A For-profit Model of Microcredit: Can Profit-driven Firms Improve Financial Inclusion in India?

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ABSTRACT

Microcredit has become a proven means of poverty alleviation. However, its implementation in India is flawed. High interest rates, incompetent use of credit, and insufficient loan sizes are just some of the problems well-documented in literature. This paper seeks to assess if these problems can be alleviated by a for-profit model of microcredit, and hence if such a model can sustainably improve financial inclusion in India. The role of profit-motives in microcredit in India has only been analysed from a theoretical perspective in literature thus far, and so this paper adds to existing research by bringing in an empirical perspective through data from Microfinance Institutions (MFIs) from the MIX Markets database. A baseline binary Logistic Classifier is trained, after which proposed models of a Decision Tree Classifier and a Gradient-boosted Tree Classifier are trained. Feature analysis is conducted on the models, and the results are used to devise profit-maximizing strategies. These strategies are then analysed to assess if profit-driven companies can improve financial inclusion in a socially desirable manner. The study finds that for-profit incentives can increase the spread, efficiency, and accessibility of microcredit while potentially fostering competent use of credit and bringing down the cost of borrowing. However, the study also notes the requirement for regulation in the growth and means of enforcing repayment in such for-profit models. Further, the study observes that a for-profit model may increase credit risk, and it will fail to allocate credit to the lowest strata of the poor. As such, for-profit firms must be complemented by not-for-profit MFIs to improve financial inclusion for all of the Indian poor.

1. Introduction

Microcredit has been hailed as a means of alleviating poverty and promoting financial inclusion. It has been at the center of the microfinance revolution that was pioneered by Dr. Muhammad Yunus, the founder of the Grameen Bank. Especially in India, where rural credit was dominated by informal local lenders who charged steep interest rates and employed inhumane methods of enforcing repayment, microcredit offered a sustainable and promising means of uplifting the poor.

Microcredit refers to the provision of small loans to low-income borrowers (Meade, 2001). These loans are typically unsecured (without collateral) and made at interest. What qualifies as a “low-income” borrower varies by region, but in Bangladesh it is more strictly defined as a borrower who owns less than 0.5 acres of land and depends solely on wages as a source of income.

Although potent in theory, microcredit in India is laden with social and financial issues, and is still limited in its reach. Small loan sizes, high transaction costs, and a high proportion of NPAs (Nonperforming Assets) are amongst several well-documented factors that limit the spread and efficiency of microcredit. This paper will aim to assess if profit-maximizing in microcredit can overlap with social goals, and as such, if the expansion of for-profit models of microcredit is a suitable manner to increase financial inclusion in the country. To devise profit-maximizing strategy, profit is modelled using chosen features from selected companies. Data is obtained from the MIX Market database, and companies in regions economically comparable to India are included. A baseline Logistic Classifier is trained, as well as proposed models of a Decision Tree Classifier and a Gradient-boosted Tree Classifier. Feature analysis is conducted on the models, and the results are used to devise profit-maximizing strategies. Economic analysis and literature are then used to assess if profit-oriented companies can improve financial inclusion in an ethical and socially desirable manner.

The outline of the paper is as follows: section 2 will cover a brief overview of microcredit in India, including its history, models of implementation, and a literature review about the state of microcredit in India. Section 3 will describe the methods and sources of study. Section 4 will present and discuss the results, and section 5 will provide a conclusion.

2. A Brief Overview of Microcredit in India

2.1 History

The microcredit movement, pioneered by Muhammad Yunus and Al Whittaker, made its way to India in the early 1970s. Although rural credit cooperatives had served as a means of providing credit to the poor even before Indian Independence in 1947, significant growth in the microcredit industry was seen only in the late 20th century. Part of this can be attributed to the nationalization of banks in 1969, which resulted in the formation of Regional Rural Banks (RRBs) and the adoption of priority sector lending. State-driven initiatives resulted in the rapid growth of microcredit over the next decade, after which new models of microfinance emerged to supplement the growing industry. SHGs (Self-help groups; discussed further in 2.2) were among the first of these to emerge, and in the mid-80s, SHG-bank linkages were pioneered by NGOs (see 2.2). The SHG-bank linkage model was taken up and promoted by NABARD (National Bank for Agriculture and Rural Development), which aided in expanding the scale of the model. Around the same time as SHGs first formed, NGOs also became providers of microcredit. (Makharia, 2020)

