



# Performance of microfinance institutions and their accessibility in South and East Asia

Huong Phan

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# **THÈSE POUR OBTENIR LE GRADE DE DOCTEUR DE MONTPELLIER SUPAGRO**

**Institut Agro, Montpellier**

**L'Ecole Doctorale d'Économie et Gestion (EDEG) de Montpellier**

**UMR MOISA**

**Performance des institutions de microfinance et leur accessi-  
bilité en Asie du Sud et de l'Est**

**Performance of microfinance institutions and their accessibil-  
ity in South and East Asia**

**Présentée par Thi Thanh Huong PHAN**

**Le 1er Octobre 2021**

**Sous la direction de M. Michel SIMIONI, Directeur de Recherche**

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**UNIVERSITÉ  
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## **Performance des institutions de microfinance et leur accessibilité en Asie du Sud et de l'Est**

## **Performance of microfinance institutions and their accessibility in South and East Asia**

**Phan Thi Thanh Huong**

**Montpellier – 1er Octobre 2021**

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## **Abstract**

**Abstract of a thesis submitted in partial fulfilment of the requirements for  
the Degree of Doctor of Philosophy in Science Economics**

### **Performance of microfinance institutions and their accessibility in South and East Asia**

**by Phan Thi Thanh Huong**

This thesis investigates several topics in microfinance in South and East Asia. The appearance of microfinance has been known as a solution to alleviate poverty in rural area. Millions of poor families in developing countries have accessed to formal financial services through microfinance programs. However, many households still face major constraints in their credit access due to many reasons, such as short of collaterals or unable to access formal finance specifically in the South and East Asia where the region remains home to almost half of the world's poorest individuals.

In addition to an introduction and a conclusion, this thesis comprises three self-contained papers, each paper corresponding to one chapter. A common thread of the three papers is to provide an overview of both sides of the microfinance market: demand (borrowers) and supply (microfinance institutions). The first chapter assesses performance of microfinance institutions of South and East Asia. The second and third chapters focus on Vietnam rural credit market and investigate credit accessibility of households in rural area. The study analyses the informal credit access and finds the gap of accessibility between different ethnic minority groups to both formal and informal credit sources. This thesis aims to contribute to current knowledge on the development and the characteristics of microfinance in South and East Asia, by investigating strategic factors affecting microfinance operations. In addition, this thesis finds that the chance of getting credit is not equivalent among rural and poor areas. The below will summarize each chapter.

The first chapter presents new evidence on financial and social performances of microfinance institutions in South and East Asia region. Financial performance is assessed using return on assets and operational self-sufficiency while social performance is assessed using depth and breadth of outreach. Dynamic panel data models are used to measure the impact of different factors (board characteristics, microfinance institution characteristics and country socio-economic conditions) on these measures of performances. These models are estimated using system-GMM to take into account all potential endogeneity issues encountered in dynamic panel data. Models are fitted using data from 305 microfinance institutions in 19 Asian-Pacific countries over the period from 2006 to 2015. Results show that board size and gender diversity have negative impacts on performance while board social orientation positively affects financial performance. In addition, past performance, leverage and total assets also have positive effects on financial performance. In addition, our findings suggest that firms should have a more efficient view regarding structuring board size and having social activities, as we show that a greater proportion of social orientation creates value of, more or less, 1.2% on ROA. This increase in MFIs' economic performance which often accompanied by greater visibility and commitments to corporate social responsibilities.

The second chapter investigates the factors affecting the accessibility of households to informal credit market in rural area of Vietnam. The study used data from the Vietnam Access to Resources Household Survey (VARHS) collected in 2014. The empirical analysis aims to identify which factors facilitate accessibility to loans from microfinance institutions. An original estimation strategy is developed, combining classical logit estimation of the probability of getting a loan with less usual Random Forests estimation techniques. These latter non-parametric techniques have the advantage of making it possible to assess the order of importance of the factors in the explanation of the probability of obtaining a loan. Moreover, they have proved to surpass most other classifying techniques regarding predictive accuracy. The results show that the accessibility to informal credit is positively related to the owned area of land, the household size and the number of community groups household participated in while the age and distance to

administrative centers have negative effects. One policy implication of these results is that government policies should focus on increasing both the productive capacity, quality of infrastructure in rural area and wealth of households in order to enhance the poor's creditworthiness, formal credit accessibility and make them less susceptible to credit rationing by money lenders.

The third chapter contributes to the microfinance literature by investigating the gap of credit access between the dominant ethnicity in Vietnam, or Kinh, and the other ethnic minority groups. Accessibility to both formal and informal credit sources is discussed. As in the previous chapter, the methodological approach combines classical logit estimation of the probability of getting a loan with random forests estimation techniques. Here too, data from the 2014 wave of Vietnam Access Resource Household Survey (VARHS) is used. Our main result shows that the Kinh group has higher accessibility to loan than any other ethnic minority groups from both formal and informal credit market. Nevertheless, when focusing on the formal market, results show that minority groups have better chance to get credit from the Vietnam Bank of Social Policy (VBSP). Results indicate that there is not equal access to credit for households from the different ethnic groups and that an appropriate credit scheme needs to be considered by the Government to improve the credit access of ethnic minority groups.

Policy implications can be drawn from these studies. Thus, joining social groups can enhance credit availability of households in rural areas. In addition, supporting programs (e.g., vocational and job training programs) and designing incentive policies (i.e. attracting investment to remote rural areas) are helpful to improve credit access. Moreover, rural development is necessary to lessen the gap of credit accessibility among different ethnic groups and make them less susceptible to credit rationing by money lenders. The Government can build supply chains to connect manufacturers and exporters with producers and provide short term funding for fertilizers or other finance support to partly remove credit constraint. Those policy to support production needs to increase value added for ethnic minority area such as promotion of business start-ups, public-private partnership and innovations. Besides, Government should launch agricultural product insurance markets



and support to make the insurance market more efficient including collecting data, building of system infrastructure, awareness and education campaigns, development of technology, training of providers...

**Keywords:** Microfinance, South and East Asia, Vietnam, Financial performance, Social performance, Accessibility to credit, Ethnic minority, Dynamic panel model, Random Forests.

**Jel codes:** G21, O17, Q14

## Résumé

Cette thèse étudie plusieurs thèmes de la microfinance en Asie du Sud-est. La microfinance a été conçue comme une solution pour réduire la pauvreté dans les zones rurales. Des millions de familles pauvres dans les pays en développement ont eu accès à des services financiers formels grâce aux programmes de microfinance. Cependant, de nombreuses personnes sont encore confrontés à des contraintes majeures dans leur accès au crédit et cela pour de nombreuses raisons, telles que le manque de garanties ou l'incapacité d'accéder à des financements formels, en particulier en Asie du Sud-est qui abrite près de la moitié des individus les plus pauvres au monde.

En plus d'une introduction et d'une conclusion, cette thèse regroupe trois articles, chaque article correspondant à un chapitre. Le fil conducteur de ces trois articles est de fournir une vue d'ensemble des deux côtés du marché de la microfinance : la demande (emprunteurs) et l'offre (institutions de microfinance). Le premier chapitre évalue la performance des institutions de microfinance en Asie du Sud-est. Les deuxième et troisième chapitres se concentrent sur le marché du crédit rural au Vietnam et étudient l'accessibilité au crédit des habitants en zone rurale. L'étude analyse les déterminants de accès au crédit informel et constate l'écart d'accessibilité entre les différentes minorités ethniques aux sources de crédit formelles et informelles. Cette thèse vise à contribuer aux connaissances actuelles sur le développement et les caractéristiques de la microfinance en Asie du Sud-est, en étudiant les facteurs stratégiques qui affectent les opérations de microfinance. En outre, cette thèse constate que les chances d'obtenir un crédit ne sont pas égales entre les zones rurales et les zones pauvres. Les contenus des chapitres sont résumés ci-dessous.

Le premier chapitre présente de nouvelles résultats quant aux performances financières et sociales des institutions de microfinance en Asie du Sud-est. La performance financière est évaluée par le rendement des actifs et de l'autosuffisance opérationnelle, tandis que la performance sociale est évaluée par la profondeur et

l'étendue de la couverture. Des modèles dynamiques en données de panel sont utilisés pour mesurer l'impact de différents facteurs (caractéristiques du conseil d'administration, caractéristiques de l'institution de microfinance et conditions socio-économiques du pays) sur ces mesures de performances. Ces modèles sont estimés en utilisant la méthode économétrique appelée system-GMM. Cette méthode permet de prendre en compte tous les problèmes potentiels d'endogénéité rencontrés dans les modèles dynamiques en données de panel. Les modèles sont estimés à partir de données sur 305 institutions de microfinance dans 19 pays de l'Asie-Pacifique sur la période de 2006 - 2015. Les résultats montrent que la taille du conseil d'administration et la diversité de genre ont un impact négatif sur la performance, tandis que l'orientation sociale du conseil d'administration a un effet positif sur la performance financière. En outre, la performance passée, l'effet de levier et le total des actifs ont également des effets positifs sur la performance financière. En outre, nos résultats suggèrent que les entreprises devraient avoir une vision plus efficace de la structuration de la taille du conseil d'administration et des activités sociales, car nous montrons qu'une plus grande proportion d'orientation sociale crée un surplus de valeur d'à peu près 1,2% sur le ROA. Cette augmentation de la performance économique des institutions de microfinance doit s'accompagner d'une plus grande visibilité et d'engagements en matière de responsabilités sociales des entreprises.

Le deuxième chapitre étudie les facteurs affectant l'accessibilité des ménages au marché du crédit informel dans les zones rurales au Vietnam. L'étude utilise les données de l'enquête sur l'accès aux ressources des ménages au Vietnam (VARHS), recueillies en 2014. L'analyse empirique vise à identifier les facteurs qui facilitent l'accessibilité aux prêts des institutions de microfinance. Une stratégie d'estimation originale est développée, combinant l'estimation classique de la probabilité d'obtenir un prêt par régression logistique, avec les techniques d'estimation des forêts aléatoires moins usuelles dans la littérature. Ces dernières techniques sont non paramétriques et ont l'avantage de permettre d'évaluer l'ordre d'importance des facteurs dans l'explication de la probabilité d'obtenir un prêt. De plus, elles se sont avérées surpasser la plupart des autres techniques de classification en termes de qualité prédictive. Les résultats montrent que l'accessibilité au crédit

informel est positivement liée à la surface de terre possédée, à la taille du ménage et au nombre de groupes communautaires auxquels le ménage participe, tandis que l'âge et la distance aux centres administratifs ont des effets négatifs. L'une des implications politiques de ces résultats est que les politiques gouvernementales devraient se concentrer sur l'augmentation de la capacité de production, de la qualité des infrastructures dans les zones rurales et de la richesse des ménages afin d'améliorer la solvabilité des pauvres, l'accessibilité au crédit formel et de les rendre moins sensibles au rationnement du crédit par les prêteurs.

Le troisième chapitre contribue à la littérature sur la microfinance en étudiant l'écart d'accès au crédit entre l'ethnie dominante au Vietnam, ou Kinh, et les autres groupes ethniques minoritaires. L'accessibilité aux sources de crédit formelles et informelles est examinée. Comme dans le chapitre précédent, l'approche méthodologique combine l'estimation classique de la probabilité d'obtenir un prêt par régression logistique, avec des techniques d'estimation par forêts aléatoires. Ici aussi, les données de la vague 2014 de l'enquête sur l'accès aux ressources des ménages du Vietnam (VARHS) sont utilisées. Notre principal résultat montre que le groupe Kinh a une plus grande accessibilité au prêt que tous les autres groupes de minorités ethniques, tant sur le marché formel que sur le marché informel du crédit. Néanmoins, si l'on se concentre sur le marché formel, les résultats montrent que les groupes minoritaires ont plus de chance d'obtenir un crédit auprès de la Vietnam Bank of Social Policy (VBSP). Les résultats indiquent qu'il n'y a pas d'égalité d'accès au crédit pour les habitants des différents groupes ethniques et que le gouvernement doit envisager un programme de crédit approprié pour améliorer l'accès au crédit des groupes ethniques minoritaires.

Des implications en termes de politiques économiques peuvent être tirées de ces études. Ainsi, l'adhésion à des groupes sociaux peut améliorer la disponibilité du crédit des ménages dans les zones rurales. En outre, les programmes de soutien (par exemple, les programmes de formation professionnelle et d'emploi) et la conception de politiques d'incitation (par exemple, attirer les investissements dans les zones rurales éloignées) sont utiles pour améliorer l'accès au crédit. En outre, le développement rural est nécessaire pour réduire l'écart d'accessibilité au

crédit entre les différents groupes ethniques et les rendre moins sensibles au rationnement du crédit par les prêteurs. Le gouvernement peut mettre en place des chaînes d'approvisionnement pour relier les fabricants et les exportateurs aux producteurs et fournir un financement à court terme pour les engrais ou d'autres aides financières afin de lever partiellement la contrainte du crédit. Les politiques de soutien à la production doivent augmenter la valeur ajoutée dans les zones de minorités ethniques, notamment en encourageant la création d'entreprises, les partenariats public-privé et les innovations. En outre, le gouvernement devrait lancer des marchés d'assurance des produits agricoles et soutenir l'efficacité du marché de l'assurance, notamment en collectant des données, en construisant l'infrastructure du système, en menant des campagnes de sensibilisation et d'éducation, en développant la technologie, en formant les prestataires...

**Mots clés :** Microfinance, Asie du Sud-est, Vietnam, Performance financière, Performance sociale, Accessibilité au crédit, Minorités ethniques, Modèle de panel dynamique, Régression logistique, Forêts aléatoires.

## **List of Conference and Published Papers**

### **Chapter 3: Microfinance institution performance assessment– New evidences for East and South Asia**

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### **Chapter 4: Rural household access to informal credit in Vietnam: Evidence using random forest**

Presented at Wilfrid Laurier University, Waterloo, Ontario, Canada in September 2019

### **Chapter 5: A formal and informal rural credit accessibility of ethnic minority households: Evidence from Vietnam**

Presented at New Zealand Finance Colloquium - Lincoln University, February 2019.

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## **List of Acronyms and Abbreviations**

ADB	Asian Development Bank
ANZ	Australia and New Zealand Bank
BDT	Bangladesh taka
BIDV	Bank of Industries and Development of Vietnam
BRDB	Bangladesh Rural Development Board
CEMA	Committee for Ethnic Minority Affairs
CEP	HCMC Labour Confederation
CI	Credit institutions
JCB	Joint Stock Commercial Bank
HCI	Human Capital Index
GDP	Gross Domestic Products
GMM	Generalized Method of Moment
GLP	Gross Loan Portfolio
HSBC	Hongkong and Shanghai Banking Corporations
KUR	Kredit Usaha Rakyat
LR	Logistic Regression
MENA	Middle East and North Africa
MFIs	Micro Finance Institutes
MIX	Microfinance Information Exchange
NGOs	Non-Government-Organizations
NBFCs	Non-Banking Financial Companies
IMF	International Monetary Fund
OSS	Operational Self Sufficiency
PPP	Purchasing Power Parity

UNDP	United Nations Development Programs
UNEP	United Nations Environment Programs
RF	Random Forests
RBI	Reserved Bank of Indonesia
ROA	Returns on Assets
ROSCA	Rotating Savings and Credit Associations
SOCB	State Owned Commercial Bank
PAR	Portfolio annual return
PCF	People's Credit Funds
TYM MFI	Tinh Thuong One-member Limited Liability Microfinance Institution
SBV	State Bank of Vietnam
VBP	Vietnam Bank of the Poor
VBARD	Vietnam Bank for Agricultural and Rural Development
VARHS	Vietnam Access to Resources Household Survey
VBSP	Vietnam Bank of Social Policy
VCB	JSC Bank for Foreign Trade of Vietnam
VND	Vietnam Dongs
VWU	Vietnam Women's Union

# **Chapter 1 Introduction**

## **1.1. General Introduction**

Microfinance is an important part of rural finance. Concentrating on low income and poor households, microfinance provides small loans as working capital for income generating activities at individual, household and microenterprise levels. Microfinance is also used as an efficient tool of the government in many poverty reduction programs (Ledgerwood (1998); Morduch (2002); Khandker (2003); Ledgerwood (2013)). However, providing microfinance to a large proportion of rural households remains a tough task because of the nature of the rural credit market as well as the lending system which are controlled by government.

According to IMF (2018), the Asia – Pacific region has been recently identified as the world's fastest-growing economic area while this region remains home to almost half of the world's poorest (UNEP, 2018). In this region, 47 percent of the population in developing countries still does not have a bank account and only 9 percent can access formal loans (IMF, 2018). In addition, the value of collateral for developing countries in Asia-Pacific is 239 percent of the loan value while the global average is 196 percent (Jahan, 2019).

For these reasons, financial institutions including micro finance institutes have been viewed as a contributing factor to economic growth and development. Most of government interventions in rural credit markets are based on this ground and they have been further justified on the basis of improving MFI's performance.

The interest of this thesis is to figure out and analyze potential factors affecting the performance of microfinance institutions in South and East Asia. MFIs can be considered sustainable if they maintain a proportional balance between certain critical elements: long-term profitability; providing sustainable microfinance facilities to the poor and contributing benefits to society, community and environment. How to measure and improve the performance of MFIs is therefore an issue. In this study, we, therefore, address this issue by assessing the impact of various factors which may affect to profitability and social performance of MFIs.

However, in order to improve micro finance performances, it is vital to look for both side of the rural credit market: demand and supply. For the supply side, the performance of MFIs is key element. On the other side, credit demand from households is also important to banks and financial institutions to define the market and supply sufficiently. However, the credit demands of rural household are difficult to measure due to a number of reasons: lacking of appropriate sharing mechanisms and methods for dealing with asymmetries in credit markets; risky environments; small scale economies and weak legal systems (Bardhan and Udry, 1999; Besley, 1994; Gosh et al., 1999; Ray, 1997).

In South and East Asia region, the Vietnam rural credit market is dominated by different types of credit providers (e.g., banks, credit funds, private money lenders) offering credit for a variety of rural clients. Poor physical infrastructure (e.g., roads, bridges, public transports and communication) in rural areas, particularly in remote areas, associated with market fragmentation increase the outreach of credit delivery. In addition to formal credit providers which provides 80% of the total rural credit needs, informal credit sources are often sought by households with free collaterals and more flexible terms (Vietnam Bank Association, 2019). While Vietnam is not the country with the highest level of informal economy in Asia, it is one of three countries with a highest growth rate of the informal economy of 1.2% per year. This is the reason why informal credit is chosen to study. In addition, since the gap of living quality among different areas is still high, we would like to concentrate on credit access of different ethnic minorities households in Vietnam.

## **1.2. Research Problems and Questions**

The purpose of this thesis is to measure the performance of MFIs and address the problem of access to rural finance in Vietnam. The mixture of credit supply including formal and informal sources may change the way a rural household decides to borrow from a certain type of credit provider. Given accessibility to formal microcredit is quite transparent, impact evaluation of the informal credit is not easy to valuate and it needs to be further examined. In addition, ethnic minority households often live in remote area so their access to formal credit is limited leading to

be over-reliance on informal sources. To investigate these problems, the following questions need to be answered:

- Research question 1. What are factors influence performance of microfinance institutions in South and East Asia?
- Research question2. What factors influence informal credit accessibility for rural households in Vietnam?
- Research question 3. What are the differences in credit constraints of ethnic minority households between formal and informal credit market?

### **1.3 Objective of the thesis**

Generally speaking, the objective of this thesis is to bring the broad view of microfinance institutions performances and of their access in South and East Asia. Microfinance has been known as a solution to alleviate poverty in rural area. Millions of poor families in developing countries have accessed to financial services through microfinance programs. However, many households still face major constraints in their credit access due to many reasons, specifically in the South and East Asia where the region is home to almost half of the world's poorest individuals. This is the reason why we choose this region to study about performance of the MFIs. Each of the three above-mentioned research questions is the focus of each of the three self-contained essays: one focusing on performance of MFI in South and East Asia and the other two on credit access in Vietnam. As we recognize that Vietnam is one of the countries in the South and East Asia region with highest growth rate of the informal economy of 1.2% per year, we decided to choose this market to study informal credit and outreach of ethnic minority households.

The specific objectives of the three essays can be summarized as follows. The central idea of the first essay is to develop an empirical model that can be of use in analyzing the performance of MFI in South and East Asia. We estimate dynamic panel data models to analyze the impact of different factors (board characteristics, microfinance institution characteristics and country socio-economic conditions) on different measures of MFIs' performances. These models are estimated using sys-



tem-GMM to take into account all potential endogeneity issues that may be encountered when using dynamic panel data models. The second and third essays exploit the idea that non-parametric techniques, which have proved to overcome most other classifying techniques regarding predictive accuracy, can be used to assess the order of importance of factors that may explain the probability of obtaining a loan. Therefore, an original estimation strategy is developed using the mix of classical logit estimation of the probability of getting a loan and random forests estimation techniques. Although the three essays are self-contained and focus on two different geographic regions, a unified picture of credit market can be drawn from the thesis. The next section explains in detail the analysis and the contribution of each essay.

#### **1.4 Contribution of the thesis**

The contribution of this study to microfinance literature is twofold: performance of MFIs and microcredit accessibility of rural households. First, it is necessary to gain an understanding of the performance of MFIs before improving their credit supply activities. In addition, this study brings additional elements to our understanding of the dynamic nature of MFIs performance. Regarding rural households in Vietnam, this study also is the first to show the gaps of credit access among different minorities and indicates that there is not equal access to credit for households from the different ethnic groups and an appropriate credit scheme needs to be considered by the Government to improve the credit access of minorities. These contributions to the knowledge of rural credit markets in Vietnam are based on the use, for the first time, of an estimation strategy which combines classical logit estimation of the probability of getting a loan with new random forests estimation techniques.

#### **1.5 Structure of thesis**

The thesis is organised as follows. This first chapter presents a brief introduction on microfinance, the research issues and questions, objectives and contributions of the thesis. Chapter 2 deals with broad concept of microfinance, microfinance institutions regulatory frameworks and its performance globally and particularly in South and East Asia. The chapter also analyzes the Vietnam financing system and

credit accessibility factors in domestic market. Chapter 3 presents new evidence on financial and social performances of microfinance institutions in South and East Asia region. Chapter 4 investigates the factors affecting the accessibility of households to informal credit market in rural area of Vietnam. The fifth chapter contributes to the microfinance literature by investigating the gap of credit access between the dominant ethnicity in Vietnam, or Kinh, and the other ethnic minority groups. Accessibility to both formal and informal credit sources is also discussed. Finally, chapter 6 will provide conclusions of the study, proposes relevant policy implications and outlines future research based on the research findings and limitations. Therefore, the detail structure of thesis is as follows:

Chapter 1: General Introduction

Chapter 2: Microfinance markets in South and East Asia countries

Chapter 3: Micro finance institution performance assessment – New Evidence for East and South Asia

Chapter 4: Rural household access to informal credit in Vietnam: Evidences using random forest.

Chapter 5 Formal and informal rural credit accessibility of ethnic minority households in Vietnam

Chapter 6: Conclusion

## **Chapter 2. Microfinance markets in South and East Asia countries**

This chapter describes microfinance market in South and East Asia, including regulatory framework, credit supply, credit demand and disparity of access of rural households. Due to geographical heterogeneity, the Vietnam rural credit market may differ from its umbrella, the South and East Asia credit market. This chapter will first describe the global and then South and East Asia credit market, the market performance and diversity of credit access in the region. The operation of MFIs and credit accessibility of the rural area in Vietnam will then be studied. The chapter is organized as follows. Section 2.1 provides a global overview of microfinance. Section 2.2 is devoted to microfinance in the South and East Asia. Section 2.3 provides an in-depth description of Vietnam rural credit market, including formal and informal sectors.

### **2.1 Overview of global micro finance**

Microfinance provides financial services to very poor people for purpose of helping them to create more income to support their families. In the last 50 years, microfinance institutions (MFIs) have played a vital role in alleviating poverty in developing countries (Barry and Tacneng, 2014). According to the World Bank, microfinance programs are identified as an approach to solve income inequality and lessen poverty. World Bank stated 2005 as a year of promote their poverty reduction goal. In addition, United Nations set up the agenda of “Transforming our world: the 2030 Agenda for Sustainable Development” in the year 2015 to implement a plan of actions which has been adopted by 193 countries around the world. This agenda comprises of 17 sustainable development goals, and poverty abolition is one of the greatest targets for member countries (Saeed et al., 2018).

There is a general understanding that access to financial services plays an important role for the poor to improve productivity, generate assets, create income, and maintain food security. Earlier than the 1970s, the main provider of financial services to the poor was public sector often at subsidized interest rates while customers were mainly small and marginal farmers (Matin et al., 2002). High costs

associated with institutional weaknesses caused formal institutions failing to operate effectively (World Bank, 2001). During period between 1980 and 1996, semi-formal financial institutions were created to focus their attention on poor women microbusinesses with no collaterals. A new lending methodology, known as microfinance, was developed in YEAR by non-government organizations (NGOs) and banks with special charter. These institutions, now usually known as microfinance institutions (MFIs), targeted the poor through a diversity of advanced approaches. These approaches, which help maintain high repayment rates, include group lending, regular repayment plans, and collateral alternatives. Particularly, microfinance programs involve small credit, savings, and insurance to offer to poor producers. It also provides work-based training to improve productivity and organizational connection, and building training to the poor. It has become a crucial tool for poverty alleviation in many countries in the world, including South and East regions (Thapa, 2006).

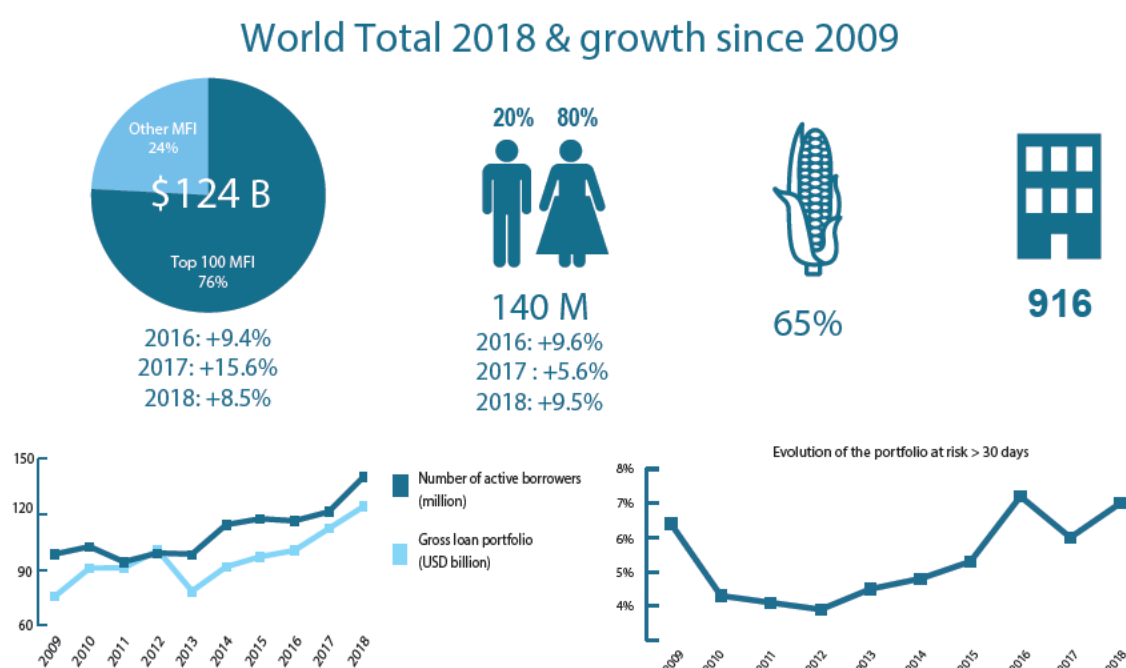
Recent researches proved that access to microfinance helps to alleviate poverty, encourage women empowerment and increase living quality at the village level (Khandkar, 2005). It also contributes to women's rights by encouraging mobility, political involvement, and decision-making.

Over the past decade, MFIs have also showed recording improvement in their efficiency (Figure 2.1). In ten years, MFIs have provided loans of some hundred billion dollars, with an annual growth rate of 11.5% in ten years (Microfinance Barometer, 2019). The number of borrowers continued to increase globally at the same time, however at a slower rate than in the 2000 to 2010 period. In addition, although there was a sharp increase of 56 % in the cost per borrower from an average of \$68.4 in 2009 to \$106.7 in 2018, the operating expense ratio diminished by 2.7 points at the same time. During this period, MFIs also achieved an increase in their returns on assets of 1.3 points and equity of 2.9 points. In 2018, 139.9 million borrowers used services of MFIs, compared to only 98 million in 2009. Particularly, 80% borrowers are women and 65% are in rural area. This remains stable over the last decade, although the total number of borrowers is increasing.

MFIs recorded a growth in 2018 (+8.5% compared to 2017) with an estimated credit portfolio of \$124.1 billion.

South Asia continues to be the leader in global microfinance with the largest borrowers (85.6 million in 2018) and a growth rate faster than in other regions (+13.8% in financial year 2018). It also in the top three markets of borrowers including India, Vietnam and Bangladesh. It should be noted that most borrowers are female (89% in 2018). Although South Asia is accounted for almost two-thirds of global borrowers, it is only second in terms of credit portfolio with an outstanding amount of \$36.8 billion as of 2018.

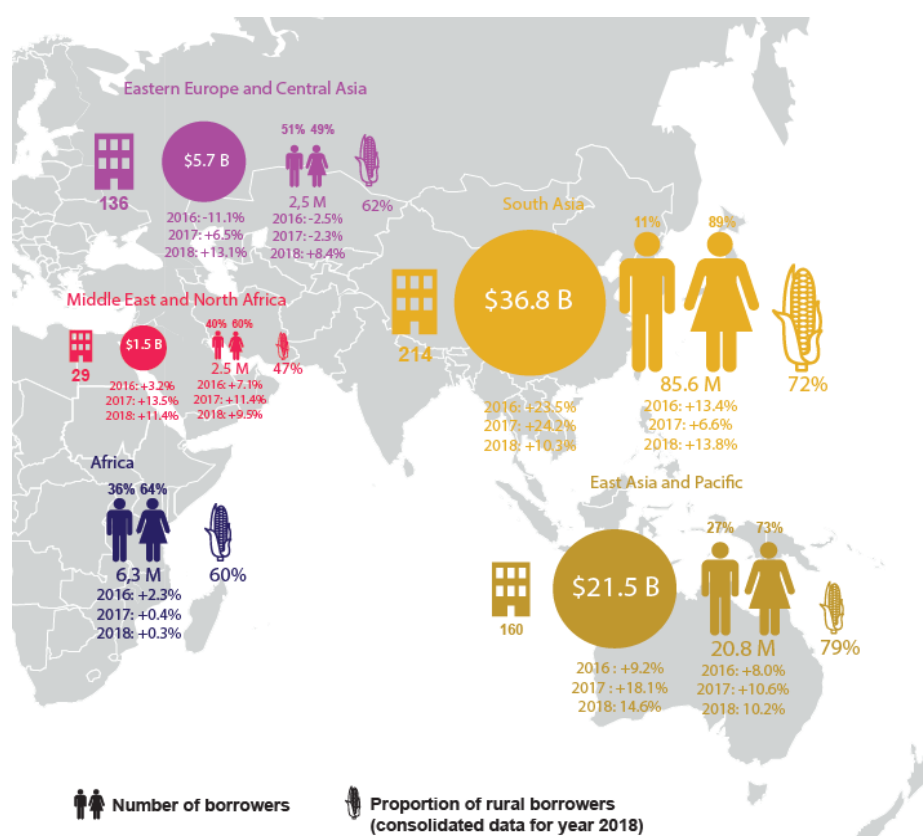
**Figure 2.1: Global Microfinance**



*Source: Micro finance Barometer 2019*

On the other side, Latin America and the Caribbean were accounted for 44% of the total microfinance market, with \$48.3 billion in outstanding loans with the average growth rate of 5% per year since 2012). This is the second largest market with number of borrowers, with 22.2 million customers in 2018. MFIs in this region are the least rural-oriented, with rural market is accounted for only 23% of their clients.

**Figure 2.2: Micro finance by regions**



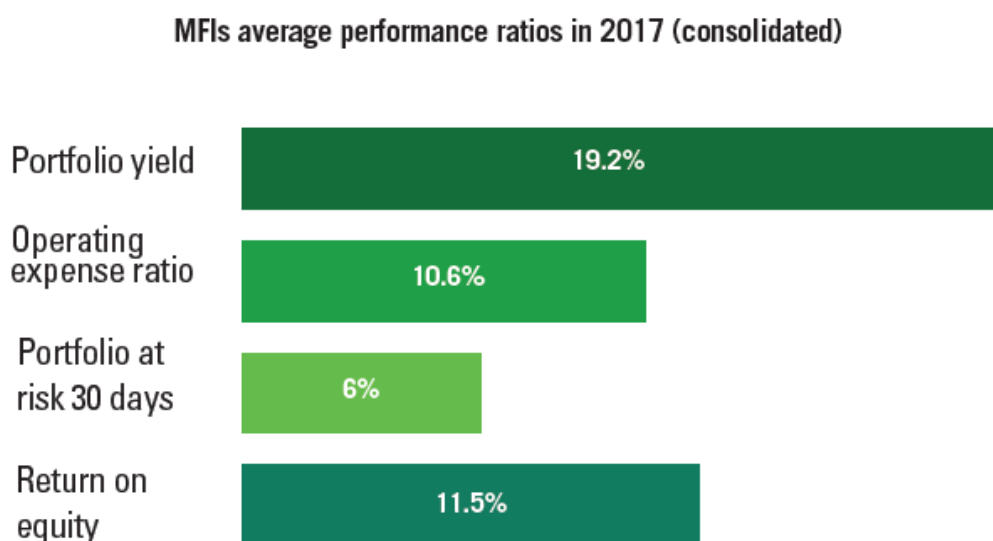
*Source: Micro finance Barometer 2019*

In contrast to these leading markets, Eastern Europe and Central Asia as well as Middle East and North Africa (MENA) are smaller markets (Figure 2.2). Nevertheless, they continue to grow both in terms of the number of customers and the size of credit portfolio. Eastern Europe and Central Asia have seen their number of borrowers increase by more than 30% since 2012 to around 2.5 million in 2018, a similar evolution is being also observed for the MENA region (Microfinance Barometer, 2019). MFIs in these two regions also have the lowest proportion of women borrowers, with 49% in Eastern Europe and Central Asia and 60% in MENA area in 2018, respectively. However, credit portfolios in these two regions also increased during the period. While the MENA region only has weak growth of 1% in the year end 2018, Eastern Europe and Central Asia achieved an increase of 5% after the decrease in 2015 and 2016.

In African region, the outstanding amount has increased by 56% since 2012, although the number of borrowers increased by 46% to achieve 6.3 million people in

2018. While quality portfolio is still low (13.6% of portfolio annual return (PAR) > 30 days in 2017) and costs per borrower is high, the portfolio continues to achieve a good yield of 20%. However, it still showed the decrease of 6.6 points. The return on assets decreases by 1.4 points though it still gets the result of 1.9%. Figure 2.3 below summarizes the average performance ratio of MFIs in 2017.

**Figure 2.3: Global microfinance performance**



*Source: Micro finance Barometer 2019*

## **2.2 Micro finance market in South and East Asia**

The role of microfinance in Asia is increasing and it is recognized legally as a provider of credit to the poorest who normally may not be able to get the loan from formal providers. In countries such as Bangladesh, Philippines, India and Indonesia, microfinance has developed well, whereas in other Asian countries such as Myanmar, China and Laos, this sector is still developing.

