An analysis of the factors influencing choice of microcredit sources and impact of participation on household income

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Abstract:

It is widely accepted that rural microcredit has the potential to contribute to poverty reduction in developing countries. This paper examines the factors that affect rural residents' decisions to participate in different types of microcredit, and how these factors impact on household income and consumption, using cross-sectional data from a survey in China. A multinomial endogenous switching regression model is employed to account for selection bias and treatment effects. The empirical findings indicate that family size, dependency ratio, local casual wage rate, credit information and shocks mainly determine the selection of different credit sources. Furthermore, the estimates reveal that participation in microcredit tends to increase both per capita income and consumption significantly.

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Key words: microcredit, self-selection, impact assessment, multinomial endogenous switching, China

1 Introduction

As a result of market failure, rural residents often face problems in accessing credit from financial institutions, making it difficult for them to invest in income generating activities (Imai et al., 2010; Attanasio et al., 2015; Mookherjee and Motta, 2016). Microcredit has therefore received significant attention over the last two decades as a strategy of enhancing rural residents' access financial sources. The main sources of microcredit for the rural poor include commercial banks, individuals, nonbank credit organizations, as well as specific programs that are tailored to meet the needs of poor rural households. Given the different types of microcredit programs and sources, there is still disagreement as to which type is more beneficial for rural households. The selection is important because microcredit not only provides credit for rural residents and the poor to help eradicate poverty and improve food security, but also plays a significant role in the financial inclusion system that helps to avoid rural areas falling into the trap of long-term backward development. Therefore, understanding the barriers and drives of participation in microcredit selection, and the impact of participation on household welfare will help in the design of effective policies to reduce rural poverty.

Given the significance of microcredit in rural poverty alleviation, the Chinses government has launched many microcredit programs to reform and strengthen the rural financial system. One of such efforts is the Village Mutual Aid Funds, which is designed to provide loans to rural households facing financial constraints, and having difficulties in accessing credit from both financial institutions and money lenders.

To the extent that microcredit schemes have significant impacts on rural livelihoods, several studies have analyzed the determinants of participation in these schemes, and the impacts of participation on household welfare (e.g., Nghiem et al., 2012; Kaboski and Townsend, 2012; Bruhn and Love, 2014; Lahkar and Pingali, 2016). These studies secondly show that participation in microcredit tends to contribute to welfare and poverty alleviation, by helping households purchase agricultural inputs or invest in nonfarm activities.

However, some studies have indicated that these benefits are limited, since microcredit only lead to fewer businesses and lower subjective well-being (Karlan and Zinman, 2011), and that contributions rely on investments in income generating activities (Hermes and Lensink, 2009). Recent studies show microcredit does not significantly impact smallholders' welfare (e.g., Angelucci, Karlan and Zinman, 2015; Banerjee, 2015; Crépon et al., 2015). For example, in a study on Morocco, including both control and treatment groups, Crépon et al. (2015) emphasized that microcredit access is able to significantly increase self-employment income, but they found no net impact on total labor income and consumption. Mazumder and Lu (2014) also found that microfinance helps to increase the basic rights of participants, and improve the quality of life of rural households in Bangladesh. The findings from the previous studies on the impact of microcredit appear to be mixed and inconclusive. Hence, more research is needed to shed more light on this important issue.

In addition, empirical literature focuses more on participation in microcredit, without any analysis on the choice of microcredit sources. Some studies here argued that formal and informal financial institutions are complementary (Ayyagari et al., 2010; Mallick, 2012). Turvey and Kong (2010) indicate that informal borrowing is preferred to formal because of community trust between borrowers and lenders. Other studies have analyzed the participation and impact of some financial programs (e.g., Takahashi et al., 2010; Dineen and Le, 2015). However, the studies do not compare the impacts of different credit sources to ascertain which microcredit programs are more beneficial.

The present study contributes to the literature by examining the determinants of participation in various microfinance programs, and the impact of participation on household welfare in rural China. We employ a multinomial endogenous switching regression model that accounts for selection bias arising from both observable and unobservable factors. The various microcredit sources we consider include commercial banks, village mutual aid funds, friends and relatives. To the extent that these three categories of credit sources have their own outstanding characteristics, understanding these difference would help in developing more beneficial microcredit programs for rural residents.

2 Background and data

2.1 Background

In China, rural microcredit plays an important role in the financial system, and its importance has been increasing during the last decade. For example, the agricultural loan balance nearly quadrupled from 849.03 billion yuan in 2004 to 3339.40 billion yuan in 2014, with the rural household loan balance increasing about 7.88 times in 2014, to 5358.70 billion yuan over that in 2004 with 679.56 billion yuan. These represented average growth rates of 14.82% and 23.09% respectively. By contrast, the average growth rate of per capita income was only 13.63% during that period[1]. This trend contributes to, as well as accompanies a dramatic expansion, innovation and pilot experiment of rural-related financial institutions. At this moment, rural banking institutions compose of traditional commercial banks such as Agricultural Development Bank of China, Agricultural Bank of China, Rural Credit Cooperatives and Postal Savings Bank of China, and three new type of financial institutions such as Rural Mutual Fund Cooperatives, Village or Township Banks and Loan Companies.

