

Key Determinants of for-Profit Micro Finance Institutions Credit: A Study on Rural Manufacturing Households

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Abstract: *The pathetic condition of Indian agriculture speaks volumes about the distress in its rural economy. Manufacturing activity, though providing hope, is constrained by the availability of credit. From social banking to for-profit micro finance institutions (MFIs), the rural economy has witnessed a sea change in the public provisioning of credit. The phenomenal growth of for-profit MFIs in recent years is associated with growing concerns over their unethical practices and exploitation of the rural poor. The present study attempts to trace the factors that influence rural households' dependence on for-profit MFI credit, despite the abovementioned concerns. The study is based on a primary survey and uses logit and probit models. The estimated results suggest that the factors like access to bank credit and household poverty factors – such as per capita income, number of male workers, and the existence of wage labour – significantly influence the probability of accessing for-profit MFI credit. Accordingly, the present study proposes remedial policies like the expansion of scheduled commercial banks (SCBs) and not-for-profit MFIs, apart from strict regulation of for-profit MFIs.*

Keywords: Credit; Debt; For-profit; Households; MFI

JEL Classification: C50, G21, O12

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Introduction

The distress in rural India is evident from the fact that nearly 43% of the working population is engaged in agriculture but it contributes a meagre 17% to gross domestic product (GDP). Besides, Indian agriculture is characterised by low productivity and the dominance of small and marginal farmers. As per the agricultural census 2015-16, nearly 86% of Indian farmers are either small or marginal, i.e., having a total holding size of fewer than two hectares, and around 70% are marginal farmers, i.e., having a total holding of less than one hectare. The overburdened agriculture feeds into poverty and disguises unemployment in the rural economy. Under such circumstances, if anything can be a panacea for India's rural economy, it is the rural non-farm sector (RNFS). The RNFS provides more than 30% of total employment and contributes nearly 65% to the net domestic product in the rural economy (Reddy et al., 2014). Manufacturing is one of the significant economic activities within Indian RNFS owing to its employment, value addition, and linkage potential. As per the National Sample Survey (NSS) 73rd round, in the RNFS, the manufacturing sub-sector accounted for around 37% of total workers engaged and around 26% of total gross value added (GVA). Thus, manufacturing activity in rural India, which is largely unorganised in nature, can play a pivotal role in addressing the distress described above. Undoubtedly, the delivery of timely and affordable credit plays an essential role in the survival and growth of manufacturing enterprises in rural India.

In recent years, there has been growing emphasis on micro-finance institutions (MFIs) for providing micro-enterprise loans. Apart from commercial banks, these include the National Bank for Agriculture and Rural Development (Nabard), Small Industries Bank of India (SIDBI), etc. The Micro Units Development and Refinance Agency (Mudra) bank, established under the Pradhan Mantri Mudra Yojana (PMMY) in April 2015, provides both direct and refinance support to MFIs for micro-enterprise loans (Shahid & Irshad, 2016).

In fact, with the objective of improving efficiency and profitability, the reliance on MFIs, as a new set of institutions has been emphasised since the early 1990s (Rangarajan, 1998). Following the success of the Grameen Bank model in Bangladesh, thanks to Muhammad Yunus, the role of MFIs in alleviating poverty through the delivery of microcredit was recognised the world over. In 2000, the United Nations (UN) considered microfinance

as means to achieve its Millennium Development Goals (MDGs) and declared 2005 as the year of microcredit. And in 2006, Muhammad Yunus and Grameen Bank shared the Nobel Peace Prize. Before that, in 1992, microfinance was formally introduced in India by Nabard through its self-help group Bank Linkage Programmes (SBLP) (Bansal, 2003).

MFIs associated with SBLP were non-governmental organisation (NGO) MFIs or not-for-profit MFIs. However, later, realising profit possibilities, for-profit MFIs, alternately known as non-bank finance company (NBFC) MFIs, joined the bandwagon and slowly replaced the not-for-profit or NGO type MFIs. In fact, many for-profit MFIs, like SKS Microfinance Ltd and Ujjivan Financial Services Ltd, Equitas Holding Ltd, etc., were NGO MFIs in their earlier avatars (Pati, 2021). As a result, the share of for-profit MFIs has increased considerably over the years, whereas it has been the opposite for not-for-profit MFIs (Sangwan & Nayak, 2021). If we focus only on not-for-profit and for-profit MFIs, as per computed figures from the Reserve Bank of India (RBI) (2011), in 2007-08, SBLP (i.e., not for-profit MFIs) accounted for around 78% and 74% of microfinance borrowers and their outstanding loan amounts respectively. In contrast, the remaining 22% and 26% accounted for the for-profit MFIs.