Financial services in developing economies, particularly those in South and East Asia, are currently facing challenges. In particular, less than 27% of adults in Asia has an account in a formal financial institution and only 33% of enterprises has credit or loan from a financial institution.

This section presents an overview of regulatory framework, market performance and disparity of access of micro finance in South and East Asia.

### 2.2.1 Regulatory frameworks of microfinance institutions in different countries

The banking system is practically standard in most countries. However, Asian countries have different frameworks in terms of microfinance industry due to their regulatory environments. Examples of different kinds of institutions are as follows:

- deposit taking non-banking financial companies
- non-governmental organizations (NGO)
- banks
- non-deposit receiving NBFCs (Non-Banking Financial Companies)
- co-operatives and
- digital finance companies

The types of institutions providing microfinance are wide variety since it is recognized as an attractive business opportunity and a tool for social services. Table 2.1 below shows a presentation of the leading institutions in microfinance and their regulators in Asian countries (PricewaterhouseCoopers, 2017).

**Table 2.1: Type of leading institutions in microfinance and regulators in Asian countries**

Country	Institutions	Regulator
India	NBFC-MFIs, Banks, NGOs	Reserve Bank of India Self-Regulating Bodies- MFIN, Sa-Dhan
Bangladesh	MF- NGOs, Specialised Institutions, Commercial Banks	Microcredit Regulatory Authority
China	Deposit-taking Village and Township Banks, Micro-credit companies, Digital Financial companies, Rural Credit Companies, MFI-NGOs	Unregulated
Russia	MFIs, Credit Consumer Society, Agricultural Cooperatives	Unregulated
Cambodia	MFIs deposit taking, Banks	Cambodia Microfinance, Association/ Central Bank
Laos	Non-Deposit Taking MFIs, Village Funds, Savings & Credit Unions	Bank of Laos
Vietnam	Vietnam Bank for Agriculture and Rural Development & Vietnam Bank of the Poor	State Bank of Vietnam (limited)
Indonesia	Banks Commercial Banks	Indonesian Financial Services Authority
Philippines	MFI NGOs Banks Cooperatives	Central Bank of Philippines
Myanmar	State-owned Banks Cooperatives Agriculture Development Companies	Ministry of Finance and Revenue

*Source: PricewaterhouseCoopers (2017)*



From Table 2.1, it is worth noting that:

- Deposit taking microfinance companies are dominant in many countries such as Bangladesh, Cambodia, Laos, Nepal, Philippines, Myanmar and Vietnam. However, in India, regulations do not allow NBFC MFIs and NGO MFIs to take deposits.
- In Philippines, the microfinance NGOs are dominant. The relationship with their group and the regulator's role enhances the development of the Philippines microfinance NGO industry.
- In Indonesia, commercial banks have an important role in microfinance industry. This has primarily been due to a regulation issued in 2007 by the government to banks to offer 20% loans to micro, small and medium enterprises. This mandate has permitted banks to create smaller units that act independently in remote areas to provide loans to the poor and low-income population. Recently, Islamic microfinance has served the large Muslim population of the country.
- In most countries, the Central Bank is in-charge for the microfinance industry, except for Myanmar when the Ministry of Finance and Revenue is supervising the microfinance sector. Hence, the Central Bank is the regulator which can control growth and expansion of microfinance in an objective manner. The regulator has the important role in creating regulatory environment to develop and lead the microfinance sector.

A balanced regulatory environment for micro finance industry is often required. In fact, since the undoubtful value that the microfinance sector offers to low-income population, it can be claimed that the regulations should be very favorable. Particularly, MFIs developed in India in 1970s and the liberalization of the economy in the following two decades enhanced growth in this sector. In the 2000s, MFIs grew at a fast rate due to the huge demand from the low-risk and low-income customers for collateral free loans. The Andhra Pradesh microfinance crisis in 2010 created a strong response from the RBI, resulted in the formation of the Malegam Committee to mentor this sector. Since new regulations were issued in 2011 and the sector then continued to strongly develop. Capturing the growth of micro finance industry and future opportunities, RBI

granted licenses for seventeen small finance institutions in which eight of them were microfinance institutions.

Bangladesh is another example of a well-known regulator for the microfinance sector, which has contributed to the growth of the industry by creation of a Joint-Committee with major stakeholders who can help the MFI industry. This occurs in other Asian countries as well. In India, the microfinance sector provides loan in areas that banks do not necessarily reach; the regulator needs to help this segment being success. Demonetization also affects the operation of MFIs, as it a mostly a cash transaction business.

In majority of Asian countries, microfinance institutions are naturally deposit-taking. Examples are Cambodia, Bangladesh, Vietnam and Laos, where the capability to attract deposits has been helpful in providing better service for the poor and access to cheaper source of funds. MFIs in India have developed in the recent decade and now face strong competition from Small Finance Banks and Payment Banks. They also face criticism for high interest rates due to high cost of funds. Another example is the government of Indonesia who offers banks with special capital called Kredit Usaha Rakyat (KUR), with cheaper cost so banks can provide lower interest to customers.

In Vietnam, microfinance institutions are facing competition with the Vietnam Bank for Social Policies, which offers loans at low rates from 1 to 8%. Since MFIs provide loans at higher rates, they face criticism from customers that their interest rates are more expensive. This creates intense pressure on MFIs in Vietnam to reduce interest rates even when their operating costs are larger and this situation creates an unhealthy environment.

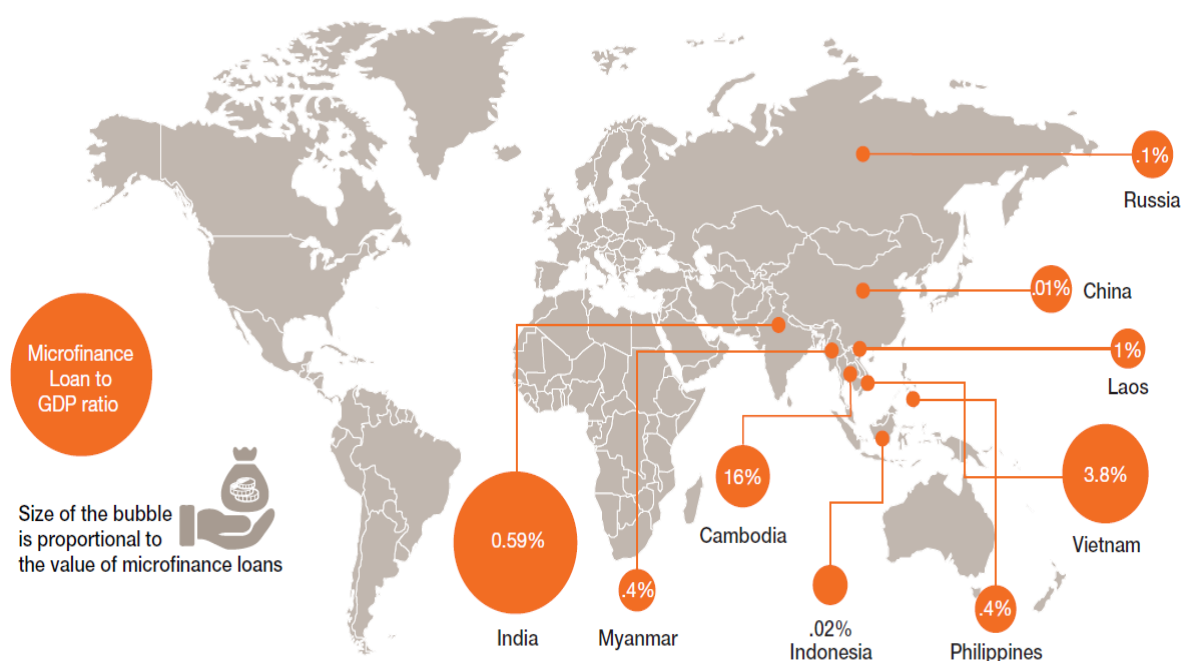
To protect borrowers from overpriced rates of interest, most South and East Asian countries have put a ceiling on interest rate offered by MFIs. Particularly, the interest rate is around 13% in Vietnam and up to 30% in Myanmar. Indian ceiling interest rate on microcredit is one of the highest in the region although this country has a developed and active micro-finance industry. The regulator allowed MFIs in India not to fix ceiling interest rate limit which created many difficulties for both the low-income borrowers and MFIs.

### ***2.2.2 Performance of microfinance in South and East Asia***

Microfinance in Asia has seen its fair share of ups and downs. The industry has gradually gain legal recognition as a credit provider to customers who often may not be able to access credit through formal systems. While industry in the countries such as India, Indonesia, Bangladesh and Philippines have developed, in other Asian countries such as China, Laos and Myanmar, the market is still developing. It is proved that microfinance industry contributed significantly to the improvement of financial inclusion in most of the Asian countries, i.e., Philippines, Sri Lanka, Vietnam, Nepal, Thailand and Bangladesh (PricewaterhouseCoopers, 2017). While microfinance is a main source of funds for the lower income population class, it still does not contribute significantly to overall lending in some countries. While in mature market, there is a concentration of MFIs, in immature markets there is a lot of room for growth. Particularly, an indicator of the growth in the sector is the ratio of microfinance loans to the Gross Domestic Product (GDP), which is still low in mature markets such as India, Indonesia and Philippines. However, India is the leader with gross loan portfolio of USD 12.3 billion for MFIs. In addition, Bangladesh is high not only in the size of the microfinance loan portfolio but also in the contribution of this loan size to GDP. In summary, Figure 2.4 provides an overall picture of Microfinance Penetration in Asia (Pricewaterhouse Coopers, 2017).

MFIs in East Asia and the Pacific have grown by 13.1% in 2018, achieving a portfolio of \$21.5 billion. In the same year, the number of borrowers increased by 10.2%, raising by 0.8 million borrowers with 73% of female clients and 79% clients from rural area. Since 2012, MFIs in this region showed an average increase of 16% per year, supported by a moderate growth of 6% per year in the number of clients (Financial Barometer, 2019).

**Figure 2.4: Microfinance Penetration in Asia (Loan to GDP Ratio)**



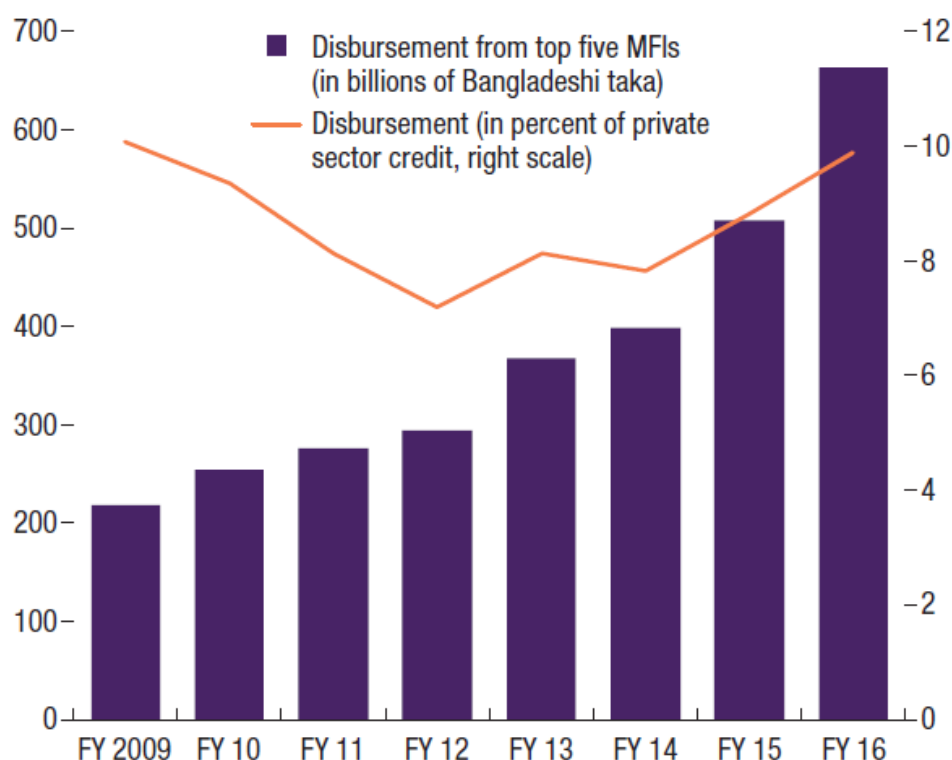
*Source: MixMarket, World Bank, UNCDF (2017)*

Banks with sponsorship from Government are vital source of fund to micro-finance in countries such as India, Sri Lanka, Indonesia, and Vietnam. Many of these organizations often receive large amounts of subsidy for its operation. However, Bank Rakyat Indonesia (BRI) is major exception since it does not only operate by it self but also lend to the nonpoor households (Morduch, 1999). BRI requires individual borrowers to put up collateral instead of performing group lending which can lead their work more efficiency. BRI assists a large number of households, including poor families. The Bank's consolidated assets, was \$105 billion by the end of 2019 and was the largest Indonesia's financial group (BRI bank, 2019).

In Bangladesh, Nepal, Cambodia, Sri Lanka and Philippines, NGOs play important role in microfinance services. In particular, the total microcredit and microenterprise loans disbursed in Bangladesh in 2008-2018 reached an amount of BDT 1,201.91 billion, increasing by 14.91%. Sequentially, the number of customers increased to 25.40 million in which 93% of them are female. This accounts for 15.88% of the total population of Bangladesh. Three major MFIs include Grameen

Bank which offers loan up to 207.85 billion BDT, BRDB of 13.96 billion BDT and Jubo Unnayan Adhidoptor of 1.44 billion BDT, respectively. This microcredit program directly provides a source of working capital to the poor (Bangladesh Microcredit Regulatory Authority, 2018).

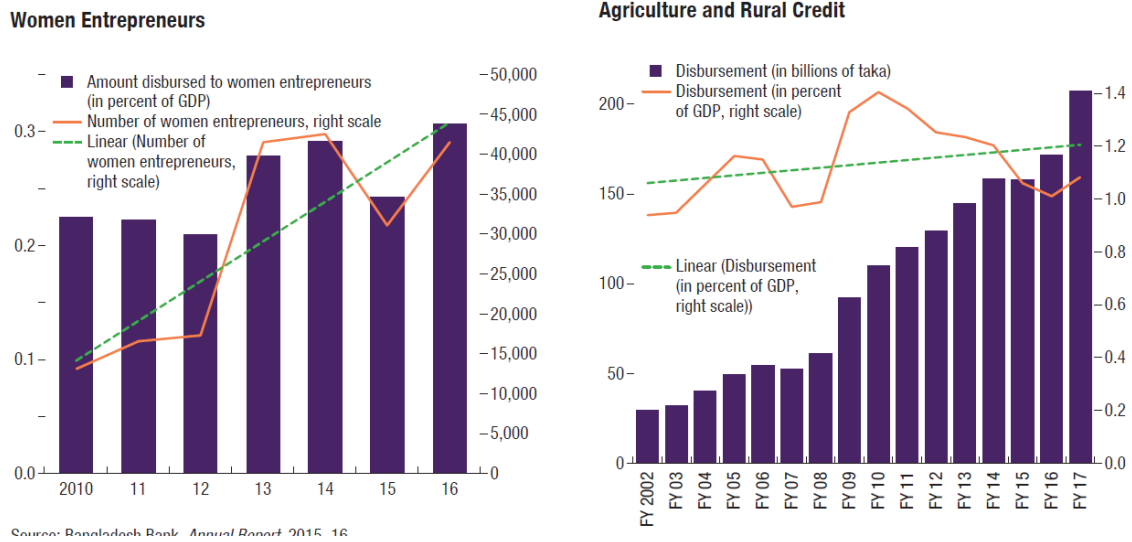
**Figure 2.5: Bangladesh: Disbursements—Five Largest Micro-Finance Institutions (MFIs)**



*Source: Bangladesh Bank (2016)*

Bangladesh has known a success story in providing financial access to groups that were little served by traditional credit institutions. Historically, Bangladesh's strategy has focused on microcredit. In 2016, total outstanding disbursements of the top five MFIs were around 10 percent of private sector credit provided by the banking system (Figure 2.5). Grameen Bank's success in poor alleviating has been widely imitated. Policy measures on financial access have been expanded, with the requirement that banks must open at least 50% of new branches in rural zones, set floors on credit to the agricultural and rural sectors on concessional terms and support to small and women entrepreneurs.

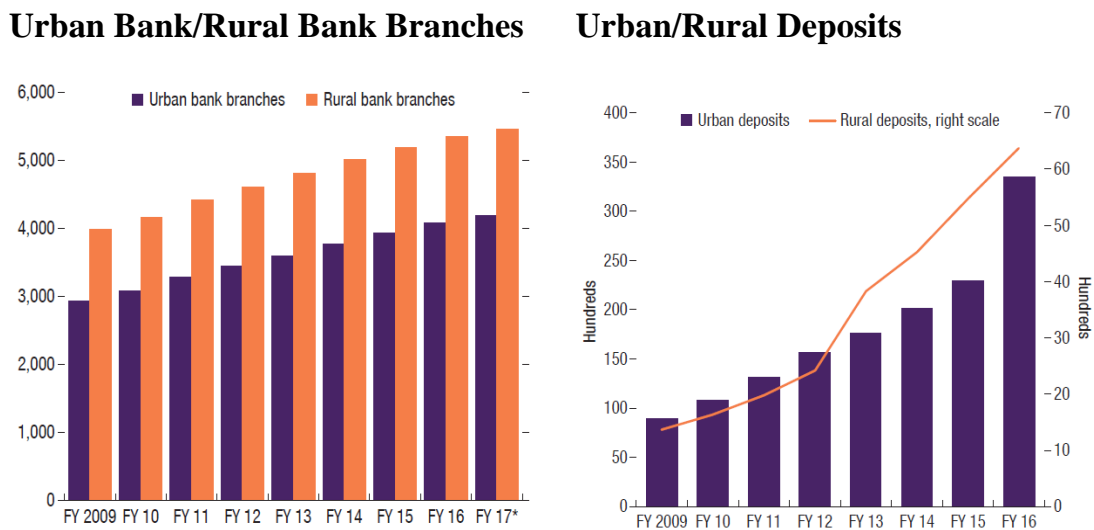
**Figure 2.6: Bangladesh rural credit performance**



*Source: Bangladesh Bank, Annual Report, 2015–16.*

**Figure 2.7: Bangladesh Bank operation by regions**

*(In billions of taka)*

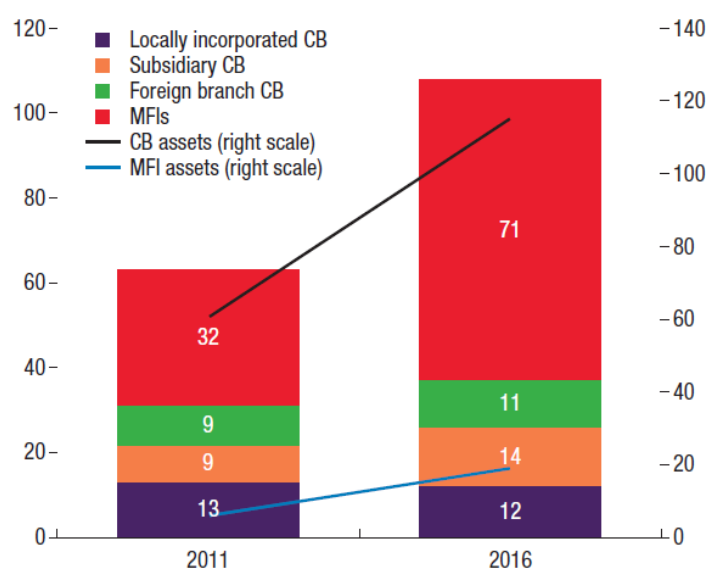


*Source: Bangladesh Bank, Annual Report, 2015–16.*

Bangladesh increases the effectiveness of its efforts with a pilot financial inclusion strategy. This strategy formed a principal framework to grow credit in priority sectors, micro-financing, gender priority, rural areas, and green financing (Figure 2.6). A digital ecosystem to make financial services more accessible for the customers has also been set up. However, the higher level of informal finance, the lower use

of formal financial services such as credit and debit cards, and bank accounts. Bangladesh has also applied experiences from other nations, such as strengthening the regulatory framework, requiring the payment of subsidized energy through bank system.

**Figure 2.8: Cambodia: Number of Institutions and Assets to GDP**  
(In percent)



*Sources: National Bank of Cambodia, Annual Supervision Report 2011–2016; and IMF staff estimates.*

Another case in the region is Cambodia. The Cambodian government has set up financial access as a priority. Financial access belongs to the objectives of the Financial Sector Development Strategy for the period from 2016 to 2025. Rapid growth in microfinance industry has led to improvement in financial access. MFIs are providing affordable financial services for the rural and poor groups. In the period from 2011 to 2016, the number of MFIs almost tripled, and the MFI-assets-to-GDP ratio raised from 4 to 20 percent (Figure 2.8). In 2016, MFIs offered loans to more than 2 million borrowers (20% of the adult population). As MFIs are now an important part of the financial sector, they may be a source of financial stability risks, depending on external sources of fund rather than the banking sector, and are expanding at a faster pace

due to severe competition in the market. Despite this progress, financial access remains low and inefficient. The rate of Cambodian adult population having bank accounts is much lower than the global rate of 60 percent (IMF, 2018).

In addition, another popular type of lending which is efficient is group lending, a model initiated by Grameen Bank has been imitated in many countries including China, India, Malaysia, Sri Lanka, Philippines, Vietnam and Thailand. Another model of lending is the self-help group model (SHG) which was recommended by NGOs (MYRADA) in India and was imitated by both banks and MFIs, in many countries in South East Asia and Africa. Each SHG has approximately 20 members and are based mostly on their members' savings. They also look for of another source of funding to increase their capital. The groups set up the terms and conditions of loans to their members. This model is entirely suitable for microfinance for the health and education purpose. In addition, cooperatives create the major providers of microfinance in countries such as Philippines, India, Thailand, Sri Lanka and Vietnam. In Sri Lanka, there were 1,933 cooperative rural banks at the end of 2010, with 9.6 million savings accounts being maintained by CRBs (Jayamaha, 2014).

### ***2.2.3. Disparities in microfinance access in South and East Asia***

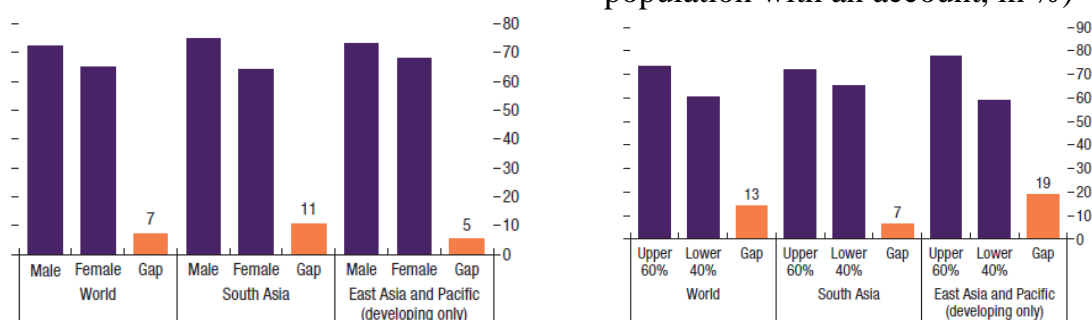
The gap of micro finance access in South and East Asia is also important within countries. Although there are recent improvements, large inequality still remains between urban and rural areas, men and women. For instance, only about 10 % adults of the poorest quintile class in Indonesia have a access to banks compared with around 60 % of the richest quintile. Similarly, only about 46% of male adults of the poorest quintile in India have a bank account, compared with 79% of the richest one. India's inequality between the highest income and lowest income groups is even more obvious when comparing the borrowings from a financial institution (almost three-time difference). Moreover, Figure 2.9 shows gender gap in South Asia which is still significant where less than 40% of women have a bank account, compared with nearly 60% of men (IMF, 2018). South and East Asia needs to have intensive efforts to narrow the large gap in financial access. Other



groups such as the uneducated, young, unemployed and the poor in rural areas have similar concerns.

**Figure 2.9: Average Within-Country Inequalities (Aggregated by Subregion)**

**Inequality of Access by Gender, 2017** (Share of population with an account, in %) **Inequality of Access by Position in Income Distribution, 2017** (Share of population with an account, in %)



Source: IMF (2018)

**Table 2.2: Financial Inclusion Index—Ranking 2015**

	Country	Rank		Country	Rank
Fourth Quartile	Singapore	1	Second Quartile	New Zealand	16
	South Korea	2		Marshall Islands	17
	Japan	3		Fiji	18
	Maldives	4		Vietnam	19
	Thailand	5		Australia	20
	Brunei	6		Vanuatu	21
	Indonesia	7		Nepal	22
	Tonga	8			
Third Quartile	India	9	First Quartile	Mongolia	23
	China	10		Bhutan	24
	Sri Lanka	11		Cambodia	25
	Philippines	12		Timor-Leste	26
	Bangladesh	13		Lao P.D.R.	27
	Samoa	14		Solomon Islands	28
	Malaysia	15		Myanmar	29
				Papua New Guinea	30

Source: IMF (2018)

Table 2.2 shows the country ranking in terms of financial inclusion, from the highest (dark green) to lowest position (orange), with Malaysia being the country with median level of financial access in Asia. Particularly, Vietnam is ranked in the third quartile with position of 19th, little below the median level. This financial inclusion index is based on three indicators: the number of ATMs per 100,000 adults, the number of bank branches per 100,000 persons and the number of bank branches per 1,000 km<sup>2</sup>. Greater financial inclusion is associated with significant

poverty reduction (IMF, 2018). Particularly, if all countries Asia-Pacific group with low financial inclusion would improve to equal to Thailand, the country of Asia's emerging market frontier, the population in poverty could fall by about 4 percent (equivalent to 20 million people).

## **2.3 Financing system and rural financing activities in Vietnam**

This part provides an overview of the social economic and legal environment of Vietnam, the national financial structure and the main microfinance providers in rural areas. The chapter aims to present a picture of Vietnam microfinance operation and evaluate the achievements and challenges of Vietnam's MFIs during the development progress.

### ***2.3.1 Country overview***

Vietnam's development during last 30 years is remarkable. Launching in 1986, economic and political reforms (Đổi Mới), have triggered fast economic growth which changed from one of the world's poorest countries into a lower middle-income country. From 2002 and 2018, GDP per capita increased by 2.7 times up to over US\$2,700 in 2019 and around 45 million people (50% population) were lifted out of poverty. Vietnam is successful in considerably reducing poverty rates from over 70 percent to below 6 percent (US\$3.2/day PPP). However, ethnic minorities are accounted for 86% of Vietnam's remaining poor group. In 2019, Vietnam's real GDP increased by 7 percent in 2019, showing one of the fastest growth rates in the region. Its economy continues to show fundamental strength, supported by dynamic export-oriented manufacturing and extensive local demand.

The Vietnamese economy has been affected seriously by the COVID-19 pandemic, but has showed magic adjustment. The impact of the pandemic had not been as serious in Vietnam as in other countries due to active solutions at the national and provincial levels. The domestic economy remains strong with a projected GDP growth rate of 6.3 percent in 2021 (ADB, 2021). Although Vietnam does not expect a recession, the influence of the ongoing COVID-19 pandemic is difficult to predict due to its uncertainty. COVID-19 also requires tougher reforms

to recover the economy, such as creating business atmosphere, promoting the digital connection and improving efficiency of public investment. Those are the key steps for Vietnam to consider faster and stronger reform strategies.

Vietnam is facing social change and rapid demographic. Its population has reached 96.2 million inhabitants in 2019 (up from around 60 million in the year 1986) and is expected to raise to 120 million by 2050. In accordance with the 2019 Population Census, 55.5% of the population is under 35 years old with life expectancy increasing to 76 years, the highest among the group of countries with similar income level. However, the population is fast aging and Vietnam's middle class, accounted for 13 percent, is expected to increase to 26 percent of the population by 2026.

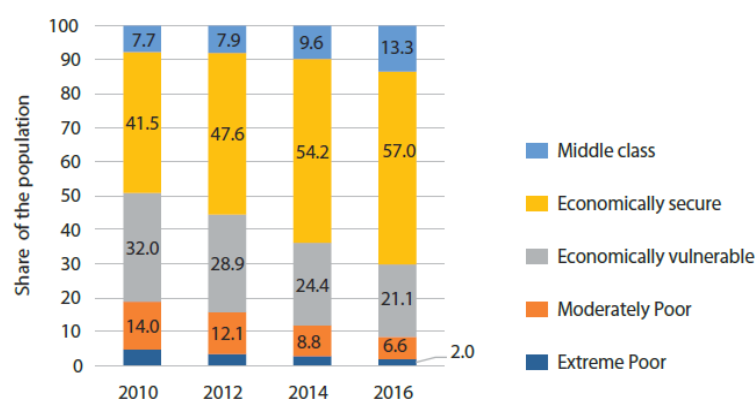
For the period from 2010 to 2020, the Human Capital Index (HCI) of Vietnam was from 0.66 to 0.69, which is highest among the group of lower-middle income countries. According to World Bank (2019), figure 2.10 shows that Vietnamese households are divided into five economic classes according to their daily consumption per head in 2011 using purchasing power parity (PPP):

- the extremely poor is the one who live on less than US\$1.90 per day
- the moderately poor is whose per capita consumption from US\$1.90 to US\$3.20 per day
- the economically vulnerable, who consume from US\$3.20 to US\$5.50 per person per day
- the economically secure, who consume from US\$5.50 to US\$15 per person per day, and
- the global middle class whose per capita consumption is larger than US\$15 per day.

The last two groups are defined as the “consumer class” since they have sufficient income to afford daily expenses, alleviate income shocks and are ready to pay for some non-necessity goods and services. The Vietnamese population is becoming richer and more urban. Vietnam's consumer class is growing rapidly mainly from 2014 to 2016, with 3 million people belonging to the global middle class. This class mostly lives in urban areas, where about 89 percent of the inhabitants are

economically secure and 29 percent in the middle class. The Southeast provinces have biggest population of economic security class (91 percent), while the Midlands and Northern Mountainous provinces have lower one of only 44 percent (World bank, 2019). Richer consumers have consumption patterns which can affect to connectivity needs in Vietnam, particularly in urban and peri-urban areas.

**Figure 2.10 Population by Economic Class from 2010 to 2016**



*Source: World Bank, 2019*

In the rural areas, there are 8,978 communes, 79,898 villages and around 16 million households nationwide. Population in rural area is 60.9 million persons, accounting for 65% of the total population. The labor force over 15 years old in rural regions is 37.18 million, around 67.8% of the total labor force in the whole country. By the end of 2017, the number of poor households is 1.99 million (accounting for 6.7% of total households) while the number of near poor group was 1.48 million (around 5.32% of total households) (Vietnam Microfinance Working group, 2019).

Vietnam has 54 ethnic minorities which include main ethnic group of Kinh (Viet) making up 86% of the total population while 14% remaining are from the 53 small, diverse ethnic groups. Labor market improved in the ethnic minority regions over the past five years. While agriculture is still the major source of employment, participation in both formal and informal labor market has increased, particularly for ethnic minority youth. Nonfarm income sources are now larger than income generated from agricultural industries. Specifically, wage and other income from non-farm activities account for around 50 percent of total family income for all ethnic

minorities. This shows that the top performers ethnic minorities earn their main income outside agriculture while the bottom groups still heavily depend on agriculture as their main income (World Bank, 2019).

Though Vietnam is currently defined as a lower middle-income country, the gaps among the ethnic minority groups have become more apparent and have widened. Poverty rates among these minority groups differ extensively, ranging from 27.09 percent to 88.17 percent using the poverty line of the Government of Vietnam and the 53 Ethnic Minorities Socio-Economic Survey. Recent evidence showed that some minority groups have “out-performed” other groups in poverty reduction and human capital development (CEMA, UNDP and Irish Aid 2017). WellsDang (2012) explain the success of those ethnic minorities in escaping poverty because government provides support on credit, infrastructure, agricultural training and their own efforts. These efforts include changes to commercial agricultural production and willingness to modernization (World Bank, 2019).

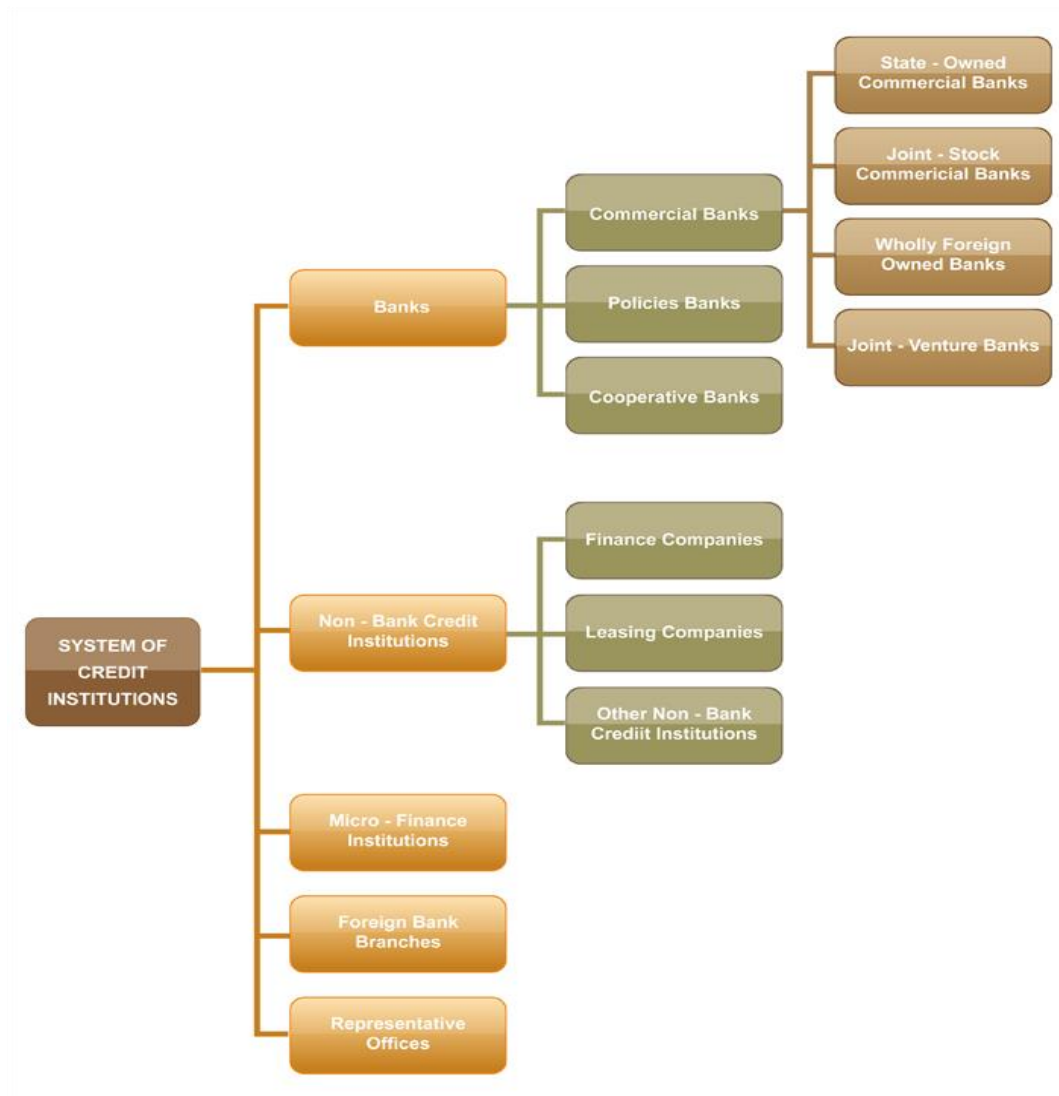
### ***2.3.2 Financing system and rural financing activities in Vietnam***

This part provides an overview of the social economic and legal environment of Vietnam, the national financial structure, main microfinance suppliers as well as their characteristics. It presented a picture of Vietnam microfinance operation, evaluated the achievements and challenges to Vietnam’s MFIs during the sustainable development progress.

