribution with the Thai households' distribution of that variable while holding the contribution of the rest of the variables constant. Then, the sum of the contributions of each independent variable will be equal to total contribution of all of the independent variables estimated using the full sample.

5.4.2.2 Oaxaca-Blinder Decomposition Method

To compute the level of household debt and indebtedness gap between rural households in Thailand and Vietnam and decompose these gaps into their separate underlying factors, we use the mean-based Oaxaca-Blinder decomposition method. This method is based on the assumption that the relationship between log of debt or indebtedness and a vector of household characteristics is linear and additive:

$$Y_c = X_c\beta_c + \varepsilon_c,\ E(\varepsilon_c) = 0,\ c \in \{T, V\} \tag{11}$$

where X is a vector of explanatory variables, β is a vector of estimated coefficients including the intercept and ε is the error term. Given that $E(\varepsilon_c) = 0$, the total difference in the mean log of debt or over-indebtedness, Δ_Y^μ or $\mu\left(F_{Y_V} - F_{Y_T}\right)$, can be decomposed as follow:

$$\Delta_Y^\mu = E(Y_V) - E(Y_T) = \underbrace{E(X_V)\beta_V - E(X_V)\beta_T}_{i} + \underbrace{E(X_T)\beta_T - E(X_V)\beta_V}_{ii} \tag{12}$$

where $E(X_V)\beta_T$ is the unconditional counterfactual distribution of log of debt or indebtedness at the mean. As discussed in the identification strategy section, this counterfactual distribution is constructed at the sample means $\mu\left(F_{Y_V}^C\right) \to E(Y)_V^C = E(X_V)\beta_T$. The terms i and ii in equation (12) are also analogues to components (i) and (ii) described in the identification strategy section. Rearranging equation (12), we get:

$$\Delta_Y^\mu = (E(X_V)[\beta_V - \beta_T]) + ([E(X_V) - E(X_T)]\beta_T) \tag{13}$$

Replacing $E(X_V)$ and $E(X_T)$ by their sample means $\bar{X}_V$ and $\bar{X}_T$, as well as β_V and β_T by their ordinary least square regression estimates, $\hat{\beta}_V$ and $\hat{\beta}_T$, equation (13) can be written as:

$$\hat{\Delta}_Y^\mu = \underbrace{\bar{X}_T(\beta_V - \beta_T)}_{\hat{\Delta}_\theta^\mu} + \underbrace{(\bar{X}_V - \bar{X}_T)\hat{\beta}_T}_{\hat{\Delta}_X^\mu} \tag{14}$$

The first term, $\hat{\Delta}_\theta^\mu$, captures contributions of the coefficient effect to the total differences in log of debt between rural households in Thailand and Vietnam. The second term, $\hat{\Delta}_X^\mu$, captures the contributions of the covariate effect i.e. differences in the distribution of mean characteristics. Due to the additive linearity assumption of the Oaxaca-Blinder decomposition method, these two effects can be further decomposed into contributions attributable to each covariate. Then, the total covariate and coefficient effects are simply the sum of the contributions of individual characteristics:

$$\hat{\Delta}_X^{\mu} = \sum_{j=1}^{j} (\bar{X}_{Vj} - \bar{X}_{Tj}) \hat{\beta}_{Tj} \tag{15}$$

and

$$\hat{\Delta}_\theta^{\mu} = (\hat{\beta}_{V0} - \hat{\beta}_{T0}) + \sum_{j=1}^{j} (\hat{\beta}_{Vj} - \hat{\beta}_{Tj})\, \bar{X}_{Tj} \tag{16}$$

where j represents the jth household characteristics and $\hat{\beta}_{V0}$ and $\hat{\beta}_{T0}$ are the estimated intercept coefficients of the rural households in Vietnam and Thailand respectively.

In the detailed decomposition, identifying the contribution of categorical variables is not easy because the result is not invariant to the choice of the omitted base category. Changing the omitted category alters the contribution of the other categories and the contribution of the entire categorical variable to the coefficient effect. To solve this problem, we use a normalization approach proposed by Yun (2005b). The idea behind this approach is to restrict the coefficients of the individual categories to sum to zero and express the effects as deviations from the grand mean (Jann, 2008). The decompositions results with normalization approach are analogous to the simple average of the results generated from a series of decompositions in which the categories are alternated one after the other as the base category (Yun, 2005b).

5.4.2.3 Re-centered Influence Function Regression Decomposition Method

The distribution of household debt is important in assessing financial market risk and sustainability of household debt. The detailed decomposition of the distribution of household debt gap based on household characteristics such as age, occupation, income and wealth can map vulnerabilities in household debt. Hence, the Recentered Influence Function Regression (RIF-regression) method (Firpo et al., 2009) is used to decompose the level of household debt and indebtedness gap across the two countries and identify the contribution of individual covariates and the economic environment at different quantiles of the unconditional (marginal) distributions. The RIF-regression method is an extension of the Oaxaca-Blinder decomposition method that is based on an unconditional quantile estimator. The RIF-regression method provides a way of estimating the marginal effect of a vector of explanatory variables, X, on the quantiles of the unconditional distribution of a dependent variable, Y. The marginal effects of the explanatory variables are estimated by regressing a transformed version of the dependent variable, known as the recentered influence function (RIF), on X.

The RIF of log of debt and indebtedness is estimated by first calculating the sample quantile q and then estimating the density at that quantile using kernel density methods. The RIF of each observation is then estimated using the following equation:

$$RIF(Y; q_\tau) = q_\tau + \frac{\tau - 1[Y \leq q_\tau]}{f_Y(q_\tau)} \qquad (17)$$

Where q_τ is the τth quantile of log of debt and indebtedness and $f_Y(q_\tau)$ is the unconditional density of log of debt and indebtedness at the τth quantile and $1[Y \leq q_\tau]$ is an indicator function for whether the log of debt and indebtedness are less than or equal to the τth quantile. The coefficients of the covariates for the Vietnamese and Thai rural households are then estimated at each quantile by regressing the RIF on X:

$$q_{c\tau} = E_X\left[E\left[\widehat{RIF}(Y_c; q_{c\tau})\middle|X_c\right]\right] = E[X_c]\hat{\gamma}_{c\tau}, c \in \{T, V\} \qquad (18)$$

where $q_{c\tau}$ is the unconditional τth quantile of log of debt and indebtedness for rural households in Thailand and Vietnam and $\hat{\gamma}_{c\tau}$ is the coefficient of the vector of covariates from the unconditional quantile regression that captures the marginal effect of a change in the distribution of each covariate on the unconditional log of debt or indebtedness. Equation (18) is comparable to the Oaxaca-Blinder decomposition at the mean. Therefore, using the same logic as the Oaxaca-Blinder decomposition, the log of debt and indebtedness gap across the two countries at the τth quantile can be decomposed as follows:

$$\Delta_Y^\tau = \left[\widehat{RIF}(Y_V; q_{V\tau})\right] - \left[\widehat{RIF}(Y_T; q_{T\tau})\right] \tag{19}$$

$$\Delta_Y^\tau = \underbrace{\bar{X}_T(\hat{\gamma}_{V\tau} - \hat{\gamma}_{T\tau})}_{\hat{\Delta}_\theta^\tau} + \underbrace{(\bar{X}_V - \bar{X}_T)\hat{\gamma}_{T\tau}}_{\hat{\Delta}_X^\tau} \tag{20}$$

Then, the detailed decomposition of the composition and coefficient effects into contributions of individual covariate at the τth quantile can be computed as:

$$\hat{\Delta}_X^\tau = \sum_{j=1}^{j} (\bar{X}_{Vj} - \bar{X}_{Tj})\hat{\gamma}_{Tj\tau}$$

(21)

and

$$\hat{\Delta}_\theta^\tau = (\hat{\gamma}_{V0\tau} - \hat{\gamma}_{T0\tau}) + \sum_{j=1}^{j} (\hat{\gamma}_{Vj\tau} - \hat{\gamma}_{Tj\tau})\, \bar{X}_{Tj\tau} \tag{22}$$

where $(\hat{\gamma}_{V0\tau} - \hat{\gamma}_{T0\tau})$ indicates the omitted group effect, $\bar{X}_{cj\tau}$ and $\hat{\gamma}_{cj\tau}$ indicate the jth element of $\bar{X}_c$ and $\hat{\gamma}_c$ at τth quantile respectively. $(\bar{X}_{Vj} - \bar{X}_{Tj})\hat{\gamma}_{Tj\tau}$ and $(\hat{\gamma}_{Vj\tau} - \hat{\gamma}_{Tj\tau})\bar{X}_{Tj\tau}$ are the respective contributions of the jth covariate to the composition and coefficient effect at τth quantile.

5.5. Results

In this section, we present the results from the decomposition analysis based on the three methods discussed above. First, we discuss the results from the non-linear decomposition method used to decompose the observed cross-country difference in the prevalence of debt holding and over-indebtedness among rural households in the two countries. The non-linear decomposition analysis is based on coefficient estimates from pooled logit models with dependent variables that take the value one when the rural households either have outstanding debt or are over-indebted based on the DSR or default indicators. Second, we discuss the results from the Oaxaca-Blinder decomposition analysis used to decompose the observed difference in the conditional log amount of outstanding debt, DSR, DIR and DAR between rural households in Thailand and Vietnam. This method is based on pooled linear regression model estimated using either the log of conditional debt holding, DSR, DIR and DAR as a dependent variable. Finally, we discuss the results from the RIF-regression decomposition method. This method is based on RIF-regression models at different percentiles of the conditional debt holding, DSR, DIR and DAR distributions.

As explained in the previous section, throughout the decomposition analysis we estimate the observed differences in debt situation as the gap between the observed debt situation among rural households in Thailand and of those in Vietnam $(Y_T - Y_V)$. Hence, a positive coefficient effect would mean that the economic environment in Thailand is more favorable for rural households to participate in the credit market and hold high amounts of debt than the environment in Vietnam. Alternatively, if the covariate effect is positive that would mean that rural households in Thailand have a configuration of characteristics that allows them to participate in the credit market and shoulder higher amounts of debt compared to those in Vietnam.