At present, for-profit MFIs dominate the microcredit segment in India, barring commercial banks and traditional formal financial institutions in India. In the microcredit segment, apart from commercial banks, for-profit and not-for-profit microfinance institutions, there are small finance banks and NBFCs. For-profit MFIs account for the highest number of lenders and have the second-highest position, as far as the number of loans and the outstanding amount are concerned. They account for more than one-fifth of loans and close to one-third of the total microcredit disbursed (Table 1). On the contrary, not-for-profit MFIs account for less than 1% of the same. Pertinently, the dominant share of for-profit MFIs vis-à-vis not-for-profit MFIs has been increasing even though since September 2015, one of the largest for-profit MFIs, i.e., Bandhan, became a full-fledged commercial bank while eight other NBFC-MFIs became small finance banks, and since early 2020, the private microfinance sector has been severely affected by the Covid-19 pandemic.

Table 1: Share of Various Institutions in Micro Credit

SL No.	Institutions	Lenders		Loans			
		No.	% share	No. (in lakhs)	% share	Outstanding amount (INR in crore)	% share
1	Banks	15	7.6	1,030.0	60.7	93,432	41.0
2	SFBs	8	4.1	203.4	12.0	42,689	18.7
3	NBFCs	55	27.9	85.8	5.1	19,848	8.7
4	Not-for-profit MFIs	33	16.8	10.6	0.6	1,777	0.8
5	For-profit MFIs	86	43.7	367.4	21.6	70,196	30.8
	Total	197	100.0	1697.2	100.0	22,7942	100.0

Source: Computed from RBI (2021).

Strikingly, for-profit MFIs have achieved phenomenal growth despite severe criticisms about their lending and recovery practices. From the state of Andhra Pradesh in the year 2010 to the state of Assam in the year 2020, the media holds them responsible for abetting the cause of suicide on the grounds of over-indebtedness and coercive recovery practices. Even the committee appointed by RBI and headed by YH Malegaon did not dispute this. Apart from the Malegaon committee, various other studies (Lewis, 2008; Taylor, 2011; Bateman, 2012; Mader, 2013; Datta & Ghosh, 2013; etc.) have highlighted the perils of for-profit MFI lending. By contrasting the role of for-profit MFIs in India with that of the Grameen bank model in Bangladesh, Halder and Stiglitz (2016) suggest that in the context of the former, the concept of social capital, which is the backbone of microfinance, is not just misinterpreted, but also grossly absent. Of course, there is a limit to which the concept of microfinance can be extended to for-profit institutions and scaled up. Nevertheless, despite severe criticism, for-profit MFIs have spread into the nooks and corners of India.

Against this backdrop, the major research question that arises is: What are the key determining factors that influence Indian rural households, engaged in manufacturing activity, in accessing for-profit MFI credit?

2. Review of Literature

Since the phenomenon is of recent origin there is hardly any empirical literature in the Indian context to answer this research question. Hence, without restricting the focus to India, we tried to extract the available literature through bibliometric analysis using the bibliometrics package (Aria & Cuccurullo, 2017) from R software. Chronologically, a few important studies among them are presented below.

Bezboruah and Pillai (2013) analysed women borrowers' participation rates in MFIs using data from 105 developing countries. The sample MFIs were selected following various criteria, such as legal status, outreach, external control, and target clients. Their findings suggest that in the absence of equivalent loan opportunities from commercial banks, there is a preference for unregulated MFIs. Although commercial banks provide microcredit, their insistence on collateral drives the women towards MFIs. Thus, the unavailability of commercial bank credit could be an important factor in accessing for-profit MFI credit. In contrast to Bezboruah and Pillai's (2013) multi-country study, Datta and Ghosh (2013) studied the determinants of participation in for-profit MFI credit in an Indian context. Their study was based on primary survey data collected from four states: Chhattisgarh, Maharashtra, West Bengal, Tamil Nadu, and erstwhile Andhra Pradesh. Their study suggests that rural households' dependence on semi-formal sources of finance, such as for-profit MFIs, is determined by factors like distance from the banks, household income, asset holdings, percentage of the irrigated land, etc. Among such factors, distance from the bank positively influences the probability of participation in for-profit MFI lending, while all other factors almost negatively influence the same. The negative influence suggests that the poverty of the households compels them to borrow from for-profit MFIs. Further through marginal effects, they established that relatively fewer poor households are more likely to depend on for-profit MFI credit. In a subsequent study, again in the Indian context, Dattasharma et al. (2015) examined the burden of for-profit MFI debt on 90 poor households in Ramnagaram town of Karnataka using the financial diary methodology. They found that the household's cash flows are severely affected by for-profit MFI loans. The equated monthly instalment (EMI) outgoes severely erode their usual consumption pattern, leading to malnutrition and impoverishment. This suggests that a household's cash flow and its frequency could be important

determinants in accessing for-profit MFI loans.