Rural credit market has some certain characteristics leading to market failure, which are scarcity of collateral security, underdeveloped complementary institutions, covariant risks and information asymmetry (Cole, 2009; Karlan and Zinman, 2011). Therefore, in order to target the poor rural residents, Chinese government launched Village Mutual Aid Funds projects in depressed villages since 2007. Majority of this funds is composed by the state poverty reduction funds, and the rest is combined with allocated funds from participants. Different from previous poverty reduction projects, this program manages the funds using endogenous operating method that only members are able to access. It employs the joint-guarantee mechanism that each loan

[1] Source: China Rural Finance Service Report 2014, The People's Bank of China. China Statistical Yearbook. 1 yuan ≈ 0.15 US dollar at the time of survey.

contract requires guarantees from two to five households. Even informal credit sources such as friends and relatives have been the supplementary to the services provided by formal services (Cheng and Ahmed, 2014), not all people have equal access even to informal credit, the poorest of the poor may still have credit constraints that be excluded from informal credit markets (Yuan and Xu, 2015). So the meaning of VMAFs is to cover the gap of poor groups on microcredit.

2.2 Data

The data used in this study were collected from household interview conducted between October and December 2015 in Sichuan province, China. Many types of agricultural products and distinctive economic situations, as well as pilot projects on microcredit and village mutual aid funds make this province an appropriate study area.

A multistage random sampling approach was used to select reasonable study sites and respondents. Using information from the Sichuan Statistical Yearbook, we selected six regions from the province, taking into consideration the per capita income and consumption in the regions, as well as the availability of participants and non-participants in microfinance programs. We then randomly selected 552 households from 72 villages in proportion to their populations. Information from individuals were collected via face-to-face interview, including questions on demographic characteristics, economic and financial status, agricultural production practices, and village mutual aid funds situations. Enumerators were hired to assist in conducting the interviews.

Table 1 presents the descriptive statistics of the variable used in the analysis. Table A2 presents the descriptive statistics for the different status[2]. It can be seen from table 1 that roughly 60% of

[2] 552 respondents have 574 total selections for the three credit sources, since 22 samples who selected more than one options. For example, 4 samples chose both commercial banks and village mutual aid funds, 11 samples chose both commercial banks and friends and relatives, and 7 samples chose both village mutual aids funds and friends and relatives. In the following analysis, we excluded 22 samples who selected more than one sources since they are quite small for each intersection term.

individuals had participated in microcredit in recent 5 years. The income presents the per capita household total income, including agricultural cultivation, breeding, business, rent, wage and salary, transfer. Consumption includes daily living expenses, productive expenditure, education, medical costs, water, electricity and fuel costs. The average farm size of the respondents is about 3.35 mu (1 mu = 1/5 hectare). Off-farm employment ratio is the number of off-farm employment labor divided by the number of all employment labor. This variable is used to proxy for participation in off-farm activities. Dependency ratio is estimated by the number of families outside the working age range divided by the number of families aged within that age (16-60 years). Education is captured by using the household head's level of education. Business considered in this study is the small and retail business, such as grocery store, kiosk and some other small shops. The general crop cultivation and sales of smallholders are not included in the business. Distance to the nearest financial institution and to the nearest vehicle usable road were used to represent the load conditions. In particular, the variable for distance to nearest financial institution provides information about transaction costs involved to access credit from financial institutions. The off-farm wage rate and off-farm agricultural wage rate capture the reginal economic difference. The off-farm wage indicates the casual wage from the junior works such as construction workers, service personals, and sanitation workers; and off-farm agricultural wage indicates the agricultural works that employed by other farmers or organizations. In order to put the numbers on a reasonable scale and ensure the variables are linear, we use log transformation for these two casual wage rate variables. Shocks here is used to control if the selection and impact are caused by any unexpected events.

3 Conceptual framework

3.1 Theoretical model

In this section, we specify model of participation in microcredit and how participation impacts on household welfare. Thus, we model the choice of microcredit under the assumption that individuals choose between non-participation and participation in microcredit. Participation involves credit sources from commercial banks, village mutual aid funds, friends and relatives.

We assume individual i is risk neutral, and maximizes expected utility Y_{ij} derived from choosing option j ($j = 0,1,\cdots M$), where M indicates the number of options. The utility function can be specified as:

$$Y_{ij} = X_i\beta_j + \mu_{ij} \tag{1}$$

where X is a vector of relevant explanatory variables; β is vector of parameters; μ represents the error term and is assumed to be independent and identically distributed. Individuals will choose an option, if the expected utility obtained by selecting (j) is higher than that obtained from selecting another choice (k), i.e. $Y_{ij} > Y_{ik}$.

Since the expected net benefit is unobserved, we represent it with a latent variable D_i, that can be expressed as a function of observed households' characteristics. The latent variable model can then be specified as:

$$D_{ij} = Z_i\alpha_j + \varepsilon_{ij} \tag{2}$$

$$D_i = \begin{Bmatrix} 0 & iff & D_{i1} > \max_{k\neq 1} D_{ik} \\ \vdots & \vdots & \vdots \\ M & iff & D_{iM} > \max_{k\neq M} D_{ik} \end{Bmatrix}$$

(2a)

where α is a vector of parameters to be estimated; ε denotes an idiosyncratic unobserved stochastic component, Z is a vector of variables that represent socio-demographic and household characteristics. D_i is a dummy variable indicating that individual i will choose a certain option if it provides greater expected outcome than other strategies.

3.2 Empirical specification

The previous discussion shows that individuals are assumed to choose credit sources to maximize their expected utility. These microcredit sources considered include financial banks (J_1), village mutual aid funds (J_2), friends or relatives (J_3). The deterministic component includes household characteristics (e.g., age, gender, education, family size, farm size, and dependent ratio), village traits (e.g., casual wage rate and road condition), economic zones, and the experience of previous shocks such as pests, natural disasters, illness, death.