Before 1988, Vietnam operated a mono-tier banking system, including the State Bank of Vietnam (SBV), which played the role of central and commercial bank, and two wholly state-owned banks: The Bank for Investment and Development (BIDV) and the Bank for Foreign Trade (Vietcombank). In 1988, the Government of Vietnam reformed the financial system: SBV plays only the role of central bank and four wholly state-owned commercial banks are formed, comprising of VBARD, BIDV, VCB and Vietinbank. Vietnam Bank of the Poor (VBP), a not-for-profit organization, was established in 1995, with a role in poverty alleviation. However, the financial reforms also decrease traditional credit cooperatives and loss of trust in the domestic financial system from the general public. Traditional

credit cooperatives are responsible in attracting deposits and offering credit to households, small businesses and manufacturing cooperatives.

**Figure 2.11: Banking system in Vietnam**



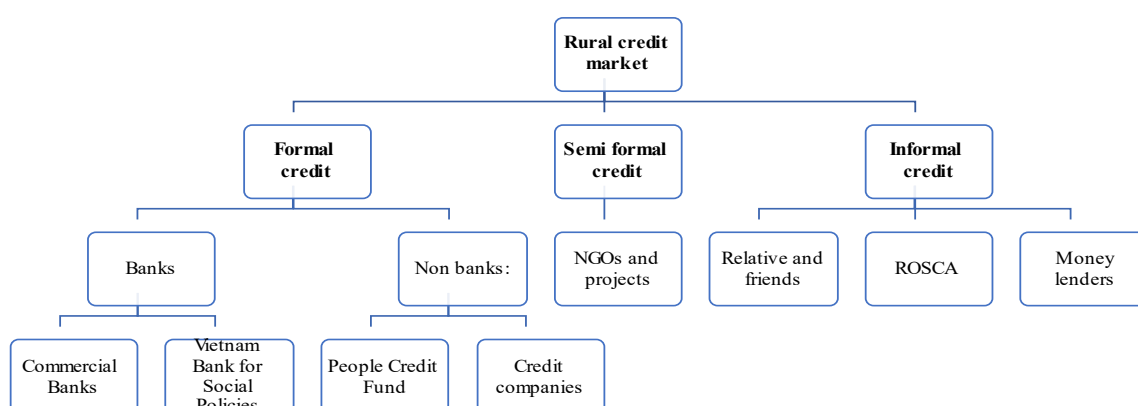
*Source: SBV (2016)*

The collapse of the credit cooperatives and the establishment of public banks, cause the government to form new People's Credit Funds (PCFs) in 1993 to attract domestic savings. After the reforms of credit system in the late eighties, the Government of Vietnam launched the Hunger Eradication and Poverty Reduction (HEPR) which focused on improving poor access to financial services, especially in rural areas. Government-owned banks (VBARD and VBP) are the leading pro-

viders of financial service to low-income households, while PCFs focuses on savings and also credit (Figure 2.11). In addition, rural local banks play a much smaller role. Microfinance programs are established in the 1990s with supervision by international programs and NGOs and partnership with highly reputed organizations such as the Vietnam Women's Union (VWU). Social funds started to concentrate in microfinance, such as the CEP (HCMC Labour Confederation) and TYM Fund (VWU). By 2018, the formal financial sector including three leading banks such as VBARD, BVSP and PCFs accounts for 70% of the rural financial market in Vietnam.

The Vietnam rural credit market is segmented and structured with the formal, semi-formal and informal credit sectors co-existing. The formal credit sector, led by the Agribank, mainly provided credit for agriculture with a collateral requirement. Most poor cannot access loan from Agribank. In 1995, the Vietnam Bank for the Poor was created to provide credit to this segment. Besides formal market, a proportion of families seek credit from the informal market such as friends, relatives and moneylenders at very high interest rates which may increase up to 80% per annum in 1993. At present, the Vietnam rural financial market consists of three sectors: the formal, semi-formal and informal markets. Figure 2.12 below shows the types of lenders in each credit sector in Vietnam rural financial market.

**Figure 2.12: Structure of rural credit market**



*Source: author (2020)*

### 2.3.2.1 Formal credit market

The Vietnamese banking system consists of a wide range of players, from large state-owned and joint-stock commercial banks to small privately held banks. There are two tiers in banking sector in Vietnam. The first one is State Bank of Vietnam (SBV) which is responsible for monetary policy and supervision/regulation of the banking system in Vietnam. The second one consists of commercial banks, financial companies, credit co-operatives, people's credit funds, and insurance companies. The main group driving Vietnamese banking system is commercial banks which include 4 state-owned commercial banks, 28 joint stock commercial banks, 2 joint venture commercial banks and 9 foreign owned banks (Figure 2.13). State-owned commercial banks represented 45% of market share in terms of total assets as of December 2017, in which Agribank is the leading bank in terms of total assets, network and still 100% state owned, followed by Vietcombank, Vietinbank and BIDV.

**Table 2.3: Lists of formal financial institutions**

No	Type	2018	2019
1	SOCBs	4	4
2	Compulsory acquired banks	3	3
3	Social Policy Bank	1	1
4	Development Bank	1	1
5	JCBs	28	28
6	Joint-ventured bank	2	2
7	100 percent foreign-owned bank	9	9
8	Foreign bank branch	49	49
9	Non-bank CIs	26	26
10	Cooperative Bank	1	1
11	PCFs	1,183	1,182
12	Microfinance Institutions	4	4

*Source: SBV (2019)*

Vietnam's banking sector has shown intensive improvement due to steady inflation and interest rate, favorable business environment for foreign investment and



a move from deficit to surplus of the current account. This plays a vital role in Vietnam's economic development in the last decade.

Vietnamese banks are open for foreign investments but they are limited to 30% only. Joint-venture and 100% foreign-owned banks account for around 10% of total assets, but 22% in terms of charter capital (PricewaterhouseCoopers, 2017).

Joint stock commercial banks (JCB) have smaller capital/deposit requirement and more diversified shareholder structures compared to state owned commercial banks. There are currently 28 JCBs, which the leading ones are SaiGon Joint Stock Commercial Bank (SCB), Military Joint Stock Commercial Bank (MBB), Vietnam Export Import Commercial Joint Stock Bank (EIB), Asia Commercial Bank (ACB) and SaiGon Thuong Tin Commercial Joint Stock Bank (STB).

**Table 2.4 Financial performance of Banking sector**

*Unit: percent*

	ROA	ROE
SOCBs	0.88	15.94
Social Policy Bank	0.15	0.79
JCBs	1.07	14.00
Joint-ventured foreign banks	1.13	8.02
Finance, leasing companies	3.32	17.51
Cooperative Bank	0.56	5.10
PCF	0.79	11.90
<b>Total</b>	<b>1.01</b>	<b>12.95</b>

*Source: The SBV (2019)*

The Vietnam Bank for Social Development (VBSP) has strategy to develop saving and lending for the group of poor, including microfinance products (loans incorporated with small value savings from VND30,000 to VND50,000). The group leader is in charge to collect savings and debts of the group members and each member has a personal account to conform a strict procedure. Following to this

channel, there are over 6,410,702 poor people, saving and lending group members with 190,000 saving and lending groups in villages across the country.

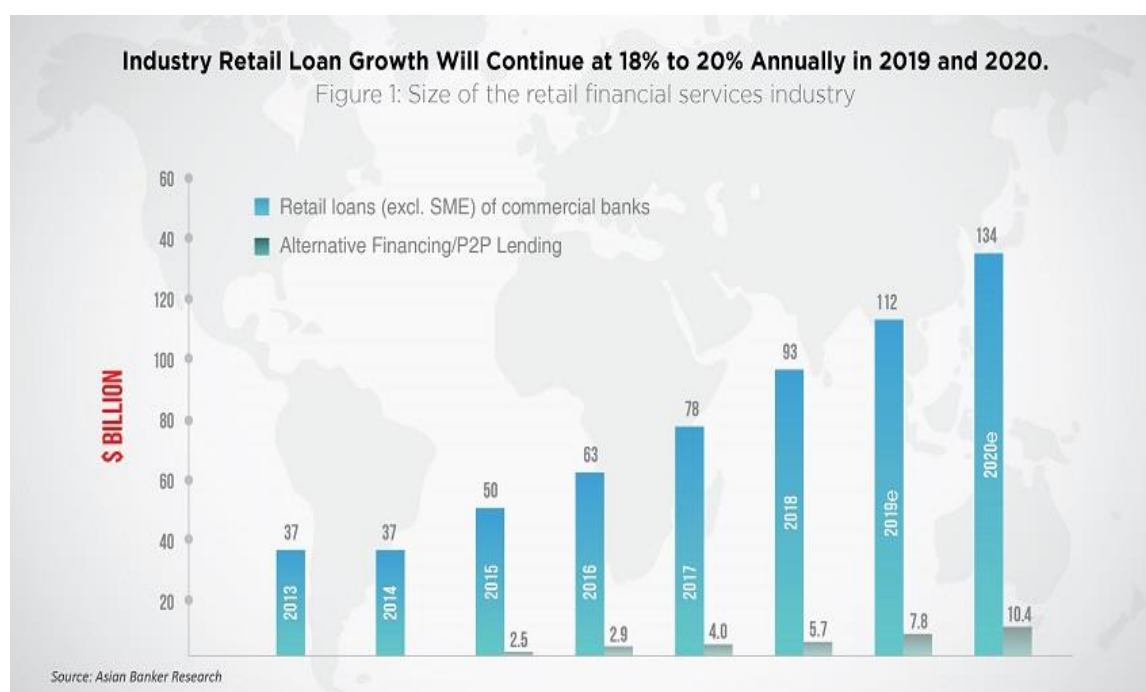
In addition, SBV had granted 5 licences to HSBC, Standard Charter Bank, ANZ Bank, Shinhan Bank and Hong Leong Bank to operate as wholly-owned foreign banks.

Table 2.4 above provides bank sector financial performances.

Between 2019 to 2022, bank system can promote fully digital banking and make more changes to enhance fully into a fast-growing consumer banking market. The annual growth rate of retail loan is 20% in 2019 and 2020 with consumer finance being the key business driver.

Banks in Vietnam readjusts their business towards retail financial sector in the last decade. Particularly, the retail income to total bank income improved from 17% in 2010 to 50% in 2018 by the top three retail banks. In addition, figure 2.15 shows the retail financial services market for commercial banks which has expanded to \$134 billion by 2020.

**Figure 2.13: Retail loan industry**



*Source: The Asian Banker (2019)*

### *2.3.2.2 The Informal Credit market in Vietnam*

The informal credit market plays an important source of loan for poor households in rural area. This consists of (i) lending from families, relatives and friends carrying zero interest (ii) private lending by unrelated individuals and friends charging interest. Both types of credit do not need asset collaterals and are highly flexible. Informal credits are popular both in the arrangement of production working capital and cash. Hence, they may help to increase capital and mitigate consumption fluctuations and thus help the poor to alleviate poverty.

Informal credit from moneylender, is often known as “black credit” in Vietnam. This is a widely associated in the media with unlicensed operations, overpriced interest rates and strong loan sharking recovery. It has increased serious public concern in last two decades. Extensive media is reporting about the abuse that dishonest moneylenders impose upon borrowers and requirement for strong political action. In order to fix this issue, the government is enhancing credit liberalization to limit black credit or informal credit (Lainez, 2019).

The term ‘black credit’ in Vietnam is a synonym of ‘loan shark’ in English, which refers to a moneylender who imposes unlawfully very high rates of interest on personal loan. However, unlike ‘usury’ which mentions to the offering a loan at an interest rate that is five times higher than the cap interest rate for a profit purpose ranging from VND 30 million to VND 100 million (US\$1,290-4,300), the term ‘black credit’ is not legally defined in Vietnam. In fact, many loans offered by moneylenders may reach up interest rate up to 1,000% per annum. However, legally speaking, moneylender cannot be considered usurious if their profit is less than VND30 million. Media will define moneylender as ‘black credit’ if the term and conditions of recovery are strict. Black credit may exist due to many reasons. Firstly, commercial banks are blamed for continuing financial exclusion, in particular for imposing complicated loan procedures and requiring collateral and paperwork that applicants take time to provide. Secondly, borrowers are increasing their demand of capital for consumption and investment. This leads to poor farmers with

little or no collaterals and ethnic minorities living in remote areas to be most affected. These borrowers are mostly often financially illiterate and thus unable to plan well spending and saving and to follow the terms and rates requested by moneylenders especially when they borrow to face with economic shocks. Hence, moneylenders know the situation to develop their operations. They hide behind legitimate businesses including pawnshops, financial and car rental companies. The key to make their success is that they provide quick and easy unsecured loans without requiring fees or paperwork except, in rare cases, copies of household registration book, ID card and driver's license. However, they have aggressive method to ask recovery: they come to borrowers' homes to take assets, to play music loudly, or to lock the main door and install cameras. They may follow their borrowers' children and throw eggs at them, they throw shrimp sauce on the front doors of their clients, they harass relatives, in few cases, they may kidnap and murder. These harsh methods force many borrowers to sell their house and borrow from other to repay their loans, or to escape with their family. In the worst cases, borrowers may commit suicide.

#### *2.3.2.3 Access to formal and informal credit market in Vietnam*

People often believe on credit liberalization which can create superiority of a formal credit over an informal one epitomized by the dishonest moneylender. However, this prejudice of the informal credit sector may be biased. First, the frequent confusion of informal credit with black credit is arguable. Since the Renovation reforms in 1986, informal credit has served as a powerful tool for development. Specially, small, short-term and unsecured loans have been important in financing the needs of immediate capital for households and entrepreneurs. Research shows that households, garment and fish traders and migrant continue to demand extensively on informal credit source. Therefore, the immediate disappearance of this market segment is unlikely to happen soon. Furthermore, informal credit cannot be reduced to moneylending, as it is but one of its many diversified sectors. While some moneylenders charge high interest rates and use harsh procedures on loan recovery, others offer cheaper and valuable services to market under more flexible

conditions. In many cases, moneylender illustrated their kinder people and hesitate motives for lending which are showed as combining of profit purpose and a help the community. While some of them earn profit on moneylending, others just express their willing to make ‘pocket money’ and help the poor in their capacity.

Second, formal credit is often known as being cheaper than informal credit. Many credit institutions are actually imposing very high annual interest rates of 40 to 50 % on consumer loans (Thien Ly, 2019). While this rate is lower than that of informal credit, it is irrelevant for borrowers who applied short term loans within some days, weeks or months. They can use this capital to solve their urgent demand. In addition, many borrowers do not have enough time to calculate the real cost and the terms of short-term loans, which is in the fine print of the contract that few borrowers read carefully prior to disbursement. This problem becomes more serious with automated lending technologies, which make the borrowing faster and easier but more problematic when reading fine print in accordance with terms and conditions of contracts.

Third, formal credit is described as being free from harsh recovery practices. However, Deville (2015) proved that debt collector in Europe bother defaulters in indirect ways to trace repayment, including letters, persistent calls and visits that creating stress and mental health to borrowers’ family and social life. Moreover, according to Lainez (2019), some persons borrowed from FE Credit and Home Credit blamed about harsh recovery methods including harassment, threats and akin to borrowers from black credit operators. According to Lainez (2019), some banks and financial institutes contract with debt collecting businesses to recover their bad debts. This clarifies why borrowers are under the impression that financial institutes and black credit gangs use similar strict recovery methods. In case the borrower cannot pay the loan, the bank hires legal deb collector to collect the money.

Fourth, formal credit is known to be more accessible than informal credit. However, this is likely the case if borrowers are able to clarify their residential situation. Nowadays, about 5.6 million people do not have household registration, including

36% of the residents in Ho Chi Minh City and 18% in Hanoi. Many unregistered residents are internal migrants who accounted for 13.6 percent of the population. The household registration is evidence to secure permanent residence and access to public services including consumer loan and subsidized credit. Overall, this encourages financial exclusion, helplessness and dependence on informal credit. It also threatens the fast expansion of consumer lending with purpose of deactivating black and informal credit.

#### *2.3.2.4 Microfinance activities in Vietnam*

Microfinance is the provision of various of financial services such as loans, deposits, money transfers, payment services and insurance to poor and low-income families. It supports the idea that low-income persons can lift themselves out of poverty if access to financial services is adequate.

Microfinance institutions (MFIs) in Viet Nam comprises of two groups: organizations performing officially their operation according to the Law on Credit Institutions (including TYM, Thanh Hoa MFI, M7-MFI and CEP); and more than 50 microfinance programs/projects/organizations. Moreover, there are more than 400 microfinance programs of various social organizations. MFIs in Viet Nam acknowledge the contribution of political and social organizations, particularly the Women Union. The MFIs have advantages in developing and providing products and services, including: (i) convenient access points in remote area; (ii) well trained skilled staff; (iii) flexible procedures for the poor and low-income households with no collaterals required; and (iv) comfortable products and services, including small value deposits.

Operational efficiency of licensed MFIs has been well improved. The savings/credit ratio of the four licensed MFIs has raised from 7-47% in 2010 to 35-86% in 2015, helping MFIs to have appropriate operating capital. At present, the number of licensed MFIs remains low while many semi-formal MFIs try to apply a license as the most important objective. MFIs currently encounter problems in expanding their clients due to some recent regulations which lift out low-income people from

microfinance customers. In fact, MFIs usually have strategy to focus on niche markets, primarily low-income households who encounter difficulties in full access to formal credit market. MFIs also face up with some limitations such as: fragile network of branches and transaction offices, and adequate working capital. Deposit mobilization at MFIs is still mainly compulsory savings (76%), while voluntary contribution is still very rare. Products provided are not diversified. Majority of them are lending, deposits and services associated with credit packages. MFIs can expand their range of products and services through the agent banking model to offer a full range of services (including savings, lending, money transfer, and insurance) but this model is not allowed by the current legal framework. Current regulations only allow MFIs to be established in the form of limited liability companies with great dependence on socio-political organizations. It is therefore difficult for MFIs to mobilize capital from private sector due to limited ability in capital contribution of socio-political organizations. This creates significant barriers to the transformation from semi-formal MFIs to licensed MFIs, as well as flexibility and efficiency in operational management of MFIs. On the other hand, MFIs are also facing difficulties in seeking for capital from banks due to compulsory collateral requirements, while in popular operation models in the world, MFIs can borrow from banks basing on outstanding loans. Appeared in the 80s of the 20th centuries, but until 2010, “microfinance” appeared specifically in the Law. In Credit Law 2010, Article 2, Clause 5 “Microfinance institution means a type of credit institution which mainly conducts some banking operations to meet the needs of low-income individuals and households and super small-sized enterprises”.

In fact, in Vietnam, microfinance organizations operate in two forms, licensed MFIs and unlicensed MFIs:

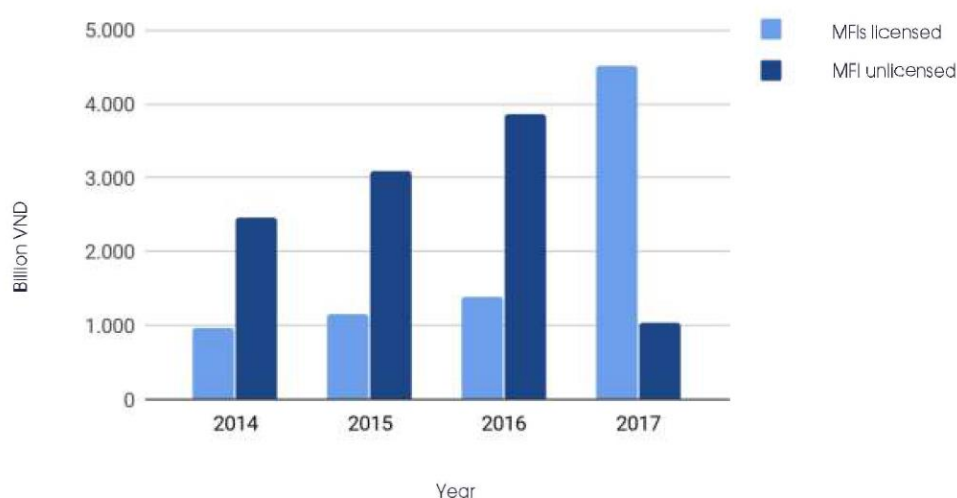
- Licensed MFIs: In 2018, there are four licensed MFIs operating under Credit Law. Under current regulations, licensed MFIs are limited companies. Three formal MFIs have direct and indirect connections with Vietnam social organizations (Vietnam Women’s Unions (VWU) or Vietnam General Confederation of Labor).

However, the fourth MFI, is different in terms of customer base, ownership and governing body.

- **Unlicensed MFIs:** Unlicensed MFIs in Vietnam can be divided into three groups:
  - Microfinance projects is financed by foreign organizations and work in partnership with local organizations (mostly WUs) or other leading organizations (Association of Labor) with small scale in few provinces.
  - Unlicensed microfinance program is formed by two types of NGOs, local and international. These programs are often medium-sized, operated and financed by NGOs so legal representative is not required.
  - The social fund microfinance is established by Government for social and charity purpose. They are financed from international NGOs or other aid sources and associated with socio-political organizations (e.g. local Women Union) to provide microfinance to the poor. These funds have official legal status and their own seals.

Figure 2.14 shows overview of GLP of MFIs in Vietnam. For the period from 2014 to 2017, GLPs of all licensed MFIs shows strong increase trend. In contrast, that of unlicensed MFI showed the decrease of 73% to VND 1,025 billion in 2017 due to the transformation of social fund CEP into a licensed MFI. This also created a sudden increase of 26% in GLPs of the licensed MFIs compared to 18% of period from 2014 to 2016.

**Figure 2.14: Gross loan portfolio**

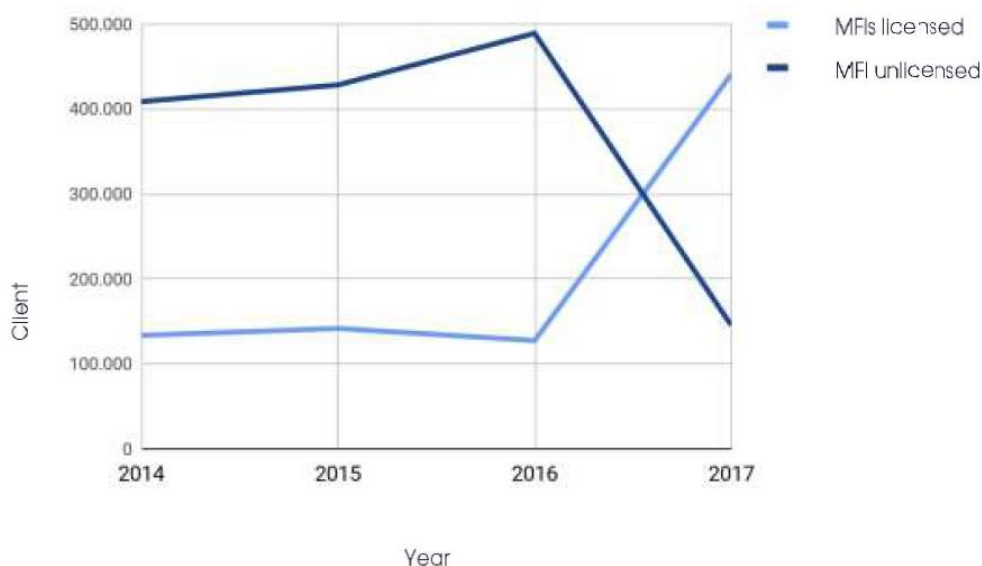


*Source: Vietnam Microfinance Working group (2019)*



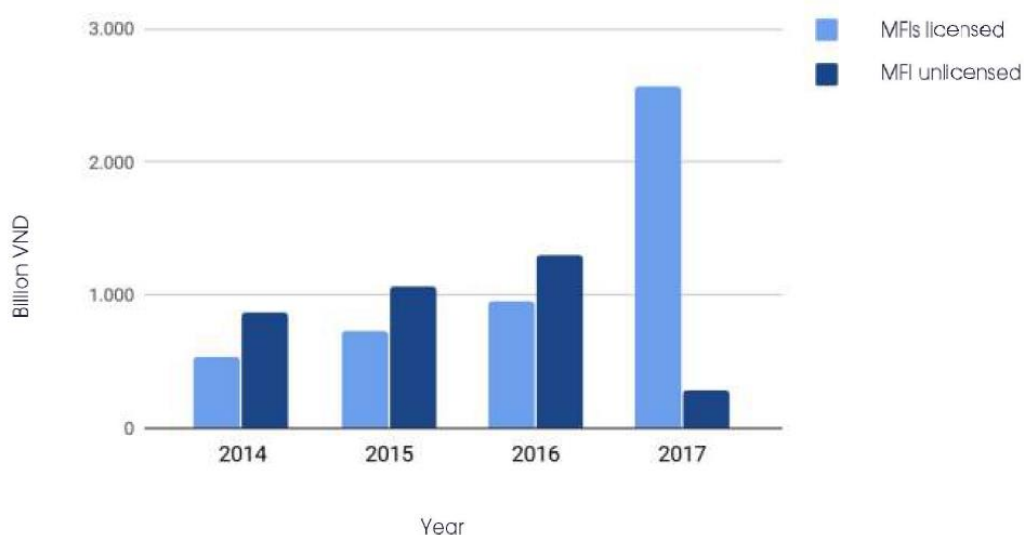
Figure 2.14 shows triple increase in the number of borrowers to around 450,000 of licensed MFIs in 2017 while that of unlicensed MFI going down seriously to 130,000.

**Figure 2.15: MFIs clients**



*Source: Vietnam Microfinance Working group (2019)*

**Figure 2.16: Saving**

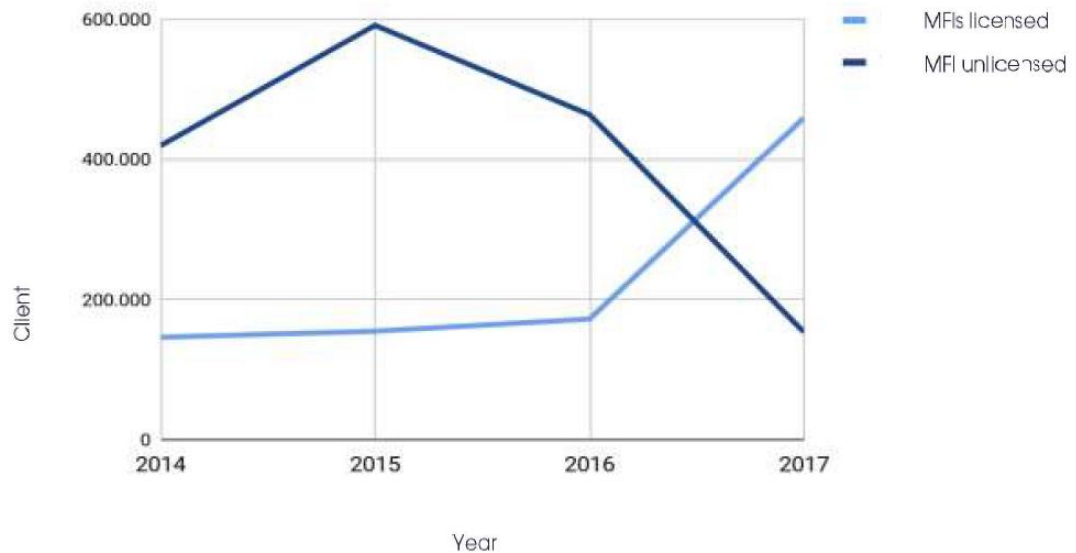


*Source: Vietnam Microfinance Working group (2019)*

For the same period, total savings of the unlicensed MFIs was more than VND 2,000 billion which shows an average increase of 22% per annum, lower than 33% annual growth rate of licensed one (Figure 2.16). The number of saving clients of

unlicensed MFIs was 500,000 in 2017 which is triple that of licensed MFIs (Figure 2.17). With the transformation of MFI named CEO, total saving of unlicensed MFIs decreased seriously to VND 286 billion due to the decrease of 150.000 savers.

**Figure 2.17: MFIs saving clients**



*Source: Vietnam Microfinance Working group (2019)*

## **Chapter 3. Microfinance Institution Performance Assessment: New Evidence for East and South Asia**

This chapter presents new evidences on financial and social performances of microfinance institutions in Asia-Pacific region. Financial performances are assessed using return on asset and operational self-sufficiency while social performance is assessed using depth and breadth of outreach. Dynamic panel data models are used to analyze the impact of different factors (board characteristics, microfinance institution characteristics, and country socio-economic conditions) on these measures of performances. These models are estimated using system-GMM to take into account all endogeneity issues encountered in dynamic panel data models. Data from 305 microfinance institutions in 19 Asian-Pacific countries over the period from 2006 to 2015 are investigated. Results show that board size and gender diversity have negative impacts on performance while board social orientation positively affects financial performance. In addition, past performance, leverage and total assets also have positive effects on financial performance. This suggests that microfinance institutions focus more on social orientation as well as board structuring to improve their performances. This also recommends for policy makers to develop MFIs in poor rural market to improve the rural living condition and alleviate the rich poor gap. The rest of the chapter are as follows: Section 1 introduces about assessment of MFI performance while section 2 presents the existing literature on determinants of MFIs' performance, theoretical considerations and hypotheses development and shows the remaining research gaps. Section 3 follows by providing a description of the specific variables used in the estimation, presenting the data and outlining the estimation procedure taking into account endogeneity concerns. Section 4 presents and discusses the empirical results while Section 5 concludes the research with some remarks for practitioners and policymakers.

### **3.1. Introduction**

Microfinance is recognized as an efficient tool for economic and social development, especially for developing countries (Ledgerwood (1998); Morduch (2002);

Khandker (2003); Ledgerwood (2013)). Recently, the Asia – Pacific region has been known as the world’s fastest-growing economic region (IMF, 2018). Although millions of people have been lifted out of poverty, the region remains home to almost half of the world’s poorest individuals (UNEP, 2018). UNEP, considers the rich – poor gap as a “price of growth”, so while the region is expected to stay the fastest-growing region of the world through 2030 (Fensom, 2017), how do households pay for this “price”?

Microfinance seems to be the most appropriate answer as its main roles are improving living condition as well as helping people to get out of poverty. In fact, 47 percent of the population in low- and middle-income countries still does not have a bank account and only 9 percent can borrow from formal financial institutions (IMF, 2018). In addition, the value of collateral for low-income countries in Asia-Pacific is 239 percent of the loan value while the global average is 196 percent (Jahan, 2019).

How to improve the performance of MFIs is therefore an open question. In this chapter, we look into this issue by assessing the impact of various factors which may influence to profitability and social activities of MFIs. Most empirical studies are based on fixed effect model, while there is evidence suggesting that dynamic modeling is more appropriate in estimating effects of factors on MFIs’ performance. Indeed, endogeneity bias can lead to unreliable estimates and inappropriate inferences, which may deliver misleading conclusions and incorrect interpretations. Sometimes such bias can even result into coefficients having the incorrect sign. According to Dang et al.. (2020), most empirical corporate finance works acknowledge at least three potential sources of endogeneity. First, omitted or unobserved firm characteristics may simultaneously influence both the corporate governance issue and firm performance. Second, reverse causality can occur due to the fact that corporate governance may affect firm performance, but it is also possible that well performed firms are more likely to change their corporate governance structure. Lastly, one source of endogeneity that is often ignored (explic-

itly or implicitly) arises from the possibility that current values of governance variables are a function of past firm performance. Neglecting this source of endogeneity can have serious consequences for inference.

We argue that the inconsistency in results mentioned by Post and Byron (2015) is due partly to this issue. To deal with this, we have two broad goals in this paper: (1) to understand the dynamic relation between performance and relevant factors, and (2) to use dynamic panel estimators.

In addition, there are some factors which are proved to affect the MFIs' performance in theoretical framework but have never been supported by empirical evidence such as board's social orientation, rural target, deposits to loans ratio, and country's infrastructure rate. This paper will take in to account the impact of these variables when assessing MFIs' performance.

Using a sample of 305 MFIs in 19 countries in Asia – Pacific region, this paper estimates dynamic models which use lagged value of the dependent variable as explanatory variable to analyse MFIs' performance. The results provide evidences that using System-GMM allows to control for various sources of endogeneity and highlights factors which have relevant effects on MFIs' performance.

### **3.2. Literature review**

There are various ways to analyze MFIs performance. Zeller and Meyer (2002) defined MFIs' performance in 3 dimensions: financial sustainability, outreach and impact on poverty. Besides, Hartaraska (2005) measured performance based only on sustainability and outreach. Moreover, many authors divided MFIs' performance into financial performance and social performance (Saeed et al., 2018; Dato et al. (2018); Tchakoute - Tchuigoua (2010); Postelnicu et al. (2015)). Consistent with Hartaraska (2005), the most common indicators for financial performance are Return on Asset (ROA), Operation self sufficiency (OSS) which measures the capability to cover its costs through operating revenues while the indicators for social performance include the number of borrowers (breadth) and the size of loans (depth).

Besides, many studies are also interested in the trade-off between financial performance and social performance and showed different results on this relationship. Quayes (2012), using a sample of 140 MFIs in Central - Western Europe, and Meyer (2015), using 124 MFIs in 49 developing countries, have shown that outreach will impact positively to MFI's performance. In addition, Kinde (2012), based on 126 observations from 14 MFIs in the years 2002 to 2010 in Ethiopia, has showed a positive relationship between sustainability and outreach. In contrast, Hermes et al.. (2011) have concluded that social performance and financial performance have opposite relations. Similarity, Manos et al. (2009) and Bassem (2009) have also found a trade-off between social and financial performance. Moreover, Crawford et al.. (2014); Schmie (2014) have not exhibited any relationship between social and financial performance.

Based on previous studies, different factors which affect MFIs' performance can be divided into three groups: (1) Board characteristic, (2) MFI characteristics, and (3) country socioeconomic conditions. This chapter will focus mainly on the board structure to check the impact on MFIs' performance.

First, board characteristics include the number of board members (Board\_size), the number of female chairs in board (FM\_Board), and the social and/or work experience of board members (Social\_Exp). Mersland et al. (2009) based on their study of 278 MFIs in 60 countries and concluded that number of board members (Board\_size) have negative effects on financial performance which related to ROA, OSS and investment portfolio. In contrast, Saeed et al.. (2018) found out the positive relation between board size and financial performance from sample of 215 MFIs in 6 countries in South Asia.

There are two theoretical perspectives on the relationship between the board size and the performance of the enterprise: The Agency Theory and the Resource-dependence Theory. The agency theory of Jensen and Meckling (1979) refers to the manager as an Agent, who unlike a Principal, does not own the resources of the organisations. MFIs' managers may work toward fulfilling the mission of the MFIs, but they may also have preferences for nonpecuniary rewards, creating

agency costs. Agency Theory claimed that board size has negative effect on the performance of businesses (Eisenberg, Sundgren, and Wells (1998); Yermack (1996); Hartarska (2005); Mersland et al. (2009); Mersland et al. (2011)). Other studies concluded about the positive relationship between these two factors (Bassem, 2009; Saeed et al., 2018; Dato et al.; 2018). In addition, Resource-dependence Theory supported a positive relationship between board size and MFIs' performance which was also proved by Carter et al., (2010) and Klein (1998)).