However, in a study specific to farmers in China, Kong et al. (2015) explained farmers' decisions in joining the group-based lending programme by applying a combination of cluster analysis and logit regression to survey data. The study found that access to formal credit is the major motivating factor for joining the group-based lending programme. Similarly, Tinh and Tuyen (2015) explored the factors that affect the source of microcredit for the poor, apart from other things. They used survey data from Ho Chi Minh City, Vietnam. Their findings suggest that the poor usually require credit for consumption smoothening, and their constraints in availing credit increase with distance from the bank and decrease with their income levels. Also, the credit constraints for the poor increases in the absence of interpersonal trust in the community. Again, in a multi-country study, Shahriar et al. (2016) examined the plausibility of for-profit MFIs extending MFI loans to business startups using the data of 198 MFIs across 65 countries and by applying advanced econometric techniques. They found that for-profit MFIs are less likely to provide financial support to startups, owing to the riskiness of the project. In particular, the authors maintained that the for-profit MFIs avoid risky lending to maximise their profit. Thus, it may be said that the purpose of the loan could be an important determinant for the delivery of for-profit MFI credit.

In a recent study, Olateju et al. (2019) investigated the factors that influence the participation of microentrepreneurs in for-profit microfinance programmes, based on the case study of Cowries Microfinance Bank, in the Lagos state of Nigeria. They had a sample size of 550 microentrepreneurs, out of which 305 were poor and microfinance participants, while the remaining 245 were non-poor and non-participants of microfinance. The former was considered the target group while the latter was the control group. Using Tobit regression, they found that the determinants like gender, educational level, business experience, political party membership, household size, income, and marital status influence the participation in the microfinance programme. Thus, it appears that a wide range of factors influence participation in for-profit microfinance programmes. In another recent study, Ding and Abdulai (2020), apart from other aspects, examined the factors that affect rural residents' decision to access different types of microcredit sources, including for-profit MFIs, in China. Using cross-sectional survey data and applying a multinomial endogenous switching

regression model, the authors found that the factors like family size, dependency ratio, casual wage in the local area, and credit information determine the choice of credit source. Similarly, Sangawan and Nayak (2021) examined the factors behind the changing outreach focus of for-profit MFIs in India in recent years. They found that the outreach of for-profit MFIs is more inclined toward wealthier, younger, and non-agricultural clients, who have longer loan experiences and greater social networks. They also find that the for-profit MFIs charge higher interest rates for small-sized loans, which is like a penalty for their poverty. They opined that the outreach of for-profit MFIs is broadly influenced by financial sustainability and profitability.

Similar to Kong et al. (2015), Ouattara et al. (2022) examined the key determinants for the small rice farmers in Cote d'Ivoire for participating in the credit market. Using a sample survey of 588 rice farmers, they found that the factors like gender, age, education level, experience in rice farming, rice plot size, lowland rice farming, extension contact, membership of a farmer-based organisation, marketing of paddy rice, and off-farm income significantly influence the use of different credit sources, including for-profit MFI.

Thus, the available literature across the board suggests that various household characteristics like income, age, gender, education levels, household size, political party and membership affect participation in group lending programmes in general, and for-profit MFIs. However, we do not find a single study that examined the determinants of participation from the perspective of rural manufacturing households, either per se or in the Indian context. Thus, given the importance of rural manufacturing in India and its credit constraints, the present study intends to fill the aforesaid gap in the literature. In particular, the present study explores the role of various factors like direct access to bank credit, a variety of household poverty characteristics, including income and factors representing debt servicing potential, on the probability of accessing for-profit MFI credit.

The paper is organised as follows. Section 2 describes the data and methodology while Section 3 discusses the nature of explanatory variables and the expected outcomes. The results are discussed in Section 4, and finally, in Section 5, the entire discussion is concluded.

3. Data and Methodology

The survey was conducted during the pre-Covid period and focused on rural households that were engaged in manufacturing activities and had outstanding debt from for-profit MFIs. However, the head of the household borrows either through self (if women) or through female members of the family, since the for-profit MFIs lend only to women members by forming joint liability groups (JLGs). In each JLG there are at least five members. As far as the distribution of for-profit MFIs in the sample data is concerned, the surveyed borrowers were spread over six for-profit MFIs. Their relative strength in the sample in terms of the total number of loans, loan amounts, and operational experiences in the study area is depicted in Table 2.

Table 2: Distribution of For-Profit MFIs in Sample Data

For-profit MFIs+	Total number of loans (clients*)	Share in total (%)	Amount of loan (INR)	Share in total (%)	Average size of loan (INR)
MFI-1	55	35.3	8,76,000	40.0	15,927
MFI-2	47	30.1	6,63,000	30.3	14,106
MFI-3	38	24.4	4,61,000	21.1	12,132
MFI-4	10	6.4	1,19,000	5.4	11,900
MFI-5	5	3.2	55,000	2.5	11,000
MFI-6	1	0.6	14,000	0.6	14,000
Total	156	100	21,88,000	100	14,026

Note: + indicates the names of MFIs that have not been mentioned taking sensitivity issues into consideration. * For MFIs, each loan implies a client since none of them provides more than one loan to the same client.

