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Microfinance Participation in Thailand

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Abstract: Income inequality is a major problem in Thailand. A key determinant of income inequality in Thailand is the lack of financial access to financial institutions for low-income families. Microfinance institutions (MFIs) play an important role in enabling poor households to access financial resources at a reasonable cost. The purpose of this paper is to investigate factors that affect Thai households participating in microfinance programs in Thailand. A multinomial logit model is used to investigate the factors that impact the Thai households' access to microfinance. The study employs secondary data from the Thai Socioeconomic Survey (cross-sectional data in 2017) to identify factors affecting Thai household participation in microfinance programs. The results show that the Village Fund (VF) targets low-income rural households and encourages those with older household heads who have lower levels of education, and female household heads, to participate in their program. Larger households are more likely to access the VF. Households with higher dependency ratios are less likely to borrow from the VF. Households with well-educated, young household heads in regional areas are more likely to borrow money from Saving Groups for Production (SGPs). SGP borrower households have higher household incomes than VF borrower households. Our findings indicate that VFs and SGPs are credit sources in the rural credit market; these sources enable rural households to access credit to meet their needs. In addition, rural Thai households borrow from many sources so that they can rotate their loan repayments. Low-income households refinance their loans by borrowing from different sources.

Keywords: microfinance participation; Village Funds; Saving Groups for Production; Thailand; income inequality

1. Introduction

Over the past six decades, Thailand has been developing its economy based on national and social-development plans. These plans have encouraged economic growth by supporting the manufacturing industry, with the aim of increasing exports. As a result, the Thai economy has been one of the fastest growing economies in the world; GDP grew 10% per year in the 1990s (Warr 2000). Between 1988 and 2017, the poverty rate dramatically declined from 65.17% of the population, or 34.2 million people, to 7.9%, or 5.47 million people (ADB 2019; NESDB 2015; Warr 2011). However, income inequality remains a significant problem in Thailand. The Gini index shows that income inequality in Thailand is the highest in Southeast Asia (Bird et al. 2011). The index changes between 1988 and 2017 from 0.487 to 0.365, despite a declining poverty rate over the period (WB 2019). The lowest 10% of the Thai population had a 3% share of the income, whereas the highest 10% had 28.40% (WB 2019). These figures demonstrate the need to address income inequality, and suggest that it must be a national priority.

Thailand Development Research Institution [TDRI] (2004) concludes that one of the major causes of poverty is low education. Because of low education levels, it is difficult for the poor to find jobs and improve their income. A study by the Bird et al. (2011) concluded that a key determinant of income inequality in Thailand is the lack of financial access to financial institutions for low-income families. Poor households cannot access formal financial institutions because of high transaction costs. The private sector is also reluctant to provide financial services to this group of clients (Bird et al. 2011). TDRI (2004) and Bird et al. (2011) suggest that microfinance programs can assist in reducing income inequality. By providing small loans to individuals who typically do not have access to loans from formal financial institutions, microfinance programs can invest in productive or income-generating activities.

Thailand Twelfth National Economic and Social Development Plan (12th NESDP), established in 2017 over a 5-year period, shows the overall development vision linked to the vision of the 20-year national strategy (2017–2036). Significantly for this study, two of the strategies relate to financial inclusion. The strategy for creating a just society and reducing inequality is designed to increase the productivity of the poorest sector of the population (set at 40%); the lowest income group, the disadvantaged, women and the elderly. This strategy also supports small and medium-sized enterprises (SMEs), community and social enterprises, the development of microfinance institutions (MFIs) and greater financial access for job-creation. All these activities are deemed important for achieving inequality alleviation. The 12th NESDP strategy, for strengthening the economy and underpinning sustainable competitiveness, has one objective: to improve financial services access by creating a network of financial institutions (NESDB 2017). MFIs enable poor individuals to access financial resources at a reasonable cost. MFIs play a vital role in helping the poor households' access to financial services (NESDB 2017).

Many poor Thai households still depend on informal lenders because they lack collateral or have established patronage with informal lenders (Jitsuchon 1989; Yostrakul 2018). As Siamwalla et al. (1990) note, the poorest households cannot access formal rural finance because they present a high credit risk. The groups that benefit most from formal finance are middle-income households and the rich. As Bird et al. (2011) note, low-income Thai households have access to a limited range of financial services.

Microfinance programs play an important role in encouraging the poor to participate in financial services, which can ultimately help them escape poverty. Previous studies have documented positive effects of microfinance programs. For example, microfinance programs can improve household income and reduce income inequality (Bird et al. 2011; Khandker 2005; TDRI 2004). Microfinance programs also improve household's consumption, such as education and health (Coleman 1999). However, not every household can participate in microfinance programs. There is a debate about who really benefits—poor or non-poor households—from microfinance programs. Many studies have found that microfinance programs benefit poor households (Boonperm et al. 2013; Khandker 2005), while some studies have argued that non-poor households are more likely to take loans (Coleman 2006; Li et al. 2011).

The question—who benefits from microfinance programs—leads to our research question in this study: What are the determinants of households' credit participation in microfinance programs in Thailand?

Studies have shown that, in Thailand, most low income and poor households can access financial services from community-based MFIs, such as VFs and SGPs (Microfinance Services Ltd. 2013; Suwaruchiporn 2016). There are many studies on this issue, but no specific study has addressed the factors that impact credit participation in Thailand at the village level. This can be done by comparing the determinants of credit participation of VFs and SGPs. A VF is a microfinance program established by the government, whereas SGPs are semi-formal MFIs established by village leaders. It is important to understand the key factors that affect households' participation in VFs and SGPs at the same time. Previous researchers have focused on the participation in VFs (Fongthong and Suriya 2014; Menkhoff and Rungruxsirivorn 2011), but the participation in both VFs and SGPs remains under-researched.

Thus, this paper investigates the factors that affect Thai households with regards to participating in VFs and SGPs simultaneously.

We find that the VF targets certain individuals to participate, that is, low-income rural households, those with older or female household heads and/or those households with lower levels of education. Households with well-educated, young household heads in regional areas are more likely to borrow money from SGPs. SGP borrowers have higher household incomes than VF borrowers.

The rest of the paper is organized as follows. Section 2 describes microfinance institutions in Thailand. Section 3 provides the literature review. Section 4 describes the methodology and data. Section 5 provides results and discussion. Section 6 concludes the study.

2. Microfinance Institutions (MFIs) in Thailand

In Thailand, MFIs can be divided into three main groups (Bird et al. 2011). The first group includes formal MFIs, such as banks and non-bank institutions. This group is controlled by prudential regulations. The second group consists of semi-formal MFIs, such as cooperatives, SGPs and VFs. Semi-formal MFIs are not governed by prudential regulations but have legal status (Tambunlertchai 2015). The last group covers informal MFIs. This group consists of saving groups which operate at the village level (Bird et al. 2011; Tambunlertchai 2015). Informal MFIs are not established by government legislation. This group is smaller than the formal and semi-formal groups.

Studies have shown that in Thailand, most low income and poor people can access VFs, cooperatives and SGPs (Microfinance Services Ltd. 2013; Suwaruchiporn 2016). Microfinance Services Ltd. (2013) reveals that over 50% of VF borrowers and 40% of SGPs borrowers have average incomes of less than THB 6000 per month. Therefore, these Thai MFIs are important in encouraging the poor to participate in financial services, which can ultimately help them escape poverty. This study focuses on VFs and SGPs.

2.1. Village Funds (VFs)

The VF program, the largest government microfinance program in Thailand, was launched by the government in 2001. The Thai government provided THB 1 million (about USD 22,500 at the average exchange rate of USD 1 = THB 44.5 in 2001) per village, to more than 77,000 villages and urban communities across the country (Fongthong and Suriya 2014). After the general election in 2011, the government increased funding to THB 2 million (about USD 65,800, at an average exchange rate of USD 1 = THB 30.4 in 2011) per village. This program plays an important role in the credit market in Thailand, especially for the poor who live in rural areas and who are often unable to access formal financial services (Fongthong and Suriya 2014).

Based on the National Village and Urban Community Fund Act in 2003, the VF has four main objectives. First, the program provides loans for investment, job creation, income generation, welfare improvement and expense reduction. Second, it provides emergency funds, a form of non-productive credit. These loans are small and have maturity dates of less than one year. Third, it may supply loans to other VFs for economic and social strengthening. Fourth, this program aims to develop the rural economy.

The Act also established the VFs' guidelines. People cannot borrow more than THB 30,000. In some cases, loans were extended to THB 75,000 if borrowers met a higher standard of creditworthiness. Emergency loans are limited to THB 15,000. The interest rate must not exceed 15% per year. A borrower must have two guarantors and repay the loan within two years.

The VF is administered at the national and village level. The National Committee of the Central Government oversees VFs at the national level. There are 76 provincial and 928 district sub-committees. The village level committees have 9 to 15 members elected by the villagers who have lived in the village for at least two years. At least half of the committee members must be women. The committees set the rules and manage the funds. The local committees also decide which loans to grant and how much money is lent to the borrowers (Fongthong and Suriya 2014). In 2012, there were 79,255 VFs, with 13 million members and THB 162 billion in capital for all funds. The repayment rate is high, approximately 90% (Meagher 2013).