As in equation (2), the basic assumption is that the observed variable Z is uncorrelated with the stochastic component ε, i.e., $E(\varepsilon|Z) = 0$, which implies that ε is independent and identically distributed. In the first stage estimation, in line with McFadden (1973), the probability can be stated by a standard multinomial logit model:

$$P_{ij} = \frac{exp\left(Z_i \alpha_j\right)}{\sum_{k=1}^{M} exp\left(Z_i \alpha_k\right)} \tag{3}$$

where P_{ij} represents the probability that individual i chooses option j, Z_i represents represent household i characteristics, α_j is the vector of parameters relating to option j.

To the extent that individuals take self-selection into participating in microfinance credit, selectivity bias could lead to biased and inconsistent estimates. In particular, unobserved attributes may affect the choice decisions of individuals and impact on the outcomes. Conceptually, selection bias occurs when unobservable factors affect the error terms in the selection equation (μ), and the outcome equation (ε), which means there is a correlation between the two error terms, i.e. $corr(\mu, \varepsilon) = \rho$. Examples of unobservable factors include innate skills and risk attitudes. Standard regression techniques such as OLS lead to inconsistent estimates in the presence of selectivity bias.

In the absence of randomized controlled trials (RCTs), Heckman selection, instrumental variable (IV), propensity score matching (PSM) and endogenous switching regression (ESR) have been widely used in addressing selectivity bias problem with cross sectional data. However, each method has its limitations. The ESR model proposed by Lee (1978) and Maddala (1983) has been widely used to account for selection bias and endogeneity, by taking both observable and unobservable factors into consideration. This method has increasingly being used in estimating the determinants of participation and impacts on general economic outcomes (e.g., Di Falco et al., 2011; Kleemann and Abdulai, 2013; Tran et al., 2016). The standard ESR model involves two regimes such as participants and non-participants. However, when there are more than two alternatives, the multinomial ESR is more suitable (e.g., Di Falco and Veronesi, 2013; Park et al. 2014; Kassie et al., 2015). We therefore employ the multinomial endogenous switching regression model to capture the influence of microcredit sources on individuals' per capital income and consumption.

According to the framework, given three credit selections and one non-participation status, the outcome estimation model for each possible regime (j) can be stated as:

$$\begin{cases} E(Y_{i0}|D_i = 0) = X_i\beta_0 + \mu_{i0} \\ E(Y_{i1}|D_i = 1) = X_i\beta_1 + \mu_{i1} \\ \qquad\qquad\vdots \\ E(Y_{ij}|D_i = j) = X_i\beta_j + \mu_{ij} \end{cases} \tag{4}$$

where Y_{ij} is the outcome of household (i) in regime(j) $(j = 0,1,2,3)$; X_i is a vector of household characteristics; D_i represents participation status, with $D_i = 0$ being non-participants; β is a vector of parameters to be estimated; μ presents the unobserved disturbance, which satisfies $E(\mu_{ij} | X_i, Z_i) = 0$ and $Var(\mu_{ij} | X_i, Z_i) = \sigma_j^2$. Notably, though X and Z could overlap, since identification regression that at least one variable in z should not appear in X.

We follow the Dubin and McFadden (1984), Bourguignon et al. (2007) framework to account for the potential bias that arisen from the correlation of the error term μ andε in equations (1) and (4). Given the normalized linearity assumption $\mu_{ij} = \sigma_j \sum_j \rho_j \varepsilon_j + \omega_{ij}$, the outcome equations can be specified as:

$$\begin{cases} Y_{i0} = X_i\beta_{i0} + \sigma_0\lambda_0 + w_{i0} & if\ D_i = 0 \\ Y_{i1} = X_i\beta_{i1} + \sigma_1\lambda_1 + w_{i1} & if\ D_i = 1 \\ Y_{i2} = X_i\beta_{i2} + \sigma_2\lambda_2 + w_{i2} & if\ D_i = 2 \\ Y_{i3} = X_i\beta_{i3} + \sigma_3\lambda_3 + w_{i3} & if\ D_i = 3 \end{cases} \tag{5}$$

where ω_j is the residual term which is orthogonal to ε_j due to the basic IIA assumption; σ_j refers to the covariance between μ and ε; w_j is the residual. λ_j is the bias correction coefficient that can be computed from the estimated probabilities in equation (3), which is specified as $\lambda_{ij} = \rho_{ij}\, m(P_{ij}) + \sum_J \rho_{ij}\, m(P_{ij}) \frac{P_{ij}}{P_{ij} - 1}$. Here P_{ij} represents the probability that individual i chooses option j as equation (3); ρ_j is the correlation coefficient between μ_j and ε_j ; $m(P_{ij})$ is the conditional expectation, which is used to correct for selectivity effects with $m(P_{ij}) = \int J(v - logP_j) g(v)\, dv$, where $J(\cdot)$ is the inverse transformation for the normal distribution function, $g(\cdot)$ is the unconditional density for the Gumbel distribution, $v = \varepsilon_{ij} + logP_j$.

As previously discussed, the first-stage involves a multinomial logit regression to estimate the probability of participation, and the parameter α in equation (2). These probabilities are then used in the outcome equation (5). The drawback of this two-step approach that has been detailed in Bourguignon, Fournier, and Gurgand (BFG) (2007) is the heteroscedasticity that results in biased stand errors. Bootstrap method is normally used to deal with this heteroscedastic problem in empirical estimation (e.g., Wu, 2010; Parvathi and Waibel, 2016).