5.5.1. Decomposing the Prevalence of Debt and Over-indebtedness

Table 5.3 shows the differences in the prevalence of debt and over-indebtedness between rural households in Thailand and Vietnam and their decomposition into covariate and coefficient effects that denote configuration of household and economic environment characteristics effects, respectively. These results are estimated with the Oaxaca-Blinder decomposition method using coefficients from a pooled logit regression models as explained in sub-section 4.2.1. The aggregate decomposition shows that the observed differences in the prevalence of debt and over-indebtedness are mainly due to the coefficient effect that is always in favor of rural households in Thailand. In other words, the cultural, institutional and economic environment in Thailand appears to be much more conducive to rural households having debt or being over-indebted measured both in terms of defaulting on a loan or having a high debt burden than in Vietnam. If Vietnamese rural households faced the same cultural, institutional and economic environment as their Thai counterparts, the observed gap in the prevalence of debt and over-indebtedness would completely disappear and the Vietnamese households would face the problem of over-indebtedness just the same as their Thai counterparts.

Table 5.3: Decomposition of Differences in the Prevalence of Debt and Over-Indebtedness in 2008

	Debt	Debt-Service Ratio>40%	Default
Overall			
Thailand	0.817***	0.427***	0.111***
	(0.01)	(0.01)	(0.01)
Vietnam	0.662***	0.113***	0.056***
	(0.01)	(0.01)	(0.00)
Total difference	0.155***	0.314***	0.055***
	(0.01)	(0.01)	(0.01)
Covariate effect	-0.033***	-0.009	-0.004
	(0.01)	(0.02)	(0.01)
Coefficient effect	0.188***	0.324***	0.059***
	(0.01)	(0.02)	(0.01)
Covariate effect			
Female	-0.001	0.003	-0.002
	(0.00)	(0.00)	(0.01)
Age	-0.015***	-0.015**	-0.003
	(0.00)	(0.01)	(0.01)
Education	-0.010*	-0.021	0.017
	(0.01)	(0.01)	(0.05)
Married	-0.001	-0.001	-0.000
	(0.00)	(0.00)	(0.00)
HH size	0.003***	0.002**	0.004
	(0.00)	(0.00)	(0.01)
Occupation	-0.001	0.002	0.003
	(0.00)	(0.00)	(0.01)
Income	-0.001	0.004	0.000
	(0.00)	(0.00)	(0.00)
wealth	-0.003	0.023***	-0.016
	(0.00)	(0.00)	(0.03)
Financial expectation	-0.001	0.001	0.003
	(0.00)	(0.00)	(0.01)
Adverse shocks	-0.007***	-0.008*	-0.011
	(0.00)	(0.00)	(0.02)
Income fluctuation *(t-1)*	0.006***	0.004*	0.009
	(0.00)	(0.00)	(0.02)
Risk preference	-0.001	-0.003	-0.008
	(0.00)	(0.00)	(0.02)
Coefficient effect			
Female	-0.020**	-0.015*	0.001
	(0.01)	(0.01)	(0.01)
Age	-0.032	0.017	-0.042**

	(0.02)	(0.03)	(0.02)
Education	-0.020	-0.043	0.029
	(0.04)	(0.04)	(0.02)
Married	-0.040	-0.059	-0.007
	(0.04)	(0.04)	(0.03)
HH size	-0.074*	0.022	-0.012
	(0.04)	(0.04)	(0.02)
Occupation	0.000	-0.007	0.004
	(0.01)	(0.01)	(0.01)
Income	0.023	0.096***	0.023
	(0.03)	(0.03)	(0.02)
wealth	0.030	-0.026	-0.003
	(0.02)	(0.02)	(0.01)
Financial expectation	-0.064	-0.051	-0.019
	(0.04)	(0.05)	(0.03)
Adverse shocks	-0.042**	0.010	0.023*
	(0.02)	(0.02)	(0.01)
Income fluctuation *(t-1)*	0.002	-0.024	0.018
	(0.02)	(0.02)	(0.01)
Risk preference	-0.038	-0.098***	0.029*
	(0.03)	(0.03)	(0.02)
Constant	0.462***	0.501***	0.013
	(0.09)	(0.10)	(0.06)
Observations	4211	4211	4211

Notes:

1. Results are from decomposition analyses that compare the prevalence of debt and over-indebtedness among rural households in Vietnam to those in Thailand using coefficients from pooled logit regression models.
2. Results are based on the Oaxaca-Blinder Decomposition Method.
3. Numbers in brackets represent standard errors.
4. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.

A detailed decomposition of the coefficient effect for being indebted and over-indebted according to the DSR indicator, also displayed in table 5.3, show that the constant term that represents the base category is what mainly generates the positive coefficient effect. In this study, the base category was selected in such a way that it represents rural households that are expected to be economically disadvantaged, i.e. households with the oldest, less educated and single household head whose main income sources is agricultural production and those that have worst financial future expectation and low income and wealth. Hence, the constant term in the decomposition analysis reflects to what extent the prevalence of debt and over-indebtedness among the most economically disadvantaged rural households in Vietnam would differ if they were to face the same cultural, institutional and economic environment as their Thai counterparts. The results reveal that the economically disadvantaged rural households in Thailand are much more likely to participate in the credit market and become over-indebted than their counterparts in Vietnam. This means that the economic environment in Thailand is significantly more conducive for the economically disadvantaged rural households to participate in the credit market and become over-indebted than in Vietnam. This finding is in line with the notion of a higher incidence of debt and over-indebtedness among the poor and vulnerable groups of the population in Thailand that are more likely to face difficulty in repaying their debt, especially when faced with adverse economic conditions (ADB, 2013). Additionally, we note that income is also one factor that contributes significantly to a positive coefficient effect for the difference in the prevalence of over-indebtedness measured with the DSR indicator. This means that at any given amount of household income, the economic environment in Thailand favors having high debt burden more than in Vietnam. On the other hand, the main factors contributing to a significant coefficient effect for the differences in prevalence of default are adverse shocks and risk preferences.

The covariate effect is estimated to be negative and is significant only in the case of differences in the prevalence of holding debt. This shows that if rural households in Thailand had the same characteristics as the rural households in Vietnam, they would be more likely to participate in the credit market. This implies that the observed higher household debt among rural households in Thailand is not really explained by endowment effects such as higher amount of income or wealth. Looking further at the detailed decomposition of the covariate effect, it is noticeable that the estimated negative total covariate effect is largely due to age and education level of the household head. The explanation is that since age and level of education are related negatively and positively with being indebted respectively and Vietnamese rural households are younger and more educated than the Thai rural households, their prevalence of debt should be higher indicating a higher demand for debt and higher debt repayment capacity in the future. However, the economic environment effect is so strong that it takes over the opposite effect of the population characteristics. Finally, experiencing adverse shocks significantly reduces the difference while income fluctuation increases the difference. Though experiencing adverse shocks and income fluctuation both increase the likelihood of holding debt, the two factors had a different effect on the covariate effect because their incidence differed among rural households in the two countries (see table 5.2).

5.5.2. Decomposing the Amount of Debt Holdings

Table 5.4 reports the results of the decomposition analysis at the mean using the Oaxaca-Blinder decomposition method. Once again, the results from the Oaxaca-Blinder decomposition show that the coefficient effect largely explains the observed difference in debt holding indicating that the economic environment in Thailand is generally more favorable to holding higher amount of debt than the economic environment in Vietnam. If the rural households in Vietnam were to face the same economic environment as those in Thailand, the total difference in average log of debt between the households in the two countries would decrease by about 0.497 points (top panel, table 5.4). Therefore, about 71% of the total difference in average log of conditional amount of debt is explained by differences in the economic environment. According to the detailed decomposition analysis, financial wealth and financial expectation mainly contributed to the estimated positive coefficient effect. This means that for any given amount of financial wealth or type of financial expectation, the economic environment in Thailand is more favorable for rural households to hold higher amount of debt than in Vietnam.

Table 5.4: Decomposition of Differences in Average Log of Debt, Debt-Service Ratio, Debt to Income Ratio and Debt to Asset Ratio in 2008

	Amount of Debt	Debt-Service Ratio	Debt to Income Ratio	Debt to Asset Ratio
Overall				
Thailand	8.133^{***}	48.346^{***}	106.224^{***}	17.956^{***}
	(0.03)	(1.34)	(2.96)	(0.64)
Vietnam	7.436^{***}	15.590^{***}	63.779^{***}	11.861^{***}
	(0.03)	(0.77)	(2.11)	(0.43)
Total difference	0.697^{***}	32.755^{***}	42.445^{***}	6.095^{***}
	(0.04)	(1.54)	(3.63)	(0.77)
Covariate effect	0.200^{***}	12.303^{***}	10.881^{**}	-2.805^{**}
	(0.07)	(2.16)	(5.43)	(1.14)
Coefficient effect	0.497^{***}	20.452^{***}	31.564^{***}	8.900^{***}