However, though microcredit had been proven effective, conventional banks were hesitant to loan to poor sections of society without collateral. In the late 20th century, successful experiments by Muhammad Yunus birthed the Grameen Bank, dedicated to microfinancial services. This spurred a paradigm shift in the microfinance industry, seeing the birth of for-profit microcredit institutions and the assimilation of microcredit into mainstream banking in India. The commercialization of microfinance took place in India in the early 21st century, which resulted in microcredit becoming not just a tool for poverty alleviation, but also a financially sustainable means of accessing an untapped market. Since, there have been both successful and unsuccessful attempts at scaling private microcredit. An issue that arose with the expansion and commercialization of microcredit resulted was exploitative methods of collection employed by unregulated MFIs, which ultimately resulted in farmer suicides in Andhra Pradesh and a changed perception of microcredit in India.

2.2 Structures of Microcredit

Self-Help Groups (SHG-Bank Linkage Model)

From Malegam (2011): As of 2011, the SHG-Bank Linkage Model accounted for 58% of all microcredit in India. Under this model, rural inhabitants, typically women, are encouraged to form a group and contribute their savings to this group. This pool of savings, supplemented by bank loans, acts as a source of credit for members of the group for income-generating or livelihood-promotion activities. Meetings are held at regular intervals (typically weekly or monthly) in which savings are contributed and repayments are made. The state, through NABARD, aids in the establishment and training of Self-Help Promoting Institutions (SHPIs), which facilitate credit-linkages for SHGs.

Joint-Liability Groups (JLG)

NBFCs, both for-profit and not-for-profit, encourage rural inhabitants to form a group. The NBFCs lend to individual members of this group. The loans are guaranteed by all members of the group, and so the members are "jointly liable" for loans. Default on a payment by a single member results in the entire group being cut off, and in this manner social pressure is effective in reducing the number of NPAs. For-profit models of NBFCs that work with JLGs have attracted significant investment.

NBFCs and SHGs accounted for 92% of the outstanding microcredit loan portfolio in 2011. The balance 8% was made up by trusts, societies, and thrift and credit-cooperatives. The discussion in this paper will focus mainly on NBFCs, operating both for-profit and not-for-profit.

2.3 Literature Review

Problems in the Industry

While the benefits of microcredit are well established and talked about, recent research has also worked to expose some prominent issues relating to microcredit. This section will use existing literature to identify such issues. The discussion in this section will be used as a reference in 4.1.3, to analyse if profit-maximisers can alleviate some of these issues.

Shankar (2007) analysed the costs of lending in microcredit, and found that operational costs were very high. These costs translated into higher interest rates (up to 30%) for poor borrowers. Results of an empirical analysis identified field worker compensation and a small number of borrowers per field worker as the primary drivers of high operational costs. As such, this paper highlighted productivity and efficiency as important factors in bringing down operational costs, which further could reduce the cost of borrowing.

Swaminathan (2007) compares microcredit provided by NGOs versus that provided by banks, considering the reach and costs of lending. Further, the effect of scale of operations on microcredit was assessed. The paper finds that NGOs incur higher operational costs than banks, and in accordance with Shankar (2007), Swaminathan notes that these costs are transferred to borrowers in the form of greater interest rates. Unlike Shankar (2007), however, Swaminathan identifies costs of monitoring as the greatest contributor to high interest rates, though not from empirical analysis. The paper comments on the strengths of rural banking systems in the form of scale, specialization, and cross-institution coordination, though notes that these banks still fail to meet social goals.

Research has also found problems in the effectiveness of microcredit. Guérin et. al (2015) finds that, in their area of study in south India, microcredit and self-employment are not correlated. They attribute this to social constructs specific to India, such as gender-based norms and power systems. Most notably, this paper suggests the implementation of supporting financial schemes - such as self-employment and saving schemes - to improve financial inclusion and enhance the effect of microcredit. A study by Basix, an NGO in the field of microcredit, found that 52% of their three-year-plus borrowers reported increases in income, 23% reported no change, and 25% reported a decrease in income. In their assessment, they also identified issues that could be resolved with the provision of complementary financial services. In agreement with this, Mahajan (2007) criticizes the idea that microcredit is sufficient to generate self-employment, and argues for the need for complementing financial services of saving and insurance in order to truly help alleviate poverty.

Mahajan also emphasizes on the risk of funding microcredit versus funding social development programs in health and education becoming a policy choice, and further comments on the ineffectiveness of small loan sizes (on average Rs. 2000) typically given by microcredit institutions. Dasgupta (2005) further notes the role of inadequate monitoring in producing a large number of NPAs and consequently too small an average loan size. Due to these small loan sizes, Bateman and Chang (2009) find that the effects of microcredit are prevalent only in the short-run, and they tend to disappear in the medium-to-long run.