Consequently, we assert the following:

**H1: Smaller size board achieves better performance compared to larger board.**

Second, many research papers confirmed the positive effect of female participation on board to social performance (Wale (2009); Strom et al.. (2014); Mori et al.. (2015); Thrikawala et al.. (2017)).

Agency theory and Stakeholder theory have been used to explain the impact of female members on board of directors on MFIs' performance. When board member is female, they often have new perspectives on complex issues that can help to correct information bias in strategy formulation and problem solving (Dewatripont, Jewitt and Tirole, 1999). Moreover, female leaders may also have a positive influence on other female employees, improving corporate image in community environment (Smith and Verner, 2006). In addition, the study by Strom et al.. (2014) on 329 MFIs also pointed out that having female members in board of directors will positively affect both financial and social performances. In addition, Wale (2009) and Mori et al.. (2015) proved that women often take better care of poor customers so MFI's social performance could increase. However, Thrikawala et al.. (2017) had investigated 300 MFIs in Sri Lanka and got opposite result as compared with Smith et al.. (2006), Strom et al.. (2014) and Salim et al. (2016).

Our second hypothesis is therefore:

**H2: The higher the percentage of female members on board, the better the performance.**

Third, in addition to size and gender diversity, board members' social orientation is also considered to be important to MFI performance. According to Babu (2016), MFI's breadth and depth may increase due to social orientation. Particularly, Beisland et al. (2020) proved that social ratings of MFIs are significantly related to financial performance. He uses global database of 204 MFIs from 58 countries and evaluates the factors that influence the social performance ratings of MFIs. Overall, their results confirms that social ratings of organisations are significantly related to financial performance, greater outreach in rural areas. It also enhances better social objectives, staff commitment, customer service and service quality. It can be seen that improvement in facility and customer service will attract more clients and increase the revenue which can directly contribute to the ROA.

Therefore, we propose a third hypothesis:

**H3: MFIs with board members having social orientation will achieve better performance**

Undoubtedly, endogeneity plays important while estimating panel data of MFIs' performance. In order to mitigate endogeneity, historical performance should be taken into account (Wintoki, 2012). According to Raheja (2005) and Harris and Raviv (2008), past performance has a direct influence on the firm's information environment, profit potential and the opportunity cost of outside directors, all of these factors that may affect the optimal current performance. In addition, Wintoki (2012) found empirical evidence that firm characteristics that is relevant to these factors (e.g., firm size, leverage ratio, etc.) are themselves related to past firm performance. While the theoretical models do not look to the dynamic nature of the business, the implications he mentioned suggest that any empirical estimation of the effect of board structure on past firm performance that ignores the dynamic relation between current board structure and past performance (e.g. traditional fixed effects model) will deliver bias estimates. Next, he shows that the dynamic nature of the relation between corporate governance and performance creates powerful methodology for identifying the causal effect of governance on performance.



Therefore, adding the lagged variables into the model will help getting more reliable estimation by minimizing the endogeneity problem, and past performance is expected to have a positive effect on the current performance of MFIs. Specifically, when MFIs have good past performance, it can be shown that MFIs have more resources to perform in near future. The number of customers MFIs served in the past reflects reliability and trust of customers for those MFIs in the current and near future. If the MFIs perform well, market will be expanded, then these customers may bring another future customers which result in better social performance. Therefore, we have:

**Hypothesis H4: Past performance of MFIs has a positive effect on its current performance.**

### **3.3. Research design**

#### ***3.3.1 Samples***

The initial sample included 305 MFIs in 19 countries in South and East Asia over a period from 2006 to 2015 listed MFIs from database themix.org. Since its founding in 2002, MIX has built the digital information infrastructure needed to bring greater transparency to financial sectors serving low-income populations in emerging markets, including providing market data on over 3,000 financial services providers in 125 countries. This index has already been used in previous studies (Chikalipah, 2017). The final sample consisted of 305 firms and 2227 firm-year observations. Observations with insufficient data were also excluded from the analysis.

In financial year 2015, there are 1033 institutions reported to MIX including 116.6 million borrowers, corresponding to a gross loan portfolio of USD 92.4 billion. These organisations also have saving that reach 98.4 million depositors and account for USD 58.9 billion of deposits. The South Asia area continues to access greater market in the microfinance sector with the primary concentration

on female borrowers which represents around 92.0% (Center for Financial Inclusion, 2017). This shows that the data is sufficiently represented for the South and East Asia.

Finally, all variables except the dummy variables are at the 1% and 99% levels to reduce the potentially effects of outliers.

### ***3.3.2 Variable definitions***

#### ***3.3.2.1 Dependent variables***

Microfinance involves both business activities and social activities, so to analyze MFIs' performance, it is necessary to rely on both aspects: financial performance and social performance. Therefore, we will use two groups of variables to evaluate MFIs' performance: (1) Financial variables group such as Return on Assets (ROA) and Operational self-sufficiency (OSS); (2) Social variables group includes both Depth and Breadth of Outreach (Hartarska, 2005).

Variables used in the regression analysis are defined in Table 3.2.1. Financial performance (Sustainability) is measured either by return on assets (ROA) or by operational self-sufficiency (OSS) (Hartarska, 2005). In line with Wintoki (2012), ROA is calculated as operating income before depreciation divided by total assets. Besides, operational self-sufficiency is calculated by ratio of operating revenue divided by total financial expense, provision and operating expenses which measures how well the MFI can cover its costs through operating revenues.

Social performance comprises of two characteristics - breadth and depth. Breadth is measured by the logarithm of the number of active borrowers while depth is measured by the ratio of average loan size divided by the annual GDP per capita. Since the loan is often non collateral, the value of the loan is preferred.

#### ***3.3.2.2 Independent variables:***

Following Hartarska (2005), Mersland et al.(2009), Bassem (2009), Saeed et al.. (2018)), Board size is calculated as number of board members. In addition, consistent with Wale (2009), Strom et al.. (2014), Mori et al..(2015), and Thrikawala et al.. (2018), we will include percentage of female board members (FM\_Board)

which is calculated as the number of female directors divided total number of directors.

Lagged values, as proposed by Wintoki (2012), are used for the four dependent variables of ROA (L1.roa), OSS (L1.oss), depth (L1.depth) and breadth (L1.breadth). As discussed, we expected a positive relationship between lag variables and MFI performance.

### *3.3.2.3 Control variables*

Following Adams and Ferreira (2009), we control for firm characteristics that may affect our measure of performance. Specifically, first, we will include Ln\_Assets which is the logarithm of the total assets of the MFI. Total assets include all assets minus loan loss reserve and accumulated depreciation (Sekabira (2013), Kipsha (2013), Kar and Swain (2014)). Second, we include leverage which is the ratio of debt divided by total assets and deposit to loan ratio (DTL) which assesses MFI's liquidity by comparing bank's total loans to its total deposits for the same period (Muriu, 2011). As a result, we expect a negative relationship between leverage and firm financial performance (Kara and Swain, 2014). Third, we will use social orientation as a dummy variable, with Social\_Orientation=1 if board has orientation on social mission and goals, and 0 otherwise. Fourth, we include Social Experience of the Board members as a dummy variable, with Social\_Exp =1 if board members have social experience, and 0 otherwise (Hartarska (2005), Pascal et al.. (2017)). Then we will include rural variable as a dummy (Rural =1 if the MFI are targeting the clients living in rural areas) and poor variable as a dummy (A dummy =1 if the MFI are targeting poor and very poor clients, 0 otherwise). Table 3.1 below summarises literature reviews on determinants which can affect to the MFI's performance indicators.

**Table 3.1: MFIs' performance indicators and factors affect MFIs' performance**

	<b>Variables</b>	<b>Definition</b>	<b>Expectation</b>	<b>Authors</b>
<b>Financial performance</b>	ROA	Return on assets measures how well the MFI uses its total assets to generate returns	+	Saeed et al.. (2018), Wale (2009), Ahmed et al.. (2016), Churchill (2017), Hartarska (2005)
	OSS	Operational self-sufficiency = operating revenue/(financial expense + loan loss provision + operating expense). Measures how well the MFI can cover its costs through operating revenues	+	Saeed et al.. (2018), Ahmed et al.. (2016), Wale (2009), Churchill (2017), Mersland et al. (2009), Strom et al.. (2014), Hartarska (2005)
<b>Social performance</b>	DEPTH	Average loan balance per borrower / GNI per capita. Higher values mean that the MFI serves richer borrowers	+	Saeed et al.. (2018), Hermes et al.. (2011), Wale (2009), Churchill (2017), Mersland et al. (2009), Mersland et al.. (2018)
	BREADTH	The number of active borrowers, that is the number of individuals that currently have an outstanding loan balance with the MFI or are responsible for repaying any portion of the gross loan portfolio	+	Saeed et al.. (2018), Crawford et al.. (2014), Wale (2009), Mersland et al. (2009), Dato et al.. (2018), Hartarska (2005)

	Variables	Definition	Expectation	Authors
<b>MFI specific</b>	Ln_Assets	Logarithm of the total assets of the MFI. Total assets include all assets net of contra asset accounts such as the loan loss reserve and accumulated depreciation	+	Sekabira (2013), Kipsha (2013), Kar and Swain (2014)
	Leverage	Debt /asset ratio. Higher values mean that the MFI uses financial leverage at higher lever.	+	Dissanayake and Anuranga (2012), Tehulu (2013), Kara and Swain (2014)
	DTL	Deposits to loans	-	Muriu (2011)
	Rural	A dummy =1 if the MFI are targeting the clients living in rural areas	+	
	Poor	A dummy =1 if the MFI are targeting poor and very poor clients	+	
<b>Board Specific</b>	Board_size	Number of board members	+	Hartarska (2005), Mersland et al.(2009), Bassem (2009), Saeed et al.. (2018)
	FM_Board	Percentage of female board members	+	Wale (2009), Strom et al.. (2014), Mori et al..(2015), Thri-kawala et al.. (2018)
	So- cial_Orien- tation	=1 if board has orientation on social mission and goals, 0 if not.	+	

	Variables	Definition	Expectation	Authors
	Social_Exp	A dummy =1 if board members have social performance education and/or work experience	+	Hartarska (2005), Pascal et al.. (2017)
<b>Lag</b>	L1.roa	ROA of MFIs in the previous fiscal year.	+	Glen, Lee, and Singh (2001) and Gschwandtner (2005) Wintoki (2012)
	L1.oss	OSS of MFIs in the previous fiscal year.	+	
	L1.depth	Average loan balance per borrower / GNI per capita in the previous fiscal year.	+	
	L1.breadth	The number of active borrowers in the previous fiscal year.	+	
<b>Country specific</b>	Ln_GDP per capita	Logarithm of the total GDP (gross domestic product of the country) for year t	+	Imai et al.. (2012), Hartarska (2005)
	BHR_Rate	CPIA building human resources rating (1=low to 6=high)	+	Mersland et al. (2009), Mersland et al. (2013)
	Infra_Rate	Quality of port infrastructure, WEF (1=extremely underdeveloped to 7=well developed and efficient by international standards)	+	Hartarska (2005)
	Internet_Usage	The proportion of population who use the internet	+	(Choi and DiNitto, 2013)

### **3.3.3. Methodology**

#### **3.3.3.1. Dynamic endogeneity**

In this section, we present a brief review of theoretical work related to our model. Issues in endogenous factors should always be considered when quantifying econometric models. According to Roberts and Whited (2013), endogeneity comes from potential correlation between explanatory variables and errors in the model. There are three main reasons for the endogeneity: omitted variables, simultaneity and dynamic endogeneity. In order to solve endogeneity problems in the models, previous studies often use lagged values of either independent variables or dependent variables, as instrumental variables (Bellemare et al., 2017; Mersland et al., 2011).

According to Hermalin and Weisbach (1998), Raheja (2005), and Harris and Raviv (2008), there is a dynamic element to the determinants of board structure, which may deliver endogeneity into an estimation of firm performance. We propose that there are at least two ways by which past performance can explicitly affect current board structure. Specifically, board composition will be related to the firm's past performance. If board structure is determined by firm characteristics (Raheja, 2005) and these characteristics are related to past performance, then board structure is related to past performance through the effect of performance on firm characteristics. For example, following arguments presented by Boone et al. (2007), since big firms are more complex, the boards need to supervise more managerial levels so larger firms often have larger boards. Coles (2008), Linck et al. (2008), and Lehn et al. (2009) proved that board size and firm size are of positive relation. As a result, board size will be positively related to past firm performance through the effect of performance on size.

According to Wintoki (2012) dynamic endogeneity is defined as the endogeneity that occurs when a firm's current actions would affect its control environment and future performance. Specifically, endogeneity could arise when the current corporate governance and financial performance are influenced by past performance. For instance, poor performance company is likely to replace its board structure and

control characteristics to improve governance efficiency (Hermalin and Weisbach, 1998). Furthermore, corporate decisions are likely to be dynamic (Wintoki et al., 2012). Raheja (2005), Harris and Raviv (2008) stated that past performance has a direct influence on a firm's innovation environment or foreseeable profits. All these reasons might influence the optimal board structure, including size and gender diversity. In brief, dynamic endogeneity might be a problem and it should be carefully controlled.

#### *3.3.3.2 Omitted factors*

Omitted variable bias and unobserved heterogeneity are variables which can cause a major problem since they can deliver another explanation (Gippel et al., 2015). This is because firm's characteristics across the time may affect both size and number of female members on board when estimating the relationship between board structure and financial performance of the MFIs.

For instance, large organizations often have to comply with social responsibility by diversifying board members from various stakeholders and gender to create better perception by public. Improper firm size in estimating the relation between board structure and firm performance can create observe correlation leading to bias (Wintoki, 2012).

Similarly, according to Hillman et al. (2007), socially responsible firms may be more likely to appoint female member on board. In additions, socially responsible companies may appear to be very attractive to female.

Unobserved variables across time such GDP per capita, human resources rating and infrastructure rate, social oriented board (Grosvold and Brammer, 2011) or corporate culture can seriously affect the relationship between board structure and performance. Moreover, Grosvold and Brammer (2011) stated that government institutions played an important role in the female representation on boards, and corporate cultural significantly impacted a firm's performance. However, these may be difficult to observe and measure, so they are usually omitted from econometric specifications.

#### *3.3.3.3 Simultaneity*



The third problem is simultaneity (Adams and Ferreira, 2009). According to (Gippel et al., 2015), simultaneity (or reverse causality) is another problem associated with endogeneity since dependent variable and the variable of interest can be determined simultaneously (Gippel et al., 2015). In particular, corporate boards and board size or gender diversity might arise from the relationship of Board characteristics/ structure and financial performance (Adams, 2016). Therefore, corporate performance and board structure (size and gender diversity) may be correlated. In performance specifications, number of females on board or number of members on board may affect MFI performance, but it is also possible that financially successful firms may be more likely to appoint female directors (Adams and Ferreira, 2009) or to increase the number of board member (e.g. performance drive governance). Ignoring reverse causality might lead to biased results, because the causality could have feedback loop (Gippel et al., 2015).

#### 3.3.3.4. Model and estimation strategy

In line with Wintoki (2012), any estimation regarding the impact of board structure on firm performance can be presented as follows:

*Performance* = *f*(*past performance, board structure, firm characteristics, countries specific score*).

Therefore, we consider the following dynamic panel data model:

$$P_{it} = \gamma P_{it-1} + \beta_1 S_{it} + \beta_2 B_{it} + \beta_3 M_{it} + \eta_i + \varepsilon_{it} \quad (1)$$

Where is:

- ✓  $P_{it}$  = MFI is performance on time t, either financial or social, i.e. either ROA, OSS, DEPTH or BEADTH
- ✓  $S_{it}$  = MFI specific variables: MFI\_size, Leverage, DTL, FM\_Borrowers, Rural, Poor
- ✓  $B_{it}$  = Board specific variables: Board size, FM\_Board, SPM\_Board.
- ✓  $M_{it}$  = country-specific macroeconomic variables: Economy\_size, BHR Rate, Quality of Port Infrastructure, Internet Usage.

- ✓  $P_{it-1}$  = lagged past performance could affect to current performance (Wintoki et al., 2012).
- ✓  $\eta_i$  = unobserved firm effect
- ✓  $\varepsilon_{it}$ : random error term
- ✓  $\gamma, \beta_1, \beta_1\beta_1$  are parameters to be estimated given a panel sample of firm observations.  $i$  denotes firms in the sample, and  $t$  refers to time period.

According to Wintoki (2012), fixed effects are introduced to capture unobserved time-unvarying heterogeneity. Its data can be internally transformed so unobserved heterogeneity which is ‘constant’ over time can be eliminated. For example, unobserved time-invariant individual effects can be managerial capability or institutional system which cannot be measured quantitatively and are thus captured by fixed effects. Therefore, endogeneity can be eliminated in case MFI specific characteristics (time invariant) are correlated with the explanatory variable. So part of the omitted variable problem is treated, those linked to unobserved time-unvarying factors.

Different strategies can then be used to estimate this model, including pooled OLS and within estimator. By definition, when using model 1,  $P_{it-1}$  is correlated with fixed effect  $\eta_i$ . As a consequence, classical pooled OLS and fixed effect (within) estimators are biased (Wintoki et al. (2012)). These two strategies are known to produce biased estimates values of the effect past performance, due to the correlation between past performance and fixed effect. So within transformation is not the good solution, even if it gets rid of the fixed effect term. However, differencing transformation appears then to be a better solution and is at the base of GMM for the following reasons:

First, fixed effects are disappearing from the specification of Eq. (1) writing in differences. In addition, GMM, which was developed in a series of papers by Holtz-Eakin, Newey, and Rosen (1988), Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998), exploits all the moment conditions

that can be defined between the error term in the differenced model and past values of dependent and independent variables.

Secondly, these moment conditions allow to define a set of internal instrumental variables and thus to deal with the endogeneity issues encountered in Eq. (1) reducing the need of external instrumental variables. Specifically, if the underlying economy is dynamic e.g if current performance is related to past performance so some combination of variables from the firm's history as valid instruments can be used to account for simultaneity. Thus, an important aspect of the methodology is that it relies on a set of "internal" instruments in the panel: past values of governance and performance can be used as instruments for current performance. This reduces the need for external instruments (Wintoki, 2012).

System GMM goes further by considering not only the differenced model but also the original one, and additional moment conditions arising from the second model imply improvements in efficiency of estimators. Therefore, it helps the dynamic nature of the relation between board structure and MFI performance actually creates a powerful tool for identifying the causal effect of governance on performance.

However, system GMM still have certain disadvantages. According to Roodman (2009a), when applying system GMM, the number of internal instruments increases while the number of time periods  $T$  increases and can be presented as a quadratic in  $T$ . In fact, instrument proliferation creates some asymptotic results for system GMM estimators and makes related specification tests appear misleading. A large instrument number often leads to overfitting endogenous variables and weakening the Hansen J-test of the instruments' joint validity ((Andersen, 1996), (Roodman, 2009b)). Estimated variances of coefficients and the Hansen J-test can be too small, resulting in overfitting lagged dependent variables and too much confidence in the validity of internal instruments. Given that, one recommendation when dealing with the instrument proliferation issue is cautiousness when choosing internal instruments. Roodman (2009b) suggested restricting the number of lagged levels used in the instrument matrix, collapsing the instrument matrix or

combining the two. Finally, as Roodman (2009b) stated, the system GMM might work but “under arguably special circumstances”.

### 3.3.3.5 Descriptive Statistics

Table 3.2 reports the descriptive statistics of all the variables. Mean of ROA are 0.77% proves that MFIs in datasets can cover their expense by their revenue even their income is quite small around 0,77% total assets compared to 3% of Eastern Europe market (Harkarsta , 2005). In contrast, OSS mean is 116% which is higher than Harkasta (2005) of 91%. In addition, MFIs has mean of number of customer (breadth) is 264,255 while value of debt compare to GDP per capita is 31.4%.

**Table 3.2 Descriptive statistics**

Variable	Obs	Mean	Std. Dev.	Min	Max
ROA	2227	0.0076561	0.1034934	-1.4542	0.5627
OSS	2227	1.162588	0.5028023	-0.1224	11.3969
Depth	2227	0.3140197	0.547744	0	6.3257
Breadth	2181	264.555.4	907,069.6	52	8,166,287
Board_size	2227	6.962281	3.479683	0	27
Fm_Board	2227	0.1439299	0.233281	0	1
Social_Orientation	2227	0.5999102	0.4900263	0	1
Social_exp	2227	0.0722946	0.2590332	0	1
Leverage	2227	0.7741091	0.2379148	0	3.7798
Ln_Assets	2227	16.13661	1.873903	10.34433	22.61219
Rural	2227	0.8100584	0.3923429	0	1
Poor	2227	0.68837	0.4632635	0	1
DTL	2227	0.3302176	0.4988749	0	6.9054
Ln_GDP	2227	25.97884	1.937391	19.72749	30.02962
Bhr_rate	2227	3.885047	0.3502483	2.5	4.5
Infra_rate	2227	3.537796	0.6082863	1.561029	5.031006
Internet_usage	2227	12.71704	11.299	0.116628	52.72

Variable	Obs	Mean	Std. Dev.	Min	Max
Rural	Poor	Social_orientation		Social_exp	
0: 423	0: 694	0: 891		0: 2066	
1: 1804	1: 1533	1: 1336		1: 161	

Board of MFI has mean of 7 members which is quite low compared to Rey et al. (2020) while the percentage of female on board is quite low of 14.39% compared to 23% in Central and Eastern Europe. However, there is a large variation in board size within the sample firms up to maximum 27 members. Not surprising, 60% of MFI boards has social orientation while minority of board member has social experience (161 observations equivalent to 7.23%).

Min of total asset is around USD 10mn while mean of *LnAsset* is 16,14. In addition, average leverage of 77.41% and deposit to loan is 33.02%. 81% MFI has rural orientation and 68.84% has poor customer target.

*BHR\_rate* distributed from 2.5 to 4.5 and had mean around 3.89. This is reasonable BHR rate for developing countries while infrastructure rate of 3.54 and internet user of 12.72%. These figures show quite low rate of access internet implying for low level of technology.

### 3.4. Results

When applying the GMM model, there are two post-estimation tests to determine that an appropriate econometric model need to be applied. These tests are: (i) the Sargan/Hansen test; and (ii) the Arellano-Bond test for first-order and second-order correlation. A critical assumption for the validity of GMM estimates requires that instruments are exogenous. In other words, the findings from GMM will not be valid if the instruments are endogenously determined. The Sargan test is used to determine whether the econometric model is valid, and whether the instruments are correctly specified. In other words, if the null hypothesis is rejected, the researcher needs to reconsider the model or the instruments used in the estimation process. Subsequently, if the Sargan test turns out to be insignificant it implies that the instruments included in the econometric specifications are exogenous.

To examine the validity of a strong exogeneity assumption, the Arellano-Bond test for no auto-correlation (or no serial correlation) is used under the null hypothesis that the error terms of two different time periods are uncorrelated. Moreover, it means that the lagged variables are not correlated with the error term in the governance-performance equation.

Our GMM panel estimation uses the orthogonality conditions under the assumption that there is no serial correlation in the error term. The orthogonality conditions imply lagged levels as instruments for our differenced equations and lagged differences as instruments for the levels equations, respectively. Later, rigorous tests of the validity of the orthogonality assumptions as well as the strength of the instruments that are implied by these assumptions.

Table 3.3 shows results from estimation of Equal (2) through the use of alternative models of impact of board structure to the sustainability (on ROA and on OSS) and outreach (DEPTH and BREADTH) through two-step system GMM. To test our hypothesis, we only consider results that have significance levels of 1% and 5%.

Following Wintoki (2012), we used the two-step system GMM estimator to examine the effect of board structure on MFI performance. We used internal instruments which were collapsed in order to mitigate instrument proliferation (Roodman, 2009b).

To examine the validity of the system GMM estimator statistically, we conducted a Hansen J-test. Table 4.1 shows that the Hansen J-test yields a p-value of 0.848, 0.904, 0.222 and 0.527 for our four models respectively, clearly indicating the validity of the chosen instrumental variables.

In addition, the Arellano-Bond test for no auto-correlation (or no serial correlation) is used under the null hypothesis to examine the validity of a strong exogeneity assumption that the error terms of two different time periods are uncorrelated. In other words, it means that the lagged variables are not correlated with the error term in the governance-performance equation.

**Table 3.3: The relationship between organization governance structure and MFI performance**

	(1)	(2)	(3)	(4)
VARIABLES	RoA	OSS	Depth	Breadth
Lagged ROA	0.411***	0.454***	0.872***	0.656***
	(0.058)	(0.085)	(0.068)	(0.137)
Leverage	0.125***	0.341***	0.036	-0.985**
	(0.043)	(0.093)	(0.043)	(0.465)
Ln Assets	0.009***	0.022***	0.029***	0.192*
	(0.003)	(0.008)	(0.008)	(0.110)
Deposit to loan	-0.005***	-0.021***	0.033	-0.084
	(0.001)	(0.005)	(0.025)	(0.074)
Female_borrowers	0.004	-0.016	-0.097	0.393
	(0.009)	(0.043)	(0.100)	(0.342)
Rural	0.011*	0.013	0.010	-0.031
	(0.007)	(0.031)	(0.036)	(0.301)
Poor	-0.008	-0.001	-0.036	0.277
	(0.005)	(0.021)	(0.028)	(0.215)
Board_size	-0.000	-0.003	-0.005**	-0.000
	(0.000)	(0.002)	(0.002)	(0.018)
Female_board	0.010	0.048	0.048	-0.679**
	(0.007)	(0.030)	(0.062)	(0.296)
Social_orientation	0.012**	-0.033	-0.005	-0.427
	(0.006)	(0.030)	(0.026)	(0.295)
Social_experience	0.008	0.014	-0.019	0.688
	(0.007)	(0.024)	(0.030)	(0.448)
LnGDP per Capita	0.008	-0.004	-0.031	-0.103
	(0.007)	(0.018)	(0.020)	(0.121)
Bhr_rate	0.012	0.091	0.015	0.045
	(0.008)	(0.056)	(0.040)	(0.155)
Infra_rate	-0.017***	-0.032**	0.017	0.125**
	(0.006)	(0.016)	(0.015)	(0.060)
Internet_usage	-0.000	0.001	0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.005)
Constant	-0.213**	0.019	-0.217	0.859
	(0.098)	(0.272)	(0.157)	(0.872)
Hansen test (p value)	0.848	0.904	0.222	0.527
AR (1) test (p value)	0.002	0.099	0.001	0.004
AR (2) test (p value)	0.666	0.836	0.564	0.57
Observations	1,843	1,843	1,843	1,787
Standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

The evidence for Hypothesis 1, namely, smaller boards are more efficient in social performance, is confirmed. Model 3 in table 4.1 estimated the impact of board size while controlling for other board characteristics and external factor) on DEPTH showed the impact of board size is negative and significant at 5%. This is in consistency with Van Tuan (2016) but in contrary with Bassem (2009), Saeed (2018), Dato (2018).

The evidence for Hypothesis 2, namely, the higher the percentage of female members on board, the better the performance is contradictory. Model 4 in table 4.1 showed a negative effect of percentage female on board on social performance which is significantly different from zero (at 5% significant level). This is consistent with Adams (2009). In particular, studies find that women seem to be more risk averse than men (Agnew et al.. 2003, Charness and Gneezy 2007), which might lead female on board hesitate to grant loan to very poor family which may be obstruct MFIs in expanding their market and increasing their number of customers. Other studies have showed that men are more overconfident than women (e.g. Barber and Odean 2001, Niederle and Vesterlund 2007).

As expected, the social orientation of board indicated in Hypothesis 3 proved a positive impact on financial performance (ROA) in Model 1, indicating that MFIs with more social orientation will have higher sustainability. This is supported by Beisland et al. (2020).

Hypothesis 4 is confirmed very strongly with past performance coefficients that are significantly different from zero at 1% significant level regardless of the considered model. It showed that past performance has a significant effect on current performance, and this must be taken into consideration when estimated the effect of board structure such as size and gender diversity on MFI performance. Van Tuan (2016), among others, found a similar result.

MFI's characteristics such as leverage and total assets have positive effect on sustainability of MFI (see Model 1 and 2 where corresponding coefficients are significantly different from zero at 1% significant level). In addition, the larger assets, the better financial performance. On the contrary, Models 1 and 2 show that the



higher deposit to loan ratio, the lower financial performance. This can be explained by MFI hesitating to grant loans resulting in lower operational income. In addition, as expected, if MFI targets rural areas, they can expand their market to improve their returns.

Now consider the control variables we included in Eq. [1]. By definition, these control variables are introduced because they might control directly for confounding factors. In other words, these variables are added to the regression model to control for potential unobserved time variant factors that may cause the causal variable to be endogenous. The results demonstrate the importance of infrastructure when assessing MFI performance. They show the negative effect on financial performance and positive on social performance (significant effects at at 5% significant level). Surprisingly, the results concerning the infrastructure rate are interesting. It indicates that if the infrastructure rate increases, the financial performance is reduced perhaps due to less demand from borrowers.

### **3.5. Concluding Remarks And Policy Implication**

#### **3.5.1. Remarks**

This paper focuses on the effect of board structure, MFI specific characteristics and country specific variables on MFIs' financial and social performance. This study uses a developed dynamic panel generalized method of moments (system GMM) estimator to mitigate endogeneity concerns which runs regression of 04 models corresponding to four dependent variables on financial performance (ROA, OSS) and social performance (DEPTH, BREADTH) of MFIs.

There are many studies focused on the relation between board structure and firm performance. However, there is no consensus in the literature regarding the effect of board size and gender to MFI's performance. This paper considers the problem of endogeneity arising from unobservable characteristics across firms, reverse causality and dynamic endogeneity, which may influence the relationship between board structure and MFI performance.

Although attractive for addressing endogeneity issues, the system GMM approach might have some limitations.

First, consistently with Roodman (2009a) and Wintoki (2012), we found that past performance has a significant effect on current performance, confirming their point of view regarding dynamic endogeneity.

Moreover, our study confirms the results of Pascal (2017), Wegge (2008), Tran (2014), regarding social orientation and showing its positive effects on social performance. In addition, our findings confirm the results of Wale (2009), Mori, (2015), and Strøm et al. (2014) where a negative relationship between gender diversity and firm performance was found. In line with Pascal (2017), total assets have a positive effect on current performance in both the social and financial dimensions. This suggests the MFIs should focus more on social orientation as well as board structuring to improve its performance.

### ***3.5.2. Implications***

Our results offer some managerial insights and policy implications. First, the study supports the fact that the social orientation of the MFI board members have significant and positive relationship with MFIs' performance. Second, our findings suggest that firm should increase leverage and total assets and reduce the deposit to loan, to some extent, to maximise their performance. Third, this research has strong implications for government and law maker to enhance human resource toward performance of MFIs.

### ***3.5.3. Limitations***

#### ***Limitations***

As La Porta et al. (1998) and Grosvold and Brammer (2011) mentioned, institutional, cultural and political systems can influence the relation between Board structure and firm performance. Therefore further cross-country studies are necessary to reconfirm our result since national specificities may influence the relation.

## **Chapter 4: Rural households access to informal credit in Vietnam: Evidences using random forest**

This chapter investigates the factors affecting the access of households to informal credit market in rural area of Vietnam. The study uses data from the Vietnam Access to Resources Household Survey (VARHS) collected in 2014 to identify which factors facilitate accessibility to loans from microfinance institutions. An original estimation strategy is developed, combining classical logit estimation of the probability of getting a loan and Random Forests estimation techniques. The approach originated in this study offers a significant advantage over most of the existing credit scoring literature, as it possible to assess the order of importance of the factors in the explanation of the probability of obtaining a loan. Moreover, they have proved to be superior accuracy in predictive performance out of most other classifying techniques. The chapter is organized as follows. Section 4.1 introduce the Vietnam rural credit market, including credit supply, credit demand and credit accessibility by rural households. Section 4.2 provides a brief literature review on informal credit accessibility. In Section 4.3, we present research design, including samples, variable definitions, methodology and data description. Section 4.4 presents the classifiers and a comprehensive result and discussions. Our summary and conclusions are provided in Section 4.5.

### **4.1. Introduction**

Vietnam is an agricultural country with 80% poor live in rural areas and around 20% of the rural population has access to any kind of institutional finance sources. It is worth noting that almost 70% of the working population coming from rural areas which is a challenge for rural development policies. Therefore, rural households play an important role in the development of the country's economy.

The Vietnam rural credit market is segmented and consists of formal semi formal and informal credit sectors (Pham & Lensink, 2007). The formal and semi formal credit sector is led by the dominance of the three state-owned commercial financial

institutions, namely the Vietnam Bank for Agriculture and Rural Development (VBRAD), the Vietnam Bank for the Social Policies (VBSP) and the People's Credit Funds (PCFs) which accounted for 80% of the total credit. In addition to regular formal credit market, a proportion of households who do not have collateral often seek alternative credit from the informal sources such as friends, relatives, moneylenders and informal associations, at excessively high interest rates. This informal source plays an undeniable role in providing credit to poor households. In some circumstances, informal credit is a relatively optimal form of credit because it helps most of the poor households to get support whereas they cannot access to formal credit institutions.

Although Vietnam is not the country with the highest level of informal economy in Asia, it is one of three countries with a highest growth rate of the informal economy of 1.2% per year (Hoa, 2019). According to Vietnam Bank Association (2019), informal credit in Vietnam was about 20% of the total credit of the economy which remains an important source of finance for the poor in Vietnam. Although many people think that informal moneylenders are usurers, informal loans may help to increase capital and enable the poor to lessen poverty (Viet Cuong, 2012). As the informal credit value is supposedly limited, government policies could help enhancing available resources and therefore indirectly motivate informal loans. Hence, lenders could be connected to formal credit institutions to provide loans to the poor (Varghese, 2005).

Since informal credit is an important tool to alleviate poverty, the government may want to reconsider its policy focus. Vietnam is often mentioned as an example of a country successful in poverty reduction. Over the past decade, Vietnam has witnessed amazing reduction in poverty. According to World Bank (2020), the poverty headcount ratio by national standard decreased strongly from 4.2 percent in 2010 to 1.9 percent in 2018. Although it is possible to enhance the availability of informal credit, the Vietnamese government has no policies to do so and focuses solely on direct provision of microfinance. Vietnam is an interesting case to examine because its economy is changing very fast and credit volume increased signif-

icantly in recent years. However, information asymmetry and other market imperfections of Vietnamese credit markets results in difficulties in credit scoring. Another reason for our interest in Vietnam is that Vietnam banks is in a transitional process of international integration.

In this chapter, getting a better insight in the reasons causing the gap between demand and supply of informal rural credit at household level is indispensable for evaluating the current outreach of the microfinance institutions and for improving credit accessibility in Vietnamese rural areas. This chapter investigates the factors affecting the access of households to informal credit market in rural area of Vietnam using data on 3648 households from the Vietnam Access to Resources Household Survey (VARHS) collected in 2014. Specifically, this study proposes a framework that combines a number of determinants from a variety of dimensions of individual characteristics, household characteristics, financial factors and geographic factors.

Analyzing these determinants is very important for banks and money lenders to distinguish between strong and weak customers when offering credit to the households. The credit risk analysis plays an important role in classifying customers in two groups: good and bad. Many models and classification algorithms are used to evaluate credit risks (see Van Sang et al., 2016, for an overview). The objective in credit risk prediction is to create the best classification model from available data.

Many methods have been investigated to improve the accuracy in measuring the determinants of access to informal credit. Some studies of Barslund and Tarp (2008), Khoi (2013), Viet Nguyen and Berg (2014) and Lainez (2014) use mainly traditional parametric methodologies to estimate the accessibility of credit. To date, other novel modeling nonparametric approaches such as Random Forests (Breiman, 2001) have not been employed to assess loan failures in Vietnam, regardless of these models being really popular for modeling classification problems in recent years.