Source: Field survey.

3.1 Selection of counterfactual

Further, to examine the relevance of the microfinance programme for manufacturing households, the methodology of random experimental design (Heckman & Smith 1995) is followed. Accordingly, the data on non-participants i.e., manufacturing households not exposed to for-profit MFIs, was collected as a control group. The non-participants surveyed based on random sampling constitute 40% of the targeted samples. Further, the non-

participants' proportion is maintained at the overall level and at each level of stratification.

Also, the selection of non-participants from the population satisfies the property that the control group is not conditional upon any criterion. Therefore, the control group's average outcome may be better or worse off depending upon the factors that affect the participation of manufacturing households in the for-profit microfinance programme.

3.2 Methodology

As maintained earlier, our objective is to examine whether some observed factor(s) influence the probability of participation in a for-profit MFI lending programme. The households surveyed were either the participants (1) or non-participants of the for-profit MFI programme (0). This implies that the dependent variable is a categorical discrete variable, whereas our independent variables are both discrete and continuous. In such cases, the very nature of the dependent variable violates the ordinary least squares (OLS) assumptions (Pindyck & Rubinfeld 1981). For the dependent variable, with the responses limited to 0 or 1, neither the error terms are normally distributed nor is the error variance constant. Hence, we use logistic regression, which uses a binomial distribution instead of a normal distribution, to describe the distribution of errors in the model. Further, it converts the dependent variable, a discrete binary variable, into a continuous one, such as the probability of having a value of 1 or 0. In particular, the model predicts the probability of choosing one of the alternatives as the sum of the probabilities over two alternatives is 1. The alternative choice/category that is not explicitly modelled is called the base group. The choice of the base group does not affect the outcome of the econometric analysis.

To formalise our model: Participation in the for-profit microfinance programme (y): 1 = yes; 0 = otherwise. The possible factors that can influence participation, i.e., regressors (x) = constant access to bank credit, gender of the working owner of the enterprise, whether the working owner is educated or not, the existence of wage labour in the household, and the number of male and female workers in the family. Each of these variables and their expected roles are explained in the succeeding section.

The probability of participating in the for-profit microfinance programme ($y = 1$) is defined as

$$F(x'\beta) = \Pr(y = 1|x)$$

Where β is the vector for the unknown parameters; Pr stands for probability. Assuming a logistic distribution function, F would imply the following:

$$F(x'\beta) = \frac{e^{x'\beta}}{1 + e^{x'\beta}} = \frac{1}{1 + e^{-x'\beta}} = \Pr(y = 1|x)$$

Taking natural log on both sides we can see that

$$\left[\frac{\Pr(y = 1|x)}{1 - \Pr(y = 1|x)} \right] = x\beta +$$

where u is the error term. Further, since the data set is not large enough and taking the non-independent and identically distributed (IID) errors into consideration, instead of OLS or generalised least squares (GLS), we follow the maximum likelihood estimation (ML) procedure, the functional form of which may be represented as follows.

Let D be the set of observations for which $y_i = 1$, the logit model parameters are obtained by maximising the following log likelihood function:

$$\ln L = \sum_{i \in D} \ln \left[\frac{e^{x_i'\beta}}{1 + e^{x_i'\beta}} \right] + \sum_{i \notin D} \ln \left[\frac{1}{1 + e^{x_i'\beta}} \right]$$

For testing the hypotheses that $\beta = 0$, we use the usual ML based testing procedures such as the Wald test. However, in measuring goodness of fit, we follow McFadden's likelihood ratio index or pseudo-R-squared value, which is analogous to the R^2 in conventional regression.

McFadden's likelihood ratio index or pseudo R^2 value is defined as

$$1 - \frac{L_F}{L_C}$$

Where, L_F is the log-likelihood computed from the full model, and L_C is the log-likelihood computed from with only a constant term.

Finally, we perform receiver operating characteristic (ROC) analysis to assess the predictive ability of the model. It is a graph of *sensitivity* (fraction of $y = 1$ that are correctly predicted or classified as $y = 1$) versus $1 - \textit{specificity}$ (fraction of $y = 0$ that are incorrectly classified as $y = 1$), across all cut-off points. The area under the ROC curve gives by how much the probability that a randomly selected household with $y = 1$ will be classified as $y = 1$ is greater than the probability of the same thing happening to a randomly selected household with $y = 0$. A model with no predictive power would have a 45° line, with a ROC area of 0.5—the greater the area under the ROC, the better the performance of the model.

Further, in the binary choice nonlinear regression models such as the above, β cannot be interpreted as the coefficient of marginal effects like those of the conventional regression models. In the above logit model, a marginal effect may be interpreted as the effect of a unit increase in a continuous variable in x on the probability that $y = 1$. The expression for which may be represented as follows.