In summary, there are two overarching problems in the Indian microcredit industry identified in literature: 1) High operational costs translating to high interest rates and 2) Inability of borrowers to make competent use of loans. These problems will be the focus of the discussion in this paper.

3. Methods

3.1 Data

The data is sourced from the MIX Market data catalog, consisting of 3,114 firms from regions across the world. To accurately capture the situation in India, only firms in regions with a level of economic development similar to South Asia were included: East Asia and the Pacific, South Asia, North Africa & The Middle East, and Latin America and the Caribbean. A single firm may have multiple entries corresponding to different years. Each entry is treated independently. Various indicators from each firm are used as regressors in the model. The indicators and their descriptions are provided in table 1.

Each feature was normalized to between 0 and 1 such that they were on a comparable scale for feature analysis. To improve the accuracy of the model, 7 additional engineered features were included, the descriptions of which are present in table 1. Each entry underwent binary classification into 0 (in loss) or 1 (in profit). A train-test split with a 25% test-set weight was carried out, and to correct a class imbalance in the training set, entries for firms in loss were resampled (randomly repeated).

Table 1 Included Features and their descriptions

Indicator	Description
Number of Loan Officers	The number of employees whose main activity is to manage a portion of the gross loan portfolio. A loan officer is a staff member of record who is directly responsible for arranging and monitoring client loans
Gross Loan Portfolio	All outstanding principals due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off.
Number of Active Borrowers	The number of individuals who currently have an outstanding loan balance with the financial institution or are primarily responsible for repaying any portion of the gross loan portfolio. Individuals who have multiple loans with a financial institution should be counted as a single borrower.

Number of Loans Outstanding	The number of loans in the gross loan portfolio. For financial institutions using a group lending methodology, the number of loans should refer to the number of individuals receiving loans as part of a group or as part of a group loan.
Short Term Delinquency	All outstanding principals due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off. Segmentation based on the principal balance of all loans outstanding that have one or more installments of principal past due or renegotiated. The total principal value outstanding of loans that have at least one payment at least 1 and up to 30 days overdue.
Long Term Delinquency	All outstanding principals due for all outstanding client loans. This includes current, delinquent, and renegotiated loans, but not loans that have been written off. Segmentation based on the principal balance of all loans outstanding that have one or more installments of principal past due or renegotiated. The total principal value outstanding of loans that have at least one payment more than 180 days overdue
Average Loan Per Borrower	Gross Loan Portfolio / Number of Active Borrowers
Cost Per Borrower	Operating Expense / Number of Active Borrowers
Borrowers Per Loan Officer	Number of Active Borrowers / Number of Loan Officers
Profit	The total of income less expenses, excluding the components of other comprehensive income.
Feature 1	Gross Loan portfolio / Number of Officers
Feature 2	Number of Loans Outstanding / Number of Officers
Feature 4	Number of Officers^2
Feature 5	Gross Loan Portfolio^2
Feature 6	Number of Active Borrowers^2
Feature 7	Number of Loans Outstanding^2

3.2 Models

Inputs in profit were given a label of 1 and inputs in loss were given a label 0. Binary classification models were trained using the regressors in table 1.

3.2.1 Baseline Model: Logistic Regression

Logistic Regression is a supervised classification algorithm that models the probability of a certain class or event. Consider the following linear model:

$$M(X_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} \ldots . + \beta_p x_{pi} + \varepsilon$$

Where X_i is a p-dimensional feature vector for example i, $\beta_1, \beta_2, \ldots \beta_p$ are the regression coefficients, x_{1i},x_{2i},...$x_{pi}$are the features of example i, β_0 is the bias term, and ε is the error term where ε is normal with mean 0 and standard deviation σ^2. In other words, if X_i is a feature vector and $\beta$is a vector of regression coefficients, then

$$M(X_i) \ = \ \beta^T X_i$$

The sigmoid function, g, is defined as follows:

$$g(z) \ = \ \frac{1}{1 + e^{-z}}$$

Next, we define the hypothesis, h, as follows:

$h(X_i) \ = g(\beta^T X_i)$ or $h(X_i) = g(M(X_i))$

We can now define conditional probabilities of each class for example i:

$$P(y_i = 1 \mid X_i) \ = \ h(X_i)$$
$$P(y_i = 0 \mid X_i) \ = \ 1 - h(X_i)$$

The model is trained using a standard optimization function. The optimization function is defined as follows:

$min[J(\beta)]$, where

$$J(\beta) \ = \ \sum_{i=1}^{n} -y_i log(h(X_i)) - (1 - y_i) log(1 - h(X_i))$$

Gradient descent is run on the cost function J until convergence.