	(0.08)	(2.46)	(6.22)	(1.33)
Covariate effect				
Female	0.001	0.244	-0.764	-0.135
	(0.01)	(0.28)	(0.66)	(0.14)
Age	0.016	-0.199	-0.798	0.311
	(0.01)	(0.41)	(1.08)	(0.25)
Education	-0.171***	-1.838**	-5.655***	-2.490***
	(0.03)	(0.89)	(2.19)	(0.53)
Married	-0.010*	-0.383**	-0.159	-0.083
	(0.01)	(0.18)	(0.48)	(0.10)
HH size	0.001	0.074	-0.014	0.015
	(0.00)	(0.07)	(0.15)	(0.03)
Occupation	0.012	0.109	0.793	0.206
	(0.01)	(0.21)	(0.65)	(0.15)
Income	0.021***	-0.691	-1.005	0.184**
	(0.01)	(0.51)	(1.49)	(0.09)
Financial wealth	0.164***	12.115***	10.967**	1.697*
	(0.06)	(1.61)	(4.27)	(0.87)
Real wealth	0.166***	3.006***	6.341***	-2.979***
	(0.02)	(0.50)	(1.17)	(0.35)
Financial expectation	-0.001	-0.043	1.716*	0.049
	(0.01)	(0.34)	(0.91)	(0.21)
Adverse shocks	-0.013	-0.459	-2.839***	-0.094
	(0.01)	(0.35)	(0.94)	(0.21)
Income fluctuation *(t-1)*	0.011**	0.285	0.513*	0.170**
	(0.00)	(0.18)	(0.30)	(0.08)
Risk preference	0.003	0.081	1.787*	0.343
	(0.01)	(0.40)	(1.02)	(0.21)
Coefficient effect				
Female	-0.008	-0.917	-2.949	-1.120**
	(0.03)	(1.01)	(2.23)	(0.50)
Age	-0.045	1.457	-0.982	-0.641
	(0.09)	(2.76)	(6.61)	(1.49)
Education	0.092	-1.946	7.409	2.331
	(0.15)	(6.36)	(13.69)	(2.76)
Married	0.055	-1.164	-0.753	-1.949
	(0.12)	(3.91)	(10.24)	(2.21)
HH size	0.103	-0.590	-1.014	4.366*
	(0.12)	(3.78)	(11.43)	(2.23)
Occupation	0.046	-0.502	1.102	0.758
	(0.03)	(1.14)	(2.51)	(0.61)
Income	-0.121	-17.249***	-6.301	0.297
	(0.10)	(5.41)	(12.47)	(2.03)
Financial wealth	0.179***	7.400***	10.766***	2.167***
	(0.04)	(1.56)	(3.48)	(0.67)
Real wealth	-0.093	4.436	-8.637	-7.298***
	(0.08)	(3.12)	(7.18)	(1.91)
Financial expectation	0.248*	-3.278	14.408	3.060
	(0.15)	(4.40)	(10.87)	(2.56)
Adverse shocks	-0.097	2.604	-1.871	-1.515
	(0.06)	(1.93)	(4.75)	(0.98)
Income fluctuation *(t-1)*	-0.012	0.127	-2.637	0.319
	(0.06)	(1.82)	(4.42)	(0.95)
Risk preference	-0.118	-12.082***	-4.558	-1.524
	(0.08)	(2.91)	(6.89)	(1.47)
Constant	0.267	42.155***	27.581	9.649*
	(0.31)	(11.02)	(27.09)	(5.49)
Observations	3117	3975	3141	3397

Notes:

1. Results are from decomposition analyses that compare the average amount of debt, DSR, DIR and DAR of rural households in Vietnam to those in Thailand using coefficients from pooled linear regression models.

2. Outstanding amount of debt is conditional on participation in credit markets.
3. Results are based on the Oaxaca-Blinder decomposition method.
4. Numbers in brackets represent standard errors.
5. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.

However, the coefficient effect does not entirely explain the total observed difference in amount of debt holding instead approximately 29% of the difference is attributed to the covariate effect. As can be seen from the detailed decomposition, evidently rural households in Thailand have combination of characteristics that make them more likely to hold larger amounts of debt, particularly income, financial and real wealth reflecting a higher ability to repay debt. Income fluctuation in the previous year also contributed to the positive covariate effect since Thai rural households experienced more income fluctuation in the previous year than those in Vietnam and income fluctuation is positively related with holding higher amount of debt. On the contrary, education contributes significantly to a negative covariate effect implying that on average Vietnamese rural households are more educated than their Thai counterparts and education is positively related with holding higher amount of debt. Overall, rural households in Thailand have configuration of characteristics, such as better endowments, and an economic environment that's conducive to holding higher amounts of debt and hence have higher amounts of debt outstanding than rural households in Vietnam.

Having reviewed findings from the decomposition analysis at the mean, we now move on to the results from RIF-regression decomposition method to get deeper insights into the factors that explain the observed debt holding differential. Results from the RIF-regression decomposition analysis at different percentiles of the conditional debt distribution are presented in table 5.5. At the aggregate level, we can see that the cross-country difference in debt holding increases along the debt distribution. Interestingly, the observed difference in log of debt holding attributable to the covariate and coefficient effect also differs along the debt distribution. Evidently, from the lowest percentile up to the median, the covariate effect or differences in composition of rural households' characteristics positively and significantly explain the observed cross-country difference in the amount of debt holding. This means that up to the median, differences in the distribution of household characteristics accounts for the large portion of the difference between rural households' debt in Thailand and Vietnam. In contrast, from the median onwards, the covariate effect becomes insignificant reflecting that the distribution of households' characteristics such as higher endowments do not actually explain the higher amount of debt holding observed for rural households in Thailand in the top percentiles. Instead, the difference in debt holding beyond the median debt is fully explained by the coefficient effect. This indicates that the economic environment is what mainly contributes to the higher amount of debt holding observed among rural households in Thailand.

Table 5.5: Decomposition of Differences in Log of Debt at the 10th, 25th, 50th, 75th and 90th Percentiles in 2008

	Log of debt				
	10th	**25th**	**50th**	**75th**	**90th**
Overall					
Thailand	6.509***	7.188***	8.064***	8.905***	9.880***
	(0.06)	(0.05)	(0.04)	(0.05)	(0.08)
Vietnam	6.138***	6.896***	7.518***	8.154***	8.707***
	(0.06)	(0.03)	(0.04)	(0.04)	(0.05)
Total difference	0.371***	0.292***	0.546***	0.751***	1.173***
	(0.08)	(0.06)	(0.05)	(0.06)	(0.09)
Covariate effect	0.280*	0.209**	0.221***	0.130	-0.048
	(0.15)	(0.10)	(0.08)	(0.09)	(0.14)
Coefficient effect	0.090	0.083	0.325***	0.621***	1.221***
	(0.18)	(0.11)	(0.09)	(0.10)	(0.16)
Covariate effect					
Female	-0.023	-0.002	-0.000	0.008	0.006
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Age	0.046	0.013	0.021	0.003	-0.014
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
Education	-0.173***	-0.161***	-0.128***	-0.122***	-0.266***
	(0.05)	(0.03)	(0.03)	(0.04)	(0.07)
Married	-0.008	-0.017*	-0.008	-0.013*	-0.012
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
HH size	0.001	0.001	0.001	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Occupation	0.009	0.010	0.018**	0.023**	0.016
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Income	0.018**	0.014**	0.015**	0.022**	0.029**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Financial wealth	0.323***	0.215***	0.143**	0.026	-0.081
	(0.13)	(0.08)	(0.06)	(0.07)	(0.11)
Real wealth	0.112***	0.118***	0.147***	0.182***	0.243***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
Financial expectation	-0.005	0.004	0.001	-0.003	-0.007
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)

Adverse shocks	-0.054**	-0.011	-0.009	-0.010	0.014
	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)
Income fluctuation (t-1)	0.017**	0.011*	0.007	0.011*	0.014
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Risk preference	0.015	0.015	0.013	0.002	0.009
	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)
Coefficient effect					
Female	-0.027	-0.012	-0.046	0.012	0.061
	(0.05)	(0.04)	(0.03)	(0.04)	(0.05)
Age	-0.085	-0.041	0.074	-0.008	-0.234
	(0.18)	(0.12)	(0.11)	(0.12)	(0.16)
Education	-0.156	0.052	-0.143	0.122	0.443
	(0.35)	(0.24)	(0.19)	(0.21)	(0.31)
Married	0.036	0.235	-0.119	0.158	0.302
	(0.26)	(0.17)	(0.14)	(0.16)	(0.23)
HH size	-0.221	-0.006	0.078	-0.007	0.336
	(0.24)	(0.16)	(0.14)	(0.18)	(0.27)
Occupation	0.008	-0.007	0.039	0.070	0.227***
	(0.06)	(0.04)	(0.04)	(0.04)	(0.07)
Income	0.091	-0.005	0.097	0.144	1.540*
	(0.75)	(0.50)	(0.46)	(0.53)	(0.87)
Financial wealth	0.347***	0.251***	0.121**	0.137**	0.058
	(0.10)	(0.06)	(0.05)	(0.06)	(0.09)
Real wealth	-0.528	0.534	0.149	0.577	2.747**
	(1.18)	(0.76)	(0.67)	(0.79)	(1.20)
Financial expectation	0.313	0.302*	0.439***	0.196	0.403
	(0.27)	(0.17)	(0.16)	(0.17)	(0.25)
Adverse shocks	-0.053	-0.038	-0.064	-0.101	0.035
	(0.12)	(0.09)	(0.08)	(0.09)	(0.13)
Income fluctuation (t-1)	0.047	-0.016	0.066	-0.109	-0.050
	(0.11)	(0.08)	(0.07)	(0.08)	(0.12)
Risk preference	-0.167	-0.181*	0.007	-0.195*	-0.164
	(0.15)	(0.11)	(0.09)	(0.11)	(0.18)
Constant	0.484	-0.985	-0.372	-0.373	-4.484***
	(1.27)	(0.80)	(0.68)	(0.79)	(1.33)
Observations	3005	3005	3005	3005	3005

Notes:

1. Results are from decomposition analyses that compare the distribution of amount of debt of rural households in Vietnam to those in Thailand using coefficients from pooled linear regression models.
2. Outstanding amount of debt is conditional on participation in credit markets.
3. Results are based on the RIF-Regression decomposition method.
4. Numbers in brackets represent standard errors.
5. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.

The detailed decomposition further explains these observed differences by capturing the contribution of each characteristic to the estimated log of debt equations. We find that, similar to the results at the mean, income, financial wealth, real wealth and income fluctuation mainly explain the estimated positive covariate effect at the lower percentile of the debt distribution. This suggests that the Thai rural households had higher endowments that explain the higher amount of debt they hold especially at the lower tail of the debt distribution. Turning to the coefficient effects at the top percentiles of the debt distribution, again the detailed decomposition shows that income, financial and real wealth are the key significant contributors to the estimated positive effect. If we interpret the coefficient effect as capturing the economic environment then this finding suggests that Vietnamese rural households would have higher amount of debt if they were to experience the economic environment that Thai rural households with comparable level of income, financial and real wealth face.