In this chapter, addressing the aforementioned gap in the current literature, we combine Random Forests (Breiman, 2001) and traditional logistic regression to

estimate determinants of informal credit access. Specifically, we use Random Forests classifier in ranking determinants to accessing informal credit in rural area of Vietnam which is quite new in studying informal credit. This will make significant contribution to micro finance literature a new method to value the importance of determinants and estimate these determinants of informal credit.

This study will be helpful to policymakers when designing programs restructuring financing sectors, given that we now have more precise knowledge about informal market and importance of the determinants of credit access to this source of funding.

#### **4.2. Literature review**

The informal credit market remains an important source of finance for the poor (Conning and Udry, 2007; Guirking 2008). While many people argue that informal credit comes mainly from moneylenders, who are usually known as usurers, a large proportion informal credit is in fact coming from friends and family, often at zero or very low interest rates. Since both types of credit do not require physical collateral and are highly flexible, therefore, they may help to call for fund and enable the poor to grow out of poverty.

Chaudhuri (2001) gives a reason for the formation of informal credit due to lack of formal capital. In addition, Teranishi (1994) argues that the informal credit market in emerging economies cannot be easily removed by the effectiveness of communication channels between informal lenders and their customers. Besides, Cole et al. (2011) indicate that a lack of financial knowledge remains a significant barrier to the need to access formal financial services, leaving the room for informal markets. Those who do not fully understand about formal versus informal loan will not acquire the most reliable option (Cole et al., 2011). However, several other studies show informal loans from friends and relatives are a very important factor in the economy (Wang et al., 2012). The proportion of informal credit in Vietnam is increasing with around 20 % of informal loans coming from family and friends with lower interest rates than formal credit. (Viet Nguyen and Berg, 2012).

Credit rationing depends on education and credit history, but Barslund & Tarp (2008) found no evidence of a bias against women. Following Khoi (2012), factors

influencing microcredit accessibility include local government employee status, credit group membership, poor family, educational attainment, working skills and village access to road infrastructure. In particular, Khoi et al. (2013) showed that informal credit access is depending on age, education, landownership, savings, income levels, purposes of informal loan, interest rate, duration of loan, living in a village with access to road and living in an urbanized commune. In additions, several studies (Pham and Lensink, 2007; Barslund and Tarp, 2008) have investigated the determinants of households' demand for credit from different institutions using probit models. In particular, Pham and Lensink (2007) confirmed that the supply of credit from formal, semi-formal and informal sources in Vietnam depends on the possible profits that can be made from the use of the loans. They stated that credit supply may also increase if borrowers provide collateral, a guarantor and/or if the credit is for business-related activities.

In this chapter we build on the analysis of Pham and Lensink (2007) but we focus on lending from informal sources. We analyze how household characteristics' affect obtaining a loan. Understanding the reasons causing the gap between demand and supply of rural credit at household level can help to evaluate the current outreach of the microfinance institutions and for improving credit accessibility in Vietnamese rural areas. Reportedly, very few empirical studies have so far dealt with the determinants of a households' access to informal credit in rural area. Pham and Lensink (2007) argue that the decision to borrow from informal sources is less constraining in collateral and also to be arguably less influenced by policy makers. Lainez (2014) explained three social aspects that formal financial institutions cannot meet which are the popularity, adaptability and continuity of informal sources. Since then, the author affirmed the essential existence and the role of informal credit for rural Vietnamese household economy. Finally, it is important to note that our analysis is based on the borrower's characteristics. Lenders need to check the credit rationing of the borrowers and decide to grant loan.

Specifically, these factors to access informal credit will be divided in to four groups, including personal characteristics, household factors, financial factor and geographic factors as following:

#### ***4.2.1. Individual characteristics***

In terms of age, it is expected that people from the age 40 to 50 can earn best in their life, therefore they can have better access to informal credit in that age. According to Mwangi (2006) and Asiamah (2010), households in middle working age have positive relationship with informal credit demand. In contrast, Barslund and Tarp (2008) and Khoi et al. (2012) show an inverse relationship between access to informal credit and age in Vietnam. Older household heads are likely demanding lesser amounts of informal credit. In addition, Barslund (2008) argues that older and better educated households reduce their informal credit demand.

In terms of education, Mwangi (2010) shows that clients with higher educational level will have better chance to get credit. In contrast, Asiamah (2010) stated that household head who has tertiary education will reduce the credit constraints. Khoi et al. (2012) also states that a negative relationship between education and informal credit suggests that household heads with high levels of education tend to demand less informal credit compared to the one with lower educational degree. This provides a disadvantage for illiterate persons in accessing informal credit. Therefore, we propose to test the following hypothesis:

**Hypothesis 1:** The individual characteristics: age and education of household head have a negative impact on accessibility to informal credit.

#### ***4.2.2. Household characteristics***

Related to the household size, a larger number of dependents tend to increase a household's informal credit demand (Barslund and Tarp, 2008). Another factor that is closely related to family size and family income is the dependency ratio. The more dependent members a family has, the higher the probability of being poor or the fewer the number of household members having regular income. Therefore, the household is very likely to be subjected to informal credit constraints (Okurut et al., 2005, and Li et al., 2011).

In addition, social capital can be a crucial determinant of financing decision. According to Luan et al. (2016), social capital is defined as the numbers of helpers



and number of contacts in the last 12 months. Moreover, Khoi et al.. (2013) define social capital/social networks more precisely as the participation in a credit group. Furthermore, Barslund et al.. (2008) also define social capital or social network as households having contact with existing credit institutions or receiving help from local authority to get loan. In other words, social capital can be viewed as reputation and social status (Duong and Izumida, 2002). Reputation reflects the household's economic position as well as its position in a village, which is classified into five groups: top group, upper middle, middle, lower middle, and bottom group. Similarly, social status is the position of the head of household having higher social position which can share information among credit group members and also can support networks and educate borrowers. In this paper, social capital is defined as participation of a household in a social group in which it can get more information helping it in obtaining a loan.

Following this discussion of the literature, we can make the following hypothesis:

**Hypothesis 2:** Household characteristics: size of family and numbers of joined social group, have a positive impact on household access to informal credit.

#### ***4.2.3. Financial factor***

In many studies, although land owned right certificate is almost not collateral in granting informal loan, the area of land is the most important determinant of access to agricultural credit (Linh et al., 2019). This is consistent with Zeller (1994) and Ali (2014) who show that most informal lenders grant loans based on borrowers' assets that can be viewed as indicators of borrowers' wealth and prove their repayment capacity. Similarly, Nguyen and Berg (2012) proved that land owned is important factor to reduce credit constraints. The greater the household's landholdings the more likely a household to demand a credit in order to have access to fertilizers and other inputs (Barslund, 2008).

In term of credit history, informal lenders employ various screening strategies to avoid adverse selection and moral hazard in their lending process. For example, Pham and Lensink (2007) and Khoi et al. (2013) disclose that informal lenders link

default risk to household characteristics, particularly to the lender-borrower relationship history. The capacity of loan repayment as part of the customer's previous credit history is an important factor when granting an informal loan. However, a bad formal credit history tends to increase a household's informal credit demand (Barslund, 2008). As such, we make the following hypothesis:

**Hypothesis 3:** Registered possession of land and credit history has a positive impact on household access to informal credit.

#### ***4.2.4. Geographic factors***

Distance to district center is important determinant of accessing to informal credit. The further away the household residence from the district center, the more costly to obtain the loan, due to transportation and travel costs, for example. This will not be necessarily corrected if the household directly asks for loan towards a local moneylender. However, since in remote villages local moneylenders are likely to hold more monopoly lending power, demanding stricter repayment conditions therefore lowers demand for credit (Barslund, 2008). Another reason is that borrowers want to travel in short distance to credit sources. Therefore, distance between lender and borrower or distance to credit sources significantly affect to credit accessibility. In addition, Khoi et al. (2012) also prove that informal credit demand increases when rural households dwell in areas with direct road access to a town center. Thus, we are making the following hypothesis:

**Hypothesis 4:** Distance to district center has a negative relation on informal credit access.

### **4.3. Research design**

#### ***4.3.1. Sample***

The data set comes from the Vietnam Access to Resources Household Survey (VARHS) in which 3,648 households were surveyed in 2014. The survey was conducted in 12 provinces covering Northern, Central and Southern Vietnam. The survey provides a large database on diverse aspects of rural areas and rural socio-economic development. Key data were generated in a comprehensive household survey of land, labor and credit markets in the 12 provinces. This paper uses the

credit component, including instructive questions on the sources and uses of loans, and on full credit history of households during the recent past. The general purpose is to clarify the functioning of rural credit markets and to assess the credit constraints.

#### **4.3.2. Variable definitions**

Tables 4.1 and 4.2 describe the variables used thereafter. Thus, ***Loan accessibility*** that will be our response variable, is a dummy variable indicating whether the borrower have got a loan. Following the four hypotheses discussed above, the independent variables are grouped in four categories. Then, the ***Personal*** category includes four variables related to the personal characteristics of the household head, i.e. age, ethnicity, gender and education. Age of the head of household ranges between 21 and 103 years. ***EthnicMinority*** is a dummy variable which is equal to 1 if the head of the household belongs to Kinh ethnic group, the majority ethnic group in Vietnam, and to 0 if the household head belongs to other ethnic groups. ***GenderID*** is the dummy variable which is equal to 1 if the head of the household is male and has a value of 0 if the head of household is female. ***EducationID*** is the dummy variable, which is equal to 0 if the head of household does not have a high school diploma, equal to 1 if the head of household has been trained in short courses and equal to 2 if the head of the household has a bachelor's degree or higher (Table 4.2).

The ***household*** characteristics group includes the household size, or the number of household members (***Household\_size***), the marital status (***MarriedID***), and the number of social groups that household participate in (***NumberGroup***). Particularly, ***MarriedID*** is the dummy variable of the marital status of the head of household which equals to 1 if the head of household is currently married (still alive), which is worth 0 if the household head is currently not married (still alive). ***NumberGroup*** is the number of social groups that the household participates in, and ranges from 0 to 6.

The next group consists of ***financial*** factors. This group consists of five variables: the total area of household owned land, the poor certificate, the land area devoted to agriculture, the savings deposit and the historical credit status. Thus, ***AreaTotal*** is the variable referring to the total land area owned by the household measured in square meters, and ranging from 15 square meters to 210370 square

meters. **PoorID** is a dummy variable which is equal to 1 when the household is recognized as poor, and 0 if not. **DepositID** is a dummy variable which is equal to 1 when a household has a savings account in a financial institution, and to 0 when the household has no savings. **OwnlandID** is the dummy variable which is equal to 1 when the household owns a land use right certificate, or red book, and to 0 when the household does not own the red book. **Loan-TotalID\_2012** indicates the household's loan situation two years ago, i.e. at the end of 2012. This variable is thus a dummy variable which is equaled to 1 when the household borrowed two years ago, and to 0 when the household did not borrow two years ago.

Lastly, the group of **geographic** factors includes distance, natural disasters and living areas. **Distance** measures the distance from the commune where the household is living to the nearest administrative centre. In addition, **NaturalDisasters** is a dummy variable, valued at 1 when the household's place of residence has been affected by natural disasters, and to 0 if not. **RuralID** is a dummy variable which is equal to 1 when the household lives in rural areas, and 0 if not.

**Table 4.1: Data Description of dummy variables**

Variable	Observation	0	1
<b><i>Dependent variable</i></b>			
InformalID	3648	3014	516
<b><i>Independent variables</i></b>			
<b><i>Individual characteristics</i></b>			
EthnicMinority	3648	1208	2322
GenderID	3648	699	2831
EducationID	3648	2704	<b>1:</b> 562 <b>2:</b> 264
<b><i>Household characteristics</i></b>			
Married	3648	628	2902

<b>Variable</b>	<b>Observation</b>	<b>0</b>	<b>1</b>
<i>Financial factors</i>			
PoorID	3648	2869	661
DepositID	3648	623	2907
OwnlandID	3648	723	2807
LoanTotalID_2012	3648	2261	1269
<i>Geographic factors</i>			
RuralID	3648	126	3404
NaturalDisasters	3648	2544	986

As showed in Tables 4.1 and 4.2, household head average age is 54 years. Each household participates in about 2 community groups while the size of household is around 5 members. The average total land area owned by a household is 9200 square meters (including cultivated land). Besides, about 76% of the surveyed people are Kinh and 80% sample is married. Household heads who have not achieved high school degree is accounted for 74% while 79% of the total number of surveyed people are poor and more than 90% live in rural areas.

**Table 4.2. Data description of continuous variables**

<b>Variables</b>	<b>Obs</b>	<b>Mean</b>	<b>Min</b>	<b>Max</b>
<i>Individual characteristics</i>				
Age	3648	54.36	21	103
<i>Household characteristics</i>				
NumberGroup	3648	1.661	0	6
<i>Financial factors</i>				
AreaTotal	3648	9205	15	210370
<i>Geographic factors</i>				
Distance	3648	2.631	0	3.0000

### 4.3.3. Methodology

This study provides an empirical analysis of the determinants of access to informal credit in Viet Nam for households living in rural areas. Our aim is to identify which factors have a significant impact on the probability of getting a loan using *InformalID* as the dependent variables and the different independent variables just described. This will allow us to validate or not the four hypotheses stated above. For that purpose, we combine Random Forests (Breiman, 2001) and traditional logistic regression to estimate determinants of informal credit access (see, among others, Malekipirbazari and Aksakalli, 2015).

#### 4.3.3.1. Logistic regression model

The logistic regression model is the most widely used tool to estimate the impact of different predictors on the probability of obtaining a loan. This model can be defined as follows. Let  $(x_i, y_i)$ ,  $i=1, \dots, n$ , be a sample of size  $n$  of independent and identically distributed observations where  $x_i$  denotes the  $p$ -dimensional vector of predictors and  $y_i \in \{0,1\}$  is a binary variable taking the value one when the household gets a loan and zero otherwise. The conditional probability of getting a loan can be modeled using a logistic regression with the following specification

$$Pr(y_i = 1|x_i) = F(\eta(x_i; \beta)) = \frac{1}{1 + \exp(-\eta(x_i; \beta))}$$

with  $F(\cdot)$ , the logistic cumulative distribution function, and  $\eta(x_i; \beta)$ , the so-called index function or

$$\eta(x_i; \beta) = \beta_0 + \sum_{j=1}^p \beta_j x_{ij}$$

where  $\beta = (\beta_0, \beta_1, \dots, \beta_p)$  is an unknown vector of parameters to be estimated. An estimation can be obtained using maximum likelihood technique.

The main advantage of the logistic regression model is its simple interpretation. Indeed, this model searches for a linear combination of predictive variables when assessing the probability of getting a loan. Then, the relative contributions of predictors to this probability can be achieved by computing marginal effects as

$$\frac{\partial \Pr(y_i = 1|x_i)}{\partial x_{ij}} = \beta_j \Pr(y_i = 1|x_i) [1 - \Pr(y_i = 1|x_i)], \quad j = 1, \dots, p,$$

with estimates of these effects obtained by replacing  $\beta$  by estimated values  $\hat{\beta}$ . Thus, a predictive variable with positive (negative) significant coefficient has a positive (negative) impact on the probability of getting a loan. However, this simplicity comes at the cost of restrictive assumptions on the parametric specification of the cumulative distribution function and on the linearity of index function.

In our application of logistic regression, our binary  $y$  variable is ***LoanInformalID***, and the vector of independent variables consists in the variables described in Tables 4.1 and 4.2.

#### 4.3.3.2. *Random forest*

Decision trees, introduced in the 1960s and brought up to date by Breiman et al.. (1984) can be viewed as a nonparametric alternative to logistic regression model. Indeed, this technique consists in the application of an algorithm that recursively partitions the sample into smaller subsets, so as to group together as accurately as possible households with the same behavior, i.e. the same value of the binary target variable  $y_i$ . More precisely, consider a given tree  $l$ . The algorithm proceeds as follows. Let  $\Omega_{m,l}$  be the data subset at a given node  $m$  of this tree. Let  $\theta_{m,l} = (j_{m,l}, t_{m,l,j})$  denote a potential split where  $j_{m,l}$  indicates a given predictive variable ( $j_{m,l} = 1, \dots, p$ ) and  $t_{m,l,j}$  is a threshold value in the support of this variable. The algorithm partitions the data  $\Omega_{m,l}$  into two subsets  $\Omega_{m,l,1}(\theta_{m,l})$  and  $\Omega_{m,l,2}(\theta_{m,l})$  with

$$\Omega_{m,l,1}(\theta_{m,l}) = \{(x_i, y_i) \mid x_{ij} < t_{m,l,j}\} \text{ and } \Omega_{m,l,2}(\theta_{m,l}) = \{(x_i, y_i) \mid x_{ij} \geq t_{m,l,j}\}$$

where the parameter estimates  $\hat{\theta}_{m,l}$  satisfy

$$\hat{\theta}_{m,l} = (\hat{j}_{m,l}, \hat{t}_{m,l,j}) = \underset{\theta_{m,l}}{\operatorname{argmax}} \left( G(\Omega_{m,l}) - \frac{1}{2} (G(\Omega_{m,l,1}) + G(\Omega_{m,l,2})) \right)$$

where  $G(\cdot)$  a measure of diversity (for example, the Gini criterion) applied to the full sample and averaged across the two sub-samples, respectively. Parameter estimates  $\hat{\theta}_{m,l}$  appears as the value of  $\theta_{m,l}$  that reduces diversity the most within each subset resulting from the split. The splitting process is repeated until the terminal sub-samples, also known as leaf nodes, contain homogenous households according to a predefined homogeneity rule.

Once the tree is obtained, membership of a household in a leaf defines the predicted value of  $y_i$  for this household. This value corresponds to the predominant class (having gotten a loan or not) for households which belong to that particular leaf. Formally, the predicted value for a given household is obtained as follows. Let  $M_l$  denote the total number of splits in tree  $l$ , and  $|T_l|$  denote the corresponding number of leaf nodes. Then, the predicted value is

$$h(x_i; \hat{\Theta}_l) = \sum_{t=1}^{|T_l|} c_t 1(i \in L_t)$$

where  $\hat{\Theta}_l = \{\hat{\theta}_{m,l}, m = 1, \dots, M_l\}$  is the set of estimated parameter vector for tree  $l$ ,  $L_t, t = 1, \dots, |T_l|$ , are leaves, and  $c_t, t = 1, \dots, |T_l|$ , are the dominant classes in the different leaves.

The random forest algorithm is based on the construction of a myriad of non-correlated decision trees, creating a “forest” that is then aggregated. The diversity of these decision trees comes from two aspects of the manner of constructing the forest. First, each decision tree is built on a random sample of the observations, according to the bootstrap averaging, or bagging, method (Breiman, 1996). Predictive performance of Random Forests benefits from the variance reduction effect of bootstrap averaging for non-correlated predictions. Second, to insure a low level of correlation among decision trees, the random forest algorithm chooses the candidate variable for each split in every tree from a restricted number of randomly selected predictors among the  $p$  available ones.

At the end of the random forest algorithm, in order to generate predictions, the decision trees are aggregated. The prediction of getting a loan, or  $h(x_i)$ , is



obtained by the principle of majority rule, i.e.  $h(x_i)$  corresponds to the mode of the empirical distribution of  $h(x_i; \hat{\theta}_l)$ ,  $l = 1, \dots, L$ , where  $L$  is the number of trees in the forest.

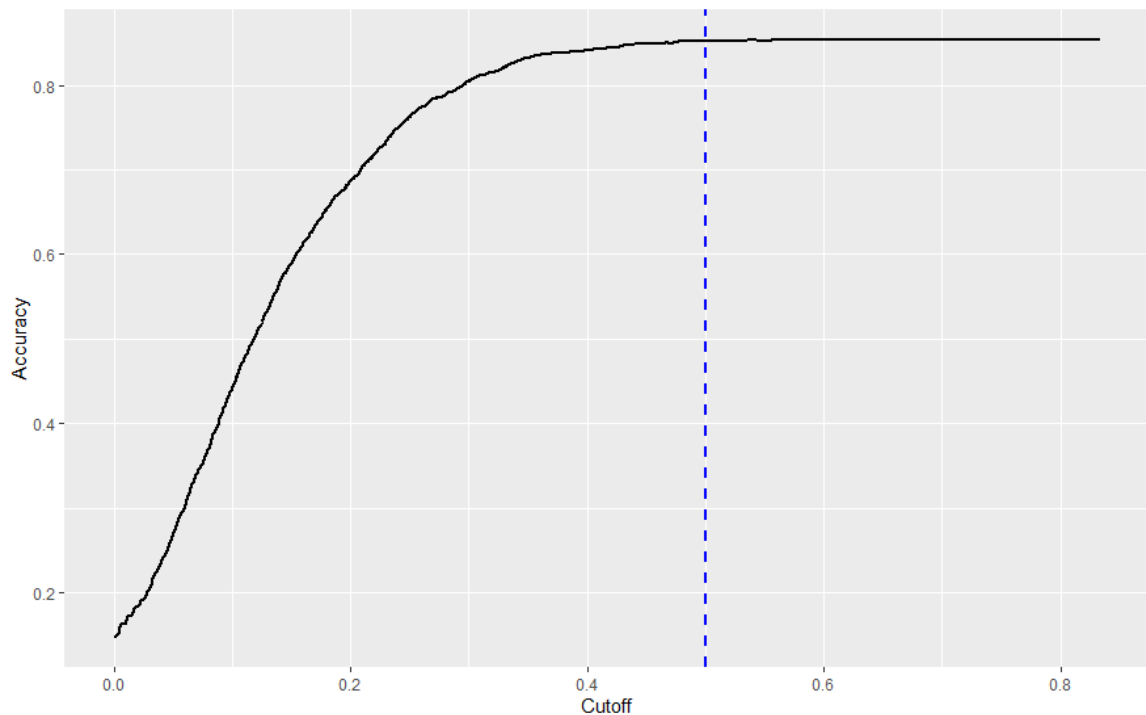
On one hand, random forest technique is known to outperform logistic regression in terms of predictive performance (see, for instance, Lessmann et al., 2015). But, on the other, as random forest's decision rules arise from aggregation of individual decision tree rules, they are less relevant when assessing the impact of predictors on the binary target variable. Indeed, Random Forests do not produce interpretable results such as marginal effects, unlike logistic regression. Nevertheless, Random Forests provide built-in means of estimating variable importance and thus identifying important predictors (Archer and Kimes, 2008). Hence, because Random Forests are an ensemble of individual decision trees, Gini importance can be leveraged to calculate Mean Decrease in Gini, which is a measure of variable importance for estimating a target variable (Louppe et al., 2013). Mean Decrease in Gini is the average (mean) of a variable's total decrease in node impurity as measured by Gini index, weighted by the proportion of samples reaching that node in each individual decision tree in the random forest. This is effectively a measure of how important a variable is for estimating the value of the target variable across all of the trees that make up the forest. A higher Mean Decrease in Gini indicates higher variable importance.

#### **4.4. Results**

Random forest algorithm is first implemented using a forest size of 500 trees. For each tree, we must define the number of variables to be used for each node tree creation. Breiman (2001) in his original work suggests the square root of the total number of variables involved in tree building, i.e. 15 leading to a random choice of 4 competing variables in each node creation. In order to evaluate the performance of the random forest classifier, we compute the accuracy of the algorithm in classifying the data into its corresponding labels getting a loan or not. Classifying data involves the choice of a cutoff when assigning data to labels and, in turn, accuracy will depend on the chosen cutoff. Figure 4.1 reports accuracy value when

the cutoff value moves from 0 to 1. Accuracy increases as cutoff increases, taking the values of about 60% and 85% of well classified individuals at the cutoffs of 0.15, the proportion of individuals having obtained a loan in the sample, and 0.50, the usual cutoff for constructing a contingency table. This information, which is very sensitive to the choice of the cutoff value, is usually summarized by taking the area under the ROC curve (AUC). This curve is a performance measurement for the classification problems at various cutoff settings. ROC is a probability curve and AUC represents the degree or measure of separability. It tells how much the model is capable of distinguishing between classes. Higher the AUC, the better the model is at predicting 0s as 0s and 1s as 1s. In our case, AUC is about 0.60. This value is greater than 0.5, the value indicating that the classifier has no class separation capacity whatsoever. It means that there a 60% chance that the chosen random forest is able to distinguish between the class of getting a loan from the class of not getting a loan. The performance of the chosen random forest is therefore average, but comparable to those obtained using Random Forests in the literature (see, for instance, Malekipirbazari and Aksakalli, 2015).

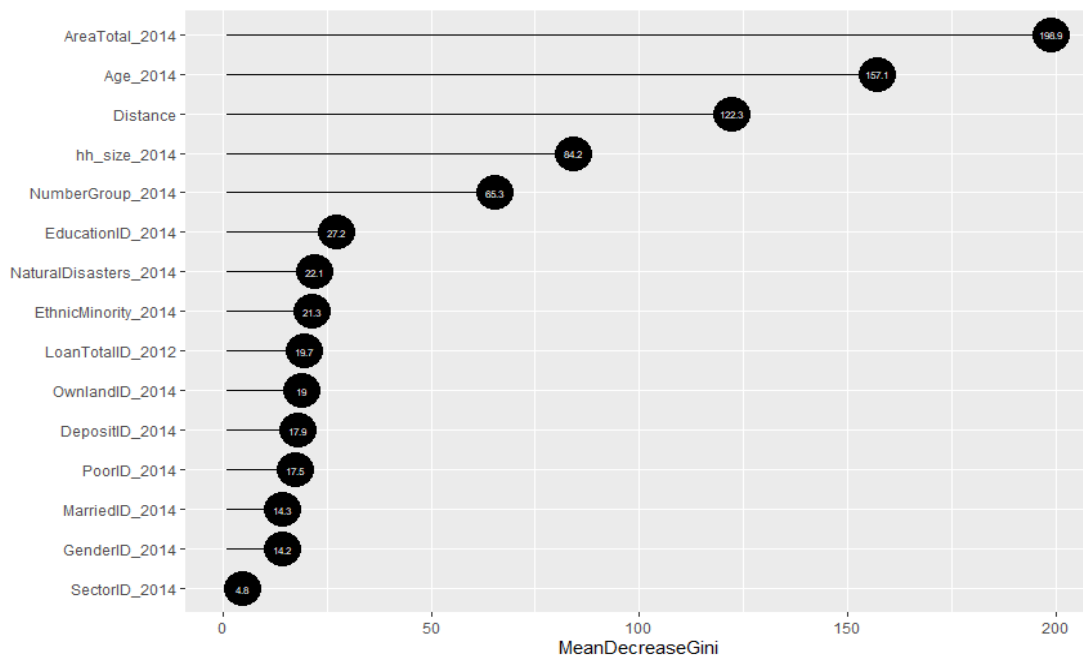
**Figure 4.1 Accuracy of random forest classifier**



*Source: Authors*

Random forest technique provides built-in means of estimating variable importance (Breiman, 2001). Figure 4.2 reports Mean Decreases in Gini for all the variables. They are ranked according to the importance of their mean decrease in Gini. Figure 4.2 shows that the following variables have the greatest importance in explaining access to informal credit of rural Vietnamese households: land ownership (**Area**), Age (**Age**), the distance from the household to the administrative center (**Distance**), household size (**hh\_size\_2014**) and the number of community groups that the household participated in (**NumberGroup**). This group of variables distinguish from the remaining ones which exhibit lower mean decreases in Gini of comparable amplitude.

**Figure 4.2. Mean Decreases in Gini**



*Source: Author*

Figure 4.2 above then provide a full picture of the relevant factors which can influence to the access to informal credit of rural households in Vietnam. Thus, this information can help bank to focus on significant factors which can cover material loan portfolio.

Table 4.3 reports the results of logistic regression model estimation. The ability of rural households to access informal credit according to the model results is explained mainly by the following variables: Age of household head (Age), education level (EducationID), ethnic groups (EthnicMinority), size of households

(household\_size), marital status (MarriedID), number of community groups that households family member joined (NumberGroup), total land area (AreaTotal), living area (RuralID), Savings deposit (DepositID), distance from household to administrative centre (Distance), credit history in year 2012 (LoanTotalID\_2012).

**Table 4.3: Estimated factor impacts on rural household access to informal credit**

	Estimate		Std. Error	dF/dx		Std. Err.
Intercept	-1.22200	**	0.46680	-2.619		0.00883
<i>Personal characteristics factors</i>						
Age	-0.02314	***	0.00427	-0.00265	***	0.00048
EthnicMinority	0.24320	.	0.12600	0.02712	**	0.01365
GenderID	0.06229		0.18420	0.00704		0.02054
EducationID1	0.10890		0.13280	0.01282		0.01607
EducationID2	-0.45660	*	0.22190	-0.04534	**	0.01881
<i>Household characteristics factors</i>						
hh_size	0.06692	*	0.02990	0.00767	**	0.00342
Single	-0.41630	*	0.19800	-0.05264	*	0.02740
NumberGroup	0.13920	**	0.04951	0.01596	***	0.00565
<i>Financial factors</i>						
AreaTotal	0.00001	**	0.00000	0.00000	***	0.00000
PoorID	-0.19550		0.14230	-0.02142		0.01488
DepositID	-0.56260	***	0.11770	-0.07363	***	0.01726
OwnlandID	-0.10240		0.13050	-0.01200		0.01563
LoanTotalID_2012	0.48650	***	0.09903	0.05876	***	0.01248
<i>Geographic factors</i>						
RuralID	0.76550	*	0.34080	0.06742	**	0.02209
Distance	-0.05929	**	0.02058	-0.00680	**	0.00234
NaturalDisasters	-0.16030		0.11570	-0.01791		0.01258

.' significant at 10%, '\*'5%, '\*\*' 1%, '\*\*\*' 0.1%

Notes: The regressions include lag variable (loan 2012 and 2014)

The logistic regression model and marginal effect was used.

Source: Estimation from VARHS 2012 and 2014

In the group of personal characteristics, results show that there is a negative relation between accessibility of informal credit and age, with a marginal effect of age which is significantly different from zero at 0.1%. This result confirms Hypothesis 1. One year older for the household head imply a decrease of 0.265 percentage points in the probability to access informal credit. We believe that the informal credit market is a quite risky source of credit for household and when household heads are getting older, they are not willing choose this risk. However, this is contrary with Mwangi (2009) since he argues that in middle age, a person's ability to access informal credit is higher than those with the same conditions but being younger.

Related to **Education** factor, the negative estimated coefficients are at the 5% significant level indicating that families with college graduated household heads will become less likely to demand informal credit than families whose head does not have any diploma. This finding is in line with Santos et al. (2010) when he believes that having little financial knowledge will increase the likelihood of using informal credit. Thus, hypothesis H1 of the education level of the household head has a negative impact on access to informal credit that has been confirmed by this model.

In addition, results for the second group of factors of household characteristics confirm Hypothesis 2. Indeed, first, the household size shows a positive and significant (at 5%) impact on the accessibility of informal credit. Specifically, with one additional member in the family, the chance to get informal credit increase by 0.767 percentage points. This result fits our expectation that the more members in a family, the more credit is needed, leading to the need of access informal credit. This is consistent with Barslund and Tarp (2008) whose study shows that the more people in a household, the more likely it is that the household will increase demand for use informal credit.

If households participate in more public groups of the community, the family will have better access to informal credit, the corresponding marginal effect being significantly different from zero at 1%. Only few studies have assessed the impact of this variable on the access to informal credit by rural households in Vietnam. Participating to one more group increases the probability to access informal credit by

1.6 percentage points. It implies that when joining those groups, household will have a larger network and they have more chance to access credit through those sources. Thus, Hypothesis 2 is confirmed. This is inline with Khoi et al. (2013).

Confirming Hypothesis 3, the area of owned land (**AreaTotal**) shows positive correlation with chance to get informal loan. Therefore, owning one additional square meter increases the probability to get informal credit by 0.0001 percentage points. Even small, this impact is significantly different from zero at 5% which is supported by Wang (2010) and Khoi (2013). In addition, historical credit (**LoanTotalID\_2012**) proved the similar results with 0.1% significance level.

Confirming Hypothesis 4, the distance from household living location to administrative center has a negative and significant (at 1%) impact on accessing to informal credit. This is in line with our expectation that a far-from-bank household is likely to find an informal source of credit. However, this also make sense as living far from a formal source of credit means living in an area with little population, and, then, it would be more difficult to find a source of credit, whatever formal or informal. This concurs with the view that distance acts as an obstacle to access to credit since borrowers prefer short distances with their financial service providers (Mwangi, 2010).

## **4.5. Concluding remarks and policy implications**

### ***4.5.1. Concluding remarks***

Identifying true creditworthiness of a potential loan borrower is important to private lender. In order to compute the risk score of an individual, financial features are divided into four main groups including personal characteristics, household's characteristics, financial factors and geographical factors, on the accessibility to informal credit. Those factors are first ranked according to their importance in explaining access to informal credit using the nonparametric random forest techniques. Owned land area, age of the household head, distance from household's location to administrative center, household size, number of social groups in which the household head participates are ranked to identify the main drivers when getting a loan. Other factors are only playing a minor role.

A direct applied consequence of this result is that lenders should focus on those main factors to value the borrowers. The results obtained from Random Forests chart show that all four hypotheses are supported with the ranking of importance of the main factors are in accordance with above mentioned order.

In a second step, we perform a logistic regression to evaluate the marginal impact of the factors, which is not possible using only Random Forests technique. The host's characteristic factor group including age, ethnic and education variables have a multiple aspects impact on the accessibility to informal credit. The household's characteristic group (size and number of groups participated) and financial factor group (total land size and history of financing variables) have a positive impact to get informal loan. The last group of factor includes distance variables has a negative impact on the accessibility to informal credit. Particularly, the land owned area is the variable which is the largest positive impact on the accessibility to informal credit of Vietnam rural household. Followed are household size, number of social groups participated and historical credit. In contrast, the most negative impact on the accessibility to informal credit is age, followed by distance and education variable.

From these results, several recommendations can be drawn to improve the effectiveness of informal credit market in rural area of Vietnam.

#### ***4.5.2. Implications***

The most important implication of this study is that the ranking of main drivers of credit accessibility is very important. In addition, credit accessibility factors are also identified. From these results, several recommendations can be drawn in order to improve the effectiveness of informal credit market in rural area of Vietnam.

First, joining community groups has a positive impact on accessibility to informal credit so rural household can be advised to join these social groups. It will help rural households increasing their network and accessing to more information on informal credit.

Second, moneylenders may invest in remoted areas where the credit market still

have not fully developed. Moneylenders should concentrate on the local borrowers, where they could get an advantage to put a supervision on. Moreover, a close relationship with the borrowers will significantly lower the risk of default.

Third, a safe and low-cost source of informal credit is the ROSCA might be developed in rural market so that households can use this source of credit.

Finally, the rate of households seeking informal source of credit in rural Vietnam is material about 20%. Although the coexistence of formal and informal credit is undoubtful, the informal credit market is quite popular in developing countries. The Government of Vietnam can combine both formal and informal credit sectors into a well-functioning rural credit market which can effectively improve credit access for rural area.

#### ***4.5.3. Limitation***

This chapter proposes a new approach of credit scoring which combines classical logistic regression and random forests. Although Random Forests proved to be substantially accuracy in predictivity, it is still generally considered challenging in the credit scoring report for regulatory purposes. In addition, other essential criterion of a good credit scoring model is interpretability which is difficult to evaluate. Despite of good performance, using Random Forests results in prediction may rise difficulties when interpreting them. This is really challenging for managers and regulators who often want simple and interpretable results. Therefore, balance between predictive performance and interpretability is key issue. This can be solved by diminishing the complexity of the random forest method by selecting only some trees or decision nodes in the forest (Deng, 2019). Moreover, remaining the simplicity of logistic regression by improving its predictive performance with univariate and bivariate endogenous threshold effects (Elena et al., 2021).