Another challenge is the fact that financial institutions are not randomized over villages. That is, some unobserved factors may be considered by microcredit providers, and this needs to be accounted for, since that could lead to inconsistent estimates. In particular, we augment the outcome equation by exploiting the average village varying variables $\bar{Z}_i$, to address the issue of unobserved heterogeneity in the second stage estimation. These unobserved variables may include useful missing information regarding loan and repay abilities and profitability. For example, since government projects are always set up at village level, the decisions of farmers may also be affected by these factors. Other methods of adding inverse Mills ratio to the second stage and using standard fixed effects do not contribute to consistent estimates (Wooldridge 2002; Di Falco and Veronesi, 2013). This varying variable approach is based on the assumption that the unobservable factors μ_i, and the average varying variables $\bar{Z}_i$ are linearly related, i.e. $\mu_i = \bar{Z}_i\theta + \varphi_i$, with $\varphi_i \sim N(0, \sigma_\varphi^2)$ and $E(\varphi_i|\bar{Z}_i) = 0$, where θ is the corresponding vector of coefficients. The village varying variables used in this study include the rate of off-farm employment ratio, education level and farm land size. These variables can be considered as inputs to income and consumption levels, tend to vary across villages. For the model identification, we use distance, road and information as instruments. As shown in table A1 in the appendix, these variables jointly influence participation, but not the outcome from participation.

The multinomial ESR specifications for participants and non-participants are specified in equations (6) and (7), respectively. Specifically, the outcome equations for actual and counterfactual scenarios are given in (6a) and (6b) for participants, while the corresponding specifications for non-participants are given in (7a) and (7b). Table 2 presents the relationships among these categories. The average treatment effect on the treated (ATT) and the average treatment effect on the untreated (ATU) are computed as the difference between equations (6a) and (6b), (7b) and (7a), respectively. This approach also controls for selection bias due to observed heterogeneity. BH in the table indicates the effect of base heterogeneity for individuals, examining the existence of sources of heterogeneity. TH is the transitional heterogeneity, capturing the total average effect.

$$\begin{cases} E(Y_{i1}|D_i = 1) = X_i\beta_{i1} + \sigma_1\lambda_1 \\ E(Y_{i2}|D_i = 2) = X_i\beta_{i2} + \sigma_2\lambda_2 \\ E(Y_{i3}|D_i = 3) = X_i\beta_{i3} + \sigma_3\lambda_3 \end{cases} \tag{6a}$$

$$\begin{cases} E(Y_{i0}|D_i = 1) = X_i\beta_{i0} + \sigma_0\lambda_1 \\ E(Y_{i0}|D_i = 2) = X_i\beta_{i0} + \sigma_0\lambda_2 \\ E(Y_{i0}|D_i = 3) = X_i\beta_{i0} + \sigma_0\lambda_3 \end{cases} \tag{6b}$$

$$E(Y_{i0}|D_i = 0) = X_i\beta_{i0} + \sigma_0\lambda_0 \tag{7a}$$

$$\begin{cases} E(Y_{i1}|D_i = 0) = X_i\beta_{i1} + \sigma_1\lambda_0 \\ E(Y_{i2}|D_i = 0) = X_i\beta_{i2} + \sigma_2\lambda_0 \\ E(Y_{i3}|D_i = 0) = X_i\beta_{i3} + \sigma_3\lambda_0 \end{cases} \tag{7b}$$

4 Empirical results

The results of first-stage and second-stage estimations are presented in table 3 to 5. In order to obtain full information for all categories, we present the marginal effects of the multinomial logit model estimates, providing results on the factors that contribute to the participation in a particular microcredit source. According to the results, Wald tests on instrumental variables suggest that distance, road and information are jointly significant in the first stage estimation, but do not influence the outcome equation (Table A1), indicating that these variables statistically and significantly improve the model fit. The x^2 statistics for over-identification test are insignificant, indicating that the instrumental variables are valid.

The estimates for the coefficients in the selection equations show that different microcredit sources are significantly driven by different factors. Generally, households with less shocks, better road conditions and less credit information are less likely to participate in microcredit. The probabilities of participating in different credit sources are diverse. The coefficient of the variable representing family size is positive and significantly different from zero, suggesting that larger families are more likely to borrow money from banking institutions. Dependency ratio significantly and negatively affect VMAFs, indicating that families with more members within working age range are less likely to borrow money from this organization. Families with fixed assets like motorcycle appear to be less likely to borrow money from friends and relatives. The results also suggest that households running small businesses do not tend to borrow money from any credit sources.

It is interesting to note that off-farm non-agricultural wage rate positively affects the probability of choosing VMAFs, while the off-farm wage rate negatively affects the probability of choosing commercial banks, suggesting that higher off-farm non-agricultural wage decreases the probability of households taking credit from commercial banks. Shocks satisfy the reality that it significantly decreases the probability of being the non-participants and choosing commercial banks, while significantly increase the probability of borrowing money from individual lenders. The distance to nearest financial institution and road condition negatively affect the probability of selecting VMAFs. This may be due to the fact that credit from the VMAFs are normally in monthly installment, making shorter distances and better traffic conditions decrease transaction costs, particularly for individuals living in rural areas. Information appears to be a significate factor influencing participation in microcredit. In particular, households with more information are more likely to participate in financial institutions, while those with less information tend to borrow from friends and relatives.

Tables 4 and 5 present the second stage multinomial ESR model estimations, providing the economic impact of participating in different microcredit sources on per capita income and consumption, respectively. The estimates generally show that the impacts on income and consumption will not only be different from observable characteristics, but are also related to specific microcredit sources. Specifically, the coefficient of age in the consumption specification is positive and significantly different from zero for the non-participants, while the coefficient of age square is significantly negative. These results indicate that for the non-participants, consumption increases with increasing age, but only up to a particular level, after which it decreases with age.