In summary, the findings from the RIF-regression decomposition analysis are broadly consistent with the results from the decomposition analysis at the mean, while adding the key insight into the varying role of the coefficient and covariate effect at the different points of the debt distribution. In the case of higher amount of debt observed at the lower tail of the debt distribution, better endowments explain the gap reflecting that Thai households possess resources that indicate a higher demand for debt and capacity to bear higher debt burden. On the other hand, in the upper tail of the debt distribution, the high debt gap between rural households in Vietnam and Thailand is overwhelmingly explained by differences in the economic environment, with this differences widening at higher debt levels.

5.5.3. Decomposing the Indebtedness Indicators

According to the findings from the RIF-regression decomposition analysis, the higher amount of debt observed among rural households in Thailand is partly due to having better resources that might make them more capable of servicing their debt and less likely to face high debt burden. Hence, we further look into differences in debt burden using the common DSR, DIR and DAR indicators of indebtedness.

At the aggregate level we can see that rural households in Thailand on average have a higher debt burden or level of indebtedness even though they tend to have higher income and wealth compared to rural households in Vietnam (see table 5.4). This observed gap in debt burden is largely attributable to differences in the economic environment regardless of the indicator used. Looking further at the detailed decompositions, table 5.4 shows that financial wealth has a strong and positive effect on the difference in indebtedness levels using all three indicators through the coefficient effect. The reason behind this finding could be that saving secured loans are common in Thailand and hence amount of saving households have determines the amount of debt they take out by signaling better repayment capacity. Especially for group loans in Thailand, the maximum amount of loan households can borrow might depend on the accumulated amount of savings they have at the village bank (Coleman, 1999). Furthermore focusing on the DSR and DAR indicators, it is clear that the economic environment in Thailand is again more tolerant to the economically disadvantaged rural households to bear higher debt burden than in Vietnam as showed by the positive significant constant.

Turning to the covariate effect, we can see that configuration of the rural households characteristics in Thailand explains about 37% and 25% of the observed difference in level of indebtedness using the DSR and DIR indicators respectively (see table 5.4). The key factors that contribute to the positive covariate are again financial and real wealth and are in favor of those in Thailand. In general, these findings are in line with the findings from the decomposition analysis of the log of debt. Additionally, financial expectation and risk preferences explain the higher level of indebtedness among rural households in Thailand in terms of the DIR indicator (see table 5.4). Since being a risk taker and having a worst future financial expectation is associated to facing higher debt burden, a positive significant contribution to the covariate effect means that more of the Thai households have these characters making them more disposed to higher debt burdens. In the case of the DAR, the covariate effect is negative indicating that rural households in Vietnam have characteristics that make them more likely to experience higher level of debt burden. However, given the favorable economic environment in Thailand that is more tolerant to rural households having higher debt burdens than in Vietnam, the negative covariate effect is neutralized.

Table 5.6, 5.7 and 5.8 present the RIF-regression decomposition results at different percentiles of the indebtedness distribution for the three indebtedness indicators. In general, the difference in the level of indebtedness increases when going along the indebtedness indicators distribution and the coefficient effect explains larger portion of the difference especially at the upper tail of the distribution. Turning to the specific results from the detailed decomposition for the DSR indicator, table 5.6 presents financial and real wealth as the key individual contributors to both the coefficient and covariate effects. This suggests that rural households in Thailand have higher amount of financial and real wealth that explain their need and capacity to bear higher amount debt relative to their income and also at any given level of wealth the economic environment in Thailand is more tolerant to rural households holding high level of indebtedness. Another notable finding is again that the economic environment in Thailand allows the economically disadvantaged group of rural households to get into high debt burden situation as shown by the high positive significant estimate of the constant term.

According to the detail decomposition analysis of the DIR indicator, table 5.7 also shows that the key individual covariates that contribute to the positive estimated coefficient effects are again financial and real wealth. While financial wealth explains the observed cross-country difference in level of indebtedness at the lower distribution of the DIR, real wealth is the factor that largely explains the high difference in debt burden observed at the top 90th percentile. The reason for the positive effect of these two individual covariates to the coefficient effect could be that both financial and real wealth are used more to secure loans than in Vietnam, or to assess future repayment capacity of rural households. Additionally, the main occupation of the household head also contributes positively to the coefficient effect at the top part of the DIR distribution. The underlying mechanism of this effect can be explained as follows. As shown in table A2 in the appendix, having a self-employed household head is associated to facing higher debt burden compared to those that have a household head involved in agricultural production. Hence, the positive coefficient effect from occupation means that the economic environment in Thailand is particularly lenient to higher debt burden for the rural households with self-employed household heads than the economic environment in Vietnam.

Moving on to the coefficient effect for the DAR indicator presented in table 5.8, once more this effect fully explains the observed cross-country difference in indebtedness and also neutralizes the negative covariate effect that is in favor of rural households in Vietnam facing higher debt burden throughout the DAR distribution. Table 5.8 further presents the detailed decomposition that shows income and financial wealth as the factors that contribute to the positive coefficient effect throughout the DAR distribution while at the middle and higher level of the distribution occupation and household size partly explain the cross-country difference in debt burden. Another finding worth noting from the DAR indicator is that the economic environment is less conducive to higher debt burden for the economically disadvantaged groups in Thailand at the lower tail of the debt distribution, while at the top 90th percentile the economic environment is more conducive to higher debt burden for economically disadvantaged groups in Thailand.

Covariate effects also play a statistically significant role although the direction of the effect varies depending on the indebtedness indicator used (see table 5.6, 5.7 and 5.8). For DSR and DIR indicators, the covariate effect is estimated to be positively significant indicating that rural households in Thailand have configuration of characteristics that make them assume larger level of debt burden than what is observed for rural households in Vietnam, especially at the lower tail of the distribution. The key characters that explain this positive effect are financial and real wealth, financial expectation, income fluctuation and risk preferences. Other characters such as age, education and income contribute negatively to the covariate effect showing that Vietnamese rural households for instance have younger and more educated household heads that should make them more prone to face higher debt burdens than Thai households as these characters are associated with higher debt burden.

On the contrary, for the DAR indicator, the covariate effect has generally a negative impact on the cross-country debt burden gap, with a particularly sizable effect at the top percentiles. This means that if it were for the composition of household characteristics, the Vietnamese rural households would have had higher level of debt burden than what is observed. According to the detailed decomposition the main contributor to this negative effect is education. However, the difference in the economic environment is so strong that it prevails over the opposite influence of the covariate effect and hence the observed higher debt burden for rural households in Thailand.

To sum up, the findings from the decomposition analysis of the three indebtedness indicators suggests that rural households in Thailand face significantly higher level of indebtedness compared to rural households in Vietnam. The main explanation for this observed cross-country debt burden gap is the economic environment in Thailand that seems to be more tolerant of high level of indebtedness among rural households.

Table 5.6: Decomposition of Differences in Debt-Service Ratio Distribution at the 50th, 75th and 90th Percentiles in 2008

	Debt-service ratio		
	50^{th}	**75^{th}**	**90^{th}**
Overall			
Thailand	29.400^{***}	70.269^{***}	139.900^{***}
	(1.37)	(2.44)	(3.53)
Vietnam	1.732^{***}	14.730^{***}	44.104^{***}
	(0.22)	(1.17)	(2.26)
Total difference	27.668^{***}	55.539^{***}	95.796^{***}
	(1.39)	(2.70)	(4.19)
Covariate effect	12.502^{***}	16.135^{***}	18.237^{***}
	(1.95)	(3.61)	(5.57)
Coefficient effect	15.166^{***}	39.404^{***}	77.560^{***}
	(2.32)	(4.20)	(6.42)
Covariate effect			
Female	-0.065	0.097	0.138
	(0.26)	(0.48)	(0.71)
Age	-1.061^{***}	-1.539^{**}	1.267
	(0.36)	(0.72)	(1.13)
Education	-1.226	-1.505	-3.869
	(0.76)	(1.57)	(2.47)
Married	-0.135	-0.566^{*}	-0.615
	(0.16)	(0.29)	(0.43)
HH size	0.170^{*}	0.089	0.068
	(0.09)	(0.12)	(0.18)
Occupation	0.221	0.057	-0.211
	(0.21)	(0.38)	(0.55)

Income	-0.787**	-2.110***	-3.720***
	(0.31)	(0.81)	(1.43)
Financial wealth	14.029***	16.427***	16.075***
	(1.58)	(2.74)	(4.19)
Real wealth	2.289***	5.062***	9.490***
	(0.42)	(0.86)	(1.41)
Financial expectation	0.387	-0.429	-0.152
	(0.32)	(0.60)	(0.91)
Adverse shocks	-0.806**	-0.090	-1.422
	(0.33)	(0.64)	(0.99)
Income fluctuation *(t-1)*	0.145	0.372	0.464
	(0.17)	(0.33)	(0.50)
Risk preference	-0.660*	0.272	0.724
	(0.38)	(0.72)	(1.09)
Coefficient effect			
Female	-0.998	-0.918	-5.291**
	(0.83)	(1.66)	(2.67)
Age	5.703**	2.380	-6.146
	(2.27)	(4.46)	(7.37)
Education	1.171	-2.438	-22.646
	(5.40)	(9.58)	(17.10)
Married	0.109	1.180	-4.562
	(3.24)	(6.30)	(10.30)
HH size	7.320**	-4.297	-17.428
	(3.28)	(6.74)	(10.70)
Occupation	0.464	-0.045	-1.021
	(1.06)	(2.08)	(3.15)
Income	-136.192***	-236.540***	-228.663***
	(12.74)	(25.62)	(48.45)
Financial wealth	9.193***	13.515***	11.377***
	(1.40)	(2.55)	(4.09)
Real wealth	83.035***	91.632**	107.448*
	(18.09)	(36.82)	(58.35)
Financial expectation	-5.271*	-6.268	-10.526
	(3.19)	(6.89)	(11.49)
Adverse shocks	2.569	2.808	3.778
	(1.79)	(3.56)	(5.41)
Income fluctuation *(t-1)*	-0.697	-2.494	-2.548
	(1.70)	(3.32)	(5.10)
Risk preference	-8.213***	-23.234***	-23.562***
	(2.65)	(5.28)	(7.88)
Constant	56.975***	204.121***	277.349***
	(18.69)	(37.36)	(57.35)
Observations	3997	3997	3997

Notes:

1. Results are from decomposition analyses that compare the distribution of debt service to income ratio of rural households in Vietnam to those in Thailand using coefficients from pooled RIF-regression models.
2. Results are based on the RIF-Regression decomposition method.
3. Numbers in brackets represent standard errors.
4. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.