2.2. Saving Groups for Production (SGPs)

SGPs were established in 1974 by community leaders in order to encourage members to save. SGPs' involve gathering people with different status in the village to help each other to solve their investment problems (Luxchaigul 2014). The local people regularly save money in their cash pool. Savings are the best means of fund accumulation (Luxchaigul 2014). SGPs' economic activities begin with savings for welfare provision and loans. Borrowers obtain loans to invest in their businesses (Luxchaigul 2014). SGPs also provide loans to improve members' livelihoods, and to deal with emergencies. SGPs play an important role in providing microfinance services to the poor (Meagher 2013).

SGPs as community-based financial institutions were established throughout Thailand. SGPs are supported by the Community Development Department (CDD) of the Ministry of Interior (MOI). CDD sets the loan guidelines and evaluates SGPs' reports. SGPs are not controlled by prudential regulations but are assessed by CDD via financial institution indicators. In 2012, there were 26,819 SGPs, with 3.6 million members and THB 36.9 billion in savings. The repayment rate is high, approximately 99% (Meagher 2013).

3. Literature Review

Microfinance programs play a crucial role in supporting rural households' access to microcredit (Petrick 2005; Phan 2012). The availability of microfinance enables rural households to invest in new technology, improve their production and productivity, and ultimately increase their income and consumption. Therefore, it is important to understand the factors that affect households' participation in microfinance programs. Understanding these factors can help improve credit access and the implementation of credit policies for rural households. This section reviews both credit rationing theory and the demand for credit as guidelines for credit participation.

Credit participation begins with the demand for credit; it assumes that an individual (or a household) wants to maximize his or her loan utility. Loans have an opportunity cost, or the cost associated with the interest rate. Therefore, an individual or household's decision to borrow money can be seen as a rational choice based on the theory of demand for credit. However, demand for credit alone cannot explain credit participation behavior, because credit is rationed under information asymmetry conditions (Stiglitz and Weiss 1981). Lenders cannot charge borrowers at the market price or interest rate because they do not have enough information about borrowers' default risks. Moreover, lenders cannot increase interest rates until interest rate equilibrium is reached in the credit market, because they need to ration every loan. This means that if lenders increase the interest rate until it reaches interest rate equilibrium, marginal borrowers may withdraw, leaving only risky borrowers in the market.

This study examines household participation in microfinance programs. Participation is defined as the decision to borrow money from a microfinance program (Doan et al. 2010). Diagne (1999) explains that credit participation relates to borrowers' potential choices and their demand for credit. Participation in the credit market is determined by household information (for example, physical and capital endowments). Some studies have used a reduced form regression equation to investigate the factors that affect credit participation (Diagne 1999; Doan et al. 2010; Zeller 1994). Zeller (1994) investigated the factors related to credit rationing in Madagascar, and notes that lenders evaluate borrowers using information from group lenders and the borrowers' creditworthiness. Diagne (1999) evaluated the determinants affecting households' access to credit in Malawi. Diagne finds that a household's total assets (land and livestock) determine the poor's access to credit. Investigating the factors affecting Vietnamese access to credit, Doan et al. (2010) conclude that household size, income, phone ownership and the home's location are important factors in determining credit participation.

Lenders use borrowers' demands for credit and their creditworthiness to determine whether they will grant loans or not. Therefore, factors determining credit participation can represent either borrowers' demands for credit or borrowers' creditworthiness (Doan et al. 2010). This means if borrowers have more endowments (physical and human resources), they are more likely to be granted a loan (Doan et al. 2010). The factors affecting credit participation are household head characteristics, demographics, occupation, income and assets (Fongthong and Suriya 2014; Li et al. 2011; Menkhoff and Rungruxsirivorn 2011).

Scholars investigating poor households have noted that the above determinants may play other roles in explaining credit participation. These factors may drive credit demand factors rather than the components of creditworthiness. This means that physical endowments (for example, assets and land ownership), and human endowments (for example, education), have a negative impact on credit participation (Doan et al. 2010). Evaluating group-lending microfinance programs and poverty in Bangladesh, Khandker (2005) finds that landless households are more likely to obtain loans from group-lending microfinance programs than households that own land. The author also finds that education and being a female have a negative effect on the number of loans granted from group-lending microfinance programs. These results suggest that group-lending systems, in which the demand for microfinance is largely derived from landholding eligibility conditions and education, matter in deciding the number of loans from group-lending microfinance programs (Khandker 2005). The various factors affecting credit participation for different groups of borrowers are the result of segmented credit markets in developing countries (Doan et al. 2010). Conning and Udry (2007) note that lenders may use diverse ways to screen applicants and evaluate their creditworthiness for different credit segments.

There are also supply-side factors that affect households' participation in credit: for example, financial lending policies and membership requirements. In short, lenders use diverse methods to screen and evaluate borrowers in different credit segments (Doan et al. 2010). Umoh (2006) points out that many households do not have access to credit because of financial lending policies. These include complicated application procedures, specified minimum loan amounts and prescribed loan purposes. MFIs also have membership requirements, policies on self-selected credit groups and group lending (Li 2010). Maes and Foose (2006) state that MFIs tend to reject very poor members because they are unable to repay loans, which destroys the entire group's creditworthiness. These screening methods affect household participation in credit (Li 2010).

Supply-related and demand-related factors jointly affect households' participation in microfinance programs. Focusing on the demand side, this study investigates the factors that affect households' participation in MFIs in Thailand. As the literature review has shown, many socio-economic factors affect a household's participation in the credit market. The factors can be divided into four levels: the individual, household, credit market and geographic levels. The literature tends to focus on the individual level (but not all four levels). Pham and Izumida (2002), Gan et al. (2007) and Li et al. (2011) focus on factors at the individual level, including household head age, gender (female household heads), head's ethnicity and head's education level. The second group (Chen and Jin 2017; Gan et al. 2007; Menkhoff and Rungruxsirivorn 2011; Nguyen 2007) focuses on household level factors: for example, land ownership, family size, membership of a credit group, membership requirements, family income and expenditure levels. Pham and Izumida (2002) concentrate on factors at the credit market level, such as an agricultural loan, trade loan and loan duration. The last group (see for example, Coleman 1999; Li et al. 2011; Pitt and Khandker 1998) investigate determinants at the geographic level, such as urbanized communes [located in rural areas adjacent to cities or towns where industrial zone(s) are present], road access, and distance to the nearest bank. Similar to Chen and Jin (2017), Gan et al. (2007), Menkhoff and Rungruxsirivorn (2011) and Nguyen (2007), we include factors such as borrowers' characteristics, demographic information, occupations, income and assets in our study.

Previous empirical studies identify that the factors that affect household participation in microfinance programs can be grouped into four groups: household head characteristics (age, gender education and marital status), demographics (household size, the dependency ratio, occupation, income and assets), location of households, and others. Fongthong and Suriya (2014) state that households and individuals with similar characteristics, such as age, education, household size and income, might have different levels of ability. These variables lead to a difference in probability to borrow. Li et al. (2011) use the logit model to investigate household characteristics that affect access to rural credit. The authors find that household demographics and socioeconomic characteristics (income, the dependency ratio, household location, access to other credit sources and attitude towards debt) affect rural households' access to microcredit. Kasali et al. (2016) examined determinants that affect poor households' access to microfinance programs in Nigeria using a logit model. The authors find that age, household size, business worth, skill or experience, education level, assets, health status, living standards and income affect access to microfinance programs in Nigeria. Chen and Jin (2017) explored the determinants affecting Chinese households' decisions to borrow from both the formal and informal sectors, find that marital status, age, employment, education, Communist party membership, household location, annual income and net worth significantly influence a household's access to formal credit. Jumpah et al. (2019) investigated factors that affect farmers' participation in microfinance programs in Ada West and East Districts, Ghana, using logistic regression. Jumpah et al. find that distance, interest rates, farming experience, membership in a farmer-based organization, the number of dependents, gender and age affect farmers' participation in microfinance programs in Ghana. Ouattara et al. (2020) identified key determinants of smallholder farmers' access to microfinance credit in Sassandra-Marahoué District, Côte d'Ivoire, using univariate statistics and probit binary modelling. Ouattara et al. find that farmers' socio-economic/demographic and credit requirements are key determinants of smallholder farmers' access to microfinance credit in the district.

In terms of Thailand, most studies investigated factors that affect households' participation in the VF in the northeast of Thailand. Coleman (2006) investigated the characteristics of village bank members in the northeast of Thailand using the logit model; Kislat and Menkhoff (2012) evaluated the role of VFs in three provinces in the northeast of Thailand. The northeast of Thailand is the country's poorest region. However, no studies have investigated the determinants affecting household participation in both VFs and SGPs in Thailand. Studies have shown that, in Thailand, most low income and poor people can access financial services from community-based MFIs, such as VFs, cooperatives and SGPs (Microfinance Services Ltd. 2013; Suwaruchiporn 2016). This study will identify the determinants that affect borrowers' decisions to participate in both VFs and SGPs in Thailand.

Discrete choice theory discusses credit rationing alongside credit demand theory. The discrete choice theory explains the relationship between utility and an individual's discrete choices, or how an individual maximizes his or her utilities through choices (McFadden 1973). This theory has been used in many fields, including consumer choice, housing and transport choice and nonmarket goods (Phan 2012). The choice theory models household behavior in the credit market. The model assumes that borrowers take out loans to maximize their utilities. A borrower's demand for credit is affected by decision processes and socioeconomic choices. A binary and polychotomous choice model can be used to describe a borrowers' behavior and the social economic factors that affect households' participation in the credit market.