Letting, $z_i = x_i' \beta$, the marginal effect of an element of x (say x_k with corresponding coefficient β_k) on the probability that $y = 1$ can be obtained as

$$\frac{\partial \Pr(y = 1 | x_i)}{\partial x_k} = \left\{ \frac{e^{z_i}}{(1 + e^{z_i})^2} \right\} \beta_k$$

From the above formula, it is clear that marginal effects of binary choice models are not constant over x . Typically, marginal effect is evaluated at a given point of the distribution (e.g., = average or median value). Of course, we can calculate marginal effects for all N observations and take the average of these effects, which is known as the as average marginal effect (AME).

For the logit model, the AME of the continuous variable x_k is

$$\text{AME} = \frac{1}{N} \sum_{i=1}^N \left[\left\{ \frac{e^{z_i}}{(1 + e^{z_i})^2} \right\} \beta_k \right]$$

However, since the independent variables chosen for the study are both categorical and continuous variables, we perform marginal analysis only for

the continuous variables, such as the per capita income of the manufacturing households.

Nevertheless, one of the alternate models for the present sort of exercise is the probit model. The probit model differs from the logit model discussed above by assuming a standard normal distribution for the error terms, in contrast to logistic distribution in case of the latter. Correspondingly, the $F(x'\beta) = \Pr(y = 1 \mid x)$, takes the following functional form:

$$F(x'\beta) = \int_{-\infty}^{x'\beta} \frac{1}{\sqrt{2\pi}} e^{-0.5u^2} du$$

And the parameters can be estimated by maximising the following likelihood function:

$$\ln L = \sum_{i \in D} \ln[F(x'_i\beta)] + \sum_{i \notin D} \ln[1 - F(x'_i\beta)]$$

As before, D is the set of observation for which $y_i = 1$.

In the probit model, we follow the same procedure as in case of logit model such as the Wald test, McFadden likelihood ratio and ROC for testing hypotheses that $\beta = 0$, goodness of fit and for assessing the predictive power of the model respectively. As before, we also assess the marginal effects and average marginal effects for the continuous independent variables present in our study. The formula for the same may be expressed as follows:

$$\frac{\partial \Pr(y = 1 \mid x_i)}{\partial x_i} = \left\{ \frac{\partial F(z_i)}{\partial z} \right\} \beta_k$$

Like that of the previous $z_i = x'_i\beta$, the marginal effect of an element of x (say x_k with corresponding coefficient β_k) on the probability that $y= 1$. Similarly, the AME may be expressed as follows:

$$AME = \frac{1}{N} \sum_{i=1}^N \left\{ \frac{\partial F(z_i)}{\partial z} \right\} \beta_k$$

Thus, we assess the influence of a chosen set of factors on the probability of participation in a for-profit microfinance programme through a logit model and cross check the findings through a probit model.

3.3 Variables and expected outcomes

In the previous section, the dependent variable is described, and a list of independent variables has been mentioned. In this section, we describe each independent variable and its expected impact on manufacturing households' participation in for-profit microfinance programmes.

Access to bank credit, be it commercial banks, regional rural banks (RRBs) or cooperatives, could have played an important role in the participation, as it is less usurious than the for-profit MFI credit. In bank credit, the rate of interest is low, and the tenure of the loan is large (RBI, 2011). The field survey observations also suggest that the for-profit MFI credit largely involves a weekly repayment system, whereas the same in the case of bank credit is either monthly or variable—depending on the borrower's convenience (as per the procedure of cash credit loans for the enterprises). Moreover, in contrast to the for-profit MFIs, which strictly follow a weekly repayment system and adopt a coercive recovery procedure, the banks even fail to send the demand notice for years in case of defaults, as observed in the field survey. Also, the loan processing charge is substantially less in the case of bank credit than that of the for-profit MFI credit. Further, the average amount of credit delivered by the banks is generally higher than that of for-profit MFIs. Thus, bank credit is always preferred over for-profit MFIs credit, but due to its inaccessibility, the manufacturing household may resort to the latter. Hence, the access to bank credit may be captured as a binary variable (yes = 1, no = 0) and its relationship with the probability of participation in the for-profit microfinance programme may be expected to be negative.

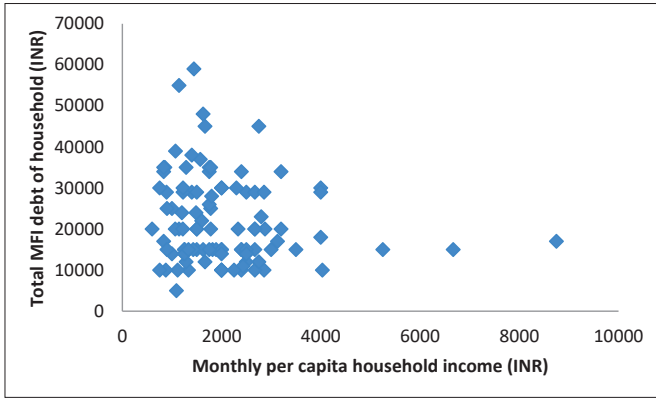
The other important variable that may explain the probability of participation in the for-profit microfinance programme could be the gender of the working owner of the manufacturing enterprise. As maintained earlier, the for-profit MFIs lend exclusively to women members of the household by forming a JLG of five to 15 members. Interestingly, in the survey, it was also observed that the working owner (if not female) borrowed from the MFIs through the female members of the household. Hence, if the working owner

is a female, the probability of participation increases. The gender of the working owner may be captured as a binary variable (1 = male, 0 = female) to explain the probability of participation and the expected relationship could be negative.