Table 5.7: Decomposition of Differences in Debt to Income Ratio Distribution at the 25th, 50th, 75th and 90th Percentiles in 2008

	Debt to income ratio			
	25th	**50th**	**75th**	**90th**
Overall				
Thailand	22.598***	63.754***	156.412***	308.169***
	(1.33)	(1.90)	(7.31)	(3.62)
Vietnam	13.661***	35.265***	83.267***	161.139***

	(0.87)	(1.67)	(3.30)	(1.60)
Total difference	8.937***	28.489***	73.145***	147.030***
	(1.59)	(2.53)	(8.02)	(3.96)
Covariate effect	5.206*	5.977	18.250	7.918
	(2.66)	(3.82)	(12.63)	(6.18)
Coefficient effect	3.731	22.512***	54.895***	139.113***
	(3.16)	(4.44)	(14.23)	(6.88)
Covariate effect				
Female	-0.335	-0.912*	-0.633	-0.416
	(0.32)	(0.47)	(1.55)	(0.79)
Age	0.028	-0.119	-0.327	-0.068
	(0.52)	(0.78)	(2.48)	(1.24)
Education	-1.929*	-5.456***	-13.356***	-5.129**
	(1.00)	(1.55)	(4.87)	(2.42)
Married	-0.060	-0.188	-0.991	-0.085
	(0.23)	(0.33)	(1.11)	(0.55)
HH size	-0.001	-0.001	-0.009	-0.009
	(0.02)	(0.02)	(0.20)	(0.21)
Occupation	-0.244	0.464	1.863	0.559
	(0.31)	(0.43)	(1.54)	(0.74)
Income	-0.647*	-1.853*	-5.883*	-2.498*
	(0.34)	(0.95)	(3.02)	(1.29)
Financial wealth	6.851***	8.129***	24.597**	8.069
	(2.19)	(2.99)	(10.09)	(5.04)
Real wealth	0.622	4.377***	13.542***	6.624***
	(0.48)	(0.78)	(2.66)	(1.39)
Financial expectation	0.028	1.250**	2.628	2.411**
	(0.41)	(0.62)	(2.12)	(1.09)
Adverse shocks	-0.601	-0.590	-4.582**	-3.224***
	(0.43)	(0.65)	(2.22)	(1.11)
Income fluctuation *(t-1)*	0.330**	0.457**	0.251	0.284
	(0.16)	(0.23)	(0.69)	(0.34)
Risk preference	1.163**	0.418	1.149	1.400
	(0.45)	(0.67)	(2.34)	(1.20)
Coefficient effect				
Female	-1.054	-2.709*	-4.399	-2.358
	(1.02)	(1.60)	(4.67)	(2.42)
Age	-3.399	0.854	-0.402	4.880
	(3.19)	(4.87)	(14.82)	(7.48)
Education	5.577	1.239	44.490	-1.243
	(6.55)	(8.95)	(29.04)	(16.14)
Married	0.496	0.449	-2.485	-8.074
	(4.49)	(7.03)	(20.19)	(10.50)
HH size	-1.330	-9.695	-18.956	17.494
	(4.40)	(7.12)	(22.44)	(12.34)
Occupation	-1.177	0.568	11.637**	5.094*
	(1.20)	(1.79)	(5.75)	(2.81)
Income	-10.327	47.608*	-254.708***	-133.948***
	(17.55)	(24.60)	(81.42)	(47.62)
Financial wealth	5.637***	10.360***	26.581***	6.070
	(1.80)	(2.63)	(7.47)	(3.75)
Real wealth	14.667	-17.652	157.170	148.682**
	(22.07)	(33.59)	(111.70)	(59.07)
Financial expectation	1.324	14.433*	40.723*	6.215
	(4.46)	(7.74)	(21.81)	(11.85)
Adverse shocks	-3.546	-2.977	13.713	3.395
	(2.32)	(3.55)	(10.85)	(5.31)
Income fluctuation *(t-1)*	0.577	-5.594*	-12.412	6.201
	(2.13)	(3.22)	(10.22)	(5.00)
Risk preference	-2.384	-0.792	-8.104	-7.051
	(3.06)	(4.64)	(15.08)	(7.63)

Constant	-1.329	-13.582	62.047	93.755
	(22.22)	(34.35)	(116.68)	(62.45)
Observations	3176	3176	3176	3176

Notes:

1. Results are from decomposition analyses that compare the distribution of amount of outstanding debt to income ratio of rural households in Vietnam to those in Thailand using coefficients from pooled RIF-regression models.
2. Results are based on the RIF-Regression decomposition method.
3. Numbers in brackets represent standard errors.
4. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.

Table 5.8: Decomposition of Differences in Debt to Asset Ratio Distribution at the 25th, 50th, 75th and 90th Percentiles in 2008

	Debt to asset ratio			
	25^{th}	**50^{th}**	**75^{th}**	**90^{th}**
Overall				
Thailand	2.963***	8.229***	19.669***	44.793***
	(0.17)	(0.44)	(0.75)	(2.64)
Vietnam	2.349***	6.425***	13.832***	27.891***
	(0.17)	(0.25)	(0.58)	(1.14)
Total difference	0.614**	1.803***	5.837***	16.902***
	(0.24)	(0.50)	(0.94)	(2.88)
Covariate effect	-0.428	-1.325*	-4.797***	-17.612***
	(0.38)	(0.79)	(1.37)	(4.74)
Coefficient effect	1.042**	3.128***	10.635***	34.514***
	(0.45)	(0.90)	(1.56)	(5.65)
Covariate effect				
Female	-0.028	-0.041	-0.392**	-0.805
	(0.04)	(0.10)	(0.18)	(0.55)
Age	-0.008	-0.101	-0.076	-0.044
	(0.08)	(0.16)	(0.28)	(0.90)
Education	-0.526***	-1.149***	-2.947***	-8.531***
	(0.15)	(0.30)	(0.60)	(1.96)
Married	-0.016	-0.074	0.006	0.008
	(0.03)	(0.07)	(0.12)	(0.40)
HH size	0.007	0.009	0.008	0.051
	(0.02)	(0.02)	(0.02)	(0.12)
Occupation	0.014	0.209**	0.346*	0.178
	(0.04)	(0.10)	(0.18)	(0.56)
Income	0.020	0.063	0.126	0.362
	(0.02)	(0.06)	(0.11)	(0.32)
Financial wealth	0.870***	1.959***	2.207**	1.187
	(0.30)	(0.63)	(1.03)	(3.54)
Real wealth	-0.871***	-2.388***	-4.431***	-11.024***
	(0.09)	(0.22)	(0.42)	(1.32)
Financial expectation	-0.025	0.244*	0.044	0.508
	(0.06)	(0.13)	(0.23)	(0.77)
Adverse shocks	-0.054	-0.113	0.070	-0.883
	(0.06)	(0.13)	(0.24)	(0.79)
Income fluctuation *(t-1)*	0.042*	0.095*	0.162*	0.350
	(0.02)	(0.05)	(0.09)	(0.27)
Risk preference	0.146**	-0.039	0.080	1.033
	(0.06)	(0.14)	(0.25)	(0.85)
Coefficient effect				
Female	-0.011	-0.242	-1.235**	-2.141
	(0.16)	(0.30)	(0.58)	(1.63)
Age	-0.190	0.364	-1.983	-0.106
	(0.49)	(0.92)	(1.69)	(5.04)
Education	0.232	4.001**	2.211	1.295
	(0.89)	(1.88)	(3.21)	(11.49)

Married	0.075	0.697	-0.750	-7.621
	(0.71)	(1.35)	(2.61)	(7.31)
HH size	-1.280*	0.847	-0.864	19.667**
	(0.68)	(1.35)	(2.54)	(8.47)
Occupation	-0.043	0.609*	1.916***	3.227
	(0.17)	(0.35)	(0.68)	(2.16)
Income	5.547***	6.291	17.488**	66.716**
	(2.11)	(4.22)	(8.28)	(27.04)
Financial wealth	0.855***	1.732***	2.506***	4.379*
	(0.27)	(0.48)	(0.86)	(2.62)
Real wealth	2.907	-18.707***	-19.689	-188.845***
	(3.24)	(6.10)	(12.07)	(44.97)
Financial expectation	0.665	0.679	6.078**	8.915
	(0.73)	(1.35)	(3.06)	(8.59)
Adverse shocks	-0.686*	-1.092	-0.449	3.676
	(0.36)	(0.70)	(1.30)	(3.88)
Income fluctuation *(t-1)*	0.272	-0.057	-0.910	0.448
	(0.32)	(0.64)	(1.18)	(3.68)
Risk preference	-0.123	-2.048**	-1.938	-0.321
	(0.45)	(0.92)	(1.82)	(5.53)
Constant	-7.177**	10.053	8.253	125.224**
	(3.32)	(6.65)	(13.27)	(48.75)
Observation	3288	3288	3288	3288

Notes:

1. Results are from decomposition analyses that compare the distribution of amount of outstanding debt to asset ratio of rural households in Vietnam to those in Thailand using coefficients from pooled RIF-regression models.
2. Results are based on the RIF-Regression decomposition method.
3. Numbers in brackets represent standard errors.
4. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.