Off-farm employment ratio and dependency ratio support the hypotheses that higher off-farm employment ratio and lower dependency ratio significantly increase income and consumption, a finding that shows the importance of the labor force in family welfare. This result is in line with the findings of Li et al. (2011), Mazumder and Lu (2014), who reported the importance of employment and labor in helping the poor with regard to microfinance. The coefficient of the variable representing local off-farm wage rate is statistically and positively influencing income and consumption, showing the importance of non-farm employment in the livelihoods of rural residents.

Some of the selectivity correction terms are significant in both tables, indicating that participations in commercial banks and friends and relatives have significantly different impacts on non-participants, if they had chosen to participate in these credit sources. For example, in table

4, the significant selectivity correction term m3 in the commercial banks column indicates that for those people who participated in commercial banks, switching to borrow money from friends and relatives will also have a significantly positive effect on income. While the significant m0 in the last column indicates that for the people who have already borrowed money from friends and relatives, only when switching to be the non-participants the impact on income would be positive. In the table 5, the significantly negative selectivity correction terms in the last column indicates that for the people who borrowed money from individuals, switching to borrow money from commercial banks, VMAFs, or to be non-participants would have significantly negative impacts on consumption.

Table 6 summarizes the average impact of participating in microcredit on individuals' per capita income and consumption under actual and counterfactual scenarios. The results on income reveal that all types of microcredit in this study could contribute to income for both participants and non-participants. According to the percent changes, credit from commercial banks would increase income to the largest extent by 106% for the participants. The large difference may be due to the fact that the loans from commercial banks tend to be closely linked to applicants' production projects. Only when the projects are assessed as economically viable that the loans are approved by the financial institutions. Loans from commercial banks therefore tend to result in higher profits and households income. For participants, credit from VMAFs, friends and relatives result in income increases by 18% and 10% from non-participants, respectively.

The significantly positive value of base heterogeneity for the participants group indicates that there is no sources of heterogeneity since participants are more productive than the non-participants, with regard to the credit from commercial banks. The significantly negative base heterogeneity in the first column denotes the existence of some sources of heterogeneity that makes participants less productive than the non-participants, with regard to the credit from friends and relatives. The insignificant base heterogeneity in the first column suggests that for the VMAFs, there would be no significant difference in income between the actual and the latent participants. In the not to participate column, the base heterogeneity effects are significantly positive, indicating that the participants are more efficient in raising income than the non-participants, even if they had not participated in any credit sources. The transitional heterogeneity effect on commercial banks is significantly positive, hinting that, averagely, rural residents who actually participated in microcredit would have increased the most income. The significantly negative values indicate that people who actually did not participate in VMAFs, friends and relatives would benefit the most, if they had participated.

In terms of the impact on per capita consumption, the results show that microcredit from these three credit sources can statistically increase consumption. It is interesting to see that the positive effects of friends and relatives are the largest for both participants and non-participants. This result is probably due to the fact that individuals normally borrow from friends and relatives to smooth consumptions. All the base heterogeneity effects for participations and non-participations are positive, suggesting that heterogeneity does not result in participants consuming more than non-participants. However, all the transitional heterogeneities are significantly negative, implying that people who did not borrow money from any credit sources would consume the most, if they had participated in microcredit.

5 Conclusions and implications

This article analyses the factors that influence rural households' decisions to participate in microcredit, the impact of participation on per capita income and consumption, using household-level data in China. We use a multinomial endogenous switching regression model to account for selectivity bias, and to capture the differential impacts of microcredit on non-participants and three categories of participants in microcredit, that include commercial banks, VMAFs, friends and relatives.

The empirical results show that various factors influence households' decisions to participate in different microfinance programs. In particular, households who earned lower wage from the off-farm sector and had better information sources took loans from commercial banks. On the other hand, households with less endowment assets rather obtained credit from friends and family members. The findings also revealed that participation in microfinance helped households to increase their income and consumption. Specifically, credit from commercial banks helped increase per capita income by 106%, while households that took loans from friends and relatives increased their income by 10%.

Overall, the findings suggest that policies that enhance financial inclusion can help increase the welfare of rural households. In particular, effective policy measures to promote the participation in microcredit should include measures to improve the education levels and availability of employment opportunities in the off-farm sector. The positive impact of participation in formal microcredit suggests that these credit providers need to help households to overcome the information barriers. Village mutual aid funds can significantly contribute to income and consumption increases with more stable changes for both outcomes. This result suggests that this program can be extended to poor rural areas, to promote financial inclusion.

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Table 1 Total sample descriptive statistics[1]

Variable	Description	Mean	Std. Dev.
Income	Household income per capita (thousand yuan/year)	13.027	22.268
Consumption	Household consumption per capita (thousand yuan/year)	6.682	8.773
Credit	1 if respondent had credit in recent 5 years; 0 otherwise	.598	.021
Age	Physical age of household head	59.071	11.423
Gender	1 if the household head is male; 0 otherwise	.911	.285
Farm size	Arable land, including the rent and cultivated land (Mu)	3.346	3.090
Family size	Number of persons live in the family and share meals	3.654	1.548
Off-farm employment ratio	The Number of off-farm employment labor divided by the number of all employment labor	.332	.013
Dependency ratio	The number of families outside the working age range divided by the number of families aged within that age (16-60 years old)	1.073	.855
Motorcycle	Ownership of motorcycle = 1; 0 otherwise	.299	.458
Head education	Household head's educational level: 0=No schooling, 1=Primary (1-6years), 2=Junior middle (7-9yesrs), 3=Senior middle (10-12years), 4=Training school (13-15years), 5=Bachelor (13-16years), 6=Master or higher	2.172	.791
Business	1if the household runs business; 0 otherwise	.078	.268
Distance	Distance to nearest financial institution (Km)	3.617	3.273
Road	Distance to the nearest vehicle usable road (Km)	.197	.571
Off-farm agricultural wage rate	Casual wage rate of local off-farm agricultural works (yuan/day)	53.659	15.963
Off-farm wage rate	Casual wage rate of local off-farm works (yuan/day)	103.986	13.243
Information	Level of knowing the credit information: 1=Very poor, 2=Poor, 3=Average, 4=Good, 5=Very good	3.080	1.131
Village runs VMAFs	1 if the village runs a village mutual aid funds organization; 0 otherwise	.321	.467
Shocks	1 if household has experienced any kind of shock such as illness, fire, natural disasters within the last 12 months prior to the survey period; 0 otherwise	.755	.430
Area 1	1 if household is located in Ya'an; 0 otherwise	.159	.366
Area 2	1 if household is located in Guangyuan; 0 otherwise	.183	.387
Area 3	1 if household is located in Nanchong; 0 otherwise	.178	.382
Area 4	1 if household is located in Mianyang; 0 otherwise	.185	.388
Area 5	1 if household is located in Guang'an; 0 otherwise	.179	.384
Area 6	1 if household is located in Leshan; 0 otherwise	.116	.320