3.2.2 Proposed Models

<u>Proposed Model 1: Decision Tree Classifier</u>

The decision tree is trained using an ID3 algorithm from the sklearn package. A decision tree model is preferred because it mimics a human decision-making process, which makes it interpretable and allows the importance of each individual feature to be easily tracked, unlike in neural networks or random forest classifiers.

We start with the root node S. S contains all the examples in the training set. The algorithm iterates through every feature in S and calculates the Entropy (E) and Information Gain (IG) of the feature. Entropy is a measure of randomness in the data set. Entropy for each feature is given as follows:

$$E(S) \ = \ \sum_{i=1}^{c} -p_i log_2(p_i)$$

Where S is the current state, c is the number of decision classes and p_i is the probability of the i^{th} class in state S.

Information gain measures how useful the chosen feature is in separating the training set into the decision classes. If a split results in little change in the distribution of classes in the subsets, the feature presents a low information gain; if a split results in a better separation of decision classes, then the feature presents a high information gain. Mathematically, information gain is defined as follows:

$$IG(S,X) = E(S) - E(S,X)$$

Where S is the current state and X is the chosen feature. $E(S)$ can be thought of as the entropy before splitting the node using feature X, and $E(S,X)$ is the entropy after splitting the node using feature X.

The algorithm splits the root node S by the feature with the lowest entropy and maximum information gain. The algorithm iterates over every unused feature and accordingly splits the subsets of S using the same principle. Each node that is split is known as a Decision Node. The algorithm runs until the entropy of a branch is 0, at which point the node does not split further: it becomes a Leaf Node.

Feature Importance

We calculate the importance of each feature to assess which factors are most valuable in predicting the profitability of a firm. To do this, the Gini Importance of each node in the tree is calculated as follows:

$$ni_j = w_j c_j - w_{left(j)} c_{left(j)} - w_{right(j)} c_{right(j)}$$

Where ni_j is the importance of node j, w_j is the weighted number of samples reaching node j, c_j is the impurity of node j, $left(j)$ is the child node from left split on node j, and $right(j)$ is the child node from right split on node j.

The importance of each feature is then calculated as follows:

$$fi_i = \frac{\sum_{j:node\ j\ splits\ on\ feature\ i} ni_j}{\sum_{k \in all\ nodes} ni_k}$$

Where fi_i is the feature importance of feature i and ni_j is the importance of node j. Feature importance values are between 0 and 1.

Proposed Model 2: Gradient Boosted Decision Tree Classifier

A gradient boosted tree classifier uses several weak machine learning models to create a model with high performance. Each successive model improves upon the errors from the previous model. A brief outline of the process is as follows:

A decision tree classifier is trained and tested. The errors are identified and greater weight is given to the incorrect predictions, which is used to train another model. This process is repeated several times, and the final model is obtained by weighting the mean of each model.

SHAP Importance

Gradient Boosting Decision trees compromises explainability using standard feature importance. A Shapley value is calculated for each feature instead. The Shapley value for a feature is the marginal contribution of the feature value across all possible coalitions. Intuitively, a Shapley value can be interpreted as the marginal contribution of a feature in explaining the "gain" on a given prediction (i.e., the difference between the actual prediction for an example and average prediction across all examples). The Shapley value for each feature is averaged across all examples in the test set. A mathematical formulation for the Shapley value for feature i is as follows:

$$\varphi_i(v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\ (n - |S| - 1)!}{n!} (v(S \cup \{i\}) - v(S))$$

Where S is a subset of the features used in the model, $N$is the set of all features used in the model, $v(S)$is the prediction value for features in set S that are marginalized over features not included in set S, and n is the number of features.

3.2.3 Training Methods

Each model was trained 10 times with a random train-test split. Results across random states have been averaged. A comparison of the models considered is provided in Table 2.

4. Results and Discussion

4.1 Model Results

4.1.1 Baseline Model

The test-set accuracies for the baseline model are reported in table 3. The average accuracy was 64.74%, which was relatively poor. Due to its explainability, the logistic classifier was used to identify if the impact of each feature on profit was "positive" or "negative", by analysing the coefficients of the model. The results are shown in table 4.