5.6 Conclusion

This paper explored cross-country differences in credit market participation, level of debt holding and indebtedness between rural households in Thailand and Vietnam. In the first instance, the non-linear extension of the Oaxaca-Blinder decomposition method is used to assess determinants of differences in the prevalence of debt and over-indebtedness. Then the mean based Oaxaca-Blinder decomposition method is used to assess differences in average log of debt and indebtedness. Finally, the analysis is extended to the RIF-Regression decomposition method to assess differences in the entire log of debt and indebtedness distribution. Such decomposition analysis provides additional insight into the concentration of debt among certain groups of households and the distinct roles played by the determinants at different points of the debt distribution.

The findings shed light on debt and household balance sheet vulnerabilities especially for certain groups of rural households that is not apparent from analysis of aggregate data. Firstly, the findings show higher prevalence of debt and over-indebtedness among rural households in Thailand than in Vietnam. Secondly, those that participate in the credit market hold also larger amounts of debt and face higher level of indebtedness in Thailand than in Vietnam. Thirdly, these observed differences arise mainly due to dissimilarity in the economic environment that rural households of similar characteristics face in the two countries. The economic environment in Thailand is more conducive for rural households to participate in the credit market and become over-indebted than in Vietnam. Particularly for the economically disadvantaged rural households, the economic environment in Thailand is more lenient to having high amounts of debt as compared to what their counterparts face in Vietnam.

Finally, the gap in debt holding and indebtedness increase significantly along the debt distribution. The factors that explain the observed differences also differ along the distribution, i.e., at the lower tail of the distributions, larger portion of the debt holding and indebtedness gaps are attributable to differences in population characteristics, such as household's endowments. Hence, the higher debt observed among Thai rural households at the lower debt distribution can be explained by the endowment effect. In contrast, at the upper tail of the distribution, the debt holding and indebtedness gaps are mainly attributable to differences in the economic environment. This indicates that the higher debt holding observed among rural households in Thailand, especially at the extreme end of the debt distribution is explained by lax economic environment than by endowment effects.

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Appendix

Table A1: Determinants of the prevalence of debt, over-indebtedness and default in 2008

	Debt	**Debt-service Ratio 40%**	**Default**
Female HH head	-0.007	0.234**	-0.061
	(0.10)	(0.10)	(0.15)
Age of HH head below 39	0.573***	0.104	0.037
	(0.11)	(0.12)	(0.20)
Age of HH head 40-49	0.600***	0.311***	0.371**
	(0.11)	(0.11)	(0.17)
Age of HH head 50-59	0.750***	0.379***	0.514***
	(0.11)	(0.11)	(0.16)
Primary education	0.532***	0.602***	-0.045
	(0.12)	(0.14)	(0.19)
Secondary education	0.257*	-0.057	-0.764***
	(0.13)	(0.16)	(0.22)
Higher education	0.249	0.037	-0.657
	(0.22)	(0.28)	(0.45)
Married HH head	0.101	0.140	0.024
	(0.12)	(0.12)	(0.19)
Household size	0.122***	0.043**	0.150***
	(0.02)	(0.02)	(0.03)
Self-employed HH	-0.070	0.130	0.233
	(0.14)	(0.15)	(0.24)
Off-farm employed HH	0.077	0.122	0.500***
	(0.10)	(0.10)	(0.15)
Inactive HH	-0.057	0.227	0.345

	(0.14)	(0.14)	(0.22)
Income quintile 2	0.042	-0.097	-0.131
	(0.12)	(0.11)	(0.17)
Income quintile 3	-0.022	-0.708***	-0.318*
	(0.12)	(0.11)	(0.18)
Income quintile 4	0.194	-1.175***	-0.411**
	(0.13)	(0.12)	(0.18)
Income quintile 5	-0.030	-1.618***	-0.675***
	(0.14)	(0.14)	(0.22)
Real wealth quintile 2	0.092	0.219**	0.025
	(0.10)	(0.11)	(0.15)
Real wealth quintile 3	0.252**	0.735***	-0.105
	(0.12)	(0.12)	(0.18)
Real wealth quintile 4	0.011	0.801***	-0.490**
	(0.12)	(0.13)	(0.21)
Real wealth quintile 5	0.347**	1.112***	-0.078
	(0.14)	(0.14)	(0.21)
Better future financial expectation	-0.240*	-0.156	-0.351**
	(0.13)	(0.11)	(0.17)
Same future financial expectation	-0.215*	-0.360***	-0.369**
	(0.13)	(0.12)	(0.17)
Unexpected shocks to expense	0.342***	0.016	0.330***
	(0.08)	(0.08)	(0.12)
Expected shocks to expense	0.116	0.158	0.042
	(0.14)	(0.13)	(0.19)
Unexpected shocks to income	0.239***	-0.102	0.333***
	(0.08)	(0.08)	(0.12)
Income fluctuation (t-1)	0.478***	0.329***	0.520***
	(0.08)	(0.08)	(0.13)
Risk averse	0.034	-0.118	-0.178
	(0.09)	(0.10)	(0.15)
Risk neutral	0.201*	0.175	-0.223
	(0.11)	(0.11)	(0.17)
Constant	-1.026***	-1.779***	-3.248***
	(0.24)	(0.25)	(0.37)
Log-likelihood	-2266.298	-2236.405	-1130.018
Pseudo R2	0.061	0.091	0.066
Observation	4211	4211	4211

Notes:

5. Results are from logistic regression models for the probability of holding debt, DSR>40% and default.
6. Numbers in brackets represent standard errors.
7. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.

Table A2: Determinants of the amount of outstanding debt, Debt-Service Ratio, Debt to Income Ratio and Debt to Asset Ratio in 2008

	Debt	Debt-Service Ratio	Debt to Income Ratio	Debt to Asset Ratio
Female HH head	0.009	1.877	-3.761	-1.054
	(0.06)	(2.02)	(5.57)	(1.06)
Age of HH head below 39	-0.053	2.800	1.086	-1.360
	(0.07)	(2.38)	(6.77)	(1.29)
Age of HH head 40-49	0.088	5.976***	13.379**	0.442
	(0.06)	(2.14)	(5.98)	(1.14)
Age of HH head 50-59	0.215***	9.277***	14.773**	1.660
	(0.06)	(2.14)	(5.94)	(1.12)
Primary education	-0.012	-0.861	4.553	-0.153
	(0.08)	(2.71)	(7.73)	(1.47)
Secondary education	0.330***	2.457	18.789**	4.954***
	(0.09)	(2.85)	(8.11)	(1.54)
Higher education	0.739***	9.669**	34.954***	9.575***
	(0.14)	(4.66)	(13.37)	(2.58)
Married HH head	0.137*	5.962**	1.402	1.086
	(0.07)	(2.41)	(6.83)	(1.31)
Household size	0.047***	0.464	2.811**	0.500**
	(0.01)	(0.40)	(1.12)	(0.21)
Self-employed HH	0.457***	5.619*	22.711***	8.949***
	(0.08)	(2.90)	(8.26)	(1.57)
Off-farm employed HH	0.030	-1.112	5.886	1.596
	(0.06)	(1.99)	(5.51)	(1.06)
Inactive HH	0.092	0.844	8.387	1.611
	(0.09)	(3.00)	(8.47)	(1.61)
Income quintile 2	-0.055	-8.993***	-64.369***	-2.503**
	(0.07)	(2.50)	(7.11)	(1.24)
Income quintile 3	0.045	-27.510***	-108.679***	-1.264
	(0.07)	(2.53)	(7.18)	(1.25)
Income quintile 4	0.033	-35.268***	-137.226***	-2.391*
	(0.07)	(2.64)	(7.42)	(1.28)
Income quintile 5	0.449***	-43.688***	-154.398***	3.801***
	(0.08)	(2.96)	(8.28)	(1.44)
Financial wealth quintile 2	0.095	18.085***	12.985	1.046
	(0.08)	(3.01)	(8.15)	(1.55)
Financial wealth quintile 3	0.344***	24.591***	30.083***	4.413***
	(0.08)	(2.96)	(8.01)	(1.51)
Financial wealth quintile 4	0.214***	18.494***	21.965***	2.134
	(0.08)	(2.82)	(7.88)	(1.49)
Financial wealth quintile 5	0.209**	6.834**	10.184	1.212
	(0.09)	(2.73)	(8.00)	(1.54)
Real wealth quintile 2	0.126**	7.129***	1.213	-13.628***
	(0.06)	(2.09)	(5.77)	(1.10)
Real wealth quintile 3	0.364***	14.409***	15.670**	-15.568***
	(0.07)	(2.34)	(6.43)	(1.22)
Real wealth quintile 4	0.549***	12.384***	36.932***	-17.989***
	(0.07)	(2.58)	(7.12)	(1.35)

Real wealth quintile 5	0.920***	19.894***	48.208***	-20.080***
	(0.08)	(2.84)	(7.72)	(1.44)
Better future financial expectation	0.020	2.939	-5.773	-1.631
	(0.07)	(2.43)	(6.66)	(1.26)
Same future financial expectation	0.013	1.016	-13.356*	-0.786
	(0.07)	(2.47)	(6.87)	(1.31)
Unexpected shocks to expense	0.024	0.828	2.780	1.589**
	(0.04)	(1.53)	(4.18)	(0.79)
Expected shocks to expense	0.043	1.261	10.672	1.407
	(0.07)	(2.56)	(6.88)	(1.32)
Unexpected shocks to income	0.058	2.455	14.876***	0.811
	(0.05)	(1.56)	(4.32)	(0.82)
Income fluctuation (t-1)	0.117***	2.367	7.669*	1.827**
	(0.05)	(1.56)	(4.29)	(0.82)
Risk averse	-0.029	-0.971	-9.897*	-1.133
	(0.05)	(1.91)	(5.28)	(1.00)
Risk neutral	-0.011	-0.242	3.438	0.633
	(0.06)	(2.16)	(5.90)	(1.12)
Thailand	0.497***	20.452***	34.549***	8.900***
	(0.08)	(2.44)	(7.18)	(1.37)
Constant	6.303***	12.160**	111.925***	14.972***
	(0.15)	(4.91)	(14.48)	(2.75)
R2	0.247	0.197	0.186	0.134
Observation	3117	3975	3178	3397

Notes:

1. Results are from linear regression models for the average amount of debt, DSR, DIR and DAR.
2. Outstanding amount of debt is conditional on participation in credit markets.
3. Numbers in brackets represent standard errors.
4. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.