## **Chapter 5: Formal and informal rural credit accessibility of ethnic minority households: Evidence from Vietnam**

The previous chapter has already contributed to the credit scoring literature by adopting a new methodological approach which combines classical logit estimation of the probability of getting an informal loan with random forests estimation techniques. Since this approach has proved to outperform most other classifying techniques in terms of prediction, we further apply it to compare credit access between the major ethnicity in Vietnam (Kinh) and the other ethnic minority groups, to both formal and informal financial sources. Heretoo, data from the 2014 wave of Vietnam Access Resource Household Survey (VARHS) is used in this chapters. Our investigation shows that the Kinh group has higher accessibility to loan than any other ethnic minority groups from both formal and informal credit market. Nevertheless, when focusing on the formal market, results show that minority groups have better chance to get credit from the Vietnam Bank of Social Policy (VBSP). It implies that there is not equal access to credit for households from the different ethnic groups and that an appropriate credit scheme needs to be considered by the Government to improve the rural credit market.

The chapter is structured into five sections. Section 1 gives an introduction while section 2 presents a literature review of the determinants of credit accessibility of rural households and gives background information on ethnic minorities in Vietnam. Section 3 will introduce the data and methodology used in analyzing the household characteristics, which may potentially influence the probability of being credit rationed. Section 4 presents the classifiers and a comprehensive results and discussions. A summary and some conclusive remarks are presented in section 5.

### **5.1. Introduction**

Vietnam has achieved good economic growth and poverty reduction over the past two decades. Over the past decade, Vietnam has witnessed amazing reduction in poverty. According to World Bank (2020), the poverty headcount ratio by national standard decreased from 4.2 percent in 2010 to 2.7 percent in 2014 and continued

to decrease to 1.9 percent in 2018. However, there is still a gap in living standards between the Kinh majority and ethnic minorities.

In Vietnam, there are 54 ethnic groups, of which the Kinh is the major group which accounts for around 86 percent of the total population (UNDP, 2017). Although the ethnic minorities' population represents only 14 percent of total population, poverty is concentrated among these ethnic groups which makes up 60 percent of the poor (WorldBank, 2017). There was still about 66 percent of ethnic minorities living below the poverty line and around 7 percent living below the extreme poverty line in 2010 while that of Kinh group were about 13 percent and 3 percent, respectively (UNDP, 2017). Moreover, most of the poor and ethnic groups live in rural and mountainous areas which populates 82 percent of the near poor and 84 percent of those below the 40th income percentile.

In order to help the poor increasing their living standard, an improvement for credit access is essential for households to develop their business and increase their income (Eswaren & Kotwal, 1990); Urdy 1994). Specifically, providing access to credit to farmers and rural households can help them to increase economies of scale in production and generate the profits necessary to lift themselves out of poverty. Diagne et al. (2000) claim that access to credit influences household welfare in at least two main ways. It increases households' risk bearing capacity and enables long term investments (Zeller, 2012). For rural families, credit can allow them to promote agricultural production and transformation (Eswaren & Kotwal, 1990), Urdy (1994). On the other side, Guirkingner and Boucher (2007) proves that 27% loss of agricultural output related to credit constraints in rural Peru.

In developing countries, the economic choices of poor households are often limited due to inefficient financial markets (Banerjee and Duflo, 2007). A key issue is the extent to which households can access to financial services, particularly in the formal sector. Therefore, the establishment of microfinance institutions aims to fill a gap on formal financial market. These institutions, many of which are non-profit basis, provide small loans to people who can not get loan from formal financial institutions (Morduch, 1999). Although the microfinance institutions seem to be

effective, they have been criticised for not being able to reach the very poor and for being cost-ineffective (Cull et al., 2009). The government, therefore, often supports the credit access for the poorest group. In this chapter, we focus on the gap in credit access in rural areas between Kinh group and other ethnic minority groups. We then analyze how household characteristics affect the credit constraints by ethnic groups. This is important for evaluating the current outreach and improving credit accessibility in rural areas. Reportedly, very few empirical studies have so far analyzed the determinants of a household access to credit in the ethnic minority region (Putzeys, 2002).

Access to credit plays an important role for economic development of countryside, especially for minority groups. In Vietnam, access to credit focuses on the three main sectors, formal, semi formal and informal markets.

Formal credit markets are understood as credit provided by formal institutions. In Vietnam, formal credit is granted mainly by Vietnam's Bank of Social Policy (VBSP) and Vietnam's Bank of Agriculture and Rural Development (VBARD), which makes up for more than two third of farmers' credit (Dinh, 2015).

Semi formal market consists of NGOs and licenced MFIs.

Informal credit market consists of (i) private lending by unrelated individuals and friends charging interest, and (ii) lending from families, relatives and friends carrying zero interest. These two segments will be referred to as 'private' and 'family'.

In the last years, various statistical methodologies have been used to aggregate client specific information into a single figure in order to project default probability. These classification methods range from simple Discriminant analysis (Kočíšová & Mišanková, 2014; Cox & Wang, 2014;) and Logit/Probit regressions (Ohlson, 1980; Cole & Wu, 2017), to advanced machine learning methods such as Support Vector Machines (Chen & Jen, 2006; Boyacioglu, Yakup, & Baykan, 2009), conditional inference trees and Neural Networks (Ravi & Pramodh, 2008, Messai & Gallali, 2015). At the same time, other novel modeling approaches such as Random Forests (RF) (Breiman, 2001) have not been commonly employed in

assessing bank failures, although these models are really popular in modeling classification. In this work, addressing the aforementioned gap in the current literature, we employ techniques in predicting credit default, including Logistic Regression (LR) and Random Forests (RF). The model evaluation measures used in this analysis are tailored to compare the credit access of different ethnic minorities in rural area of Vietnam by traditional logistic regression model. In an attempt to offer more evidence on this questionable aspect in the current literature, we rank the importance of the independent variables based on their marginal contribution by Mean decrease Gini.

This study makes three important contributions to the literature review on credit access of rural finance. First, this paper contributes to the rural credit literature by assessing the gap in credit access between the Kinh and other ethnic minority groups to both formal and informal sources. Second, the methodological approach is the first to combine a classical logit estimation of the probability of getting a loan with random forests estimation techniques which is proved to outperform other traditional methods in predicting credit accessibility. Last, but not least, this research is the first one to rank the importance of the credit access determinants so that the bank can focus on the most important determinants to better manage credit risk. Therefore, this study provides a different way of measuring the access of credit and thereby advances our projection capacity which is quite different with traditional method used by most recent papers.

This chapter will generate relevant views about the characteristics and functioning of the rural credit market which are helpful to policymakers in order to designate programs aimed at improving living standards of ethnic minorities. Furthermore, this research can help bank to review existing customer database, find good current customers to offer more financial products which can save time and cost compared to expand new client database. This approach also can suggest bank to develop early warning systems for default risk based on current database.

## **5.2. Literature review**

The success of credit provision for poverty reduction depends on the available credit that poor households can access on both formal and informal markets. This research will focus on one of the poorest household group, ethnic minorities. They often live in very remoted area and earn low income, even below the poverty line. They only have limited access to infrastructure, education, health services and non-farm employment. Some evidences show that minority group has 12 percent less chance than the Kinh and Chinese minority groups to get wage jobs (Nguyen, 2012). The low accessibility to production inputs diminishes their need to credit. A depth analysis of rural and minority householders' characteristics can, therefore, enlighten obstacles to approach the least favorite market for financial suppliers and policy makers.

Previous studies have identified a number of key factors determining rural and minority households' demand for credit which can be categorized into three following groups: (1) demographic factors, (2) social network factors and (3) socio-economic factors.

First, regarding the demographic component, Biyase and Fisher (2017) have shown that the educational level, occupation and income of household heads are positively correlated with household loans in South Africa. Other factors such as age and education background also play an important role in increasing access of rural families to formal credit. Hussien (2017) argued that the older family's head are, the more experienced, knowledge and network is built up. They, therefore, can improve their family's outputs by efficient economic decisions and progressively credit approval from formal financial institutions. In fact, the likelihood of households with successful credit history to take on new loans is also higher than other households (Dube, Mariga and Mrema, 2015). Besides, minority and disadvantaged groups often ignore the formal credit because they believe that their probability to get loan approval from a commercial bank is extremely low. However, the impact of the number of family's members in working age exhibits an inverse relationship with credit accessibility. These families have more resources for their production which will reduce the need for production expenses and capital (Yehuala, 2008; Dube, Mariga and Mrema, 2015).

Second, relating to social network factor, Guiso (2004) proves that in high social capital areas households have higher access to formal credit and make less use of informal credit. In addition, Khoi et al.. (2013) define social capital/social networks more precisely as the participation in a credit group or membership in an organization. Furthermore, according to Barslund et al.. (2008), social capital or social network can be viewed as households having contact with existing credit institutions or receiving help from local authority to get loan.

Finally, relating to socio-economic factors, Berg and Schrader (2012) state that while credit demand increases due to natural disaster, access to credit is constrained. It is found that the relationship between bank and the borrower can ease those constraints and that clients having credit history with banks has more chance to receive loans after a natural disaster has occurred. According to Natural Disasters and Credit Reporting issued by Bureau of Consumer Financial Protection (2018), natural disasters can cause negative shocks to household finances such as lost income and major unexpected expenses. Farrell and Greig (2018) estimate that checking account in flows reduced by 20 percent and outflows diminished by more than 30 percent after a natural disaster. As a result, many financial institutions offer financial relief or assistance that often includes payment relief for current customers affected by natural disasters. This proved that current socio economy factor can have effect to credit customers.

In Vietnam, the government has integrated microcredit into the National Poverty Reduction and Growth Strategy by utilizing the state-owned banks to provide credit to the rural area, such as providing credit access to the rural poor at a preferable interest rate. Different forms of credit are available to the rural market such as individual lending, group lending, and village banking. In particular, many microcredit programs have been developed to provide greater credit accessibility to rural households. These include the provision of formal microcredit through the Vietnam Bank for Agricultural and Rural Development (VBARD), and the Vietnam Bank for Social Policy (VBSP). Particularly, VBSP was established to pro-

vide preferential credit for the poor and other beneficiaries. It is not for profit purposes and is guaranteed solvency by the State (Vietnam Microfinance Working Group, 2019)

Other programs have been implemented through semi-formal credit providers, such as the Women's Union, Farmers' Association, and Youth Union, which are organized at national, provincial, commune, or district levels. Informal lenders also exist providing an alternative source of credit to a large proportion of the market. This mixture of different credit channels to serve rural households promises not only greater credit accessibility but also greater competition among the different forms of microcredit providers in the rural area.

Until now, only few studies deal with the issue of the disparity of credit access between Kinh and other ethnic minorities. This chapter will fill in the literature by focusing on the impact of accessibility of formal and informal credit in Vietnam and emphasizing the gap of credit access between the Kinh and other ethnic minority groups based on the following hypothesis:

**Hypothesis:** the Kinh group has higher accessibility than any other ethnic minority groups from both formal and informal credit market. However, minority group has better chance to get credit specifically from the Vietnam Bank of Social Policy (VBSP).

### **5.3. Research design**

#### **5.3.1. Samples**

This paper bases on two data sets from the VARHS, which were conducted by the ILSSA in 2012 and 2014 covering 3648 households, including 2869 of Kinh and 779 ethnic minority families. The 12 provinces which were all initially surveyed include the 466 communes that make up the VARHS panel. The ILSSA survey is not nationally representative, but it is representative for rural households in the 12 provinces under study. They cover a lot of the variation in geographical and socio-economic conditions present in Vietnam, including regional differences between the North, Center and South of the country.

The sample design of 2012 and 2014 VARHS follows a method of classified random group sampling in all rural provinces of Vietnam. The number of selected communes in each VARHS is 466. In each commune, about seven households were selected randomly.

Data on credit rationing were collected using very detailed questionnaires. Information on household and commune categories was collected and then aggregated into panel per household.

The samples of 2014 VARHS are presented in table below:

**Table 5.1: Number of provinces**

No	Province	District	Communes	Households
1	Ha Tay (Ha Noi 2)	14	71	589
2	Lao Cai	9	28	295
3	Phu Tho	13	49	385
4	Lai Chau	6	34	320
5	Dien Bien	9	33	317
6	Nghe An	20	69	228
7	Quang Nam	13	44	338
8	Khanh Hoa	8	29	108
9	Dak lak	14	41	350
10	Dak Nong	8	35	307
11	Lam Dong	10	24	78
12	Long An	14	43	333
	<b>Total</b>	<b>138</b>	<b>500</b>	<b>3,648</b>

*(Source: VARHS 2014)*

The ILSSA survey covered a large variety of topics related to land, labor and credit of households. In this research, we rely on the credit component, including a number of instructive questions on household resources in order to obtain the loan and full credit history of households during the recent past. The purpose of



this part of the survey was to clarify the functioning of rural credit markets in Vietnam and to assess the extent to which credit rationing constrains rural area and ethnic minority groups.

### 5.3.2. Variables definition

In this paper, *Dependent variable* will be probability whether the household has a loan (1) or not (0).

The relationship between independent and dependent variables are estimated by a logistic model with the independent variables presented in Table 5.2.

**Table 5.2: Independent variables**

Variables	Interpretation
Age	Age of household head
Household_size	Size of household
EthnicMinority	1 = Kinh ethnicity
EthnicMinority	0 = other ethnic groups
NaturalDisasters	1 = Affected by disaster
NaturalDisasters	0 = Unaffected by disaster
Gender	1 = Household head is male
Gender	0 = Household head is female
AreaTotal	Land size
Single	1 = Household with married couple (alive)
Single	0 = Household without married couple
Urban	1 = Household in urban areas
Urban	0 = Household in countryside
Poor	1 = Poor households
Poor	0 = Not a poor household
Deposit	1 = Household with saving account
Deposit	0 = Household without saving account
OwnLand	1 = Household with Registration book
OwnLand	0 = Household without Registration book

LoanTotal	Total value of the loan
LoanTotal	1 = Household with loans
LoanTotal	0 = Household with no loans
LoanVBSP	Total value of the loan at VBSP
LoanVBSP	1 = Household with loans by VBSP
LoanVBSP	0 = Household with no loans by VBSP
LoanVBARD	Total value of the loan at VBARD
LoanVBARD	1 = Household with loans by VBARD
LoanVBARD	0 = Household with no loans by VBARD
LoanFormal	1 = Household with formal loans
LoanFormal	0 = Household with no formal loans
LoanInformal	1 = Household with informal loans
LoanInformal	0 = Household with no informal loans
EducationID	0 = Household with no education diploma
EducationID	1 = Household with short-term education certificate
EducationID	2 = Household with bachelor or higher diploma
NumberGroup	The number groups that the household takes part in

(Source: Prepared by the authors)

### 5.3.3. Methodology

In this paper, random forest made of decision tree used to identify the importance of each factor for household's access to credit. In addition, logistic model is used to evaluate the influences of each factor.

#### ***Random forest***

According to Breiman (2001), Random Forests technique belongs to the family ensemble methods that aim at improving the predictive performance of given statistical or machine learning algorithm by using a linear combination (through averaging or majority rule) of predictions from many variants of this algorithm rather than a single prediction. More specifically, random forests are based on the technique of decision trees, introduced in the 1960s and up to date by Breiman et al..

(1984), can be considered as a nonparametric substitute to logistic regression model. Definitely, this technique comprises of the application of an algorithm that divides the households into smaller subcategories with the same behavior together as accurately as possible, i.e. the same value of the binary target variable  $y_i$ . More precisely, consider a given tree  $l$ . The algorithm is as below. Let  $\Omega_{m,l}$  be the data subset at a given node  $m$  of this tree. Let  $\theta_{m,l} = (j_{m,l}, t_{m,l,j})$  denote a potential split where  $j_{m,l}$  indicates a given predictive variable ( $j_{m,l} = 1, \dots, p$ ) and  $t_{m,l,j}$  is a threshold value in the support of this variable. The algorithm partitions the data  $\Omega_{m,l}$  into two subclasses  $\Omega_{m,l,1}(\theta_{m,l})$  and  $\Omega_{m,l,2}(\theta_{m,l})$  with

$$\Omega_{m,l,1}(\theta_{m,l}) = \{(x_i, y_i) \mid x_{ij} < t_{m,l,j}\} \text{ and } \Omega_{m,l,2}(\theta_{m,l}) = \{(x_i, y_i) \mid x_{ij} \geq t_{m,l,j}\}$$

where the parameter estimates  $\hat{\theta}_{m,l}$  satisfy

$$\hat{\theta}_{m,l} = (\hat{j}_{m,l}, \hat{t}_{m,l,j}) = \underset{\theta_{m,l}}{\operatorname{argmax}} \left( G(\Omega_{m,l}) - \frac{1}{2} (G(\Omega_{m,l,1}) + G(\Omega_{m,l,2})) \right)$$

$G(\cdot)$  is a measure of diversity (e.g the Gini criterion) which applied to the full sample and averaged among the two sub-samples, respectively. Parameter estimates  $\hat{\theta}_{m,l}$  appears as the value of  $\theta_{m,l}$  that reduces diversity the most within each subset resulting from the split. The splitting process is replicated until the terminal sub-samples, also known as leaf nodes, cover homogenous households according to a predefined homogeneity rule.

Since the tree is obtained, membership of a household in a leaf defines the predicted value of  $y_i$ . This value corresponds to the predominant class (having gotten a loan or not) for households which belong to that particular leaf. Formally, the predicted value for a given household is obtained as follows. Let  $M_l$  denotes the total number of splits in tree  $l$ , and  $|T_l|$  denotes the corresponding number of leaf nodes. Therefore, the predicted value is

$$h(x_i; \hat{\theta}_l) = \sum_{t=1}^{|T_l|} c_t 1(i \in L_t)$$

where  $\widehat{\Theta}_l = \{\widehat{\theta}_{m,l}, m = 1, \dots, M_l\}$  is the set of estimated parameter vector for tree  $l$ ,  $L_t, t = 1, \dots, |T_l|$ , are leaves, and  $c_t, t = 1, \dots, |T_l|$ , are the dominant classes in the different leaves.

Based on the construction of a myriad of non-correlated decision trees, the random forest algorithm creates a “forest” that is then aggregated. These decision trees are diversified from two aspects of the method of constructing the forest. Primarily, each decision tree is selected on a random sample of the observations, based on the bootstrap averaging, or bagging method (Breiman, 1996). Predictive performance of random forests benefits from the variance reduction effect of bootstrap averaging for non-correlated predictions. Moreover, the random forest algorithm chooses the candidate variable for each split in every tree from a restricted number of randomly selected predictors among the  $p$  available ones to assure a low level of correlation among decision trees.

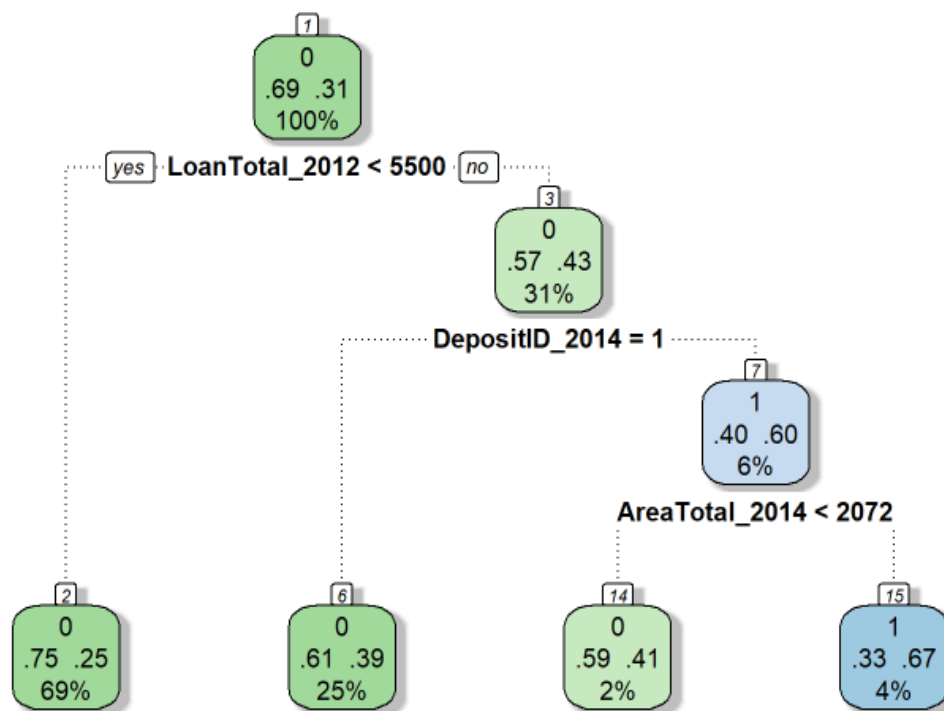
In order to produce predictions, the decision trees are aggregated at the end of the random forest algorithm. The prediction of granting a loan, or  $h(x_i)$ , is calculated by the principle of majority rule, i.e.  $h(x_i)$  corresponds to the mode of the empirical distribution of  $h(x_i; \widehat{\Theta}_l), l = 1, \dots, L$ , where  $L$  is the number of trees in the forest.

According to Lessmann et al.. (2015), random forest is proved to outperform logistic regression in terms of predictive performance. However, since random forest’s decision caused by aggregation of individual decision tree, they are less relevant when estimating the impact of predictors on the binary variable. Unlike logistic regression, random forests do not produce interpretable results such as marginal effects. However, random forests produce estimating variable importance and therefore classifying important predictors (Archer and Kimes, 2008). Therefore, because random forests combine individual decision trees, Mean Decrease in Gini, calculated by [Gini importance](#), is a measure of variable importance for estimating a target variable (Breiman et al., 1984). Mean Decrease in Gini is the mean of a variable’s total decrease in node impurity as measured by Gini index. It is weighted by the proportion of samples reaching that node in each individual decision tree in the random forest. This measure effectively importance of variable

for estimating the value of the target variable across all trees of the forest. A higher Mean Decrease in Gini shows higher variable importance.

Figure 5.1 presents an example of the decision tree for credit access, which shows the split variables are on the branches and the classification in every node. The numbers under the nodes indicate classification rates. At node 1, LoanTotal in year 2012 is the best variable to classify credit access determinants while DepositID is ranked the second. Therefore, if the household has a loan in 2012 and its loans were less than 5.500 million dong, their probability get a loan in 2014 is 0.69. DepositID is the second best to classify while the predicted results show that if the household had a deposit in the bank, its probability to access credit was 0.57.

**Figure 5.1. Demonstration of Random Forest methodology**



### Logistic model

We apply the binomial logit model to examine the determinants of the use of formal or informal credit. The binomial logit model is used to examine unordered choice sets when data are individual specific. Since our data are from a household survey that used the method of stratified random cluster sampling, we apply survey data analysis in our estimation. Following this method, we take into account the

differences between the specific design and simple random sampling and produce the correct standard errors (Pham and Lensink (2007)).

The logistic regression model is commonly used by banks and financial institutions to assess credit determinants of borrowers in order to grant a loan. This model can be described as follows.

Let  $(x_i, y_i)$ ,  $i=1, \dots, n$ , be a sample of size  $n$  of independent and identically distributed observations where  $x_i$  denotes the  $p$ -dimensional vector of predictors and  $y_i \in \{0,1\}$  is a binary variable taking the value one when the loan is granted and zero otherwise. The logistic regression model can result in the conditional probability of offering a loan as the following

$$Pr(y_i = 1|x_i) = F(\eta(x_i; \beta)) = \frac{1}{1 + \exp(-\eta(x_i; \beta))}$$

with  $F(.)$  is the logistic cumulative distribution function, and  $\eta(x_i; \beta)$  is the so-called index function or

$$\eta(x_i; \beta) = \beta_0 + \sum_{j=1}^p \beta_j x_{ij}$$

where  $\beta = (\beta_0, \beta_1, \dots, \beta_p)$  is an unknown vector of parameters to be estimated. The likelihood technique can be used to get an estimate.

Logistic regression model has main advantage is its simple interpretation. A linear combination of predictive variables can be delivered when estimating the probability of getting a loan. While computing marginal effects, the contributions of predictors to this probability can be calculated as following

$$\frac{\partial Pr(y_i = 1|x_i)}{\partial x_{ij}} = \beta_j \frac{\exp(\eta(x_i; \beta))}{(1 + \exp(\eta(x_i; \beta)))^2}, j = 1, \dots, p,$$

by replacing  $\beta$  by estimated values  $\hat{\beta}$  these effects will be estimated. Therefore, a predictive variable with positive (negative) significant coefficient has a positive (negative) impact on the probability of granting a loan. However, this simplicity

requires restrictive assumptions on the parametric specification of the cumulative distribution function and on the linearity of index function.

### **5.3.4 Descriptive statistics**

Table 5.3 below shows the value of household loans proportioned between Kinh and ethnic minorities. It confirms that 79% of the value of loan granted is to Kinh group and the remaining 21% is for ethnic minorities. In addition, table 5.4 shows the formal loan structure in 12 provinces in Vietnam. In northern mountain areas such as Lao Cai, Lai Chau and Dien Bien, the loan amount of ethnic minority accounts for 86%, 86% and 70% of total formal loan respectively, mostly funded by VBSP as the ethnic population in these provinces are widely targeted segments. For the Central Highland areas (Khanh Hoa, Daklak, Dak Nong, Lam Dong) the loan amount of ethnic minority households is from 11% to 32% while the VBSP still dominates the market. The remaining Ha Tay and Long An which are located very close to economic centers have almost no loans to ethnic minority households.

**Table 5.3: Households by value of loan obtained (2014)**

<b>By province</b>	<b>No of house- holds</b>	<b>Weighted No of loans (%)</b>	<b>Value of loans (mil VND)</b>	<b>Kinh group</b>	<b>Ethnic mi- nority</b>
Ha Tay	188	23%	2,605.80	99%	1%
Lao Cai	39	1%	780.00	14%	86%
Phu Tho	104	19%	10,389.80	90%	10%
Lai Chau	60	3%	1,570.20	14%	86%
Dien Bien	114	5%	3,014.14	30%	70%
Nghe An	69	5%	2,891.20	98%	2%
Quang Nam	57	3%	1,892.69	99%	1%
Khanh Hoa	27	1%	798.50	90%	10%
Dak Lak	184	16%	9,044.80	68%	32%
Dak Nong	121	11%	6,196.00	89%	11%
Lam Dong	37	3%	1,852.00	75%	25%

Long An	84	8%	4,347.00	100%	0%
<b>Total</b>	<b>1,084</b>	<b>100%</b>	<b>45,382.13</b>	<b>79%</b>	<b>21%</b>

*Source: VARHS (2014)*

**Table 5.4: Formal loan**

Province	Kinh		Ethnic minority		VBARD		VBSP	
	% households	% value of loan	% households	% value of loan	% households	% value of loan	% households	% value of loan
Ha Tay	98%	99%	2%	1%	51%	73%	49%	27%
Lao Cai	8%	14%	92%	86%	14%	18%	86%	82%
Phu Tho	72%	90%	28%	10%	59%	81%	41%	19%
Lai Chau	10%	12%	90%	88%	7%	8%	93%	92%
Dien Bien	13%	30%	87%	70%	6%	28%	94%	72%
Nghe An	93%	98%	7%	2%	43%	74%	57%	26%
Quang Nam	98%	99%	2%	1%	34%	59%	66%	41%
Khanh Hoa	78%	90%	22%	10%	26%	34%	74%	66%
Dak Lak	51%	68%	49%	32%	33%	44%	67%	56%
Dak Nong	78%	89%	22%	11%	21%	36%	79%	64%
Lam Dong	65%	75%	35%	25%	9%	9%	91%	91%
Long An	100%	100%	0%	0%	91%	97%	9%	3%

*Source: VARHS 2014*

In addition, loans obtained from formal and informal source are different between Kinh and ethnic minority households. The results are described in Table 5.5 below:

**Table 5.5. Formal and informal loan of Kinh group and Ethnic minority**

	Kinh		Ethnic minority	
	2012	2014	2012	2014
Formal loans	57%	71%	73%	67%
Informal loans	23%	17%	17%	17%
Semi – formal	20%	12%	10%	16%
Total	100%	100%	100%	100%

*Source: VARHS (2014)*

Credit is obtained for many purposes, such as consumption and investment. Non-



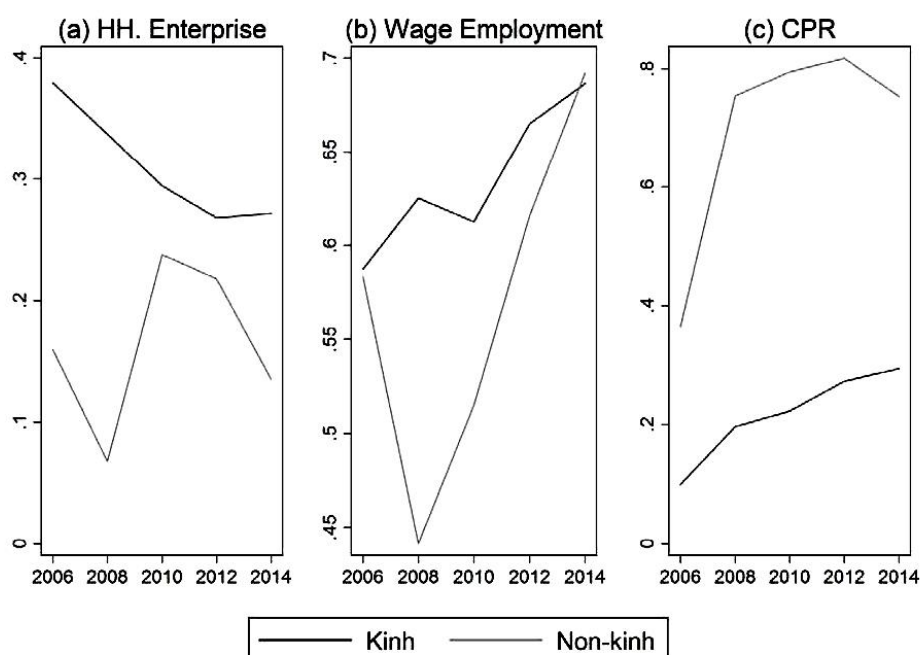
farm activities such as investing in land or real estate made up of 73% of the volume of loans and is critically important for the development of a market economy and for the efficiency of the economy in general. As land is widely used as collateral in Vietnam, it is therefore of interest to explore any interactions between the credit and land markets.

**Table 5.6: Characteristics of household**

<b>Reported use of loan</b>	<b>Households (%)</b>	<b>Loan amount (mil VND)</b>
Education expenses	6%	3,294
Farm activity	9%	5,060
Food	10%	5,580
Health expenses	2%	1,270
Non-farm activity	73%	40,178
<b>Total</b>	<b>100%</b>	<b>55,383</b>

*Source: VARHS (2014)*

**Figure 5.2. The amount of loan per household Kinh group**



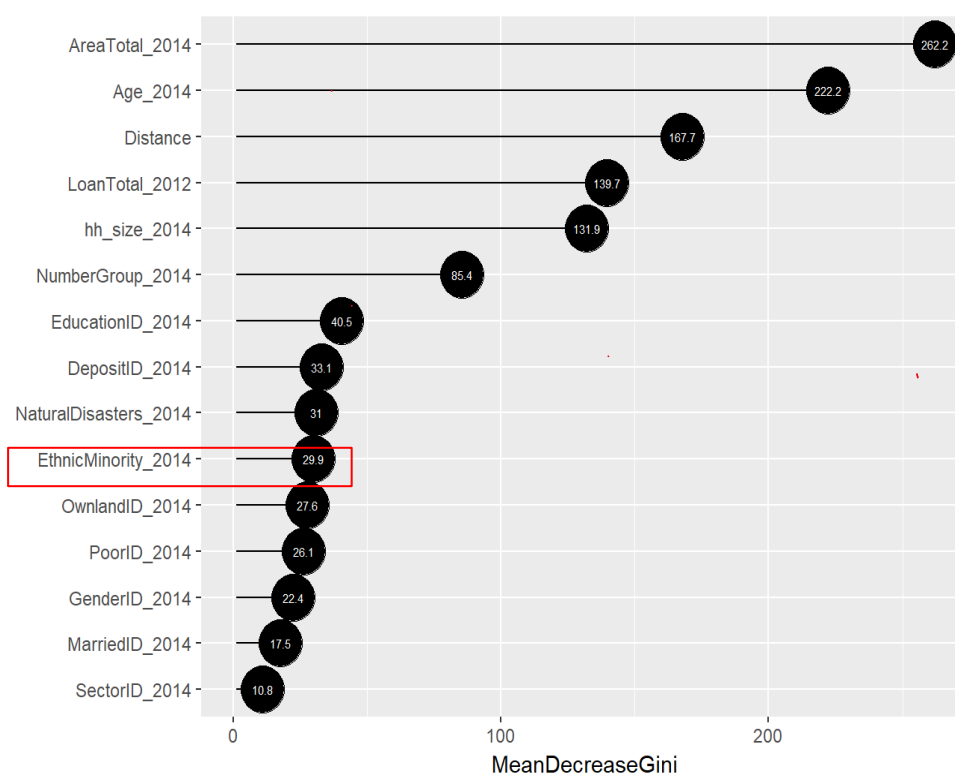
*Source: VARHS (2014)*

Over the period from 2010 to 2014, the percentage of Kinh households borrowing money increased from 45% to 48% and then fell sharply to 32% in 2014 while ethnic minority borrowing only fell to 38% in the same year (Figure 5.2). It is seen that the number of ethnic minority households being rejected was almost 6 time higher than for the Kinh group. Moreover, the value of loans per household of the Kinh group was about double that of ethnic minorities.

## 5.4. Results

The mean Decrease Gini in Figure 5.3 below shows the relative variable importance of the determinants of getting a loan (including formal and informal loans). It shows that owned land area is the most important factor influencing loan use, followed by age, distance to the central area, historic loan and household size. Lower in importance are other factors such as membership of social associations, education, bank deposits, natural disasters, ethnic minority, poor certificate, gender or marital status. It is obvious that ethnic minority is not a major determinant of obtaining credit.