4. Methodology and Data

4.1. Empirical Framework

This study uses discrete choice models (DCMs) to analyze MFI participation in Thailand. DCMs are used to predict and analyze a decision-maker's choice from a set of alternatives, the choice set (Ben-Akiva and Bierlaire 1999). The choice set has three features that fit within the framework of discrete choices (Ben-Akiva and Bierlaire 1999; Koppelman and Bhat 2006; Li 2010):

1. The alternatives, in the choice set, are mutually exclusive. This feature means that if an individual or household chooses one alternative, s/he gives up all other alternatives.

2. The alternatives are collectively exhaustive. This feature means that all the possible alternatives are included in the choice set. Our study focuses on VFs and SGPs, therefore all the possible alternatives in the choice set include borrowing from VFs (only), borrowing from SGPs (only), borrowing from both VFs and SGPs, and non-VF and SGP borrowing.
3. The number of alternatives is finite. This means the alternatives can be counted.

DCMs are probability models that are used to specify the probability of a decision-maker making a certain choice, via the utility function (Ben-Akiva and Bierlaire 1999; Koppelman and Bhat 2006; Li 2010). The decision-maker chooses the alternative that maximizes his or her utility. This means that the borrower chooses the loan/lender based on what provides the greatest utility among the available alternatives in the choice set (C_m) (Ben-Akiva and Bierlaire 1999; Li 2010).

To illustrate the decision-maker maximizing his or her utility, let us assume that U_{in} and U_{jn} are the utility that the decision-maker n obtains from alternatives i and j, respectively. The probability that the decision-maker n chooses alternative i from C_m can be shown as (Ben-Akiva and Bierlaire 1999; Li 2010):

$$P_n(i|C_m) = Pr[U_{in} > U_{jn}, \forall\ i, j\ \varepsilon\ C_m \text{ and } i \neq j) \tag{1}$$

To reflect the uncertainty, the utilities of the alternatives are modeled as random variables in DCMs. As a random variable, utility U_{in} is divided into two parts: the systematic part V_{in} and the random components ε_{in}. More specifically, V_{in} is a function related to the observed information. Observed information refers to the decision-maker's characteristics and the alternatives. The random term ε_{in} captures the uncertainty that affects the utility (Ben-Akiva and Bierlaire 1999; Li 2010). The utility function is:

$$U_{in} = V_{in} + \varepsilon_{in}, \forall\ i\ \varepsilon\ C_m \tag{2}$$

$$U_{jn} = V_{jn} + \varepsilon_{jn}, \forall\ j\ \varepsilon\ C_m \tag{3}$$

where:

V_{in}, V_{jn} is the deterministic or systematic part of the utility; and
ε_{in}, ε_{jn} is the random term that captures the uncertainty.

The decision-maker chooses an alternative that achieves the highest utility. This means substituting Equations (2) and (3) into Equation (1). The probability of the decision-maker n choosing alternative i from the choice set C_m can be shown as (Ben-Akiva and Bierlaire 1999; Li 2010):

$$P_n(i|C_m) = Pr(U_{in} > U_{jn}) = Pr(V_{in} + \varepsilon_{in} > V_{jn} + \varepsilon_{jn}) \tag{4}$$

So,

$$P_n(i|C_m) = Pr(U_{in} > U_{jn}) = Pr(V_{in} - V_{jn} > \varepsilon_{in} - \varepsilon_{jn})\ \forall\ i, j\ \varepsilon\ C_m \text{ and } i \neq j \tag{5}$$

In this study, the choice set contains more than two alternatives (multinomial choice). This situation leads to what is termed a multinomial logit model. To formalize this, suppose there is a choice between M alternatives. The alternative i is chosen by individual n if the alternative i gives the highest utility. The probability of choosing alternative i can be shown as (Ben-Akiva and Bierlaire 1999; Li 2010; Verbeek 2008):

$$P_n(i) = Pr(U_{in} = max\{U_{1n}, U_{2n}, \ldots, U_{mn}\}) \tag{6}$$

So:

$$P_n(i) = Pr(U_{in} > {}^{max}_{k=1,\ldots k,k\neq i} U_{kn}) = Pr(V_{in} + \varepsilon_{in} > {}^{max}_{k=1,\ldots k,k\neq i} V_{kn} + \varepsilon_{kn}) \tag{7}$$

The multinomial logit model is based on the assumption that the utility error term is mutually independent, which is also known as the type I extreme-value distribution (Verbeek 2008).

Following these assumptions, the distribution function of each ε_{in}, for all i, n can be shown as (Ben-Akiva and Bierlaire 1999; Maddala 1994; Verbeek 2008):

$$F(\varepsilon) = exp[-e^{-\mu\varepsilon}], \mu > 0 \tag{8}$$

where:

μ is a positive scale parameter that can be assumed to take the value of 1 for convenience (Ben-Akiva and Bierlaire 1999).

The probability that a given individual n chooses option i within the choice set C_m is (Ben-Akiva and Bierlaire 1999):

$$Pn(i) = \frac{e^{\mu Vin}}{\sum_{j\in Cm} e^{\mu Vjn}} \tag{9}$$

Equation (9) shows that $P_n(i)$ is a value between o and 1 and $\sum_{j\in Cm} e^{\mu Vjn} = 1$.

The distribution of the error term in Equation (9) sets the utility value, which is undefined. To solve this problem, we set one of the deterministic utility levels at zero, $V_{1n} = 0$. This equation is then (Verbeek 2008):

$$P_n(i) = \frac{e^{\mu Vin}}{1 + \sum_{j=2}^{m} e^{\mu Vjn}} \tag{10}$$

The systematic part of utility V_{in} is linear in the parameter (Li 2010):

$$V_{in} = \beta_i X_n \tag{11}$$

where:

β is a vector of unknown parameters associated with the variables;
X_{in} is a vector of observed variables relating to alternative i and decision maker n; and
μ takes the value of 1 for convenience (Ben-Akiva and Bierlaire 1999).

Adding Equation (11) into (10), the multinomial logit probability, it becomes (Verbeek 2008):

$$P_n(i) = \frac{e^{\beta_i X_n}}{1 + \sum_{j=2}^{m} e^{\beta_j X_n}} \quad i = 1,\ 2,\ \ldots,\ m \tag{12}$$

In this study, households choose to participate in microfinance programs (or to not participate) based on their options; they have more than two mutually exclusive alternatives. The multinomial logit model is used to determine the factors that affect credit participation in Thailand (VFs and SGPs). The model is coded as four outcomes that affect microfinance credit participation [1 = non-VF and SGP borrowing; 2 = borrowing from VFs (only); 3 = borrowing from SGPs (only); 4 = borrowing from both VFs and SGPs].

The first outcome (1 = non-VF and SGP borrowing) is the households that do not borrow from both VFs and SGPs. The second outcome [2 = borrowing from VFs (only)] is households that only borrow from VFs. The third outcome [3 = borrowing from SGPs (only)] is households that only borrow from SGPs. The last outcome (4 = borrowing from both VFs and SGPs) is households that borrow from both VFs and SGPs at the same time.

The choice of microfinance participation in this model depends on household characteristics and the financing strategies that the households chooses to maximize their utility.

If T_{in} is the dependent variable, then it can take on one of the different alternative choices.

$P_n(T_n = i)$ is the probability of observing outcome i. The probability model for T_n is (Li 2010; Verbeek 2008):

$$P_n(T_n = i) = \frac{e^{\ \beta_i X_n}}{1 + \sum_{j=2}^{4} e^{\ \beta_j X_n}} \tag{13}$$

In other words, the coefficients of the first choice-category, which can be arbitrary, are used as a base to compare the alternative choices. In this study, the first choice-category, used to compare with the other choices, is the non-borrowing group.

The multinomial logit model can be shown and interpreted in terms of odds. This means the odds of the outcome i versus outcome u (Balogun and Yusuf 2011; Durojaiye et al. 2014; Mpuga 2010; Verbeek 2008) are given as:

$$\frac{P_n(T_n = i)}{P_n(T_n = u)} = \frac{\frac{e^{\beta_i X_n}}{1+\sum_{j=2}^{4} e^{\beta_j X_n}}}{\frac{e^{\beta_u X_n}}{1+\sum_{j=2}^{4} e^{\beta_j X_n}}} = \frac{\exp(X_n\beta_i)}{\exp(X_n\beta_u)} \tag{14}$$

where:

$P_n(T_n = i)$ is the probability of observing outcome i;
$P_n(T_n = u)$ is the probability of observing outcome u;
X is a vector of characteristics including household head characteristics and demographics (including household size, occupation, income and assets); and
β is the parameter to be estimated.