Table A3: Determinants of the amount of outstanding debt at 10th, 25th, 50th, 75th and 90th percentile

	Amount of debt				
	10th	**25th**	**50th**	**75th**	**90th**
Female HH head	-0.184*	-0.035	-0.005	0.039	0.076
	(0.11)	(0.08)	(0.07)	(0.08)	(0.13)
Age of HH head below 39	-0.262*	-0.046	-0.076	0.028	0.087
	(0.14)	(0.10)	(0.08)	(0.10)	(0.16)
Age of HH head 40-49	0.050	0.049	0.041	0.017	0.121
	(0.12)	(0.09)	(0.07)	(0.09)	(0.14)
Age of HH head 50-59	0.084	0.152*	0.233***	0.244***	0.352***
	(0.12)	(0.08)	(0.07)	(0.08)	(0.14)
Primary education	-0.010	0.058	0.040	-0.013	-0.348*
	(0.16)	(0.11)	(0.10)	(0.11)	(0.18)
Secondary education	0.363**	0.423***	0.313***	0.265**	0.224
	(0.16)	(0.12)	(0.10)	(0.12)	(0.19)
Higher education	0.548**	0.555***	0.655***	0.707***	1.040***
	(0.27)	(0.20)	(0.17)	(0.20)	(0.31)
Married HH head	0.117	0.198**	0.100	0.164*	0.171
	(0.14)	(0.10)	(0.08)	(0.10)	(0.16)
Household size	0.042*	0.047***	0.031**	0.026	0.052**

	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)
Self-employed HH	0.015	0.239**	0.332***	0.649***	1.135***
	(0.16)	(0.12)	(0.10)	(0.12)	(0.19)
Off-farm employed HH	0.024	-0.042	-0.044	0.033	0.281**
	(0.11)	(0.08)	(0.07)	(0.08)	(0.13)
Inactive HH	0.099	0.054	0.173	0.222*	0.048
	(0.17)	(0.12)	(0.11)	(0.12)	(0.20)
Income quintile 2	0.073	0.116	-0.044	-0.188**	-0.290*
	(0.13)	(0.09)	(0.08)	(0.09)	(0.15)
Income quintile 3	0.423***	0.202**	0.051	-0.155*	-0.356**
	(0.13)	(0.09)	(0.08)	(0.09)	(0.15)
Income quintile 4	0.433***	0.267***	0.117	-0.165*	-0.434***
	(0.13)	(0.10)	(0.08)	(0.10)	(0.15)
Income quintile 5	0.532***	0.438***	0.423***	0.487***	0.654***
	(0.15)	(0.11)	(0.09)	(0.11)	(0.17)
Financial wealth quintile 2	0.325**	0.082	0.140	-0.044	-0.155
	(0.16)	(0.12)	(0.10)	(0.12)	(0.19)
Financial wealth quintile 3	0.676***	0.630***	0.314***	0.113	-0.080
	(0.16)	(0.11)	(0.10)	(0.11)	(0.18)
Financial wealth quintile 4	0.418***	0.279**	0.208**	0.133	-0.048
	(0.16)	(0.11)	(0.10)	(0.11)	(0.18)
Financial wealth quintile 5	0.269	0.165	0.109	0.127	0.250
	(0.17)	(0.12)	(0.10)	(0.12)	(0.19)
Real wealth quintile 2	0.249**	0.137*	0.058	0.089	0.054
	(0.11)	(0.08)	(0.07)	(0.08)	(0.13)
Real wealth quintile 3	0.361***	0.293***	0.376***	0.403***	0.296**
	(0.13)	(0.09)	(0.08)	(0.09)	(0.15)
Real wealth quintile 4	0.456***	0.465***	0.575***	0.670***	0.606***
	(0.14)	(0.10)	(0.09)	(0.10)	(0.16)
Real wealth quintile 5	0.483***	0.609***	0.798***	1.141***	1.513***
	(0.15)	(0.11)	(0.09)	(0.11)	(0.17)
Better future financial expectation	0.089	0.108	0.056	-0.090	-0.006
	(0.13)	(0.09)	(0.08)	(0.09)	(0.15)
Same future financial expectation	0.069	0.032	0.023	0.007	0.068
	(0.13)	(0.10)	(0.08)	(0.10)	(0.16)
Unexpected shocks to expense	-0.049	-0.031	0.036	0.027	0.152
	(0.08)	(0.06)	(0.05)	(0.06)	(0.10)
Expected shocks to expense	-0.042	0.081	0.099	0.192*	0.030
	(0.14)	(0.10)	(0.08)	(0.10)	(0.16)
Unexpected shocks to income	0.205**	0.033	0.053	0.021	-0.067
	(0.09)	(0.06)	(0.05)	(0.06)	(0.10)
Income fluctuation (t-1)	0.196**	0.125**	0.092*	0.148**	0.144
	(0.09)	(0.06)	(0.05)	(0.06)	(0.10)
Risk averse	-0.041	0.020	-0.024	-0.028	-0.137
	(0.10)	(0.08)	(0.06)	(0.08)	(0.12)
Risk neutral	0.038	0.068	0.029	-0.012	-0.095
	(0.12)	(0.08)	(0.07)	(0.08)	(0.13)

Thailand	0.114	0.089	0.314***	0.589***	1.192***
	(0.15)	(0.10)	(0.09)	(0.11)	(0.17)
Constant	4.831***	5.579***	6.541***	7.264***	7.781***
	(0.29)	(0.21)	(0.18)	(0.21)	(0.34)
R2	0.059	0.092	0.149	0.183	0.170
Observation	3117	3117	3117	3117	3117

Notes:

1. Results are from RIF-regression models for the log of debt at the 10th, 25th, 50th, 75th and 90th percentile.
2. Outstanding amount of debt is conditional on participation in credit markets.
3. Numbers in brackets represent standard errors.
4. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.

Table A4: Determinants of the DSR at 10th, 25th, 50th, 75th and 90th percentile

	Debt-service ratio		
	50th	**75th**	**90th**
Female HH head	-0.500	0.959	1.385
	(1.82)	(3.58)	(5.56)
Age of HH head below 39	6.637***	10.841**	-3.276
	(2.15)	(4.22)	(6.56)
Age of HH head 40-49	8.370***	13.790***	2.642
	(1.93)	(3.78)	(5.87)
Age of HH head 50-59	5.916***	14.728***	15.097**
	(1.93)	(3.78)	(5.87)
Primary education	0.855	3.322	-0.481
	(2.44)	(4.79)	(7.44)
Secondary education	2.797	5.563	5.156
	(2.57)	(5.05)	(7.84)
Higher education	10.425**	18.758**	23.025*
	(4.22)	(8.29)	(12.87)
Married HH head	1.363	8.569**	10.399
	(2.18)	(4.27)	(6.63)
Household size	1.011***	0.653	0.671
	(0.36)	(0.70)	(1.09)
Self-employed HH	1.376	10.145**	9.885
	(2.62)	(5.15)	(8.00)
Off-farm employed HH	-1.506	-0.438	-2.113
	(1.79)	(3.52)	(5.47)
Inactive HH	3.199	0.254	-4.773
	(2.70)	(5.30)	(8.23)
Income quintile 2	2.172	-11.710***	-36.703***
	(2.24)	(4.40)	(6.83)
Income quintile 3	-5.143**	-35.958***	-87.795***
	(2.27)	(4.45)	(6.91)
Income quintile 4	-12.072***	-51.971***	-100.725***
	(2.37)	(4.65)	(7.22)
Income quintile 5	-23.502***	-66.949***	-115.784***
	(2.66)	(5.21)	(8.09)
Financial wealth quintile 2	21.548***	21.343***	22.306***
	(2.71)	(5.32)	(8.27)
Financial wealth quintile 3	27.308***	31.721***	30.079***

	(2.67)	(5.23)	(8.12)
Financial wealth quintile 4	22.411***	27.590***	20.404***
	(2.54)	(4.99)	(7.74)
Financial wealth quintile 5	4.796*	8.858*	14.157*
	(2.47)	(4.84)	(7.52)
Real wealth quintile 2	3.384*	5.082	14.973***
	(1.89)	(3.70)	(5.75)
Real wealth quintile 3	8.844***	20.275***	28.285***
	(2.11)	(4.14)	(6.43)
Real wealth quintile 4	7.850***	16.391***	33.129***
	(2.33)	(4.57)	(7.10)
Real wealth quintile 5	14.795***	30.456***	46.615***
	(2.57)	(5.04)	(7.82)
Better future financial expectation	-0.924	4.102	11.677*
	(2.19)	(4.30)	(6.68)
Same future financial expectation	-2.722	4.187	5.106
	(2.23)	(4.38)	(6.80)
Unexpected shocks to expense	-0.298	1.192	1.997
	(1.38)	(2.71)	(4.21)
Expected shocks to expense	3.542	1.856	1.330
	(2.31)	(4.54)	(7.05)
Unexpected shocks to income	3.711***	0.814	7.986*
	(1.41)	(2.77)	(4.30)
Income fluctuation (t-1)	0.906	2.786	3.656
	(1.41)	(2.76)	(4.28)
Risk averse	-1.934	-3.182	2.168
	(1.72)	(3.38)	(5.25)
Risk neutral	-4.411**	-1.000	4.581
	(1.95)	(3.82)	(5.94)
Thailand	14.877***	38.598***	77.760***
	(2.21)	(4.33)	(6.73)
Constant	-10.014**	7.055	59.054***
	(4.43)	(8.69)	(13.49)
R2	0.169	0.167	0.188
Observation	4016	4016	4016

Notes:

1. Results are from RIF-regression models for the DSR at the 10th, 25th, 50th, 75th and 90th percentile.
2. Numbers in brackets represent standard errors.
3. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.