Table 2 Treatment and Heterogeneity effect for MESR

Samples	**Decision**				**Treatment effect**
	To participate		Not to participate		
Participants	$E(Y_{i1}\|D_i = 1)$	$6a^1$	$E(Y_{i0}\|D_i = 1)$	$6b^1$	ATT^1
	$E(Y_{i2}\|D_i = 2)$	$6a^2$	$E(Y_{i0}\|D_i = 2)$	$6b^2$	ATT^2
	$E(Y_{i3}\|D_i = 3)$	$6a^3$	$E(Y_{i0}\|D_i = 3)$	$6b^3$	ATT^3
Non-participants	$E(Y_{i1}\|D_i = 0)$	$7b^1$	$E(Y_{i0}\|D_i = 0)$		ATU^1
	$E(Y_{i2}\|D_i = 0)$	$7b^2$	$E(Y_{i0}\|D_i = 0)$	7a	ATU^2
	$E(Y_{i3}\|D_i = 0)$	$7b^3$	$E(Y_{i0}\|D_i = 0)$		ATU^3
Heterogeneity effect	BH_{10}^1		BH_{10}^0		TH^1
	BH_{20}^2		BH_{20}^0		TH^2
	BH_{30}^3		BH_{30}^0		TH^3

Table 3 Marginal effect of determinants of microcredit participation: Multinomial logit model[2]

[1] 1 mu = 1/5 hectare. 1 Yuan ≈ 0.15 US dollar at the time of survey.

Variable	Non-participants dy/dx	Commercial banks dy/dx	VMAFs dy/dx	Friends and Relatives dy/dx
Age	-.001(.017)	.007(.013)	-.018(.011)	.012(.017)
Age square	.0001(.0002)	-.0001(.0001)	.0001*(.0001)	-.0001(.0002)
Gender	.103(.073)	-.033(.045)	-.075(.048)	.005(.069)
Farm size	-.003(.008)	.006(.004)	-.006(.004)	.003(.007)
Family size	-.013(.015)	.027***(.010)	-.014(.010)	.0001(.015)
Off-farm employment ratio	.105(.079)	-.050(.046)	-.032(.053)	-.023(.076)
Dependency ratio	.026(.029)	-.016(.020)	-.052**(.020)	.041(.027)
Motorcycle	.057(.048)	.013(.029)	.022(.028)	-.092**(.046)
Head education	.017(.029)	-.012(.018)	.002(.017)	-.006(.027)
Business	.003*(.002)	.001(.001)	-.001(.001)	-.003(.002)
Log off-farm agricultural wage rate	.044(.082)	.022(.052)	-.134**(.062)	.068(.077)
Log off-farm wage rate	.110(.186)	-.267**(.125)	.384***(.112)	-.227(.179)
Shocks	-.110**(.052)	-.066*(.035)	.029(.035)	.148***(.051)
Area 1	.356(5.203)	.251(1.444)	-1.196(9.774)	.590(3.127)
Area 2	-.023(.075)	.049(.053)	.0157(.031)	-.042(.076)
Area 3	-.130(.091)	-.0001(.071)	.176***(.024)	-.046(.092)
Area 4	.473(4.748)	.256(1.318)	-1.177(8.919)	.709*(.418)
Area 5	.549(4.206)	.220(1.167)	-1.244(7.901)	.475(2.579)
Instrument variables				
Distance	.002(.007)	0.007(.005)	-.010**(.005)	.001(.007)
Road	.138***(.049)	-.007(.032)	-.185***(.066)	.054(.041)
Information	-.088***(.017)	.056***(.013)	.036***(.013)	-.232**(.105)
Wald test on instrumental variable (X^2)	114.81***	107.22***	340.26***	81.62***
X^2 **Statistics for over identification**	1.772[.412]	.186[.911]	1.254[.190]	.358[.836]
Number of obs.	530			
LR chi2(66)	433.58***			
Pseudo R^2	.303			

Notes: Likelihood ratio test and pseudo R square are estimated from the multinomial logit regression. Stand error in the parentheses. P values are in the square brackets. *, ** and *** represent significant at 10%, 5% and 1% level, respectively.

Table 4 MESR results for impact of microcredit participation on per capita income

[2] Variance inflation factor (VIF) is used to check for multicollinearity, where the mean VIF is 1.67. The multicollinearity is not high.