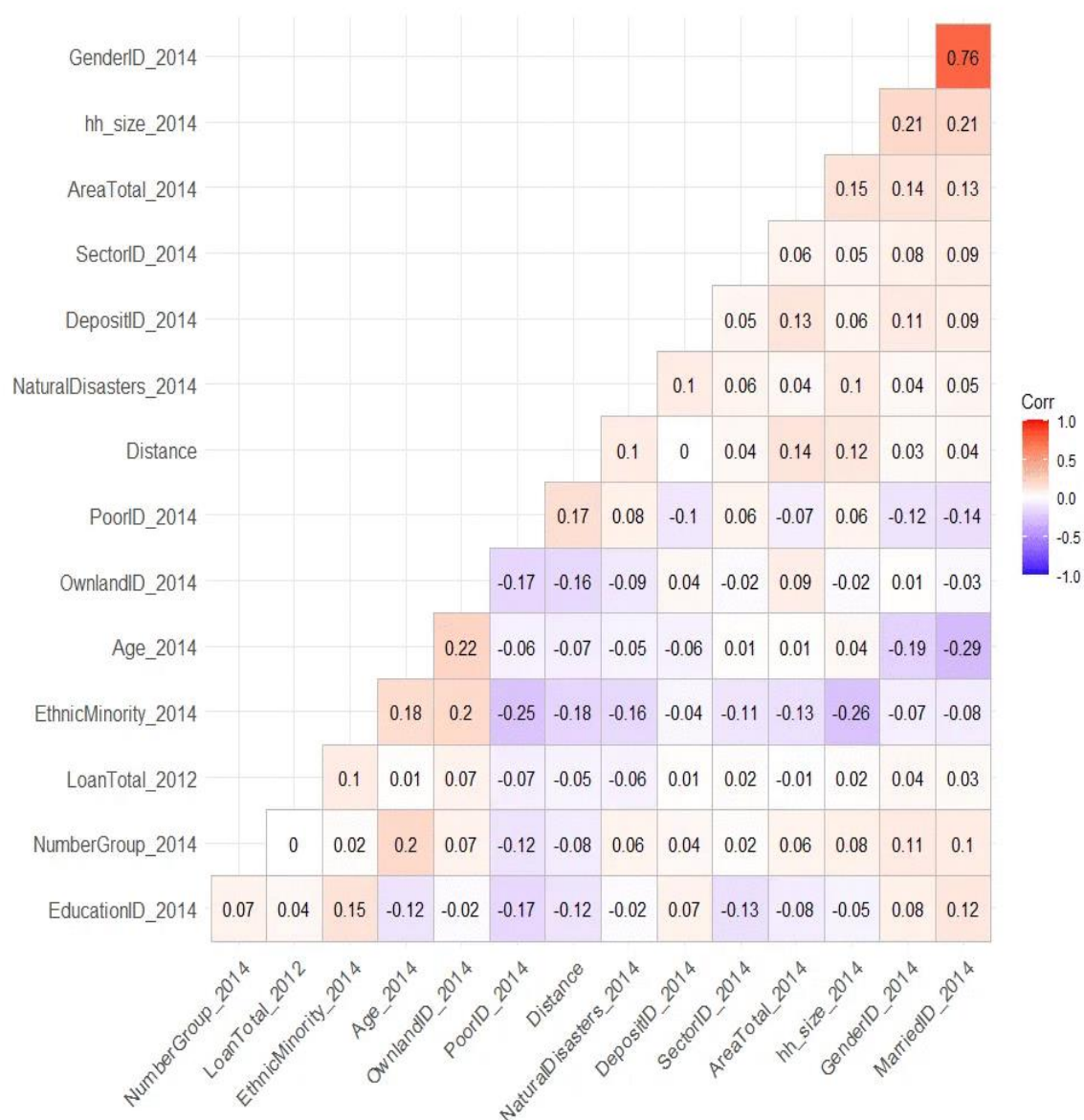
**Figure 5.3. Gini index**



*Source: VARHS (2014)*

Due to unfavorable living conditions in their remote regions, such as more frequent natural disasters, underdeveloped transportation infrastructure, limited access to education, inefficient credit environment and inadequate collateral assets, many minority households have to take loans from informal credit sources instead of formal ones (VBSP or VBARD in their provinces).

**Table 5.7. Table of correlation coefficients of dummy variables**



**Table 5.8. Table of correlation coefficients of metric variables**

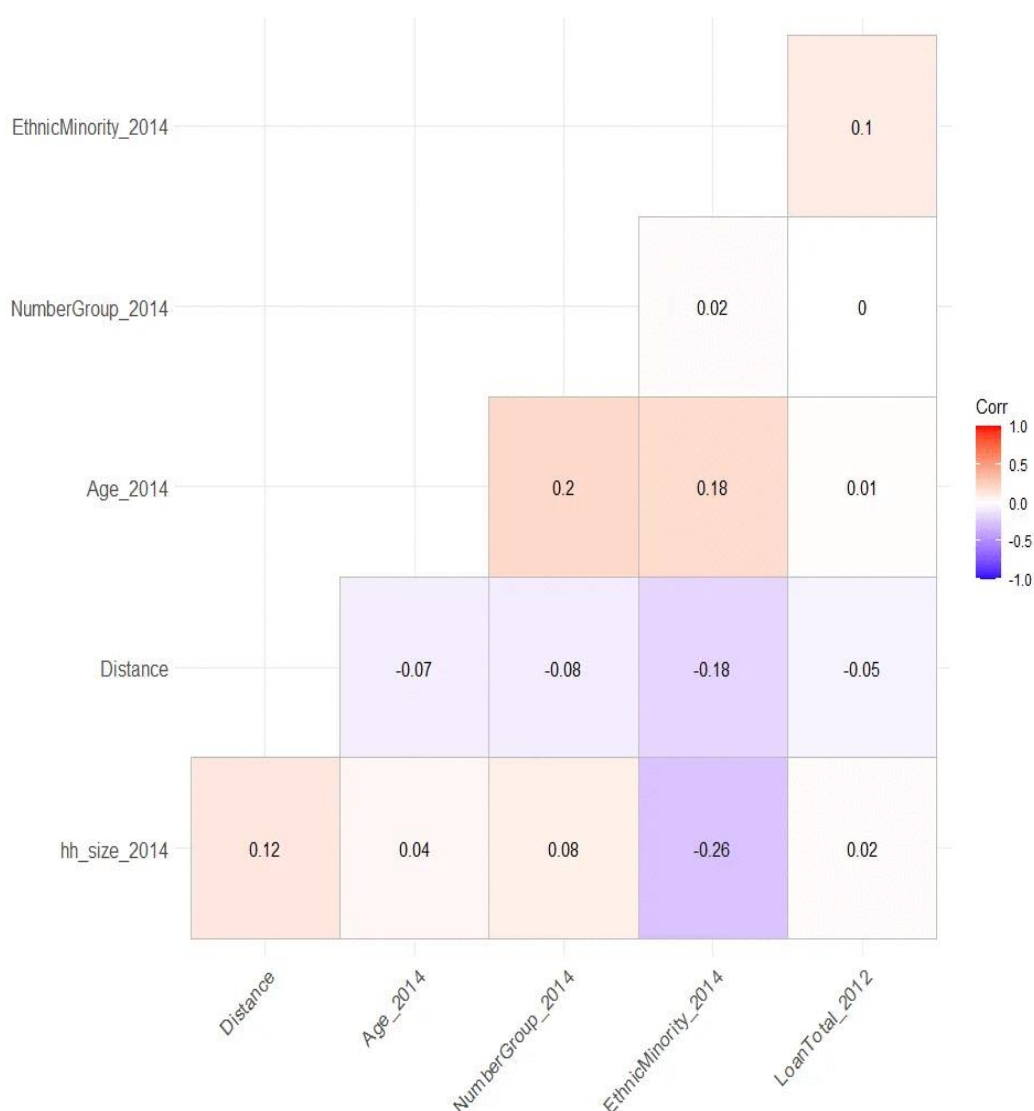


Table 5.7 and 5.8 presents the correlation coefficients for variables which are used in our estimation models. In accordance with Kennedy (2008), correlation coefficients with a value of larger than 0.8 are likely significant for the possibility of potential multicollinearity between metric variables. As showed clearly in those tables, the correlation coefficients are far below 0.8 and it is not expected a multicollinearity issue.

Table 5.9 below shows the marginal effects from logistic regression between of informal credit use. It is shown that Kinh households have better access than minority groups, at the 5% significance level. This implies that there is not an equal chance of credit access in the informal market.

**Table 5.9: Determinants of accessibility to informal credit**

Variables	Informal credit		
	Marginal effect	Standard error	
Age	-0.00302	0.00047	***
Householdsize	0.00811	0.00343	*
<b>EthnicMinority</b>	<b>0.02981</b>	<b>0.01381</b>	<b>*</b>
Gender	0.00757	0.02069	
AreaTotal	0.00000	0.00000	**
Urban	0.07066	0.02180	**
Poor	-0.02163	0.01508	
NaturalDisasters	-0.01956	0.01266	
Deposit	-0.07948	0.01758	**
Ownland	-0.00731	0.01549	
Education	0.00913	0.01595	
Education <sup>2</sup>	-0.05012	0.01839	**
Single	-0.05258	0.02758	.
SocialGroup	0.01823	0.00569	**
Historic Loan	0.00000	0.00000	
Distance	-0.00689	0.00237	**

.' significant at 10%, '\*' 5%, '\*\*\*' 1%, '\*\*\*\*' at 0.1%

Source: VARHS (2014)

Table 5.10 shows the results of regression of marginal effect while comparing access between two main players in the formal market, VBARD and VBSP. It is obvious that Kinh group has better access to VBARD while other ethnic minorities have better access from VBSP. This is in line with Viet Cuong (2008). Since VBSP has preferential policies for ethnic minority households, the results are consistent with their missions (Do and Nguyen, 2015). This confirms our research hypothesis stated above during the literature review.

The results in table 5.10 reflect the preference of each bank in reducing poverty and improving mountainous and rural areas in recent years. This result has been also found by Nguyen (2012) and Giang et al. (2015). The results show the disparity of credit access to VPSB and VBARD and informal sources for Kinh versus minority groups.

**Table 5.10. Formal credit access - VPSB's and VBARD**

Variables	VPSB		VBARD	
	Marginal effect	Standard error	Marginal effect	Standard error
Age	0.002048	0.00150	0.000016	0.00131
householdsize	0.001205	0.01006	0.017204	0.00858 *
<b>EthnicMinority</b>	<b>-0.256960</b>	<b>0.03736 ***</b>	<b>0.096737</b>	<b>0.03118 **</b>
Gender	0.014855	0.06470	-0.073813	0.06380
LandAreaTotal	-0.000004	0.00000 **	0.000001	0.00000
Urban	0.058732	0.11709	-0.012422	0.09214
Poor	0.289910	0.04450 ***	-0.142550	0.03408 ***
NaturalDisasters	0.123710	0.03840 **	0.055651	0.03132 .
Deposit	0.028278	0.03722	-0.005724	0.03350
Ownland	-0.079535	0.04522 .	0.196490	0.03034 ***
Education	-0.006559	0.04469	-0.009913	0.03674
Education <sup>2</sup>	0.046999	0.07114	-0.007911	0.05600
MarriedID	0.029596	0.06969	0.130350	0.04668 *
NumberGroup	0.016207	0.01606	-0.003667	0.01362
Historic Loan	0.000009	0.00000 ***	0.000005	0.00000 ***
Distance	0.012238	0.00774	-0.000721	0.00721

‘.’ significant at 10%, '\*' 5%, '\*\*' 1%, '\*\*\*' 0.1%

*Source: VARHS (2014)*

### **5.5. Concluding remarks and policy implications**

This chapter compares the credit use by different minority groups to both formal and informal sources in rural area of Vietnam. In this study, we implement a methodological approach combining a classical logit estimation of the probability of getting a loan with random forest estimation techniques. This has the advantage of ranking the importance of the factors in the explanation of the probability of granting a loan. Random Forests have proved to give superior accuracy in prediction compared to traditional logistic estimation

The main contribution of this study can be summarized in three major layers. First and foremost, Random Forests using the Mean Decrease Gini approach show that ethnicity is not the major determinant in credit scoring. Secondly, households who are ethnic minority are more likely to get a loan from the VBSP while the Kinh group makes better use of credit from VBARD. Finally, it is shown that the Kinh group makes more use of informal loans compared to ethnic minorities.

Our results have policy implications which will help to improve household's accessibility to credit, particularly for the ethnic minority groups. First, as ethnic minorities have lower income due to insufficient land and capital, banks and credit institutions should not only provide finance for farming activities but also for non-farm purposes such as job training programs. So borrowers can generate more income from non-farm activities or participate in other labor markets. Second, it is suggested that households should actively participate in social associations and improve their education and work skills. This is critical as education and being a member of an association increasing creditworthiness for borrowers and improve repayment ability. Therefore, the government should also consider providing incentive programs to attract more investment in ethnic minority area. However, the coexistence of formal and informal credit appears foreseeable, which suggests that any one credit sector can be replaced by the other in the rural credit market (Li et al., 2011). Hence, combination of these two credit sectors into a well-functioning rural credit market can effectively improve credit access for rural ethnic minority

households. It is therefore necessary to improve economic and social conditions of agricultural areas in order to lower the gap in living standards and income between households of different ethnicities.

Due to the limited size of survey, some policy implications are particularly relevant to the survey provinces but may not be relevant nationwide. This reflects the presumption that informal credit is popular in other regions of Vietnam as well, while formal credit is monitored and restricted by formal lending procedures.



## **Chapter 6: Conclusions**

Microfinance has played a vital role in alleviating poverty in rural area in many developing countries, particularly in Asia, the world's fastest-growing economic region. In addition, South and East Asia remains home to almost half of the world's poorest individuals. Therefore, this thesis aims to provides a full picture of both sides of the microfinance market: demand (borrowers) and supply (microfinance institutions), in South and East Asia. This area is characterized by its large-sale microfinance market. The thesis thus questions MFI's sustainability and accessibility of households to different credit sources. The interest in finding answers for these discussions encourage our motivation to explore and analyze the factors which influence the microfinance performance in this region.

In this last chapter, we conclude our study as follows. Section 6.1 presents a summary of the research objectives and questions, and Section 6.2 summarizes the major findings. Section 6.3 discusses the implications of the research findings and propose policy recommendations. Section 6.4 discusses the limitations and provides suggestions for extending this research.

### **6.1 Summary**

This thesis aims to provide assessment of MFIs' performance and their accessibility in the South and East Asia. There are four research objectives: (i) to assess the performance of South and East Asia microcredit programs; (ii) to identify factors affecting microcredit accessibility, both formal and informal microcredit; (iii) to identify the gap in credit accessibility among different minority groups in rural market and (iv) to identify policy implications in order to improve microcredit accessibility of rural households through government policies towards the rural credit market.

Chapter 2 provides first an overview of worldwide microfinance and then focuses on microfinance market in South and East Asia, including a description of regulatory frameworks, microfinance institutions performance and accessibility. Then, special attention is devoted to the Vietnam rural credit market and existing microfinance programs in this country. The rural credit market in Vietnam is segmented

with two types of credit providers: formal and informal. The formal credit sector is supervised by State Bank of Vietnam and microfinance is offered by formal credit institutions. An increase in formal microfinance loans have been recorded but a large proportion of the poor is still unable to get loan from the formal micro-credit market, so they seek alternative source of credit. The informal credit market, which coexists with the formal credit sector, is an important alternative source of finance for many rural households. Constraints in access to formal credit not only limit the rural households to expand their production, but also prevent them to improve their quality of life.

Chapter 3 analyzes the financial and social performances of microfinance institutions in the South and East Asia region. Financial performance is measured using return on assets and operational self-sufficiency while social performance is valued using depth and breadth of outreach. Dynamic panel data models, estimated using system GMM, allow us to assess the impact of different factors (board characteristics, microfinance institution characteristics and country socio-economic conditions) on MFI performance. The choice of the system-GMM estimation technique is driven by the fact that it can take into account potential endogeneity issues encountered when estimating dynamic panel data models. The chapter shows that board size and gender diversity have negative impacts on financial and social performance respectively while board social orientation positively affects financial performance. In addition, past performance, leverage and total assets also have positive effects on financial performance.

Chapter 4 discusses the factors affecting the accessibility of households to informal credit market in rural area of Vietnam. The analysis identifies factors affecting to the use of informal loans. In line with the credit scoring literature, we use a nonparametric technique, namely random forests, that has been shown to achieve better classification performances than standard logistic regression models. However, logistic regression still plays crucial role in credit scoring due to the lack of interpretability of random forest in terms of measuring factor impacts, which is incompatible with the requirements of financial regulators who want scores. In this chapter, we thus propose to combine classical logit estimation of the probability of

getting a loan with the less usual random forest estimation techniques, in order to obtain the best predictive accuracy. Random forest techniques have the advantage of making it possible to assess the order of importance of the factor in the explanation of the probability of obtaining a loan. We combine them with logistic regression in order to add estimated values of factor impacts to their importance in explaining the probability of getting a loan. The results show that the use of informal credit is positively related to owned area of land, the household size and the number of community groups households participated in, while the age and the distance to administrative centers have negative effects. Since the informal credit market is quite popular in developing countries, the Government of Vietnam can combine both formal and informal credit sectors into a well-functioning rural credit market which can effectively improve credit access for rural area.

Chapter 5 contributes to the microfinance literature by studying the gap of credit use between the dominant ethnicity in Vietnam, or Kinh, and the other ethnic minorities. As a result, accessibility to both formal and informal credit sources is discussed. As in the previous chapter, the methodological approach combines classical logit estimation of the probability of getting a loan with random forests estimation techniques. This chapter shows that the Kinh group makes greater use of loans than any other ethnic minority groups from both formal and informal credit markets. However, within the formal market, minority groups have better chance to get credit from the Vietnam Bank of Social Policy (VBSP).

## **6.2 Major findings**

Previous studies of the relationship between corporate governance structures and MFIs' performance in the South and East Asia are plagued with endogeneity issues. For this reason, chapter 3 tests the effects of corporate governance structures on MFIs' performance in South and East Asia by using a dynamic estimation approach to control for potential sources of endogeneity. After controlling for unobserved heterogeneity, simultaneity, and dynamic endogeneity, we find that corporate governance structures do matter in South and East Asia. Board size, board diversity, board social orientation, rural location and past performance have significant impacts on MFIs' performances. Specifically, it is found that smaller

boards are more efficient in term of social performance, which can be explained by more flexibility and faster decision making. On the other hand, board diversity has a negative effect on social performance. In addition, boards with a social orientation or rural market orientation have positive impacts on financial performance. Moreover, taking into account of past performance shows its usefulness in controlling for unobserved historical factors about the MFI itself and its past performances. The control variables in chapter 3 are introduced because they might control directly for confounding factors. In other words, these variables are added to control potential unobserved time variant factors that may lead the causal variable to be endogenous. The results show the importance of infrastructure which show the negative effect on financial performance and positive on social performance. Surprisingly, it indicated that if the infrastructure rate increases, the financial performance is reduced perhaps due to a lower demand from borrowers.

In the analysis of credit use, chapter 4 considers the drivers of informal credit which comprise four main groups of factors including household head characteristics, household's characteristics, financial factors and geographical factors. Firstly, the household head's characteristics, which include age, ethnic minority and higher education, have negative impacts on the use of informal credit. Secondly, the household's characteristics (size and number of groups participated) and financial factors (total land size and history of financing variables) have positive impacts on the probability of getting an informal loan. The last group of factors, which includes distance variables, has a negative impact on the use of informal credit. Our research allows also ranking the importance of determinants to access to informal credit in the following order: Land area owned, age, distance, household size, number of social groups family participated and past credit history. The positive contributors to rural informal credit use include being a member of social group and distance to town center, implying that joining a local social group improves accessibility by allowing access to more information about informal credit source. This result shows how money lenders should weight and score credit of the potential borrowers. Since informal credit accounts for 20% of the market, its importance cannot be denied in meeting the financing demand of rural households.

This includes not only households that cannot get a loan from a formal credit source (such as VBSP or VBARD), but also those who may be able to obtain a loan but choose to borrow from informal moneylenders due to flexible lending arrangements. Hence, the existence of informal credit may not simply be due to insufficient supply of formal credit or credit constraints by formal institutions, but it may arise from the development of the rural credit market by itself. As the rural credit market changes, informal lending practices have been adjusted to meet the demand of different groups of borrowers. This also explains the co-existence of both formal and informal credit segments in Vietnam.

In analyzing the determinants which impact on different ethnic minorities use of both formal and informal credit in rural area of Vietnam, chapter 5 shows that the Kinh group makes higher use of loans than ethnic minority groups from both the formal and informal credit markets. Nevertheless, when focusing on the formal market, results show that minority groups have a better chance to get credit from the Vietnam Bank of Social Policy (VBSP). It is confirmed that factors with effects on access to both formal and informal credit include age, total land owned, membership of an association, deposit and distances to the local administrative center.

In terms of formal credit, our results show that the outreach for formal credit is also affected by the following factors: household size, living in urban area, household in poor situation and past credit history. This can be considered as a bias in the selection process, though improving accessibility to microfinance using a poor family certificate is arguably a good social policy intervention. Moreover, households who belong to ethnic minorities, that are facing natural disasters and have got a VBSP loan in the past, will have better access to preferential credit from the VBSP. On the other hand, ethnic minority groups will face more difficulty in accessing credit from VBARD.

In terms of informal credit, it is shown that education, marital status and ethnic minority status can be the main determinants. It is found that the Kinh group is more likely to use informal loans compared to ethnic minorities. In addition, rural households residing in urban areas have a better chance to obtain informal credit

from private moneylenders, friends and relatives. A flexible informal loan duration can compensate for a high interest rate.

### **6.3. Recommendations**

The previous findings have various academic implications and policy recommendations.

#### ***6.3.1. Academic implications***

Many methods have been investigated to improve the accuracy in measuring the determinants of use of informal credit. Some studies of Barslund and Tarp (2008), Khoi (2013), Viet Nguyen and Berg (2014), Lainez (2014) and Bauer (2016) use mainly traditional parametric methodologies to estimate the use of credit. It is worth noting that although other novel modeling nonparametric approaches such as Random Forests (Breiman, 2001) show the remarkable improvement in projection and classification, it has not been employed popularly in credit scoring in Vietnam.

In this work, addressing the aforementioned gap in the current literature, we may use Random Forests or gradient boosting to estimate determinants of informal credit access and accessibility of ethnic minorities to rural credit. This will make a significant contribution of credit scoring techniques to micro finance literature.

#### ***6.3.2 Policy implications***

Regarding access to credit, VBSP provides different preferential loans for the poor and the near poor through the four mass organizations in the country. In addition, there are several micro-finance projects which mainly attract women, particularly from ethnic minorities, such as the Women's Union, Farmer's Union and Cooperative or production group. Rural families can access to the preferential credits from the VBSP, which are only made available for local residents with official membership in such an organization. However, it is difficult for the very poor family to benefit from microfinance because they need pre-support (e.g., special aids, community support) to overcome internal constraints. Extremely poor people suffering from illnesses, lack of skills... cannot be a target for microfinance institutions that

provide small finance for income generating activities. Intervention in the micro finance policy will not be an efficient sustainable solution but a combination of welfare and a micro-finance programs is required for these families. Micro finance should always be the next step after potential client have regular income (Gibbons et al., 2000; Seibel, 1997).

This is therefore a question about sustainably operating performance of VBSP. Restructuring VBARD microfinance operations by forming a heavily subsidized VBSP to provide preferential loans to the poor can breach the principles of efficient banking operation and sustainable poverty alleviation. In addition, banking system often lack the flexibility to meet the growing demands of the poor for a full range of financial services (Dufhues, Heidhues, & Buchenrieder, 2004). This issue should be seriously reconsidered in the strategy of rural development and poverty alleviation. However, if VBSP were not subsidized, poverty reduction would be at risk.

## **6.4 Limitations and Future research**

### ***6.4.1 Limitations***

Prior studies of the relationship between governance structures and performance of corporate firms often face endogeneity problems. Endogeneity leads to biased and inconsistent parameter estimates that make reliable inference virtually impossible. Thus, it is difficult to conclude what the parameter estimates actually suggest. In chapter 3, we re-examine the influences of corporate governance structures on both MFIs' financial and social performances in South and East Asia by using a dynamic estimation approach. This econometric technique allows to control for potential endogeneity and allows for making interpretations.

However, the system GMM estimation methodology has limitations. It uses the corporate firm's history (lagged values of dependent and independent variables) for identification. As the number of lags of the instrumental variables increases, the potential problem of having weak instruments becomes more and more striking. This is an empirical trade-off in increasing the length of lagged instruments, and thus their number, to address endogeneity issues, and the increasing risk of

their weakness. Therefore, the existence of weak instruments may be an important issue.

Moreover, another disadvantage of system GMM is the number of internal instruments that increase automatically and exponentially when the number of time periods  $T$  increases. In fact, instrument proliferation creates some important computational issues when computing the covariance matrix of system GMM estimates and, consequently, makes related specification tests misleading. A large instrument number often causes overfitting endogenous variables and weakening the Hansen J-test of instruments' joint validity. According to Roodman (2009b), restricting the number of lagged levels used in the instrument matrix, collapsing the instrument matrix or combining the two, can help to solve this problem. However, the system GMM might work but "under arguably special circumstances".

Finally, it is understood that the system GMM does not fix all endogeneity problems. When available, carefully chosen strictly exogenous instruments or natural experiments are still the key for identifying the causal effect of an explanatory variable on a dependent variable. However, given the rare occurrence of natural experiments such as unexpected regulatory or politic system changes, and the lack of exogenous instruments, inference in corporate finance studies is likely to rely on estimation using panel data (Wintoki et al., 2012). Our research contributes to the literature by introducing an economic justification for the use of system GMM in a corporate governance study.

Chapters 4 and 5 contribute to the credit scoring literature by proposing a new approach which combines classical logistic regression and random forests. Despite the development of many efficient machine learning classification algorithms, the benchmark scoring model in the credit industry remains logistic regression. This is caused mainly by the stability and robustness of the logistic regression and also the ease in interpreting its results (Dumitrescu et al., 2021). Many researchers propose the use of more complicated combining methods, such as the Random Forests and Gradient Boosting. Currently, these newly alternative models gradually replace purely logistic regression due to the substantial improvement in predictive



capability they are providing. However, it is still generally considered challenging in the credit scoring report for regulatory purposes.

Performance is not the only important criterion in credit scoring studies. The other essential criterion of a good credit scoring model is interpretability. In fact, interpretability and accuracy are commonly two competing objectives: the first is done by simple models, the latter needs more complex ones. Furthermore, the degree of interpretability of a scoring model is difficult to evaluate. According to Molnar (2019), there is no real consensus in the literature about what is interpretable from machine learning, nor is it clear how to measure this criterion. Despite of good performance, using Random Forests results in prediction may rise difficulties when interpreting them. This is harmful for credit scoring, where managers and regulators want simple and interpretable results. The key issue here is how to balance between predictive performance and interpretability. To address this problem, two pathways can be explored. First, one can try to diminish the complexity of the random forest method by selecting only some trees or decision nodes in the forest (Deng, 2019). Second, the simplicity of logistic regression can be preserved by improving its predictive performance with univariate and bivariate endogenous threshold effects (Elena et al., 2021).

#### ***6.4.2 Future research***

The current thesis investigates the determinants to credit access of rural households using combination of random forest and logistics methods. In line with thesis, future research in Viet Nam can apply this new approach to calculate credit scoring for households investing in renewable energy (RE) in rural areas of Vietnam. Viet Nam's energy industry has made considerable growth in recent years in achieving a high percentage of country electrification and a fairly diversified energy mix that is done by hydropower, gas and coal. Currently, Viet Nam energy supply is intensively based on fossil fuel energy (coal, oil, and gas) which accounts for nearly two-thirds of its domestic supply (Government of Viet Nam, 2016b). The increasing demand in the domestic market for energy in the last few years has made the country import coal since 2015. However, Viet Nam has potentially abundant

sources of renewable energy (RE), in particular solar power, wind power and biomass, that remain substantially unexploited. In 2017, renewable energy meets only 4% of the total electricity supply. The overreliance on fossil fuel is threatening the energy security of our country. Furthermore, Viet Nam has severe environmental issues relating to climate change and air pollution. This leads to the gradual replacement of fossil fuels with green and environmentally friendly energy sources. Although the Government has a national strategy to attract private investment in RE, a large number of interferences still exist, e.g the low price of electricity, which makes it difficult for RE projects in rural areas to be profitable. In addition, the uncertainty of the creditworthiness of Viet Nam Electricity (EVN) should be taken in to accounts. Moreover, the underdeveloped financial system lacks the capacity to deliver long-term capital and the banking system has weak competence in implementing green credit appraisal. Based on the existing challenges, the thesis makes recommendations including using combined the method of random forest and logistic regression to score credit of rural households who invest in renewable energy. This can encourage RE investment and develop a fully functional domestic financial system combined with sustainable business performance of EVN.

## Bibliography

- Adams, R. B. (2016). Women on boards: The superheroes of tomorrow? *The Leadership Quarterly*, 27(3), 371-386.
- Adams, R. B., & Ferreira, D. (2009). Women in the boardroom and their impact on governance and performance. *Journal of financial economics*, 94(2), 291-309.
- ADB. (2021). Economic indicators for Viet Nam. <https://www.adb.org/countries/viet-nam/economy>
- Agnew, J., Balduzzi, P., & Sunden, A. (2003). Portfolio choice and trading in a large 401 (k) plan. *American economic review*, 93(1), 193-215.
- Ali, D. A., Deininger, K., & Duponchel, M. (2014). Credit constraints and agricultural productivity: Evidence from rural Rwanda. *Journal of Development Studies*, 50(5), 649-665.
- Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance*, 23(4), 589-609.
- Amin, S., Rai, A. S., & Topa, G. (2003). Does microcredit reach the poor and vulnerable? Evidence from northern Bangladesh. *Journal of development economics*, 70(1), 59-82.
- Andersen, T. G., & Sørensen, B. E. (1996). GMM estimation of a stochastic volatility model: A Monte Carlo study. *Journal of Business & Economic Statistics*, 14(3), 328-352.
- Archer, K. J., & Kimes, R. V. (2008). Empirical characterization of random forest variable importance measures. *Computational statistics & data analysis*, 52(4), 2249-2260.
- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), 277-297.
- Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*, 68(1), 29-51.

- Asiamah, T. A. (2017). *Trends and Determinants of Household Use of Financial Services in Ghana*. University Of Ghana.
- Authority, M. R. (2018). *NGO-MFIs in BANGLADESH*. Retrieved from [http://mra.gov.bd/images/mra\\_files/Publications/volume2018.pdf](http://mra.gov.bd/images/mra_files/Publications/volume2018.pdf)
- Babu, M. M. (2016). Financial and Social Orientations of Microfinance Institutions in India. *The Indian Economic Journal*, 64, 137-154.
- Banerjee, A. V., & Duflo, E. (2007). The economic lives of the poor. *Journal of economic perspectives*, 21(1), 141-168.
- Bank, B. (2016). *Annual Report (2015–16)*. Retrieved from Dhaka:
- Bank, B. (2019). *2019 annual report*. Retrieved from <https://bri.co.id/en/report>
- Banker, T. A. (Producer). (2019). Vietnam's retail loan market to reach \$145 billion by 2020. Retrieved from [https://www.theasianbanker.com/updates-and-articles/vietnam%E2%80%99s-retail-loan-market-to-reach-\\$145-billion-by-2020](https://www.theasianbanker.com/updates-and-articles/vietnam%E2%80%99s-retail-loan-market-to-reach-$145-billion-by-2020)
- Barometer, M. (2019). *10 years already! A look back at the trends in Micro-finance!* Retrieved from
- Barber, B. M., & Odean, T. (2001). *Boys will be boys: Gender, overconfidence, and common stock investment*. The quarterly journal of economics, 116(1), 261-292.
- Barslund, M., & Tarp, F. (2008). Formal and informal rural credit in four provinces of Vietnam. *The Journal of Development Studies*, 44(4), 485-503.
- Bassem, B. S. (2009). Governance and performance of microfinance institutions in Mediterranean countries. *Journal of Business Economics and Management*, 10(1), 31-43.
- Beisland, L. A., Djan, K. O., Mersland, R., & Randøy, T. (2020). Measuring Social Performance in Social Enterprises: A Global Study of Microfinance Institutions. *Journal of Business Ethics*, 1-21.
- Bellemare, M. F., Masaki, T., & Pepinsky, T. B. (2017). Lagged explanatory variables and the estimation of causal effect. *The Journal of Politics*, 79(3), 949-963.
- Berg, G., & Schrader, J. (2012). Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation*, 21(4), 549-568.

- Biyase, M., & Fisher, B. (2017). Determinants of access to formal credit by the poor households. *Studia Universitatis Babes-Bolyai Oeconomica*, 62(1), 50-60.
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, 87(1), 115-143.
- Boone, A. L., Field, L. C., Karpoff, J. M., & Raheja, C. G. (2007). The determinants of corporate board size and composition: An empirical analysis. *Journal of financial economics*, 85(1), 66-101.
- Bowsher, C. G. (2002). On testing overidentifying restrictions in dynamic panel data models. *Economics letters*, 77(2), 211-220.
- Boyacioglu, M. A., Kara, Y., & Baykan, Ö. K. (2009). Predicting bank financial failures using neural networks, support vector machines and multivariate statistical methods: A comparative analysis in the sample of savings deposit insurance fund (SDIF) transferred banks in Turkey. *Expert Systems with Applications*, 36(2), 3355-3366.
- Breiman, L. (1996). Bagging predictors. *Machine learning*, 24(2), 123-140.
- Breiman, L. (2001). Random forests. *Machine learning*, 45(1), 5-32.
- Breiman, L., Friedman, J., Stone, C. J., & Olshen, R. A. (1984). *Classification and regression trees*: CRC press.
- Campion, A. (1998). *Current Governance Practices of Microfinance Institutions: A Survey Summary*: Microfinance Network.
- Carlsson, G., & Karlsson, K. (1970). Age, cohorts and the generation of generations. *American Sociological Review*, 710-718.
- Carter, D. A., D'Souza, F., Simkins, B. J., & Simpson, W. G. (2010). The gender and ethnic diversity of US boards and board committees and firm financial performance. *Corporate Governance: An International Review*, 18(5), 396-414.
- Center for Financial Inclusion (2017) Global Outreach and Financial Performance Benchmark Report [2015].
- CEMA, U., and Irish Aid. (2017). *The Ethnic Minority Survey Report*. Retrieved from Chaudhuri, S. (2001). Interaction of formal and informal credit markets in backward agriculture: A theoretical analysis. *Indian Economic Review*, 411-428.

- Charness, G., & Gneezy, U. (2007). Strong evidence for gender differences in investment. *Available at SSRN 648735*.
- Chen, W.-H., & Shih, J.-Y. (2006). A study of Taiwan's issuer credit rating systems using support vector machines. *Expert Systems with Applications*, 30(3), 427-435.
- Chikalipah, S. (2017). Institutional environment and microfinance performance in Sub-Saharan Africa. *African Development Review*, 29(1), 16-27.
- Child, J. (1974). Managerial and organizational factors associated with company performance part I. *Journal of Management studies*, 11(3), 175-189.
- Choi, N. G., & DiNitto, D. M. (2013). Internet use among older adults: association with health needs, psychological capital, and social capital. *Journal of medical Internet research*, 15(5), e97.
- Cole, R. A., & Wu, Q. (2017). Hazard versus probit in predicting US bank failures: a regulatory perspective over two crises. *Available at SSRN 1460526*.
- Cole, S., Sampson, T., & Zia, B. (2011). Prices or knowledge? What drives demand for financial services in emerging markets? *The journal of finance*, 66(6), 1933-1967.
- Coles, J. L., Daniel, N. D., & Naveen, L. (2008). Boards: Does one size fit all? *Journal of financial economics*, 87(2), 329-356.
- Conning, J., & Udry, C. (2007). Rural financial markets in developing countries. *Handbook of agricultural economics*, 3, 2857-2908.
- Cox, R. A., & Wang, G. W.-Y. (2014). Predicting the US bank failure: A discriminant analysis. *Economic Analysis and Policy*, 44(2), 202-211.
- Crawford, A., Skully, M. T., & Tripe, D. W. (2014). Are profitable microfinance programs less efficient at reaching the poor? A case study in Cambodia. *A Case Study in Cambodia (February 25, 2014)*.
- Cull, R., Demirgüç-Kunt, A., & Morduch, J. (2009). Microfinance meets the market. *Journal of economic perspectives*, 23(1), 167-192.
- Cuong, N. V. (2008). Is a governmental Micro-Credit Program for the poor really pro-poor? Evidence from Vietnam. *The Developing Economies*, 46(2), 151-187.