Table 3 Test Set Accuracies for Logistic Classifier

Random State	Test Set Accuracy
1	0.6859
2	0.6025
3	0.7244
4	0.6346
5	0.6218
6	0.6282
7	0.6026
8	0.6538
9	0.6474
10	0.6731

Table 4 Classification of Impact of Features on Profit

Feature	Impact on Profit
Number of Officers	P*
Gross Loan Portfolio	P
Number of Active borrowers	P
Number of Loans Outstanding	P
Short Term Delinquency	N**
Long Term Delinquency	N
Average Loan Per Borrower	N
Cost per Borrower	N
Borrowers per Loan Officer	P
Feature 1	N
Feature 2	P
Feature 4	P
Feature 5	P
Feature 6	P
Feature 7	P

*Positive coefficient in the logistic classifier
** Negative coefficient in the logistic classifier

4.1.2 Proposed Model Results

The test-set accuracies for the proposed models are in tables 5 and 6. The average accuracy of the ID3 Decision Tree Classifier was 87.94%, and the average accuracy of the Gradient-Boosted Tree Classifier was 88.78%. Both models had comparable accuracies, and low accuracy standard deviations of 0.01983 and 0.02349 respectively, indicating stable results.

Table 5 Test Set Accuracies for Decision Tree Classifier

Random State	Test Set Accuracy
1	0.8846
2	0.8782
3	0.8782
4	0.8525
5	0.8717
6	0.8974
7	0.8910
8	0.8910
9	0.9102
10	0.8397

Table 6 Test Set Accuracies for Gradient Boosted Tree Classifier

Random State	Test Set Accuracy
1	0.8974
2	0.8718
3	0.8974
4	0.8526
5	0.9423
6	0.8910
7	0.8718
8	0.9038
9	0.8782
10	0.8718

Feature Importance

Feature Importance values are averaged across each of the 10 random states in both models. They are presented in tables 7 and 8. The magnitude of Shapley values is taken into account, disregarding the sign. Both Shapley values and feature importance indicate that each non-engineered feature is significant.

Table 7 Average Feature Importance of Non-Engineered Features in the Decision Tree Model

Feature	Feature Importance
Number of Officers	0.026
Gross Loan Portfolio	0.094
Number of Active borrowers	0.086
Number of Loans Outstanding	0.118
Short Term Delinquency	0.076
Long Term Delinquency	0.056
Average Loan Per Borrower	0.068
Cost per Borrower	0.117
Borrowers per Loan Officer	0.052

Table 8 Average Shapley value of Non-engineered Features in the Gradient Boosted Tree Classifier

Feature	SHAP Importance
Number of Officers	0.373
Gross Loan Portfolio	0.421
Number of Active borrowers	0.103
Number of Loans Outstanding	0.162
Short Term Delinquency	0.564
Long Term Delinquency	0.520
Average Loan Per Borrower	0.338
Cost per Borrower	0.920
Borrowers per Loan Officer	0.124