Variable	Non-participants	Commercial banks	VMAFs	Friends and Relatives
Age	.096(.090)	.413(.864)	.136(.375)	.053(.165)
Age square	-.001(.001)	-.004(.008)	-.001(.003)	-.0003(.002)
Gender	-.307(.456)	.347(2.293)	-.632(4.035)	.178(.833)
Farm size	-.002(.063)	.099(.311)	.106(.138)	.043(.095)
Family size	.054(.070)	.564(.906)	-.072(.670)	.066(.161)
Off-farm employment ratio	1.482***(.476)	-2.663(3.209)	2.677**(1.256)	1.074**(.495)
Dependency ratio	.020(.172)	-1.194(1.651)	-.260(.499)	-.461***(.154)
Motorcycle	-.152(.224)	-2.088(2.571)	-.142(.936)	.689**(.330)
Education	.065(.130)	.562(1.071)	.132(.557)	.203(.345)
Business	.003(.008)	-.043(.060)	-.029(.065)	.004(.061)
Log off-farm agricultural wage rate	-.418(.339)	.157(3.667)	-1.400(2.677)	-.082(.568)
Log off-farm wage rate	.126(1.192)	2.019***(.750)	2.596(6.065)	.695(2.119)
Shocks	-.002(.252)	-.764***(.293)	-.207(4.659)	.192(.719)
Mean off-farm employment ratio	-2.537*(1.505)	.644(7.771)	-.400(9.622)	.562(3.657)
Mean farm size	-.043(.106)	-.258(.565)	.247(.600)	-.042(.248)
Mean high education level	.834**(.416)	3.344*(2.009)	-.382(2.117)	.429(.892)
_m0	-.156(1.181)	1.584(1.044)	-3.662(5.505)	1.873*(1.056)
_m1	-.996(1.936)	1.504(3.218)	-.449(6.498)	-2.110(3.941)
_m2	.183(1.878)	3.928(8.988)	-1.327(2.648)	-2.090(3.090)
_m3	2.755(2.150)	17.832***(6.944)	.831(5.082)	-.767(1.577)
_cons	-.442(6.784)	-7.235(6.830)	-8.461(35.126)	-6.870(16.797)

Notes: *, ** and *** represent significant at 10%, 5% and 1% level, respectively. Values in the parentheses are standard errors.

Table 5 MESR results for impact of microcredit participation on per capita consumption

Variable	Non-participants	Commercial banks	VMAFs	Friends and Relatives
Age	.086*(.052)	.082(.877)	.096(.416)	-.111(.144)
Age square	-.001*(.0004)	-.001(.008)	-.001(.004)	.001(.001)
Gender	-.313(.272)	-.924(8.810)	-.571(.958)	-.030(.504)
Farm size	.006(.037)	.113(.235)	.044(.183)	.130*(.074)
Family size	.010(.050)	-.517(.761)	-.026(.332)	-.020(.137)
Off-farm employment ratio	.666**(.329)	.569(2.103)	.753(1.250)	.126(.732)
Dependency ratio	.006(.098)	.786(1.902)	-.258(.667)	-.529(.230)
Motorcycle	-.098(.192)	-1.527(1.681)	.156(1.158)	.275(.494)
Education	.041(.078)	.337(.971)	.096(.376)	.226(.205)
Business	.003(.005)	-.025(.111)	.015(.046)	.028(.054)
Log off-farm agricultural wage rate	-.244(.237)	.353(2.732)	-.801(1.135)	-.346(.398)
Log off-farm wage rate	.343(.529)	5.276**(2.179)	.953(4.984)	3.372*(1.884)
Shocks	.017(.198)	3.017**(1.503)	-.267(1.170)	.981*(.569)
Mean off-farm employment ratio	-1.247(1.159)	-8.763**(4.353)	1.767(4.329)	-6.107**(2.284)
Mean farm size	-.031(.075)	-.330(.515)	.092(.471)	.080(.134)
Mean high education level	.519*(.273)	3.153(2.076)	-.171(1.791)	1.704**(.751)
_m0	-.267(.655)	-17.552***(5.728)	-1.836(10.375)	-8.803**(4.151)
_m1	-.930(1.235)	-3.541*(2.122)	1.046(8.351)	-4.310**(2.034)
_m2	-.368(.991)	-5.501(5.447)	-.751(2.749)	-4.076*(2.290)
_m3	1.805(1.704)	12.766**(5.680)	-.687(7.255)	1.308(.907)
_cons	-1.681(3.233)	-3.078(3.299)	-2.331(3.222)	-2.924**(1.394)

Notes: *, ** and *** represent significant at 10%, 5% and 1% level, respectively. Values in the parentheses are standard errors.

Table 6 Treatment and Heterogeneity effect for MESR

Samples		To Participate	Not to participate	Treatment effect	Changes
Per capita income					
Participants	Commercial banks	6.942(.256)	3.375(.091)	3.567***(.272)	105.70%
	VMAFs	3.777(.107)	3.213(.059)	.564***(.122)	17.56%
	Friends and Relatives	3.632(.048)	3.302(.047)	.330***(.067)	10.11%
Non-participants	Commercial banks	4.787(.162)	2.769(.042)	2.017***(.167)	72.84%
	VMAFs	3.869(.096)	2.769(.042)	1.100***(.105)	39.72%
	Friends and Relatives	3.979(.047)	2.769(.042)	1.210***(.063)	43.69%
Heterogeneity effect		2.156***(.328)	.606***(.091)	1.550***(.324)	
		-.093(.157)	.443***(.073)	-.536***(.146)	
		-.347***(.069)	.533***(.064)	-.880***(.047)	
Per capita consumption					
Participants	Commercial banks	3.543(.324)	2.799(.058)	.744**(.329)	26.59%
	VMAFs	2.732(.117)	2.673(.035)	.058(.123)	2.18%
	Friends and Relatives	4.275(.047)	2.743(.028)	1.532***(.055)	55.85%
Non-participants	Commercial banks	3.450(.166)	2.159(.026)	1.290***(.168)	59.76%
	VMAFs	2.297(.055)	2.159(.026)	.138**(.061)	6.39%
	Friends and Relatives	4.022(.078)	2.159(.026)	1.862***(.082)	86.25%
Heterogeneity effect		.094(.352)	.640***(.057)	-.546(.346)	
		.434***(.114)	.514***(.044)	-.080(.100)	
		.253**(.101)	.583***(.039)	-.331***(.100)	

Notes: *, ** and *** represent significant at 10%, 5% and 1% level, respectively. Values in the parentheses are standard errors. As the outcomes used in the second stage estimation are logarithms, the predictions are also given in logarithms.