- Dang, R., Houanti, L. H., Reddy, K., & Simioni, M. (2020). Does board gender diversity influence firm profitability? A control function approach. *Economic Modelling*.
- Dato, M. H., Mersland, R., & Mori, N. (2018). Board committees and performance in microfinance institutions. *International journal of emerging markets*.
- Deng, H. (2019). Interpreting tree ensembles with intrees. *International Journal of Data Science and Analytics*, 7(4), 277-287.
- Deville, J. (2015). *Lived economies of default: Consumer credit, debt collection and the capture of affect*: Routledge.
- Dewatripont, M., Jewitt, I., & Tirole, J. (1999). The economics of career concerns, part II: Application to missions and accountability of government agencies. *The Review of Economic Studies*, 66(1), 199-217.
- Diagne, A. (1999). *Determinants of household access to and participation in formal and informal credit markets in Malawi*. Retrieved from
- Do, T. L., Ninh, H. N., Thao, T. D., & Trach, N. X. Does cattle production contribute to improving welfare of poor ethnic minority households in Central Vietnam?
- Dube, L., Mariga, T., & Mrema, M. (2015). Determinants of access to formal credit by smallholder tobacco farmers in Makoni District, Zimbabwe. *Greener Journal of Agricultural Sciences*, 5(1), 034-042.
- Dumitrescu, E., Hue, S., Hurlin, C., & Tokpavi, S. (2018). *Machine learning for credit scoring: improving logistic regression with non linear decision tree effects*. Ph. D. thesis, Paris Nanterre University, University of Orleans.
- Dumitrescu, E., Hue, S., Hurlin, C., & Tokpavi, S. (2018). *Machine learning for credit scoring: improving logistic regression with non linear decision tree effects*. Ph. D. thesis, Paris Nanterre University, University of Orleans.
- Dumitrescu, E.-I., Hué, S., & Hurlin, C. (2021). Machine Learning or Econometrics for Credit Scoring: Let's Get the Best of Both Worlds.
- Duong, P. B., & Izumida, Y. (2002). Rural development finance in Vietnam: A microeconomic analysis of household surveys. *World Development*, 30(2), 319-335.

- Eisenberg, T., Sundgren, S., & Wells, M. T. (1998). Larger board size and decreasing firm value in small firms. *Journal of financial economics*, 48(1), 35-54.
- Eswaran, M., & Kotwal, A. (1990). Implications of credit constraints for risk behaviour in less developed economies. *Oxford economic papers*, 42(2), 473-482.
- Fantazzini, D., & Figini, S. (2009). Random survival forests models for SME credit risk measurement. *Methodology and computing in applied probability*, 11(1), 29-45.
- Farrell, D., & Greig, F. (2018). Weathering the storm: The financial impacts of hurricanes harvey and irma on one million households. *Available at SSRN 3135266*.
- Fensom, A. (2017). Asia to stay world's fastest-growing region through 2030. *The Diplomat*.
- Fensom, A. (2017). Asia to stay world's fastest-growing region through 2030. *The Diplomat*.
- Fund, I. M. (2018). *Financial Inclusion in Asia-Pacific*. Retrieved from
- Ghatasheh, N. (2014). Business Analytics using Random Forest Trees for Credit Risk. *International Journal of Advanced Science and Technology*, 19-30.
- Gippel, J., Smith, T., & Zhu, Y. (2015). Endogeneity in accounting and finance research: natural experiments as a state-of-the-art solution. *Abacus*, 51(2), 143-168.
- Glaeser, E. L., Laibson, D., Scheinkman, J. A., & Soutter, C. L. (1999). *What is social capital? The determinants of trust and trustworthiness* (0898-2937). Retrieved from
- Glen, J., Lee, K., & Singh, A. (2001). Persistence of profitability and competition in emerging markets. *Economics letters*, 72(2), 247-253.
- Grosvold, J., & Brammer, S. (2011). National institutional systems as antecedents of female board representation: An empirical study. *Corporate Governance: An International Review*, 19(2), 116-135.
- Group, V. M. W. (2019). *Report the influences of MFIs' Organisational characteristics and Performances on Financial Inclusion in Vietnam*. Retrieved from
- Group, V. M. W. (2019). Vietnam Bank of Social and Policy.



- Gschwandtner, A. (2005). Profit persistence in the 'very' long run: evidence from survivors and exiters. *Applied Economics*, 37(7), 793-806.
- Gschwandtner, A. (2005). Profit persistence in the 'very' long run: evidence from survivors and exiters. *Applied Economics*, 37(7), 793-806.
- Guirking, C. (2008). Understanding the coexistence of formal and informal credit markets in Piura, Peru. *World Development*, 36(8), 1436-1452.
- Guirking, C., & Boucher, S. R. (2008). Credit constraints and productivity in Peruvian agriculture. *Agricultural Economics*, 39(3), 295-308.
- Guiso, L., Sapienza, P., & Zingales, L. (2004). The role of social capital in financial development. *American economic review*, 94(3), 526-556.
- Ha, S. V., Nguyen, N. H., & Nguyen, N. D. (2016). A Novel Credit Scoring Prediction Model based on Feature Selection Approach and Parallel Random Forest. *Indian Journal of Science and Technology*.
- Harris, M., & Raviv, A. (2008). A theory of board control and size. *The Review of Financial Studies*, 21(4), 1797-1832.
- Hartaraska, V. (2005). Governance and Performance of Microfinance Institutions in Central and Eastern Europe and the Newly Independent States. *World Development*.
- Hermalin, B. E., & Weisbach, M. S. (2001). *Boards of directors as an endogenously determined institution: A survey of the economic literature* (0898-2937). Retrieved from
- Hermes, N., Lensink, R., & Meesters, A. (2011). Outreach and efficiency of microfinance institutions. *World Development*, 39(6), 938-948.
- Hillman, A. J., Shropshire, C., & Cannella Jr, A. A. (2007). Organizational predictors of women on corporate boards. *Academy of management Journal*, 50(4), 941-952.
- Ho, D. P., & Duc, D. (2015). Formal Credit; Policy Impact; Household Income; Difference-Indifferences Method; Panel Data Regression. *Journal of Economic Development*(JED, Vol. 22 (2)), 144-160.

- Hoa, N. T. (2019). How large is Vietnam's informal economy? *Economic Affairs*, 39(1), 81-100.
- Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica: Journal of the econometric society*, 1371-1395.
- Imai, K. S., Gaiha, R., Thapa, G., & Ananim, S. K. (2012). Microfinance and poverty—a macro perspective. *World Development*, 40(8), 1675-1689.
- IMF. (2018). *Financial Inclusion in Asia-Pacific*.
- Informal credit practise. (2019). *Saigon Investment*.
- Jahan, M. S., De, J., Jamaludin, M. F., Sodsriwiboon, P., & Sullivan, C. (2019). *The financial inclusion landscape in the Asia-Pacific region: a dozen key findings*: International Monetary Fund.
- Jayamaha, A. (2014). Cooperative Rural Banks: Can They Survive? Evidence Using all Cooperative Rural Banks in Sri Lanka. *Kelaniya Journal of Management*, 1(2).
- Jensen, M. C., & Meckling, W. H. (1979). Theory of the firm: Managerial behavior, agency costs, and ownership structure *Economics social institutions* (pp. 163-231): Springer.
- Kar, A. K., & Swain, R. B. (2014). Interest rates and financial performance of microfinance institutions: Recent global evidence. *The European Journal of Development Research*, 26(1), 87-106.
- Kennedy, P. (2008). *A guide to econometrics*: John Wiley & Sons.
- Khandker, S. R. (2003). *Micro-finance and poverty* (Vol. 2945): World Bank Publications.
- Khandker, S. R. (2005). Microfinance and poverty: Evidence using panel data from Bangladesh. *The world bank economic review*, 19(2), 263-286.
- Khoi, P. D., Gan, C., Nartea, G. V., & Cohen, D. A. (2013). Formal and informal rural credit in the Mekong River Delta of Vietnam: Interaction and accessibility. *Journal of Asian Economics*, 26, 1-13.

- Kinde, B. A. (2012). Financial sustainability of microfinance institutions (MFIs) in Ethiopia. *European Journal of Business and Management*, 4(15), 1-10.
- Kipasha, E. F. (2013). Impact of size and age on firm performance: evidences from microfinance institutions in Tanzania.
- Klein, A. (1998). Firm performance and board committee structure. *The Journal of Law and Economics*, 41(1), 275-304.
- Kočišová, K., & Mišanková, M. (2014). Discriminant analysis as a tool for forecasting company's financial health. *Procedia-Social and Behavioral Sciences*, 110, 1148-1157.
- Lainez, N. (2014). Informal credit in Vietnam: A necessity rather than an evil. *Journal of Southeast Asian Economies*, 147-154.
- Lainez, N. (2019). Debunking the informal credit myths: Is credit liberalization the magic solution to loan sharking. *ISEAS-Yusof Ishak Institute Perspective*, 87.
- Landwehr, N., Hall, M., & Frank, E. (2005). Logistic model trees. *Machine learning*, 59(1-2), 161-205.
- Ledgerwood, J. (1998). *Microfinance Handbook: An Institutional and Financial Perspective*. Washington, D.C: The World Bank.
- Ledgerwood, J., Earne, J., & Nelson, C. (2013). *The new microfinance handbook: A financial market system perspective*: The World Bank.
- Lehn, K. M., Patro, S., & Zhao, M. (2009). Determinants of the size and composition of US corporate boards: 1935-2000. *Financial management*, 38(4), 747-780.
- Lessmann, S., Baesens, B., Seow, H.-V., & Thomas, L. C. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. *European Journal of Operational Research*, 247(1), 124-136.
- Li, X., Gan, C., & Hu, B. (2011). Accessibility to microcredit by Chinese rural households. *Journal of Asian Economics*, 22(3), 235-246.
- Linck, J. S., Netter, J. M., & Yang, T. (2008). The determinants of board structure. *Journal of financial economics*, 87(2), 308-328.

- Linh, T. N., Long, H. T., Chi, L. V., Tam, L. T., & Lebailly, P. (2019). Access to rural credit markets in developing countries, the case of Vietnam: A literature review. *Sustainability*, 11(5), 1468.
- Louppe, G., Wehenkel, L., Sutera, A., & Geurts, P. (2013). *Understanding variable importances in forests of randomized trees*. Paper presented at the Advances in neural information processing systems.
- Luan, D., Bauer, S., & Kuhl, R. (2016). Income Impacts of credit on accessed households in rural Vietnam: Do various credit sources perform differently? *AGRIS online Papers in Economics and Informatics*, 8(665-2016-45113), 57-67.
- Malekipirbazari, M., & Aksakalli, V. (2015). Risk assessment in social lending via random forests. *Expert Systems with Applications*, 42(10), 4621-4631.
- Manos, R., & Yaron, J. (2009). Key issues in assessing the performance of microfinance institutions. *Canadian Journal of Development Studies/Revue canadienne d'études du développement*, 29(1-2), 101-122.
- Mersland, R. (2011). Performance and international investments in microfinance institutions.
- Mersland, R., & Strøm, R. Ø. (2009). Performance and governance in microfinance institutions. *Journal of Banking & Finance*, 33(4), 662-669.
- Messai, A. S., & Gallali, M. I. (2015). Financial leading indicators of banking distress: A micro prudential approach-Evidence from Europe. *Asian Social Science*, 11(21), 78-90.
- Meyer, J. (2015). Social versus financial return in microfinance. *Available at SSRN* 2580343.
- Molnar, C. (2020). *Interpretable machine learning*: Lulu. com.
- Morduch, J. (1999). The role of subsidies in microfinance: evidence from the Grameen Bank. *Journal of development economics*, 60(1), 229-248.
- Morduch, J., & Haley, B. (2002). Analysis of the effects of microfinance on poverty reduction. *New York: NYU Wagner Working Paper*, 1014.
- Mori, N., Golesorkhi, S., Randøy, T., & Hermes, N. (2015). Board composition and outreach performance of microfinance institutions: Evidence from East Africa. *Strategic Change*, 24(1), 99-113.

- Muchlinski, D., Siroky, D., He, J., & Kocher, M. (2016). Comparing random forest with logistic regression for predicting class-imbalanced civil war onset data. *Political Analysis*, 87-103.
- Muriu, P. (2011). Microfinance Profitability: Does financing choice matter. *Np, May*.
- Mwangi, I. W. (2010). *Determinants of access to credit by individuals in Kenya*. University of Nairobi, Kenya.
- Niederle, M., & Vesterlund, L. (2007). Do women shy away from competition? Do men compete too much? *The quarterly journal of economics*, 122(3), 1067-1101.
- Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research*, 109-131.
- Okurut, F. N., Schoombee, A., & Van der Berg, S. (2005). Credit Demand and Credit Rationing in the Informal Financial Sector in Uganda 1. *South African Journal of Economics*, 73(3), 482-497.
- Pascal, D., Mersland, R., & Mori, N. (2017). The influence of the CEO's business education on the performance of hybrid organizations: the case of the global microfinance industry. *Small Business Economics*, 49(2), 339-354.
- Petropoulos, A., Siakoulis, V., Stavroulakis, E., & Vlachogiannakis, N. E. (2020). Predicting bank insolvencies using machine learning techniques. *International Journal of Forecasting*.
- Pham, T. T. T., & Lensink, R. (2007). Lending policies of informal, formal and semiformal lenders: Evidence from Vietnam. *Economics of transition*, 15(2), 181-209.
- Porta, R. L., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (1998). Law and finance. *Journal of political economy*, 106(6), 1113-1155.
- Post, C., & Byron, K. (2015). Women on boards and firm financial performance: A meta-analysis. *Academy of management Journal*, 58(5), 1546-1571.
- Postelnicu, L., & Hermes, N. (2015). Microfinance Performance and Informal Institutions: A Cross-country Analysis. *Working Papers CEB*, 15.

- PricewaterhouseCoopers. (2017). *Microfinance in Asia: A mosaic future outlook*. Retrieved from <https://www.pwc.in/assets/pdfs/publications/2017/micro-finance-in-asia-a-mosaic-future-outlook.pdf>
- Protection, B. o. C. F. (2018). Natural Disasters and Credit Reporting. *QUARTERLY CONSUMER CREDIT TRENDS*.
- Putzeys, R. (2002). Micro finance in Vietnam: three case studies. *Rural Project Development, Hanoi*.
- Quayes, S. (2012). Depth of outreach and financial sustainability of microfinance institutions. *Applied Economics*, 44(26), 3421-3433.
- Raheja, C. G. (2005). Determinants of board size and composition: A theory of corporate boards. *Journal of financial and quantitative analysis*, 283-306.
- Ravi, V., Kurniawan, H., Thai, P. N. K., & Kumar, P. R. (2008). Soft computing system for bank performance prediction. *Applied soft computing*, 8(1), 305-315.
- Roberts, M. R., & Whited, T. M. (2013). Endogeneity in empirical corporate finance. *Handbook of the Economics of Finance* (Vol. 2, pp. 493-572): Elsevier.
- Roodman, D. (2009a). How to do xtabond2: An introduction to difference and system GMM in Stata. *The stata journal*, 9(1), 86-136.
- Roodman, D. (2009b). A note on the theme of too many instruments. *Oxford Bulletin of Economics and statistics*, 71(1), 135-158.
- Roth Tran, B., & Sheldon, T. L. (2017). Same Storm, Different Disasters: Consumer Credit Access, Income Inequality, and Natural Disaster Recovery. *Different Disasters: Consumer Credit Access, Income Inequality, and Natural Disaster Recovery* (December 15, 2017).
- Saeed, A., Javed, A. Y., & Noreen, U. (2018). Microfinancing, governance, and performance: a South Asian perspective. *Journal of Economics, Finance and Administrative Science*.
- Saint-Macary, C., & Zeller, M. (2011). *Rural credit policy in the mountains of Northern Vietnam: sustainability, outreach and impact*. Retrieved from
- Salim, R., Arjomandi, A., & Seufert, J. H. (2016). Does corporate governance affect Australian banks' performance? *Journal of International Financial Markets, Institutions and Money*, 43, 113-125.

- Santos, D. B., Mendes-Da-Silva, W., & Gonzalez, L. (2018). Lower financial literacy induces use of informal loans. *Revista de Administração de Empresas*, 58(1), 44-59.
- Sekabira, H. (2013). Capital structure and its role on performance of microfinance institutions: The Ugandan case. *Sustainable Agriculture Research*, 2(526-2016-37778).
- Sekyi, S. (2017). Rural Households' Credit access and loan amount in Wa municipality, Ghana. *International Journal of Economics and Financial Issues*, 7(1), 506-514.
- Shoji, M., Aoyagi, K., Kasahara, R., Sawada, Y., & Ueyama, M. (2012). Social capital formation and credit access: Evidence from Sri Lanka. *World Development*, 40(12), 2522-2536.
- Smith, N., Smith, V., & Verner, M. (2006). Do women in top management affect firm performance? A panel study of 2,500 Danish firms. *International Journal of productivity and Performance management*.
- Strobl, C., Boulesteix, A.-L., Kneib, T., Augustin, T., & Zeileis, A. (2008). Conditional variable importance for random forests. *BMC bioinformatics*, 9(1), 307.
- Strøm, R. Ø., D'Espallier, B., & Mersland, R. (2014). Female leadership, performance, and governance in microfinance institutions. *Journal of Banking & Finance*, 42, 60-75.
- Sumner, M., Frank, E., & Hall, M. (2005). *Speeding up logistic model tree induction*. Paper presented at the European conference on principles of data mining and knowledge discovery.
- Tchakoute-Tchuigoua, H. (2010). Is there a difference in performance by the legal status of microfinance institutions? *The quarterly review of economics and finance*, 50(4), 436-442.
- Teranishi, J. (1994). Modernization of financial markets: An analysis of informal credit markets in prewar Japan. *World Development*, 22(3), 315-322.
- Thapa, G. (2006). Sustainability and governance of microfinance institutions: recent experiences and some lessons for Southeast Asia. *Asian Journal of Agriculture and Development*, 3(1362-2016-107617), 17-38.

- ThienLy. (2019). Deposit interest rates jump as banks compete with strengthening greenback. Retrieved from <https://vietnamnews.vn/economy/521092/deposit-interest-rates-jump-as-banks-compete-with-strengthening-greenback.html>
- Thrikawala, S., Locke, S., & Reddy, K. (2017). Financial performance of micro-finance institutions: does gender diversity matters? *International Journal of Gender Studies in Developing Societies*, 2(2), 91-110.
- Tran, H. T., & Santarelli, E. (2014). Capital constraints and the performance of entrepreneurial firms in Vietnam. *Industrial and Corporate Change*, 23(3), 827-864.
- Udry, C. (1994). Risk and insurance in a rural credit market: An empirical investigation in northern Nigeria. *The Review of Economic Studies*, 61(3), 495-526.
- Ullah, S., Akhtar, P., & Zaefarian, G. (2018). Dealing with endogeneity bias: The generalized method of moments (GMM) for panel data. *Industrial Marketing Management*, 71, 69-78.
- UNDP, I. A., Ethnic Minority Committee. (2017). *Economic and social situation of 53 ethnic minorities*.
- Van Sang, H., Nam, N. H., & Nhan, N. D. (2016). A novel credit scoring prediction model based on Feature Selection approach and parallel random forest. *Indian Journal of Science and Technology*, 9(20), 1-6.
- Van Tuan, N., & Tuan, N. A. (2016). Corporate governance structures and performance of firms in Asian markets: A comparative analysis between Singapore and Vietnam. *Organizations and markets in emerging economies*, 7(2).
- Varghese, A. (2004). *Bank-moneylender credit linkages: theory and practice*. Retrieved from
- Viet Nguyen, C., & van den Berg, M. (2014). Informal Credit, Usury, or Support? A Case Study for Vietnam. *The Developing Economies*, 52(2), 154-178.
- Vroom, V. H., & Pahl, B. (1971). Relationship between age and risk taking among managers. *Journal of Applied Psychology*, 55(5), 399.
- Wale, L. E. (2009). Performance analysis of a sample microfinance institutions of Ethiopia. Available at SSRN 1398167.
- Wang, H. H., Turvey, C. G., Kong, R., & Huo, X. (2010). Borrowing amongst friends: the economics of informal credit in rural China. *China Agricultural Economic Review*.



- Wang, Y., Yuan, Y., & Gao, P. (2012). Farmers' financial choices and informal credit markets in China. *China Agricultural Economic Review*.
- Wegge, J., Roth, C., Neubach, B., Schmidt, K.-H., & Kanfer, R. (2008). Age and gender diversity as determinants of performance and health in a public organization: the role of task complexity and group size. *Journal of Applied Psychology*, 93(6), 1301.
- Wells-Dang, A. (2012). Ethnic Minority Development in Vietnam: What Leads to Success? In. *Hanoi: Background Paper for the 2012 Programmatic Poverty Assessment*, World Bank.
- Wintoki, M. B., Linck, J. S., & Netter, J. M. (2012). Endogeneity and the dynamics of internal corporate governance. *Journal of financial economics*, 105(3), 581-606.
- WorldBank. (2017). Country Partnership Framework.
- WorldBank. (2019). *Drivers of Socio-Economic Development Among Ethnic Minority Groups in Vietnam*. Retrieved from
- WorldBank. (2020). Poverty & Equity Data Portal.
- WorldBank. (2021). Vietnam Overview. <https://www.worldbank.org/en/country/vietnam/overview>
- Yehuala, S. (2008). *Determinants of smallholder farmers access to formal credit: the case of Metema Woreda, North Gondar, Ethiopia*. Haramaya University.
- Yermach, D. (1996). HigherValuationofCompanieswithaSmall BoardofDirectors. *JournalofFinancialEconomics* (40), 185-212.
- Zeller, M. (1994). Determinants of credit rationing: A study of informal lenders and formal credit groups in Madagascar. *World Development*, 22(12), 1895-1907.
- Zeller, M., & Meyer, R. L. (2002). *The triangle of microfinance: Financial sustainability, outreach, and impact*: Intl Food Policy Res Inst.
- Zhu, L., Qiu, D., Ergu, D., Ying, C., & Liu, K. (2019). A study on predicting loan default based on the random forest algorithm. *Procedia Computer Science*, 162, 503-513.

## Appendix

**Table A1. Households' ability to get credit**

	<b>Marginal Ef- fect</b>	<b>Std. Err.</b>	<b>z</b>	<b>P&gt; z </b>
Age_2014	(0.006059)	0.000661	-9.1615	< 2.2e-16
hh_size_2014	0.023244	0.004785	4.8572	1.19E-06
EthnicMinority_20141	0.041156	0.019801	2.0785	0.03766
GenderID_20141	0.004149	0.029247	0.1419	0.8871799
AreaTotal_2014	0.000003	0.000001	4.6439	3.42E-06
SectorID_20141	0.130150	0.033826	3.8475	0.0001193
PoorID_20141	0.018996	0.022641	0.839	0.4014594
NaturalDisasters_20141	(0.042340)	0.017705	-2.3914	0.0167831
DepositID_20141	(0.164250)	0.022672	-7.2444	4.34E-13
OwnlandID_20141	0.060588	0.019856	3.0514	0.002278
EducationID_20141	0.010540	0.022332	0.4719	0.6369677
EducationID_20142	(0.057205)	0.028814	-1.9853	0.0471106
MarriedID_20141	(0.053261)	0.034019	-1.5656	0.1174405
NumberGroup_2014	0.039433	0.007935	4.9693	6.72E-07
LoanTotal_2012	0.000000	0.000000	1.6177	0.1057257
Distance	(0.012508)	0.003137	-3.9868	6.70E-05

*Notes:*

The logistic regression model and one way ANOVA was used.

*Source:* Estimation from VARHS 2012 and 2014

**Table A2. VPSB credit**

	<b>Estimate</b>	<b>Std. Error</b>	<b>z value</b>	<b>Pr(&gt; z )</b>	
(Intercept)	-1.174000	0.719900	-1.630000	0.103040	
Age_2014	0.009008	0.006581	1.369000	0.171060	
hh_size_2014	0.005302	0.044260	0.120000	0.904640	
EthnicMinor-					
ity_20141	-1.102000	0.161900	-6.805000	0.000000	***
GenderID_20141	0.065770	0.288400	0.228000	0.819610	
AreaTotal_2014	-0.000017	0.000006	-2.963000	0.003040	**
SectorID_20141	0.269800	0.565100	0.477000	0.633080	
PoorID_20141	1.211000	0.188400	6.428000	0.000000	***
NaturalDisas-					
ters_20141	0.527900	0.160500	3.289000	0.001010	**
DepositID_20141	0.125700	0.167100	0.752000	0.452150	
OwnlandID_20141	-0.340100	0.188900	-1.800000	0.071790	.
EducationID_20141	-0.028930	0.197700	-0.146000	0.883650	
EducationID_20142	0.201800	0.298900	0.675000	0.499660	
MarriedID_20141	0.132100	0.315800	0.418000	0.675780	
NumberGroup_2014	0.071280	0.070680	1.009000	0.313210	
LoanVBSP_2012	0.000038	0.000009	4.379000	0.000012	***
Distance	0.053830	0.034010	1.583000	0.113500	

.' significant at 10%, '\*'significant at 5%, '\*\*' significant at 1%, '\*\*\*' significant at 0.1%

**Table A3. VPSB credit (marginal effect)**

	<b>Marginal</b>				
	<b>effect</b>	<b>Std. Err.</b>	<b>z</b>	<b>P&gt; z </b>	
Age_2014	0.002048	0.001496	1.369000	0.171008	
hh_size_2014	0.001205	0.010062	0.119800	0.904643	
EthnicMinor-					
ity_20141	-0.256960	0.037357	-6.878500	0.000000	***
GenderID_20141	0.014855	0.064704	0.229600	0.818420	
AreaTotal_2014	-0.000004	0.000001	-2.976900	0.002912	**
SectorID_20141	0.058732	0.117090	0.501600	0.615940	
PoorID_20141	0.289910	0.044497	6.515200	0.000000	***
NaturalDisas-					
ters_20141	0.123710	0.038402	3.221300	0.001276	**
DepositID_20141	0.028278	0.037218	0.759800	0.447383	
OwnlandID_20141	-0.079535	0.045219	-1.758900	0.078600	.
EducationID_20141	-0.006559	0.044691	-0.146800	0.883311	
EducationID_20142	0.046999	0.071136	0.660700	0.508810	
MarriedID_20141	0.029596	0.069687	0.424700	0.671055	
NumberGroup_2014	0.016207	0.016060	1.009100	0.312908	
LoanVBSP_2012	0.000009	0.000002	4.380000	0.000012	***
Distance	0.012238	0.007742	1.580700	0.113946	

.' significant at 10%, '\*'significant at 5%, '\*\*' significant at 1%, '\*\*\*' significant at 0.1%

**Table A4. VBARD credit**

	<b>Estimate</b>	<b>Std. Error</b>	<b>z value</b>	<b>Pr(&gt; z )</b>	
(Intercept)	-3.247000	0.717000	-4.528000	0.000006	***
Age_2014	0.000085	0.006995	0.012000	0.990335	
hh_size_2014	0.092080	0.045930	2.005000	0.045008	*
EthnicMinority_20141	0.542700	0.185000	2.934000	0.003344	**
GenderID_20141	-0.373100	0.306700	-1.217000	0.223717	
AreaTotal_2014	0.000006	0.000004	1.308000	0.190875	
SectorID_20141	-0.065460	0.478200	-0.137000	0.891127	
PoorID_20141	-0.888700	0.259100	-3.430000	0.000603	***
NaturalDisasters_20141	-0.309800	0.182100	-1.701000	0.088935	.
DepositID_20141	-0.030520	0.177900	-0.172000	0.863798	
OwnlandID_20141	1.337000	0.290600	4.600000	0.000004	***
EducationID_20141	-0.053520	0.200200	-0.267000	0.789191	
EducationID_20142	-0.042740	0.305500	-0.140000	0.888749	
MarriedID_20141	0.814300	0.349400	2.330000	0.019782	*
NumberGroup_2014	-0.019630	0.072890	-0.269000	0.787728	
LoanVBARD_2012	0.000029	0.000005	5.350000	0.000000	***
Distance	-0.003858	0.038580	-0.100000	0.920338	

.' significant at 10%, '\*'significant at 5%, '\*\*' significant at 1%, '\*\*\*' significant at 0.1%

**Table A5. VBARD credit (marginal effect)**

	<b>Marginal</b>				
	<b>effect</b>	<b>Std. Err.</b>	<b>z</b>	<b>P&gt; z </b>	
Age_2014	0.000016	0.001307	0.012100	0.990335	
hh_size_2014	0.017204	0.008583	2.004500	0.045015	*
EthnicMinority_20141	0.096737	0.031183	3.102300	0.001920	**
GenderID_20141	-0.073813	0.063802	-1.156900	0.247315	
AreaTotal_2014	0.000001	0.000001	1.307300	0.191102	
SectorID_20141	-0.012422	0.092143	-0.134800	0.892761	
PoorID_20141	-0.142550	0.034078	-4.183100	0.000029	***
NaturalDisasters_20141	0.055651	0.031318	-1.777000	0.075570	.
DepositID_20141	-0.005724	0.033497	-0.170900	0.864316	
OwnlandID_20141	0.196490	0.030343	6.475500	0.000000	***
EducationID_20141	-0.009913	0.036744	-0.269800	0.787319	
EducationID_20142	-0.007911	0.056003	-0.141300	0.887670	
MarriedID_20141	0.130350	0.046679	2.792600	0.005229	**
NumberGroup_2014	-0.003667	0.013621	-0.269200	0.787746	
LoanVBARD_2012	0.000005	0.000001	5.063600	0.000000	***
Distance	-0.000721	0.007208	-0.100000	0.920333	

.' significant at 10%, '\*'significant at 5%, '\*\*' significant at 1%, '\*\*\*' significant at 0.1%

**Table 6. Formal Credit Access**

	<b>Estimate</b>	<b>Std. Error</b>	<b>z value</b>	<b>Pr(&gt; z )</b>	
(Intercept)	-1.798000	0.390200	-4.608000	0.000004	***
Age_2014	-0.021200	0.003487	-6.081000	0.000000	***
hh_size_2014	0.108900	0.024830	4.384000	0.000012	***
EthnicMinority_20141	0.146600	0.106500	1.376000	0.168820	
GenderID_20141	0.057100	0.158300	0.361000	0.718262	
AreaTotal_2014	0.000011	0.000003	3.879000	0.000105	***
SectorID_20141	0.697200	0.276400	2.523000	0.011637	*
PoorID_20141	0.268900	0.114500	2.347000	0.018918	*
NaturalDisasters_20141	-0.100000	0.096060	-1.041000	0.297846	
DepositID_20141	-0.533400	0.103500	-5.152000	0.000000	***
OwnlandID_20141	0.540300	0.118200	4.572000	0.000005	***
EducationID_20141	-0.002248	0.116500	-0.019000	0.984602	
EducationID_20142	-0.109500	0.167300	-0.655000	0.512706	
MarriedID_20141	-0.024840	0.173100	-0.143000	0.885918	
NumberGroup_2014	0.203400	0.041500	4.901000	0.000001	***
Loantotal_2012	0.000001	0.000000	0.004428	0.004428	**
Distance	-0.026360	0.015550	-1.695000	0.090074	

.' significant at 10%, '\*'significant at 5%, '\*\*' significant at 1%, '\*\*\*' significant at 0.1%

**Table 7. Formal Credit Access (Marginal effect)**

	<b>Marginal</b>				
	<b>effect</b>	<b>Std. Err.</b>	<b>z</b>	<b>P&gt; z </b>	
Age_2014	-0.003605	0.000586	-6.155100	0.000000	***
hh_size_2014	0.018512	0.004201	4.407000	0.000010	***
EthnicMinority_20141	0.024596	0.017628	1.395300	0.162934	
GenderID_20141	0.009615	0.026386	0.364400	0.715566	
AreaTotal_2014	0.000002	0.000000	3.881200	0.000104	***
SectorID_20141	0.097395	0.030566	3.186400	0.001441	**
PoorID_20141	0.047873	0.021278	2.249900	0.024454	*
NaturalDisasters_20141	-0.016791	0.015922	-1.054600	0.291594	
DepositID_20141	-0.099337	0.020778	-4.781000	0.000002	***
OwnlandID_20141	0.083658	0.016443	5.087900	0.000000	***
EducationID_20141	-0.000382	0.019789	-0.019300	0.984595	
EducationID_20142	-0.018129	0.026941	-0.672900	0.500999	
MarriedID_20141	-0.004243	0.029706	-0.142800	0.886426	
NumberGroup_2014	0.034583	0.007016	4.929100	0.000001	***
Loantotal_2012	0.000000	0.000000	2.841400	0.004492	**
Distance	-0.004482	0.002641	-1.696900	0.089707	

.' significant at 10%, '\*'significant at 5%, '\*\*' significant at 1%, '\*\*\*' significant at 0.1%



**Table A8. Informal Credit Access**

	<b>Estimate</b>	<b>Std. Error</b>	<b>z value</b>	<b>Pr(&gt; z )</b>	
(Intercept)	-0.955700	0.462200	-2.067000	0.038688	*
Age_2014	-0.026040	0.004201	-6.198000	0.000000	***
hh_size_2014	0.069790	0.029610	2.357000	0.018445	*
EthnicMinority_20141	0.264400	0.126400	2.092000	0.036449	*
GenderID_20141	0.066110	0.183400	0.360000	0.718551	
AreaTotal_2014	0.000010	0.000003	3.303000	0.000957	***
SectorID_20141	0.800100	0.340400	2.350000	0.018763	*
PoorID_20141	-0.194700	0.142200	-1.369000	0.171005	
NaturalDisasters_20141	-0.173200	0.115400	-1.500000	0.133530	
DepositID_20141	-0.595300	0.117100	-5.082000	0.000000	***
OwnlandID_20141	-0.062080	0.129800	-0.478000	0.632586	
EducationID_20141	0.077150	0.132200	0.584000	0.559442	
EducationID_20142	-0.505400	0.221000	-2.286000	0.022236	*
MarriedID_20141	-0.411100	0.197500	-2.082000	0.037363	*
NumberGroup_2014	0.157000	0.049290	3.185000	0.001449	**
Loantotal_2012	-0.000001	0.000001	-0.980000	0.327013	
Distance	-0.059280	0.020570	-2.882000	0.003951	**

.' significant at 10%, '\*'significant at 5%, '\*\*' significant at 1%, '\*\*\*' significant at 0.1%

**Table 9. Informal Credit Access (Marginal effect)**

	<b>Marginal</b>				
	<b>effect</b>	<b>Std. Err.</b>	<b>z</b>	<b>P&gt; z </b>	
Age_2014	-0.003024	0.000475	-6.371700	0.000000	***
hh_size_2014	0.008105	0.003427	2.365100	0.018028	*
EthnicMinority_20141	0.029811	0.013810	2.158700	0.030876	*
GenderID_20141	0.007567	0.020687	0.365800	0.714539	
AreaTotal_2014	0.000001	0.000000	3.312500	0.000925	***
SectorID_20141	0.070655	0.021798	3.241300	0.001190	**
PoorID_20141	-0.021620	0.015078	-1.434300	0.151485	
NaturalDisasters_20141	-0.019562	0.012664	-1.544700	0.122419	
DepositID_20141	-0.079483	0.017579	-4.521500	0.000006	***
OwnlandID_20141	-0.007307	0.015489	-0.471800	0.637089	
EducationID_20141	0.009135	0.015951	0.572700	0.566868	
EducationID_20142	-0.050116	0.018388	-2.725400	0.006423	**
MarriedID_20141	-0.052577	0.027582	-1.906200	0.056624	
NumberGroup_2014	0.018231	0.005692	3.202900	0.001360	**
Loantotal_2012	0.000000	0.000000	-0.981200	0.326515	
Distance	-0.006886	0.002368	-2.907600	0.003642	**

.' significant at 10%, '\*'significant at 5%, '\*\*' significant at 1%, '\*\*\*' significant at 0.1%