Besides gender, the educational status of the working owner could be an important variable in influencing participation in the for-profit microfinance programme. It is generally considered that a more educated person makes better decisions for the enterprise, especially as far as exploring alternative sources of finance is concerned. Of course, whether the decision amounts to a choice of for-profit MFI lending as the best source of credit or not is a different question, but it will definitely preclude the role of ignorance in choosing the former. As observed in the field survey, many borrowers hardly knew about the effective rates of interest or the ultimate cost of for-profit MFI debt. Interestingly, it was observed that some of the borrowers even considered the for-profit MFIs as governmental agencies. Thus, education is considered as a variable to explain participation; however, taking the available information into account, education is considered as a binary variable, i.e., 1 for matriculate and above, 0 otherwise. And it is likely to negatively influence the probability of participation.

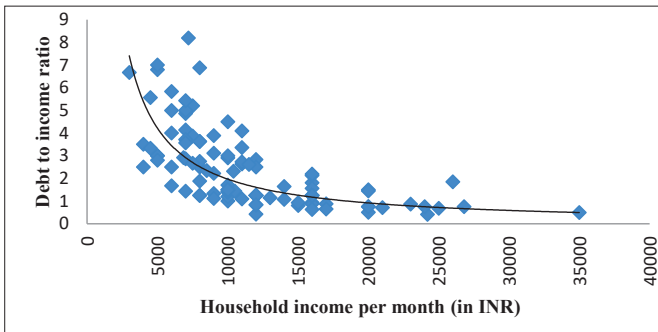
Apart from the above, the per capita income of the household could be one of the determinants of participation. Higher per capita income enhances the household's borrowing potential, and hence, its access to all the various sources of credit. Also, post-liberalisation, banks generally chose high net worth households for lending. On the other hand, from the demand side, since the for-profit MFI credits are almost as costly as that of the money lenders, any access to a relatively cheaper source of credit may lead to avoidance of the former. And the opposite may happen when the households are devoid of any alternate and cheaper sources of credit. Notably, at a low per capita income, the households are compelled to borrow from for-profit MFIs. The scatter plot presented in Figure 1 based on field survey data provides a glimpse of evidence in support of such an assertion.

Figure 1: Scatter Plots between Monthly Per Capita Income and MFI Debt of Households



Further, even if the alternate sources of credit are not relatively cheaper taking the transaction costs into account, the borrower may still shun the microfinance programme because of smaller size and shorter tenure of the loan, as observed in the field survey. Hence, there is more likely to be a negative relationship between per capita income and participation in the microfinance programme (Figure 2). And to explore the nature of relationship, the former has been considered in its logarithmic form.

Figure 2: Relationship between Household Income Per Month and Debt



As maintained earlier, debt servicing potential is one of the important aspects of for-profit MFI credit and the existence of wage labour could be one of its important indicators. In the poverty ridden low-income households,

a few of the members often work outside mainly as wage labour, despite having their own manufacturing enterprises at home. This could be due to the low profitability of their enterprises and diversification of earning sources. Nevertheless, the earnings from wage labour help them to meet the debt servicing schedules, which are of high frequency, usually weekly or monthly. Hence, one could expect a positive relationship between the existence of wage labour in a rural manufacturing household and participation in for-profit MFI lending programmes. To explore the same, wage labour may be considered as a binary variable, i.e., the existence of wage labour as 1, and the absence of it as 0 in each household surveyed.

Finally, the number of women and male workers in the household could be important factors in influencing the probability of accessing for-profit MFI credit. In rural households, a higher number of male workers could mean less economic vulnerability, given the gender disparity in wage/income earnings. The opposite could happen in the case of number of female workers. Hence, these two continuous variables, the number of male workers and female workers in the household, may affect the probability of accessing for-profit MFI credit negatively and positively, respectively.

All the various variables taken into consideration along with their expected signs have been summarised in Table 3.