Table 9 Shapley value Waterfall Plots for 10 Random States

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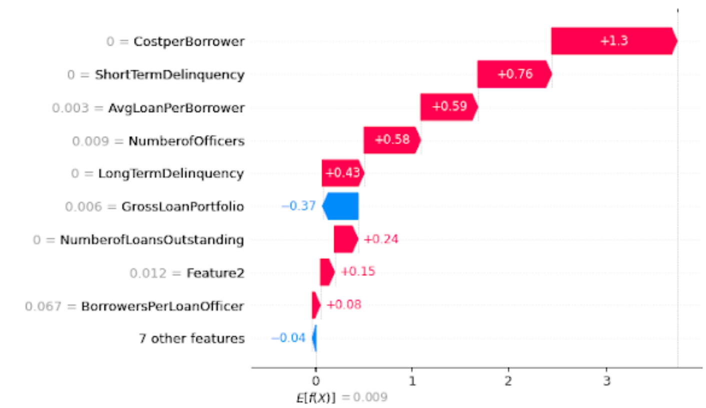
<tr><td>1</td><td>
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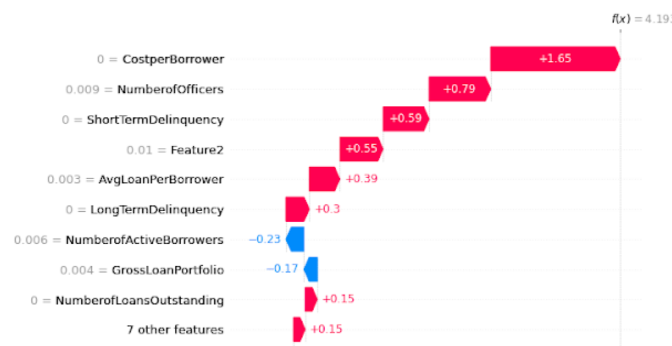
<tr><td>2</td><td>
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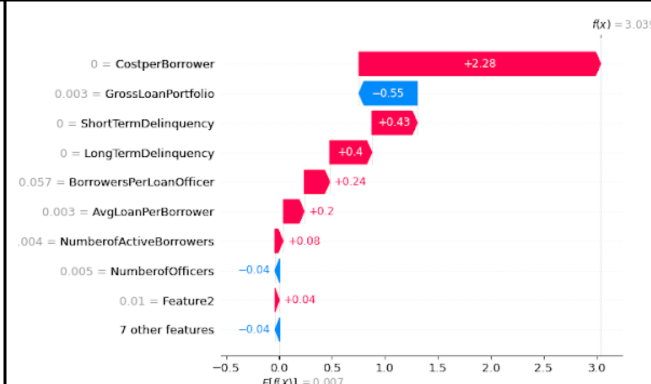
<tr><td>3</td><td>
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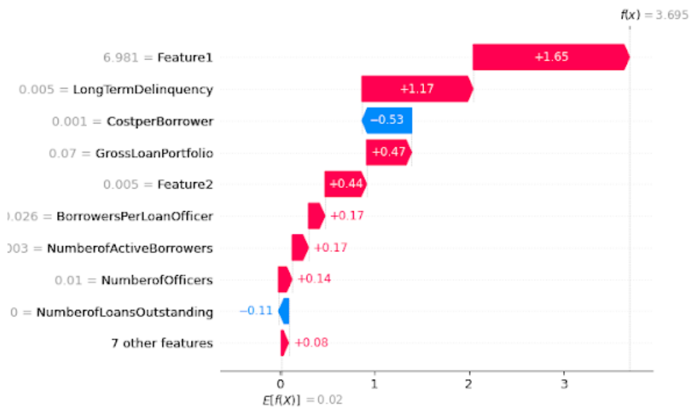
<tr><td>4</td><td>
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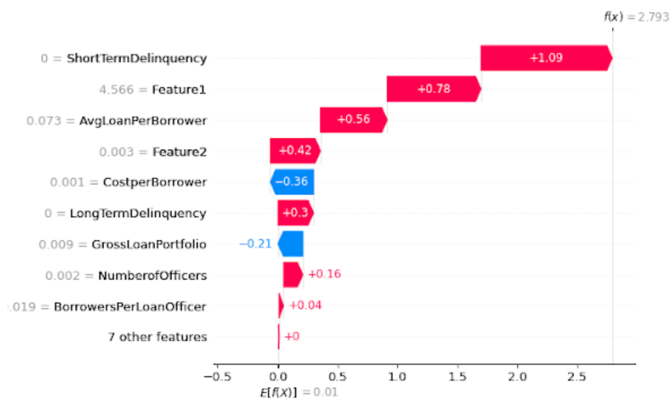