Arranging the exponent in Equation (14) leads to the following odds equation:

$$\frac{P_n(T_n = i)}{P_n(T_n = u)} = \exp[X_n(\beta_i - \beta_u)] \tag{15}$$

Equation (15) shows the odds equation in a non-linear form, which leads to difficulties in interpreting the coefficients. For the purpose of interpretation, Equation (15) is transformed into a log form. Equation (16) expresses the multinomial logit model, which is linear in the logit form (Balogun and Yusuf 2011; Durojaiye et al. 2014; Mpuga 2010; Verbeek 2008):

$$Ln\frac{P_n(T_n = i)}{P_n(T_n = u)} = [X_n(\beta_i - \beta_u)] \tag{16}$$

The difference between β_i and β_u in Equation (16) is the influence of X on the logit of outcome i versus outcome u. This equation can easily compute the partial derivative because the model is linear in logit:

$$\frac{\partial Ln\frac{P_n(T_n=i)}{P_n(T_n=u)}}{\partial X_n} = \frac{\partial X_n\ (\beta_i - \beta_u)}{\partial X_n} = (\beta_i - \beta_u) \tag{17}$$

We can interpret $\beta_i - \beta_u$ in Equation (17). Thus, holding all other variables constant, changing a unit in X_n, the logit of outcome i versus u will change by $\beta_i - \beta_u$ units.

The multinomial logit models [Equations (13)–(17)] are used to estimate the effect of explanatory variables on the dependent variable, which is an unordered response category. There are two advantages to this model: its computational ease and its relative robustness (Mpuga 2010).

The multinomial logit model is a nonlinear function of coefficients (β_n). Therefore, the ordinary least squares technique (OLS) cannot be used to estimate this model because it is not statistically appropriate (Li 2010; Verbeek 2008). This study therefore uses maximum likelihood estimation (MLE), because MLE can estimate coefficients consistently and asymptotically efficiently (Li 2010; Verbeek 2008). MLE consists of model parameters that maximize the probability (or likelihood) of the observed choices, conditional on the model, i.e., it maximizes the likelihood that the sample was generated from the model with the selected parameter values (Koppelman and Bhat 2006). The likelihood function for a sample of n individuals, each with j alternatives, is defined as (Koppelman and Bhat 2006):

$$\frac{\partial Ln\frac{P_n(T_n=i)}{P_n(T_n=u)}}{\partial X_n} = \frac{\partial X_n\ (\beta_i - \beta_u)}{\partial X_n} = (\beta_i - \beta_u) \tag{18}$$

where $\delta_{jn} = 1$ is the chosen indicator (=1 if j is chosen by individual n and 0, otherwise), and P_{jn} is the probability that individual n chooses alternative j.

The value of the parameter that maximizes the likelihood function is obtained by finding the first derivative of the likelihood function and equating it to zero. This study maximizes the log-likelihood function because the likelihood function and log-likelihood function yield the same maximum, and the log-likelihood function is more convenient to differentiate. The function is expressed as (Koppelman and Bhat 2006):

$$LL(\beta) = Log(L(\beta)) = \sum_{\forall n \in N} \sum_{\forall j \in J} \delta_{jn}\ ln(P_{jn}(\beta)) \tag{19}$$

Therefore, the maximum likelihood estimators $\hat{\beta}$ can be obtained by differentiating Equation (19) with respect to β_k (Koppelman and Bhat 2006):

$$\frac{\partial(LL)}{\partial\beta_k} = \sum_{\forall n \in N} \sum_{\forall j \in J} \delta_{jn} \frac{1}{P_{jn}} \frac{\partial P_{jn}}{\partial\beta}\ \forall k \tag{20}$$

4.2. Estimation Strategies

Several estimation tests are commonly used in association with the multinomial logit model (Freese and Long 2000). The first test is used to assess all coefficients associated with an independent variable that are simultaneously equal to zero. This study uses the Likelihood Ratio test (LR test). The LR results test whether an independent variable affects a dependent variable (Freese and Long 2000; Long and Freese 2014). Next, the variance inflation factor (VIF) is used to detect potential multicollinearity issues. VIF quantifies how much the variance is inflated. VIF values greater than 10 might need further examination (Midi et al. 2010). The third test involves assessing the combined dependent categories. The Wald test is used to test if any of the independent variables significantly affects the odds of outcome i versus outcome u. This test indicates that i and u are indistinguishable with respect to the variables in the model. This test is commonly used to determine if two outcomes can be combined (Freese and Long 2000; Long and Freese 2014; Williams 2018). The last test is to assess the Independence of Irrelevant Alternatives (IIA) assumption. The Hausman test is used to test whether the model violates the IIA assumption (Freese and Long 2000; Hausman and McFadden 1984; Long and Freese 2014). The IIA assumption implies that adding another alternative or changing the characteristics of a third alternative does not affect the relative odds between alternatives i and u (Wooldridge 2007).

This study conducts an LR test for each independent variable. The null hypotheses for all coefficients associated with given variables are zero. We use the LR test to assess if the independent variables affect the dependent variable. The results show that all variable effects are significant at the 0.01 level. This finding indicates that independent variables affect the dependent variable.

This study conducts a VIF to test for multicollinearity. This result shows that the VIF of all variables is not above 10. The mean VIF for all variables is 2.5. In short, there are no multicollinearity problems in our study.

The Wald test is used to assess the hypothesis that a pair of outcomes can be combined. The null hypotheses for all coefficients, except for the intercepts associated with a given pair of alternatives, are zero (alternatives can be collapsed). The results show that all combinations are significant at the 0.01 level. This indicates that no categories should be combined.

The Hausman test evaluates whether the IIA assumption holds for the multinomial logit model. The test statistic takes on a negative value. Cheng and Long (2011) state that this outcome provides evidence in favor of accepting the IIA hypothesis. In addition, the Hausman test shows negative chi-square test statistics. Long and Freese (2014) state that negative chi-square test statistics are common. This result indicates that the IIA property is not violated (Hausman and McFadden 1984). Therefore, the Hausman test results for IIA (see Table 1) reveal that the null hypothesis of IIA cannot be rejected. This indicates that the IIA is not violated.

Table 1. The results of the Hausman test of Independence of Irrelevant Alternatives.

Omitted Category	Hausman Test		
	Test Statistic	p-Value	Evidence
Non-Village Fund (VF) and Saving Group for Production (SGP) borrower	60.337	0.129	For IIA
VF borrower	−31.301	-	For IIA
SGP borrower	−187.635	-	For IIA
Both VF and SGP borrower	−53.004	-	For IIA

Source: Author's calculations.

4.3. Data Collection Method

The current study uses cross-sectional data (2017) to evaluate factors that affect Thai households' participation in VFs and SGPs. Cross-sectional data is obtained from the 2017 Household Socio-Economic Survey, collected by the National Statistical Office, from the Ministry of Information and Communication Technology. The survey interviewed 43,210 households (both borrowers and non-borrowers) across the country. Data was collected monthly. Of the 43,210 sampled households, 8216 (19.01%) households borrowed from VFs, 5394 (12.48%) households borrowed from SGPs, and 799 (1.85%) households borrowed from both VFs and SGPs. Two thirds (28,801; 66.65%) of the sampled households were non-VF and SGP borrowers (see Table 2). The following section provides detailed demographic information for borrowers and non-borrowers in relation to each of the microfinance programs.

Table 2. Characteristics of borrower households and non-borrower households from Microfinance Institutions (MFIs) using cross-sectional data from the 2017 Household Socio-Economic Survey.

Variable	Non-VF and SGP Borrowers	VF Borrowers	SGP Borrowers	Both VF and SGP Borrowers	All Respondents
Household head characteristic					
Age (years)	55.05	56.90	49.12	54.16	54.64
Female (yes = 1)	0.41	0.37	0.36	0.41	0.40
Education (years)	8.39	6.36	9.31	6.73	8.08
Married (yes = 1)	0.58	0.75	0.73	0.76	0.64
Single (yes = 1)	0.14	0.02	0.10	0.02	0.11
Demographic					
Household size (persons)	2.60	3.31	3.40	3.83	2.86
Dependency ratio	0.42	0.35	0.33	0.35	0.39
Number of children (age < 15 years) (persons)	0.41	0.69	0.67	0.90	0.50
Number of elderly (age > 60 years) (persons)	0.65	0.67	0.40	0.51	0.62
Occupation					
Farmer (yes = 1)	0.26	0.71	0.24	0.54	0.35
Entrepreneur (yes = 1)	0.03	0.02	0.06	0.04	0.03
Formal worker (yes = 1)	0.32	0.19	0.44	0.31	0.31
Informal worker (yes = 1)	0.33	0.61	0.33	0.51	0.38

Table 2. *Cont.*

Variable	Non-VF and SGP Borrowers	VF Borrowers	SGP Borrowers	Both VF and SGP Borrowers	All Respondents
Income, expenditure and assets					
Monthly income (THB 1000)	25.90	17.77	37.67	25.17	25.81
Monthly expenditure on food and beverages (THB 1000)	7.02	6.29	9.10	7.72	7.16
Financial assets (THB 1000)	196.40	67.08	167.52	70.80	165.88
Number of cars	0.22	0.07	0.38	0.16	0.21
Number of motorcycles	1.07	1.47	1.50	1.69	1.21
Other variables					
Central (yes = 1)	0.30	0.18	0.35	0.32	0.29
North (yes = 1)	0.23	0.31	0.19	0.27	0.24
Northeast (yes = 1)	0.22	0.47	0.19	0.35	0.26
South (yes = 1)	0.18	0.04	0.22	0.06	0.16
Rural household (yes = 1)	0.36	0.54	0.35	0.49	0.39
Difficulty obtaining an emergency loan (yes = 1)	0.08	0.03	0.05	0.04	0.07
Total	28,801	8216	5394	799	43,210

Source: Author's calculations. Note: For each of the variables presented in Table 1, the authors rejected the null hypothesis of LR test that all coefficients associated with given variables are 0 at the 0.01 level.