Table A5: Determinants of the Debt to Income Ratio at 10th, 25th, 50th, 75th and 90th percentile

	Debt to income ratio			
	25th	**50th**	**75th**	**90th**
Female HH head	-2.365	-6.526*	-3.797	-2.817
	(2.24)	(3.37)	(11.13)	(5.58)
Age of HH head below 39	0.274	1.747	2.139	0.422
	(2.72)	(4.09)	(13.53)	(6.78)
Age of HH head 40-49	6.336***	9.893***	24.256**	6.973
	(2.40)	(3.62)	(11.96)	(5.99)
Age of HH head 50-59	6.297***	13.318***	23.613**	5.747
	(2.39)	(3.59)	(11.87)	(5.95)
Primary education	4.600	4.748	15.957	-3.100
	(3.10)	(4.67)	(15.45)	(7.74)
Secondary education	8.170**	15.714***	42.261***	5.291
	(3.26)	(4.90)	(16.21)	(8.12)
Higher education	20.910***	30.834***	74.853***	8.262
	(5.37)	(8.08)	(26.72)	(13.39)
Married HH head	0.246	1.470	10.226	0.059
	(2.74)	(4.13)	(13.66)	(6.84)
Household size	0.332	0.655	3.756*	3.270***
	(0.45)	(0.67)	(2.23)	(1.12)
Self-employed HH	3.592	9.759*	50.294***	12.819
	(3.32)	(4.99)	(16.51)	(8.27)
Off-farm employed HH	-1.610	0.691	15.859	3.833
	(2.21)	(3.33)	(11.01)	(5.52)
Inactive HH	-4.038	4.385	16.434	3.806
	(3.40)	(5.12)	(16.92)	(8.48)
Income quintile 2	-3.903	-17.408***	-90.907***	-54.250***
	(2.85)	(4.30)	(14.21)	(7.12)
Income quintile 3	-8.165***	-39.850***	-160.695***	-86.809***
	(2.88)	(4.34)	(14.35)	(7.19)
Income quintile 4	-14.196***	-63.119***	-227.772***	-98.280***
	(2.98)	(4.49)	(14.84)	(7.43)
Income quintile 5	-27.284***	-78.651***	-246.678***	-104.401***
	(3.33)	(5.01)	(16.55)	(8.29)
Financial wealth quintile 2	11.117***	10.105**	30.546*	8.054
	(3.27)	(4.93)	(16.29)	(8.16)
Financial wealth quintile 3	12.159***	16.466***	56.422***	18.235**
	(3.22)	(4.84)	(16.00)	(8.02)
Financial wealth quintile 4	8.274***	10.524**	26.678*	11.467
	(3.16)	(4.76)	(15.74)	(7.89)
Financial wealth quintile 5	2.181	5.178	13.598	2.747
	(3.21)	(4.84)	(15.99)	(8.01)
Real wealth quintile 2	-1.799	-2.018	2.758	-0.575
	(2.32)	(3.49)	(11.54)	(5.78)
Real wealth quintile 3	-0.384	6.378	16.929	8.127
	(2.58)	(3.89)	(12.86)	(6.44)
Real wealth quintile 4	1.620	15.372***	46.111***	25.746***
	(2.86)	(4.30)	(14.23)	(7.13)
Real wealth quintile 5	2.215	26.916***	77.623***	30.614***

	(3.10)	(4.67)	(15.43)	(7.73)
Better future financial expectation	-3.803	-10.661***	0.771	-8.801
	(2.67)	(4.02)	(13.31)	(6.67)
Same future financial expectation	-1.566	-9.971**	-13.114	-15.386**
	(2.76)	(4.15)	(13.74)	(6.88)
Unexpected shocks to expense	2.911*	6.068**	7.903	-1.528
	(1.68)	(2.53)	(8.36)	(4.19)
Expected shocks to expense	2.966	6.248	24.822*	1.129
	(2.76)	(4.16)	(13.76)	(6.89)
Unexpected shocks to income	3.469**	4.154	21.931**	14.183***
	(1.73)	(2.61)	(8.63)	(4.32)
Income fluctuation (t-1)	3.716**	5.049*	3.433	4.437
	(1.72)	(2.59)	(8.57)	(4.29)
Risk averse	-0.923	-1.953	-7.003	-7.770
	(2.12)	(3.19)	(10.56)	(5.29)
Risk neutral	4.360*	0.422	0.285	0.820
	(2.37)	(3.56)	(11.79)	(5.91)
Thailand	3.702	20.772***	49.535***	136.938***
	(2.88)	(4.34)	(14.34)	(7.19)
Constant	9.598*	52.860***	131.488***	208.264***
	(5.82)	(8.75)	(28.95)	(14.50)
R2	0.071	0.159	0.128	0.343
Observation	3178	3178	3178	3178

Notes:

1. Results are from RIF-regression models for the DIR at the 10th, 25th, 50th, 75th and 90th percentile.
2. Numbers in brackets represent standard errors.
3. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.

Table A6: Determinants of the Debt to Asset Ratio at 10th, 25th, 50th, 75th and 90th percentile

	Debt to asset ratio			
	25th	**50th**	**75th**	**90th**
Female HH head	-0.295	-0.326	-2.506**	-4.343
	(0.32)	(0.69)	(1.27)	(4.13)
Age of HH head below 39	0.052	0.614	0.283	-0.698
	(0.39)	(0.83)	(1.53)	(5.00)
Age of HH head 40-49	0.779**	1.868**	1.725	4.319
	(0.34)	(0.74)	(1.36)	(4.42)
Age of HH head 50-59	0.999***	3.304***	2.375*	4.372
	(0.34)	(0.73)	(1.34)	(4.37)
Primary education	-0.139	1.025	-0.546	-7.250
	(0.44)	(0.95)	(1.75)	(5.71)
Secondary education	0.849*	3.468***	5.272***	9.398
	(0.46)	(1.00)	(1.84)	(6.00)
Higher education	2.336***	6.064***	11.832***	28.205***
	(0.78)	(1.66)	(3.07)	(10.02)
Married HH head	0.216	1.199	0.583	2.373

	(0.39)	(0.84)	(1.56)	(5.09)
Household size	0.245***	0.327**	0.301	1.887**
	(0.06)	(0.14)	(0.25)	(0.82)
Self-employed HH	1.253***	3.447***	8.826***	28.340***
	(0.47)	(1.01)	(1.87)	(6.09)
Off-farm employed HH	0.036	1.013	2.367*	3.004
	(0.32)	(0.68)	(1.26)	(4.10)
Inactive HH	0.118	2.632**	3.728*	0.689
	(0.49)	(1.04)	(1.92)	(6.27)
Income quintile 2	-0.341	-0.942	-0.908	-5.148
	(0.37)	(0.80)	(1.48)	(4.84)
Income quintile 3	0.117	-0.896	-0.710	-3.301
	(0.38)	(0.80)	(1.48)	(4.84)
Income quintile 4	0.285	-0.709	-1.558	-6.580
	(0.38)	(0.83)	(1.52)	(4.97)
Income quintile 5	0.656	2.687***	6.834***	15.899***
	(0.43)	(0.93)	(1.71)	(5.59)
Financial wealth quintile 2	1.032**	2.717***	2.032	-9.037
	(0.47)	(1.00)	(1.85)	(6.02)
Financial wealth quintile 3	1.873***	4.013***	3.918**	10.456*
	(0.45)	(0.98)	(1.80)	(5.87)
Financial wealth quintile 4	1.315***	3.268***	3.427*	1.926
	(0.45)	(0.97)	(1.78)	(5.81)
Financial wealth quintile 5	-0.114	0.549	2.308	2.671
	(0.46)	(0.99)	(1.83)	(5.98)
Real wealth quintile 2	-1.331***	-6.341***	-15.588***	-35.295***
	(0.33)	(0.71)	(1.31)	(4.28)
Real wealth quintile 3	-2.524***	-8.786***	-17.866***	-44.322***
	(0.37)	(0.79)	(1.45)	(4.74)
Real wealth quintile 4	-3.383***	-11.635***	-22.136***	-45.024***
	(0.41)	(0.87)	(1.60)	(5.24)
Real wealth quintile 5	-5.239***	-13.749***	-24.723***	-54.050***
	(0.43)	(0.93)	(1.71)	(5.59)
Better future financial expectation	-0.476	-1.017	-1.374	-3.014
	(0.38)	(0.82)	(1.51)	(4.91)
Same future financial expectation	0.025	-1.406*	0.019	-2.267
	(0.39)	(0.84)	(1.56)	(5.07)
Unexpected shocks to expense	0.611**	0.690	2.223**	4.620
	(0.24)	(0.51)	(0.95)	(3.09)
Expected shocks to expense	0.032	0.347	2.464	8.891*
	(0.40)	(0.85)	(1.58)	(5.14)
Unexpected shocks to income	0.424*	0.680	0.388	4.700
	(0.25)	(0.53)	(0.98)	(3.20)
Income fluctuation (t-1)	0.532**	1.218**	2.019**	4.973
	(0.25)	(0.53)	(0.98)	(3.19)
Risk averse	-0.249	-1.076*	-2.121*	-1.808
	(0.30)	(0.65)	(1.20)	(3.91)

Risk neutral	0.402	-1.076	-1.185	3.996
	(0.34)	(0.73)	(1.34)	(4.37)
Thailand	0.995**	2.706***	9.721***	31.731***
	(0.41)	(0.88)	(1.63)	(5.32)
Constant	0.871	5.788***	18.438***	31.389***
	(0.83)	(1.77)	(3.27)	(10.68)
R2	0.087	0.121	0.129	0.078
Observation	3397	3397	3397	3397

Notes:

1. Results are from RIF-regression models for the DIR at the 10th, 25th, 50th, 75th and 90th percentile.
2. Numbers in brackets represent standard errors.
3. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Source: Own calculation based on household survey 2008.