<tr><td>5</td><td>
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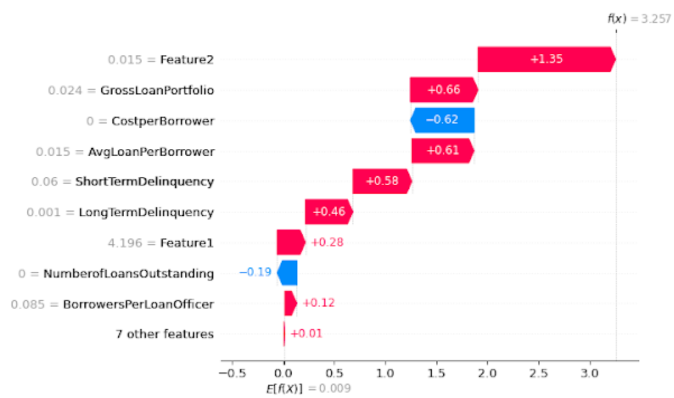
<tr><td>6</td><td>
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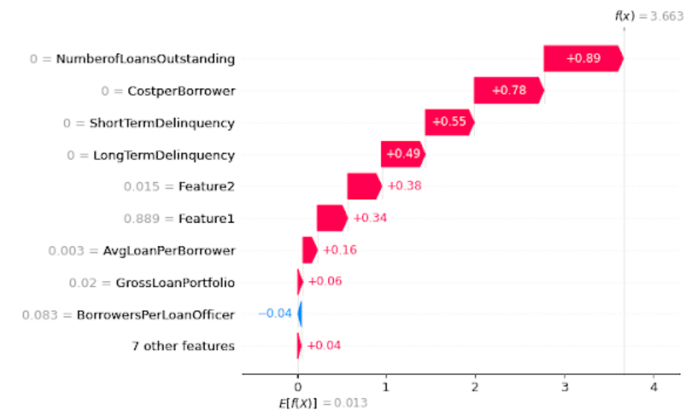
<tr><td>7</td><td>
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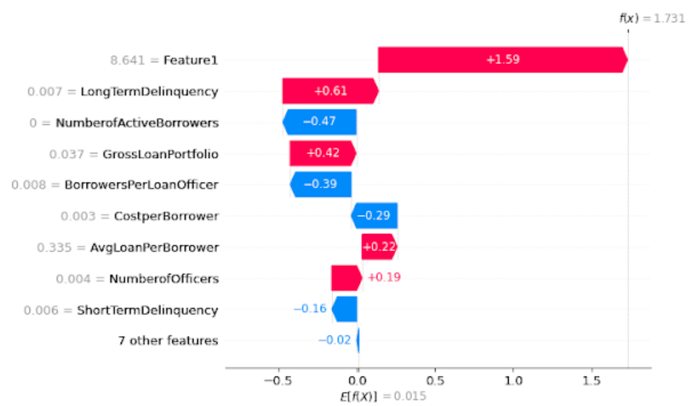
<tr><td>8</td><td>
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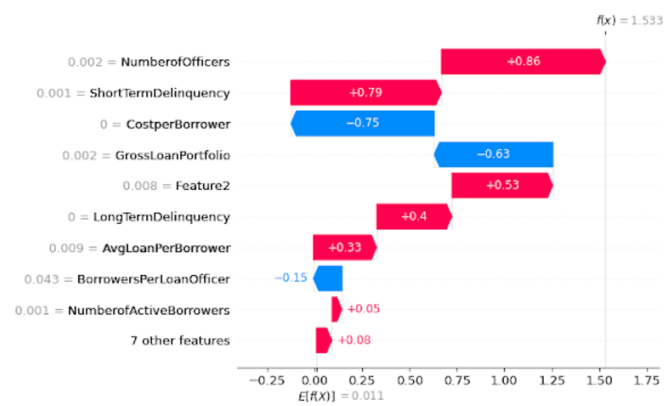
<tr><td>9</td><td>
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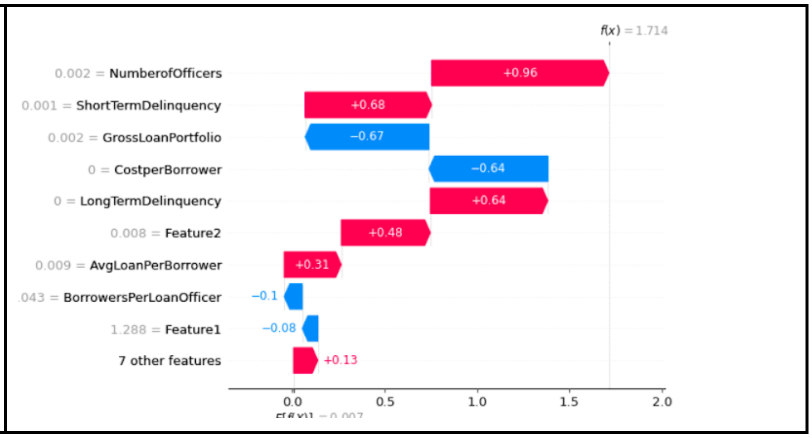
10	