Appendix

Table A1 Test on the validity of the instrumental variables

Variable	Per capital income by non-participants		Per capital consumption by non-participants	
	Coef.	Std.Err.	Coef.	Std.Err.
Age	.030	.038	.045	.030
Age square	-.0002	.0003	-.0004	.0003
Gender	-.144	.170	-.208	.135
Farm size	-.010	.024	-.003	.019
Family size	.053	.033	.014	.027
Off-farm employment ratio	1.383***	.187	.589***	.149
Dependency ratio	-.101*	.059	-.091*	.047
Motorcycle	.019	.101	.060	.080
Head education	.032	.057	.027	.045
Business	.006***	.001	.005***	.001
Log off-farm agricultural wage rate	-.536***	.204	-.382**	.163
Log off-farm wage rate	-.947**	.422	-.463	.336
Shocks	-.222**	.109	-.137*	.082
Mean non-farm worker rate	-.500	.728	-.014	.580
Mean farm size	-.002	.043	-.022	.034
Mean high education level	.116	.187	-.057	.149
Area 1	-.058	.172	-.129	.137
Area 2	-.400**	.182	-.279*	.145
Area 3	-.502*	.257	-.563***	.205
Area 4	.156	.166	.110	.132
Area 5	-.381*	.199	-.412***	.159
Distance	.002	.018	-.011	.014
Road	-.097	.069	-.024	.055
Information	.092	.070	.084	.081
_cons	7.187***	2.374	4.438**	1.893
Number of obs.	222		222	
Wald test on instrument variables	X^2 (24) =374.52***		X^2 (24) =221.59***	
R-squared	.588		.485	

Note: *, ** and *** represent significant at 10%, 5% and 1% level, respectively.

Table A2 Individuals characteristics of different selections

Variable	Non-participants	Commercial banks	VMAFs	Friends and relatives

	Mean	Std. Err.	Mean	Std. Err.	Diff.	Mean	Std. Err.	Diff.	Mean	Std. Err.	Diff.
Income	12.783	1.183	24.163	6.172	11.380***	9.616	.846	-3.167**	11.014	.969	-1.769
Consumption	6.130	.380	10.329	2.275	4.199***	6.216	.697	.086	6.248	.520	.118
Credit	-	-	.120	.014	-	.194	.017	-	.284	.019	-
Age	60.590	.774	52.985	1.211	-7.605***	60.477	1.100	-.113	58.522	.888	-2.068*
Gender	.919	.018	.894	.038	-.025	.907	.028	-.012	.911	.023	-.008
Farm size	3.177	.137	4.408	.692	1.230***	2.891	.300	-.286	3.450	.217	.273
Family size	3.662	.104	4.303	.162	.641***	3.168	.153	-.494***	3.701	.122	.039
Off-farm employment ratio	.353	.020	.382	.039	.029	.262	.031	-.091***	.330	.024	-.023
Dependency ratio	1.139	.059	.731	.080	-.408***	1.071	.073	-.068	1.126	.074	-.013
Motorcycle	.293	.031	.485	.062	.192***	.271	.043	-.022	.248	.035	-.045
Head education	2.131	.057	2.333	.095	.202*	2.187	.081	.056	2.153	.054	.022
Business	.068	.017	.227	.052	.159***	.037	.018	-.031	.057	.019	-.011
Distance	3.973	.249	4.088	.430	.115	2.575	.116	-1.398***	3.627	.267	-.346
Road	.294	.051	.125	.051	-.169*	.027	.012	-.267***	.204	.038	-.090*
Off-farm wage rate	104.595	.877	103.485	1.488	-1.110	103.271	1.346	-1.324	103.822	1.083	-.773
Off-farm agricultural wage rate	54.685	1.175	53.182	1.729	-1.503	53.178	1.409	-1.507	52.739	1.228	-1.946
Information	2.725	.077	3.621	.120	.896***	3.729	.080	1.004***	2.911	.086	.186*
VMAFs	.162	.025	.136	.043	-.026	1	0	.838***	.159	.029	-.003
Shocks	.712	.030	.621	.060	-.091*	.869	.033	.157***	.796	.032	.084**
Area 1	.149	.024	.303	.057	.154***	-	-	-	.223	.033	.074**
Area 2	.198	.027	.197	.049	-.001	.196	.039	-.002	.146	.028	-.052*
Area 3	.068	.017	.045	.026	-.023	.664	.046	.596***	.057	.019	-.011
Area 4	.207	.027	.273	.055	.066	-	-	-	.242	.034	.035
Area 5	.243	.029	.106	.038	-.137**	-	-	-	.242	.034	-.001
Area 6	.135	.023	.076	.033	-.059*	.140	.034	.005	.089	.023	-.046*
Sample size	222			55			89			164	

Note: *, ** and *** represent significant at 10%, 5% and 1% level, respectively.