5. Results and Discussion

5.1. Household Characteristics

Table 2 summarizes borrowers' and non-borrowers' household characteristics. The average household head age of the sample respondent is 54.64 years. VF borrower households are the oldest, with an average household head age of 56.90 years; SGP borrower households are the youngest, with an average household head age of 49.12 years. The average household head ages of the VF and SGP borrower households and non-VF and SGP borrower households are 54.16 and 55.05 years, respectively. In terms of the gender of the household head, approximately 40% of all the members of the four groups of borrower households are female. SGP borrower households have the highest education level (9.31 years), and VF borrower households have the lowest education level (6.36 years) (see Table 2).

In terms of marital status, 58% of non-VF and SGP borrower households, 75% of the VF borrower households, 73% of the SGP borrower households and 76% of both VF and SGP borrower households are married. There is an average of three people per household in all four groups of borrower households (VF and SGP borrowers, both VF and SGP borrowers, and non-VF and SGP borrowers) (see Table 2).

The result shows that most of the household heads of non-VF and SGP borrower households are informal workers (self-employed, contributing family workers), while most of the household heads of VF borrower households are farm workers. SGP borrower households work in the formal sector as government employees, state enterprise employees and private company employees. In terms of occupation, most borrower households in the third group (who borrow from both VFs and SGPs) work as farmers. SGP borrower households have the highest monthly income and monthly expenditure on food and beverages (THB 37.67 thousand and THB 9.10 thousand per household, respectively). VF borrower households have the lowest monthly income and expenditure on food and beverages of the three groups of borrowers (THB 17.77 thousand and THB 6.29 thousand per household, respectively). Both VF and SGP borrower households, and non-VF and SGP borrower households, have monthly household incomes between THB 25.17 thousand and THB 25.90 thousand, and monthly expenditure on food and beverages of between THB 7.02 thousand and THB 7.72 thousand, respectively (see Table 2).

Households from the four groups possess many financial assets (see Table 2). The average value of financial assets is THB 165.88 thousand per household. Non-VF and SGP borrower households have the most financial assets and VF borrower households have the least. SGPs borrower households have the highest average number of cars (0.38 cars), and VF borrower households have the lowest average number of cars (0.07 cars). Both VF and SGP borrower households have the highest average number of motorcycles (1.69 motorcycles), whereas non-VF and SGP borrower households, VF borrower households and SGP borrower households have 1.07, 1.47 and 1.50 motorcycles, respectively.

Most VF borrower households (54%) live in rural areas. A total of 36% of non-VF and SGP borrower households and 35% of SGP borrower households live in rural areas. A minority of non-VF and SGP borrower households, VF, SGP, and both VF and SGP borrower households have had trouble accessing loans when faced with an emergency: 8%, 3%, 5% and 4%, respectively (see Table 2).

The households who borrow from both credit sources live in regional areas (such as North, Northeast, Central and South of Thailand) because the credit programs encourage households in these areas to participate in the microfinance programs. Household size and the number of children in the households who borrow from the two credit sources are higher than in households who borrow only from one credit source. Households who borrow from two credit sources have more income than households who borrow from VFs, but less income than households who borrow from SGPs. They also have more motorcycles.

5.2. Results and Discussion

Table 3 presents the microfinance program participation determinants, and includes parameter estimates and marginal effects. Overall, 41,099 observations were used to calculate the estimated coefficients. The LR test (χ^2_{42} = 13,911.19) rejects the null hypothesis that the parameter estimates for the multinomial logit model are zero; the model can be used to explain the probability of microfinance program participation. The multinomial logit model estimates the coefficients via Maximum Likelihood Estimation (MLE). However, the values of the estimated coefficients from the multinomial logistic regression have no direct economic interpretation, because they are obtained using MLE techniques (Greene 2003; Li 2010). To address this limitation, this study calculates the marginal effect provided in Table 3. Marginal effects provide greater intuition in terms of interpreting the estimated coefficients of continuous explanatory variables, whereas the odds ratios are more useful for interpreting the estimated coefficients of the dichotomous explanatory variables (Greene 2003; Li 2010).

5.2.1. Determinants of VF Participation

Column 1 in Table 3 shows that VF participation is significantly explained by household head characteristics (age, female, education, married, single), demographics (household size, dependency ratio, number of children, number of elderly people), occupation (farmer, entrepreneur, formal and informal worker), income, expenditure, assets (monthly income, monthly expenditure on food and beverages, financial assets, number of cars, number of motorcycles), and other variables (central, north, northeast, south, rural households, difficulty obtaining an emergency loan).

In terms of household head characteristics, being female and/or married are significant positive predictors of VF participation at the 1% level. Age is significant and positive at the 1% level, but higher levels of education and being single are negative and significant at the 1% level (see column 1 in Table 3).

Table 3. Multinomial logit model results.

	VF Borrowers		SGP Borrowers		Both VF and SGP Borrowers	
	Coefficient	**Marginal Effect**	**Coefficient**	**Marginal Effect**	**Coefficient**	**Marginal Effect**
Constant	−6.115 ***		−1.560 ***		−8.197 ***	
Household head characteristic						
Age (years)	0.009 ***	0.001 ***	−0.024 ***	−0.006 ***	−0.001	5.30×10^{-06}
Female (1 = female, 0 = male)	0.349 ***	0.032 ***	0.065 *	0.002	0.473 ***	0.005 ***
Education (years)	−0.044 ***	−0.004 ***	0.018 ***	0.002 ***	−0.073 ***	−0.001 ***
Married (1 = married, 0 = otherwise)	0.358 ***	0.032 ***	0.030	−0.001	0.300 ***	0.003 **
Single (1 = single, 0 = otherwise)	−0.739 ***	−0.052 ***	−0.386 ***	−0.028 ***	−1.292 ***	−0.008 ***
Demographic						
Household size (persons)	0.265 ***	0.020 ***	0.400 ***	0.037 ***	0.413 ***	0.003 ***
Dependency ratio	−0.214 ***	−0.005	−1.153 ***	−0.114 ***	−0.652 ***	−0.005 **
Number of children (persons)	0.049 *	0.005 **	−0.076 **	−0.008 ***	0.099	0.001
Number of elderly people (persons)	−0.195 ***	−0.015 ***	−0.233 ***	−0.021 ***	−0.358 ***	−0.003 ***
Occupation						
Farmer (1 = farmer, 0 = otherwise)	1.050 ***	0.116 ***	−0.240 ***	−0.038 ***	0.458 ***	0.004 ***
Entrepreneur (1 = entrepreneur, 0 = otherwise)	0.641 ***	0.070 ***	0.159 *	0.004	1.060 ***	0.015 ***
Formal worker (1 = formal worker, 0 = otherwise)	0.452 ***	0.046 ***	−0.124 **	−0.019 ***	0.744 ***	0.008 ***
Informal worker (1 = informal worker, 0 = otherwise)	0.414 ***	0.043 ***	−0.256 ***	−0.031 ***	0.493 ***	0.005 ***
Income, expenditure, and assets						
Monthly income (THB 1000)	−0.007 ***	−0.001 ***	0.001 ***	2.258×10^{-04} ***	0.001	1.77×10^{-05} *
Monthly expenditure on food and beverages (THB 1000)	−0.044 ***	−0.004 ***	−0.003	2.439×10^{-04}	−0.028 **	-2.348×10^{-04} *
Financial assets (THB 1000)	−0.001 ***	-8.18×10^{-05} ***	-3.6×10^{-04} ***	-2.32×10^{-05} ***	−0.002 ***	-1.72×10^{-05} ***
Number of cars	−0.343 ***	−0.037 ***	0.360 ***	0.041 ***	0.068	0.001
Number of motorcycles	0.142 ***	0.010 ***	0.222 ***	0.021 ***	0.284 ***	0.002 ***
Other variables						
Central (1 = central, 0 = otherwise)	3.0 ***	0.416 ***	0.307 ***	−0.039 ***	3.358 ***	0.054
North (1 = north, 0 = otherwise)	3.533 ***	0.552 ***	0.222 ***	−0.066 ***	3.496 ***	0.052
Northeast (1 = northeast, 0 = otherwise)	3.722 ***	0.561 ***	0.206 ***	−0.067 ***	3.517 ***	0.046
South (1 = south, 0 = otherwise)	1.596 ***	0.213 ***	0.197 **	−0.015	1.807 *	0.027
Rural households (1 = rural households, 0 = otherwise)	0.322 ***	0.031 ***	0.015	−0.003	0.209 ***	0.002 **
Difficulty obtaining an emergency loan (1 = yes, 0 = no)	−0.749 ***	−0.052 ***	−0.293 ***	−0.021 ***	−0.610 ***	−0.004 **

Table 3. *Cont.*

	VF Borrowers		SGP Borrowers		Both VF and SGP Borrowers	
	Coefficient	**Marginal Effect**	**Coefficient**	**Marginal Effect**	**Coefficient**	**Marginal Effect**
Number of observations	41,099					
Log likelihood	−31,240.817					
LR chi2(42)	13,911.19					
Prob > chi2	0.0000					
Pseudo R2	0.1821					

Note: *, **, *** indicate significance at 10%, 5% and 1% levels, respectively. Source: Author's calculations.