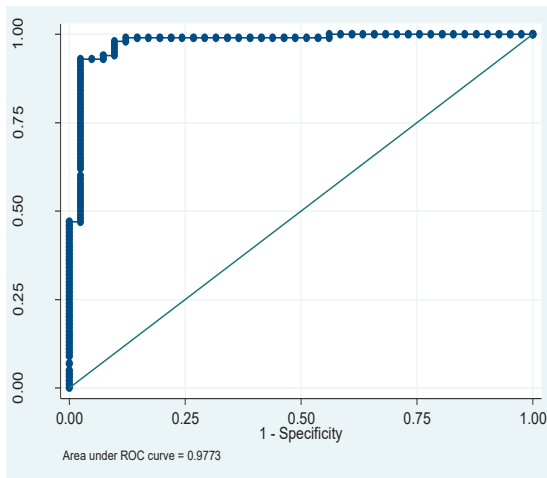
Table 3: Description of Explanatory Variables

Dependent variable: Participation in for-profit microfinance programme, y = 1 for participation, 0 otherwise		
Explanatory variables	Descriptions	Expected sign
Access to bank credit	Binary variable (yes = 1, No = 0)	Negative
Gender of working owner	Binary variable (male =1, female = 0)	Negative
Whether the working owner of the family educated or not	Binary variable (matriculate and above = 1, 0 otherwise)	Negative
Per capita income of household	Ln (per capita income)	Negative
Number of male workers in the household	Absolute number	Negative
Number of female workers in the household	Absolute number	Positive
Wage labour	Existence of wage labour in the household (1) and absence of it (0)	Positive

4. Results

The results of the estimated models are presented in Table 4. Both the logit and probit models provide similar results. However, our interpretation of β coefficients is confined to the estimated results of the logit model only. The Wald tests confirms the significance of the estimated coefficients and the high value of pseudo R^2 ensures goodness of fit. Further, the large area under ROC indicates high predictive power of the model (Figure 3).

Figure 3: ROC from Estimated Logit Model



The estimated results (Table 4) suggest that all the independent variables are significant except gender and education of the working owners, and number of female workers in the household. This implies that factors, such as whether the working owner is male or female, and above or below matriculation (as considered for being educated), do not matter as far as probability of participation in for-profit MFI lending is concerned. The former could be due to facts, such as close family ties allowing the male working owner of the manufacturing enterprise to obtain for-profit MFI loans through the female members of the household, the loan obtained might not be used for the purpose of the enterprise, etc. On the other hand, the latter could be on account of the very nature of the variable considered, i.e., hardly any differences prevail between the matriculate and non-matriculates at the

margins. Of course, the appropriate variable in this regard could have been a continuous one in the form of the number of formal education years. Further, even the number of female workers in the family does not matter as far as accessing microcredit is concerned. This could be because women members borrow for the entire family rather than for their personal need, and their earnings hardly matter as far as delivery of MFI credit is concerned.

Table 4: Results

Dependent variable: Participation of the household in the microfinance programme (1 = yes, 0 = no)				
Explanatory variables	Logit model		Probit model	
	Coefficients	Z statistics	Coefficients	Z statistics
Access to bank credit	-2.37**	-2.38	-1.17**	-2.49
Gender of the working owner	-0.19	-0.20	-0.11	-0.23
Education level of the working owner	0.10	0.11	-0.13	-0.28
Per capita income	-3.72***	-3.55	-1.91***	-3.97
Wage labour of household	2.99***	2.61	1.55***	2.98
Number of male workers in the household	-0.34*	-1.84	-0.19**	-1.99
Number of female workers in the household	0.33	0.86	0.16	0.82
Constant	31.34***	3.75	16.24***	4.24
Log pseudo likelihood	-26.26		-26.70	
Wald chi-square (7)	27.17***		36.65***	
Iterations completed	5		5	
Pseudo R2	0.69		0.69	
Number of observations	141		141	
Area under the ROC curve	0.974		0.973	
AME of per capita income	-0.20***	-6.96	-0.20***	-7.43
AME of number of male workers in the household	-0.02*	-1.81	-0.02**	-1.95

Note: *** denotes significance at 1%; ** denotes significance at 5%; * denotes significance at 10%.

However, among the other independent variables, the number of male workers in the household is significant at a 10% level whereas the rest are significant at a 5% level. Also, their influences on the household's probability of participation in accessing for-profit MFI credit are in conformity with expectations.

The negative coefficient for access to bank credit suggests that in the absence of availability of bank credit, the probability of people resorting to for-profit MFI credit increases. This corroborates the findings of Bezboruah and Pillai (2013). It appears that for-profit microfinance is certainly not a choice, but rather a compulsion on the part of the credit-needy rural households engaged in unorganised manufacturing. Possibly, it can be said that the dilution in the traditional roles of SCBs in the neoliberal policy framework has created a void in the rural financial landscape that for-profit MFIs are currently exploiting. Hence, one of the policy solutions could be a renewed thrust on expanding SCBs in the rural landscape of India.

Apart from access to bank credit, per capita income significantly influences the probability of participation in a for-profit microfinance programme. This finding is quite like that of Datta and Ghosh (2013). As expected, the negative relationship indicates that the probability of participation is higher at a sufficiently lower level of income and *vice versa*. However, this contrasts with the findings of Sangawan and Nayak (2021), which suggest that the outreach of for-profit MFIs is more inclined toward wealthier clients, as maintained in the literature review above. This could be due to area specific characteristics and the volume of for-profit MFI business. However, the estimated AME suggests that a 1% rise in per capita income will reduce the probability of accessing for-profit MFI credit to the extent of 21%.

Figure 3, which shows scatter plots between the ratio of debt to per capita monthly household income and the latter, with a superimposed non-linear fitted line, provides a better picture in this regard. The superimposed line suggests an almost inverse relationship between income and access to for-profit MFI credit. This suggests that for-profit MFIs consciously target the vulnerable poor. Given the nature of their operation, it certainly puts a question mark on the efficacy of for-profit MFIs as a policy for the poor. Hence, future poverty redressal policies, besides a course correction for for-profit MFIs, should focus on a renewed thrust for the not-for-profit MFIs.

However, among other variables, the number of male workers is significant in explaining the probability of participation. As expected, its coefficient is negative (Table 4), which suggests that the probability of participation decreases for households with higher male participation in the workforce. Also, its estimated AME reveals that a 1% per rise in the number of male workers in the family will reduce the probability of accessing for-

profit MFI credit by 2% or so. Considering the general fact that a higher number of male workers reflects relatively higher household income, it may be said that the economically better-off families generally stay away from MFI credit.

Finally, wage labour appears to be a significant determinant for accessing for-profit MFI credit. The importance of determinants like the presence of male members and the existence of wage labour in the family is supported by Ding and Abdulai (2020). As noted above, their study found that factors like family size, dependency ratio and casual wage influence access to for-profit MFI credit in China. Nevertheless, households with wage labour are more likely to participate in microfinance programme. This might be because households with wage labour have a high demand for and supply of credit—high demand for credit because they are basically low-income households, and high supply of credit because they are readily chosen by for-profit MFIs. They are chosen because their wage labour generates cash income on a regular basis, which helps them to meet the weekly instalments of loans. Finally, factors like gender and education of the working owner of the enterprise, and the number of female members in the household do not affect access to for-profit MFI credit, because unlike not-for-profit MFIs, the former focus on generating business rather than development.

Thus, the determinants like low income, lack of male employment, and the existence of wage labour in households influence access to for-profit MFI credit despite the latter being infamous. In fact, all these three determinants have one thing in common, they reflect the poverty of the household. Above all, it is the lack of access to commercial bank credit that compels households to resort to for-profit MFI credit. In other words, poor households engaged in unorganised manufacturing activity and excluded by commercial banks resort to the high costs of the highly demanding for-profit MFI credit.

5. Conclusion

The findings of this study suggest that some factors, such as access to bank credit, per capita income, number of male workers, and wage labour of the household, are the determining factors behind accessing the ‘infamous’ for-profit MFI credit. Manufacturing households’ resort to for-profit MFI credit primarily in the absence of bank credit. Further, the participation of the rural manufacturing households in the for-profit microfinance programmes

increases with the decline in their per capita incomes. Accordingly, manufacturing households with wage labour and fewer male workers are more likely to access for-profit MFI credit. Thus, the people at the bottom of the income hierarchy largely depend on for-profit MFI credit, although it continuously erodes their consumption and living standards. Indeed, the dilution of the traditional role of commercial banks has given space to for-profit credit sharks in the rural economy. In this perspective, the affirmative policy prescription could be that banking in rural India should be with a humane face. On the one hand, commercial banks should expand their operation and follow the traditional social banking norms. On the other, not-for profit MFIs should be promoted and for-profit MFIs should be nudged to deliver better results. As far as for-profit MFIs are concerned, not only should the tenure and size of credits be increased, but the frequency of repayment, rate of interest and upfront charges should be reduced. Also, coercive recovery practices adopted by for-profit MFIs for the recovery of loans should continue to be reprimanded. This can be achieved with a combination of guidelines, strictures, and incentives. Above all, the rural manufacturing activities should get priority as far as timely and affordable delivery of credit is concerned.

The present study, however, has some limitations. One of the major limitations is that it is based on a small sample survey, as far as size and coverage are concerned. Of course, the findings suggest that some of the pre-selected factors influence the target groups' access to for-profit MFI credit, but these factors are not an exhaustive list—there could be several other factors which might be influencing the same. Hence, at the most it can be said that the findings just provide a snapshot of the scenario associated with functioning of for-profit MFIs. Moreover, although the study provides a new dimension to future research on for-profit MFI credit, its findings cannot be generalised, as the sample data is area and time specific. Notably, the survey was conducted in a particular geographical setting during the pre-Covid-19 times. Undoubtedly, Covid-19 has rattled the economic condition of people in general, and the poor, and hence one can guess its impact on for-profit MFI borrowers. But to correctly assess the impact, it is essential to have an in-depth study. Thus, future research on the topic should study the impact during the post-Covid period using longitudinal data, preferably large in sample size and coverage.

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