This result indicates that households with female heads are more likely to borrow from VFs than households with male heads. The marginal effect of the female household head coefficient shows that the probability of households borrowing from the VF increases by 3.20% when the head of the household is a female (see column 1 in Table 3). Armendariz de Aghion and Morduch (2005), who evaluate different methods to reduce repayment defaults of microfinance programs, conclude that targeting women is one of the methods of decreasing repayment defaults in microfinance programs. Cull et al. (2018) explain that many microfinance programs favor women because they exhibit a lower credit risk; therefore, they are more likely to access microfinance programs. Jumpah et al. (2019) explain that women are better managers of credit compared to their male counterparts, who may use loans on unproductive activities such as smoking and drinking. Jumpah et al. (2019) state that women are faced with difficulties in accessing financial services and they conclude that MFIs can help women accessing financial services. In short, VFs not only encourage women to access loans, but also to participate as committee members. Our findings show that the VF is successful in encouraging households with female heads to access loans.

In terms of age, the results show that households with older heads are more likely to borrow from VFs. Holding all other determinants constant, the marginal effect of age indicates that an increase of a year in household head age increases the probability of households borrowing by 0.10% (see column 1 in Table 3). Our result is similar to Zeller (1994), who finds that age is likely to increase the probability of formal microcredit participation in rural Madagascar. Eularie and Vishwanatha (2016) find that young small-scale farmers are not involved in microcredit activities, but older small-scale farmers are more interested. They explain that households with older household heads are more aware of the importance of microcredit program participation for poverty reduction and improved livelihood than those with younger household heads. Fianto et al. (2019) explain that mature rural households usually have stable jobs compared to the younger ones.

The married coefficient is positive and significant at the 1% level, and the single coefficient is negative and significant at the same level. The marginal effect of the married and single coefficients indicates that the probability of becoming a VF borrower household increases by 3.20% when the household head is married, and decreases by 5.20% when the household head is single (see column 1 in Table 3). These findings support some prior studies. Mpuga (2010) shows that households with married household heads are more likely to be stable, and thus lenders are more likely to view them as reliable. Therefore, they are more likely to access credit than their single counterparts. Wachira and Kihiu (2012) explain that informal service providers are more likely to grant loans to households with married household heads because they are seen as being more trustworthy as they move from one life stage to another.

The results show that households with well-educated heads are less likely to borrow from VFs. Holding all other determinants constant, the marginal effect of education indicates that with an increase in the number of years of a household head's education, households become less likely to borrow from VF by 0.40% (see column 1 in Table 3). The findings indicate that microfinance programs may target households with lower levels of education. Kasali et al. (2016) find that microfinance borrower households tend to have lower levels of education.

For the demographic characteristics (household size, dependency ratio, number of children, number of elderly people), the results show a significant positive relationship between household size and microfinance participation. This implies that larger households are more likely to participate in VFs by 2.0% (see column 1 in Table 3). Fongthong and Suriya (2014) state that the larger a household is, the greater the likelihood that they will borrow from VFs. These households have more income sources and, as a result, are more capable of repaying their loans. Saqib et al. (2016) explain that, as the household size increases, farmers are more likely to use agricultural loans as a risk management strategy. Nguyen (2007) explains that labor demand increases during peak times (such as harvests), and this could be one reason why household size affects the probability of gaining a loan. Sarap (1990) reveals that larger household size increases credit demand, as household resources are diverted into agricultural activities. Without hiring staff, small households have a lower capacity to expand their business, which leads to a lower level of microfinance participation. Our results suggest that larger households may have more income sources and, as a result, are in a better position to repay their loans. These households are more likely to borrow money to expand their businesses.

The dependence ratio coefficient is negative and significant at the 1% level. This result implies that households with high dependency have a lower probability of borrowing from VFs. This finding suggests that households with high dependency ratios have fewer family members to help generate income, and therefore are less able to repay their loans. These households must allocate money to look after their elderly members, which potentially affects their ability to repay loans (Fongthong and Suriya 2014). Moreover, the number of elderly coefficient is negative and significant at the 1% level. This finding indicates that if a household has elderly members, the household is less likely to participate in VFs by 1.50% compared to other households, all other factors held constant (see column 1 in Table 3). Our result suggests that households that have more elderly members are less able to repay loans. In short, financial services providers may consider the elderly less creditworthy (Wachira and Kihiu 2012).

The positive number of children coefficient at the 10% level indicates that if households have more children, they are more likely to participate in VFs by 0.50% compared to other households, all other factors being constant (see column 1 in Table 3). Our finding supports Phan's (2012) study, which finds that households with a greater number of children tend to have higher levels of microcredit program participation. The author explains that households with more children have greater levels of financial stress. Likewise, Menkhoff and Rungruxsirivorn (2011) find that households with more children have a higher probability of applying for loans. Takahashi et al. (2010) explain that the poor benefit more from microcredit participation via investment in their children's schooling. Money spent on education helps to break the vicious poverty circle. Adjei et al. (2009) find that borrowers often use the loans to improve their children's education.

At the 1% significance level, farmers, entrepreneurs, formal workers and informal workers are more likely to participate in VFs by 11.60%, 7.0%, 4.60% and 4.30%, respectively, than other households based on occupation (see column 1 in Table 3). These results suggest that households who work as farmers, entrepreneurs, and in both the both the formal and informal sectors are the VF's primary borrowers. VFs were developed to provide finance for occupational development, job creation, income generation activities and welfare improvement (Fongthong and Suriya 2014). Households whose household heads are employed as farmers, entrepreneurs, and/or work in both the formal and informal sectors typically use the loans to generate income. Lewis et al. (2013) explain that the VF provides good loan coverage, reaching the lowest income groups, including unskilled occupational groups.

Income, expenditure and assets, monthly income, monthly expenditure on food and beverages, financial assets, the number of cars and the number of motorcycles are significant in explaining VF participation. The results show that monthly income and monthly expenditure on food and beverages are negative and significant at the 1% level. The marginal effect of monthly income and monthly expenditure on food and beverages show that if households have more monthly income and monthly expenditure on food and beverages for every THB 1000, they are less likely to participate in VF by 0.10% and 0.40%, respectively (see column 1 in Table 3). This finding may suggest that VF borrowers are from lower-income groups. Fongthong and Suriya (2014) state that near-poor households and lower-income households (with income above the poverty line) are more likely to participate in VFs. Likewise, Menkhoff and Rungruxsirivorn (2011) find that, though VFs reach lower-income households, commercial banks serve higher-income households. Kaboski and Townsend (2012) state that the VF program can help poor people smooth their consumption levels.

An additional THB 1000 increase in financial assets reduces a household's probability of participating in VFs by 0.01% (see column 1 in Table 3). Armendariz de Aghion and Morduch (2005) explain that financial assets (e.g., savings) can help rural households protect themselves against any disaster that may affect their income. In addition, income and assets provide an indication of a household's initial capital. A higher income level and/or level of assets reflects a less constrained household budget, which may weaken the demand for credit (Li 2010; Ruiz-Tagle 2005; Umoh 2006).

The number of cars and motorcycles is significant in explaining VF participation. The results show that the number of cars is negative and significant at the 1% level. This indicates that an additional car in a household reduces a family's probability of participating in a VF by 3.70% (see column 1 in Table 3). Households with multiple cars can use them as collateral to access financial services (Fongthong and Suriya 2014). The results show the coefficient of the number of motorcycles is positive and significant at the 1% level, indicating that if a household has an additional motorcycle, it is more likely to borrow from a VF by 1.0%. Coleman (2006) explains that, during the off-farm season, most farm households engage in non-farm activities, like petty trading and driving a motorcycle taxi. Households that use their motorcycles as taxis can borrow money for investment purposes. Households with a greater number of motorcycles are more likely to borrow money because motorcycles are important production inputs—like owning a house, they provide a way to earn additional income (Fongthong and Suriya 2014).

All geographic factor coefficients have the hypothesized signs, and are significantly associated with the probability of VF participation. The significant positive coefficients of central, north, northeast, and south imply that households living in these areas tend to have a higher probability of borrowing from VFs. In addition, the significant positive rural household coefficient suggests that households in rural areas are more likely to participate in VFs by 3.10% compared to other households (see column 1 in Table 3). Mpuga (2010) finds that location characteristics are important in the demand for credit. Households often use rural microcredit programs to reduce their borrowing from informal sources. Fongthong and Suriya (2014) explain that the VFs provide loans throughout Thailand, meaning that rural households across the country are more likely to obtain loans. Menkhoff and Rungruxsirivorn (2011) find that VFs can help rural households reduce credit constraints.

The coefficient of difficulty in obtaining an emergency loan is negative and significant at the 1% level. This indicates that households that have difficulty in obtaining an emergency loan are less likely to borrow from VFs than households that have no trouble in obtaining an emergency loan. In fact, households that have trouble in obtaining an emergency loan are less likely to borrow from the VF by as much as 5.20%, all other factors being constant (see column 1 in Table 3). This implies that most VF borrowers do not experience any difficulty accessing emergency loans. This finding illustrates that rural households in Thailand can access loans from both formal and informal financial sources, and that these households can access financial services (loans, deposits, remittances and insurance). In short, most VF borrowers do not have any difficulty in obtaining an emergency loan (Fongthong and Suriya 2014); the VF program is an alternative financial source for rural households.

While VFs serve low-income households in rural areas, they fail to reach the poor or those with more dependents. These programs target women, the elderly and those with low levels of education. The fact that most VF borrowers can access money from other sources means that they are only one of many sources of credit for rural households. Households with more members are more likely to access VFs than formal and informal workers are.

5.2.2. Determinants of SGPs Participation

Column 2 in Table 3 indicates that SGP participation is significantly explained by household head characteristics (age, female, education, single), demographics (household size, the dependency ratio, the number of children, the number of elderly), occupation (farmer, entrepreneur, formal worker, informal worker), income, expenditure, assets (monthly income, financial assets, the number of cars, the number of motorcycles), and other variables (central, north, northeast, south, difficulty obtaining an emergency loan).

Age and single are negative and significant at the 1% level, whereas education and female are positive, significant predictors of SGP participation at the 1% and 5% levels, respectively. The household head's age influences the probability of that household participating in SGP. With all other factors constant, a change in age decreases the probability of households participating in an SGP by as much as 0.6% (see column 2 in Table 3). This finding is similar to that of Mpuga (2010) and Li (2010), who state that households with younger household heads are more energetic, dynamic, and can adapt to new technology better, than households with older household heads. In short, households with younger household heads tend to save and/or borrow more for investment; households with older household heads are less inclined to save or borrow. The significant negative sign at the 1% level for being single indicates that households with single household heads are less likely to participate in SGPs. Households with single household heads are less likely to be stable (in terms of responsibility); thus, lenders are less likely to view them as reliable (Mpuga 2010; Wachira and Kihiu 2012). Therefore, they are less likely to access credit than their married counterparts.

The results show that households with well-educated household heads are more likely to borrow from SGPs. Holding all other determinants constant, the marginal effect of education indicates that an increase in the number of years of education of the household head increases the probability of households borrowing from SGPs by 0.20% (see column 2 in Table 3). A household head's education reflects human capital that, in turn, facilitates participation (through borrowing) in microfinance programs (Li et al. 2011; Mpuga 2010; Tang et al. 2010). Previous studies argue that borrower household heads' education level is positively related to participation in microfinance programs (Li et al. 2011; Mpuga 2010; Tang et al. 2010). Ouattara et al. (2020) explain that a higher level of education empowers farmers to read, understand the terms and conditions of credits, and helps them to accurately fill out credit application documents. In addition, all MFIs have credit officers who carefully analyze all credit applications. A female household head is a significant positive predictor of SGP participation at the 10% level. The marginal effect of the female household head coefficient shows that the probability of households borrowing from SGPs increases by 0.20% if the household has a female household head (see column 2 in Table 3). Many microfinance programs encourage households who have a female head to borrow because they are considered to have a lower credit risk than other households (Goetz and Gupta 1996). Goetz and Gupta (1996) state that households who have a female head may have higher incentives to repay their loans than households that have a male head, because it allows them to retain access to village groups, while men have many opportunities for social contact. Moreover, women are more vulnerable to pressure to repay the loan. Ouattara et al. (2020) explain that women are more involved in food crop production, such as of vegetables, with a quick rate of return and ready markets for their produce. This then increases their profit margins, leading to reduced credit defaults for women. Moreover, Khandker (2005) found that allocating loans to households with female heads can have a stronger impact on poverty reduction of the households than allocating funds to households with male household heads. These results may indicate that SGPs are pro-women, and these loans may help women to invest in their families.

Four demographic factors (household size, the dependency ratio, the number of children, and the number of elderly) are significant in explaining SGP borrowing status. The significant positive relationship between household size and microfinance participation indicates that larger households are more likely to participate in SGPs by 3.70% (see column 2 in Table 3). This finding is similar to the VF results.

The coefficient of the dependency ratio is negative and significant at the 1% level. This indicates that households with a higher dependency ratio have a lower probability of borrowing from SGPs. This result is similar to the VF finding. The significant negative coefficients of the number of elderly and number of children, at the 1% and 5% levels, respectively, indicate that if households have a greater number of elderly or dependent children, they are less likely to borrow from SGPs by 2.10% and 0.80%, respectively, compared to other households, when all other factors are constant (see column 2 in Table 3). The finding that households with a higher dependency ratio are less likely to borrow money may be explained by the fact that they may not have the same ability to repay the loans. These households must spend greater amounts of money taking care of non-earning members, which likely affects their repayment ability (Fongthong and Suriya 2014).

Column 2 in Table 3 also shows that farmers, entrepreneurs, formal workers and informal workers are significant in explaining SGP borrowing. Households employed in farming, and those working in both formal and informal sectors, are less likely to borrow from SGPs by 3.80%, 1.90% and 3.10%, respectively, at the 1%, 5% and 1% significance levels, respectively. In contrast, households employed as entrepreneurs are more likely to borrow from SGPs, by 0.40% at the 10% significance level. These results suggest that, apart from farming, individuals who are entrepreneurs are the primary SGP borrowers. Luxchaigul (2014) states that SGP members are local people who regularly save money in their cash pool to invest in economic activities. Luxchaigul also explains that these loans would likely solve the no cash investment problem and illegal loans. SGPs can help borrowers solve their investment problems (Luxchaigul 2014).

The expenditure and asset variables, monthly income, financial assets, the number of cars and the number of motorcycles are significant in explaining SGP participation. The results show that monthly income is positive and significant at the 1% level. The marginal effect of monthly income shows that every THB 1000 increase in monthly income increases the probability of SGP participation by 0.02% (see column 2 in Table 3). One possible explanation is that when households have more income and/or assets, they feel rich and consume more. As a result, they may also demand more credit (Cheng 2006; Li 2010; Ruiz-Tagle 2005). Fianto et al. (2019) explain that rural households with a high income have more capacity to repay the loans.

An additional THB 1000 increase in financial assets reduces a household's probability of SGP participation by 0.002% (see column 2 in Table 3). The marginal effect of financial assets on SGP participation is minimal. Financial assets can help a rural household insure themselves against the likelihood of a natural disaster that may affect their income (Armendariz de Aghion and Morduch 2005). These assets, which show a household's initial capital, reflect a less constrained household budget, which may weaken the demand for credit (Li 2010; Ruiz-Tagle 2005; Umoh 2006).

The number of cars and the number of motorcycles are significant in explaining SGP participation. The results show that the number of cars is positive and significant at the 1% level. This indicates that an additional car in a household will increase a household's probability of SGP participation by 4.10% (see column 2 in Table 3). Households that have multiple cars can use them as collateral to access financial services. Column 2 in Table 3 also shows that the coefficient of the number of motorcycles is positive and significant at the 1% level. This result indicates that an additional motorcycle will increase a household's probability of SGP participation by 2.10%. One reason why this may be so is that, during the off-farm season, most farm householders work in non-farm activities (Coleman 2006). In short, for rural households, motorcycles are important production inputs (Fongthong and Suriya 2014).

Almost all the geographic factor coefficients have the hypothesized signs, and are significantly associated with the probability of SGP participation. The significant positive coefficients of central, north, northeast and south imply that households in these areas have a higher likelihood of borrowing from SGPs (see column 2 in Table 3). The results indicate that SGPs provide loans to all regions of Thailand, and these loans act as substitutes for informal credit (Akihiko 2015). SGPs create a rural financial market using a bottom-up approach. SGPs serve as financial intermediaries by collecting savings from rural households and extending loans to their members (Akihiko 2015).

Column 2 in Table 3 also shows that the coefficient of difficulty in obtaining an emergency loan is negative and significant at the 1% level. This indicates that households that have difficulty in obtaining an emergency loan are less likely to borrow from SGPs than households that do not have any problems. The significant negative difficulty in obtaining an emergency loan coefficient suggests that households that have trouble in obtaining an emergency loan are less likely to participate in SGPs by 2.10%, compared to other households, all other factors being constant. This implies that most of SGP borrowers do not experience any difficulty gaining an emergency loan. The finding indicates that SGP borrowers can access both formal and informal financial services.

In contrast to VFs, SGPs borrowers tend to be well-educated, work as entrepreneurs, have larger families and higher incomes. SGPs borrowers consist of young household heads and they often live in regional areas. Like VF borrowers, SGPs borrowers can access other loans.

5.2.3. Determinants of Both VF and SGPs Participation

The results in Column 3 in Table 3 indicate that both VF and SGP participation is significantly explained by household head characteristics (female, education, married, single), demographics (household size, the dependency ratio, the number of elderly people), occupation (farmer, entrepreneur, formal worker, informal worker), income, expenditure and assets (monthly expenditure on food and beverages, financial assets, the number of motorcycles), and other variables (central, north, northeast, south, rural households, and difficulty obtaining an emergency loan).

The female and married coefficients are positive, significant predictors at the 1% level of both VF and SGP participation, whereas the education and single coefficients are negative, significant predictors at the 1% level. This indicates that households with female heads are more likely to borrow from both VFs and SGPs than households with male heads. The marginal effect of the female household head coefficient shows that the probability of households borrowing from both VF and SGP increases by 0.50% when the household has a female head (see column 3 in Table 3). A key objective of many microfinance programs is to encourage women's participation (Zhang and Posso 2017). Zhang and Posso (2017) state that microfinance programs can help women become financially independent, strengthening their decision-making power within the household and society. Moreover, MFI committees believe that female borrowers present a lower credit risk than men (D'Espallier et al. 2011). D'Espallier et al. (2011) found that women are generally better at managing credit risk in microfinance programs than men.

Column 3 in Table 3 also shows that households with well-educated heads are less likely to borrow from both VFs and SGPs. Holding all other determinants constant, the marginal effect of education indicates that an increase in the number of years of education of the household head decreases the probability of households borrowing by 0.10%. Thai microfinance programs target poor and low educated households (Fongthong and Suriya 2014). Kasali et al. (2016) find that microfinance programs' borrower households have lower education levels.

The coefficient of married is positive and significant at the 1% level, and the coefficient of single is negative and significant at the same level. The marginal effect of the married and single coefficients indicates that the probability of households being both VF and SGP borrowers increases by 0.30% when the borrower household head is married, and decreases by 0.80% when the borrower household head is single (see column 3 in Table 3). The marital status finding is like the VF result. One possible explanation is that MFIs are more likely to grant loans to married household heads because they are believed to be more stable as they move from one life stage to another (Mpuga 2010; Wachira and Kihiu 2012). Married household heads are thought to be more responsible and thus are seen as more trustworthy (Mpuga 2010; Wachira and Kihiu 2012).

Three demographic-related factors (household size, the dependency ratio and the number of elderly) are significant in explaining both the VF and SGP borrowing status. For household size, a significant positive relationship between household size and both VF and SGP participation shows that larger households are more likely to participate in both VFs and SGPs by 0.30% (see column 3 in Table 3). This finding is like those for the other borrower groups (VF and SGP individual findings), where larger households have more income sources and, as a result, are more capable of repaying their loans (Fongthong and Suriya 2014). Farm-households obtain loans to expand their businesses when their household size is larger (Nguyen 2007; Saqib et al. 2016).

The coefficient of the dependency ratio is negative and significant at the 1% level, indicating that households with higher dependency ratios have a lower probability of borrowing from both VFs and SGPs. The significant negative coefficient of the number of elderly at the 1% level indicates that if households have a greater number of elderly members, they are less likely to participate in both VF and SGP by 0.50% compared to other households, when other factors are held constant (see column 3 in Table 3). This indicates that households with a higher dependency ratio are less likely to borrow because they do not have the same ability to repay their loans (Fongthong and Suriya 2014).

Farmers, entrepreneurs, formal workers and informal workers are significant factors in explaining borrowing from both VFs and SGPs. Households employed as farmers and entrepreneurs are more likely to borrow from both VFs and SGPs by 0.40% and 1.50%, respectively, at the 1% significance level. Households employed in formal and informal occupations are more likely to participate in both VFs and SGPs by 0.80% and 0.50%, respectively, at the 1% significance level (see column 3 in Table 3). These results suggest that households whose household heads are employed as farmers and entrepreneurs, and those working in both formal and informal sectors, are the primary borrowers of both VFs and SGPs. The findings indicate that both VFs and SGPs provide loans to households whose household heads are employed in farming, entrepreneurship, and those working in both formal and informal sectors. As noted earlier, these loans can solve the problem of no cash investments and illegal loans (Fongthong and Suriya 2014; Lewis et al. 2013; Luxchaigul 2014).

The expenditure and assets variables, monthly expenditure on food and beverages, financial assets and the number of motorcycles are significant in explaining both VF and SGP participation. For the monthly expenditure on food and beverages, the negative coefficient is significant at the 5% level. The marginal effect of monthly expenditure on food and beverages shows that every THB 1000 increase in monthly expenditure on food and beverages decreases the probability of both VF and SGP participation by 0.02% (see column 3 in Table 3). This suggests that both VF and SGP borrower households are from lower-income groups. One possible explanation is that poor rural households need credit to maintain their consumption levels (especially for necessities like food) when faced with a cash shortage (Li 2010). In developing countries, the poor usually rely on credit to smooth their consumption expenditure (Doan et al. 2010).

An additional THB 1000 increase in financial assets reduces a household's probability of participating in both VFs and SGPs by 0.002% (see column 3 in Table 3). The marginal effect of financial assets on both VF and SGP participation is minimal. Financial assets may help rural households overcome situations that may affect their income (Armendariz de Aghion and Morduch 2005). In addition, financial assets show a household's capital. In short, more financial assets reflect a less constrained household budget, which may reduce the demand for credit (Li 2010; Ruiz-Tagle 2005; Umoh 2006).

The number of motorcycles is significant in explaining both VF and SGP participation. Column 3 in Table 3 shows that the coefficient of the number of motorcycles is positive and significant at the 1% level, indicating that an additional motorcycle in a household increases that household's probability of participating in both VFs and SGPs by 0.20%. One possible explanation is that motorcycles, which are an important input component, are used in non-agricultural activities during the off-farm season (Coleman 2006). Rural households use their own vehicles as production inputs to invest in new businesses (Fongthong and Suriya 2014).

All geographic factor coefficients have the hypothesized signs, and are significantly associated with the probability of both VF and SGP participation. The significantly positive coefficients of central, north, northeast and south imply that households in these areas have a higher likelihood of borrowing from both VFs and SGPs. In addition, the significant positive rural household coefficient suggests that households in rural areas are more likely to participate in both VFs and SGPs by 0.18%, compared to other households (see column 3 in Table 3). This mirrors earlier results for VF and SGP borrowers. These programs provide loans that help rural Thai households decrease their reliance on informal credit (Mpuga 2010).

Column 3 in Table 3 also shows that the coefficient of difficulty in obtaining an emergency loan is negative and significant at the 1% level. This indicates that households that have difficulty in gaining an emergency loan are less likely to borrow from both VFs and SGPs than households that have no difficulty. The significant negative difficulty in obtaining an emergency loan's coefficient suggests that households that have difficulty in accessing an emergency loan are less likely to participate in both

VFs and SGPs by 0.40% compared to other households, all other factors being constant. This finding implies that both VF and SGP borrower households do not have trouble obtaining an emergency loan.

The households who borrow from both VFs and SGPs tend to be larger, live in rural areas, own a motorbike, have lower levels of education and have female household heads. Borrowers in this category work as farmers and entrepreneurs, both in the formal and informal sector.

6. Conclusions

The empirical results show that VFs serve low-income households in rural areas, but do not reach the poor. Households with higher dependency ratios are less likely to borrow from VFs. Most households that borrow from VF can access loans when they need to obtain emergency loans. This indicates that the VF program is only one source of credit for households in rural areas. The program also provides loans to households with elderly and low-educated household heads. Households with female heads are more likely to borrow from VFs. Larger households are more likely to access VFs. VFs also grant loans to households who are employed as formal and informal workers.

In contrast, households with well-educated young heads, in regional areas, are more likely to borrow from SGPs. Households who borrow from SGPs have higher household incomes than households who borrow from VFs. In addition, households with SGP loans do not have any problems in accessing credit. Larger households are more likely to participate in SGPs. Households whose household heads are entrepreneurs are more likely to borrow from SGPs than farming households.

Households who borrow both from VFs and SGPs have low-educated female household heads in rural areas. These households can access loans for emergency. Larger households who own their own motorcycles have a higher probability of borrowing from both programs. Households who borrow both from VFs and SGPs are employed in a range of occupations (farming, entrepreneurship), and in both the formal and informal sectors.

Our findings indicate that VFs and SGPs are credit sources in the rural credit market; these sources help rural households access credit to meet their needs (Yostrakul 2018). In addition, rural Thai households borrow from many sources so that they can rotate their loan repayments. Low-income households refinance their loans by borrowing from different sources. This practice enables them to maintain good credit ratings (Hickson et al. 2013).

For low-income households, improving microfinance participation can start with the households themselves; households should participate in credit groups and improve their work-skills and education. Education can be used to raise collateral-free borrower households' creditworthiness, and work skills can guarantee that households will repay their loans (Phan 2012). However, MFIs do not benefit from including the very poor, because poor households need pre–support, such as special aids and community support, to overcome internal rationing. Extremely poor households often suffer from household members' illness and/or a lack of skills or education. As MFIs are designed to lend money for income generating activities, the very poor are unlikely to be granted loans. Thus, microfinance programs will not be an effective solution for this group of people; the extremely poor require both welfare and microfinance programs (Phan 2012). Microfinance program participation would therefore be the next step after the very poor receive pre-support and provide evidence of their ability to work. Thai MFIs can use the Central Public Database from the Revenue Department, the Ministry of Finance, to identify poor households. The database is a personal income database that facilitates the more effective targeting of low-income households (NESDB 2017). This database can identify the extremely poor who receive government benefits such as financial assistance, free public transport and food coupons. This strategy will help microfinance programs reach the real poor, who really need loans to improve their livelihoods.

Our study only investigates the factors that affect household participation in VFs and SGPs. Our methodologies can be applied to other sources of credit (for example, formal and informal credit sources). The results indicate that Thai households can access many sources of credit. Households with multiple sources of credit have high debt levels. As Thai households often borrow from formal credit sources to pay other (informal) debts, this can become a vicious cycle. However, high debt levels or multiple sources of credit are not always an indication of financial distress; many microfinance programs have a credit limit, so households can borrow from multiple credit sources in order to have enough capital to invest in income generation activities. Therefore, future studies could investigate factors that affect household participation in multiple sources of credit. This can show the real financial condition of Thai households.

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