4.2 Discussion

4.2.1 Practically Interpreting Results into a Profit-Maximization Strategy

Using the model results, we derive a coherent profit-maximizing strategy of a rational lender. Since both proposed models produced comparable accuracies, results from both are considered in this discussion.

(1) There is some disagreement in the relative importance of each feature as measured by feature importance and Shapley values, but both agree on the trivial case of cost per borrower being important in determining profit.

(2) Short-term delinquency and long-term delinquency both appear important, and as table 4 shows, have a negative effect on profit. This suggests stricter regulation on who can borrow as a means of risk aversion (to alleviate long-term delinquency) coupled with stricter repayment schedules to prevent defaults on individual payments (addressing short-term delinquency).

(3) Table 4 also identifies a negative relationship between average loan per borrower and profit. Table 7 suggests high feature importance (0.118, 0.094, and 0.086) for Number of Loans Outstanding, Gross Loan Portfolio and Number of Active Borrowers respectively, and table 8 also indicates Loan portfolio size (Shapley value of 0.421) as an important feature. Table 7 identifies Number of Loans Outstanding, Gross Loan Portfolio, and Number of Active Borrowers as positively related to profit. Together, these factors suggest that making smaller loans to a large borrower base is more conducive to profit than larger loans to fewer borrowers. This is unintuitive - clearly, large-ticket loans operate at lower unit costs and should be more profitable. As such, smaller ticket loans favouring greater profit could point to problems at an industry level: (1) Poorly evaluated large-ticket loans and (2) inexperienced borrowers unable to competently make use of capital. Alongside greater emphasis on risk-assessment, supplementing credit with education schemes may allow MFIs to make larger ticket loans and increase their own profitability. Insurance schemes can also help MFIs avert credit risk in case of illness or death of borrowers, per Farooqui (2013).

(4) Table 4 also indicates a positive relationship between Borrowers per Loan Officer and Profit, due to lower unit costs. Because of the hands-on nature of the work performed by loan officers, this further indicates that firms operating more densely in geographic terms are more likely to be profitable.

These findings indicate one other crucial result: under the right conditions, economies of scale are possible (contrary to the findings of Malegam, 2011 and other literature). Lending to more borrowers, issuing more loans, and establishing more branches (so as to reduce the geographical reach of each one) are all growth factors that are conducive to lower unit costs and greater profitability.

4.2.2 Evaluation: Can Profit-maximisers meet Social Goals?

There are several implications for social goals presented by profit-maximizing objectives.

(1) An emphasis on lowering unit-costs can reduce the operational area of individual branches, which (1) increases accessibility for borrowers, and (2) could potentially bring down interest rates. A criticism of Indian MFIs is that interest rates are too high; lower unit costs, while not guaranteed to bring down interest rates, can provide a mechanism and reason to do so.
(2) Expanding the range of financial services to include insurance and education schemes may be in the interest of for-profit MFIs. As noted by Mahajan (2005) and a study by Basix (an NGO), schemes to train microentrepreneurs and the provision of insurance can allow borrowers to utilise capital more effectively, thus improving their own financial situation while reducing credit risk. However, it is uncertain if such schemes are scalable, or if the associated costs outweigh the benefits received by MFIs.
(3) Stricter risk-aversion policies have mixed implications. Ensuring the ability of borrowers to repay can reduce piling debt and associated suicides. However, this is likely to contribute to greater capital being allocated to higher-strata of the poor, who are more reliable than the poorest sections of society. This is effective in a manner, because as Hulme and Mosley (1996) notes, the effect of microcredit on income is roughly proportional to starting income. As such, capital is utilised most efficiently by higher strata of the poor. However, emphasis on risk-aversion may also contribute to the "Mission Drift" in microcredit, wherein the poverty alleviation function of microcredit fails to reach the poorest sections of society. As such, for-profit MFIs are insufficient in addressing social goals alone; they benefit specific sections of society, and financial inclusion of the lowest strata must be achieved through not-for-profit models of microcredit. Moreover, risk-aversion policies that enforce stricter repayment schedules may take away from the flexibility of microcredit that has allowed it to become a useful tool in alleviating poverty.
(4) The presence of economies of scale suggests that for-profit MFIs can immensely expand the reach of microcredit. Further, larger firms operating with many branches can have cost advantages which, under regulation, could reduce the cost of microcredit by bringing down interest rates without compromising the financial sustainability of MFIs.
(5) Profitable microcredit may result in increased competition between for-profit firms. This can be an effective mechanism to bring down interest rates, but the reach of microcredit must expand to allow for competition in the first place. Moreover, increased competition resulting from profitability may also result in greater risk, as noted by McIntosh and Wydick (2005). Borrowers may be able to borrow from multiple sources simultaneously, which can both increase debt on the poor and risk on MFIs.

An important aspect that must be considered is the ethics of for-profit microcredit. Many argue that profiting off of lending to the poor is inherently unethical. Though this argument is easily circumvented if for-profit models benefit the poor, a more concerning problem is if private bodies can be adequately regulated and trusted not to exploit the poor. For-profit microcredit at a scale is not new to India; SKS Microfinance and Equitas Holdings were two MFIs operating at scale that went public in the late 2000s. However, private microcredit imploded under a series of allegations of improper and violent methods of recovering payments as well as accusations of exploitation. Farmer suicides in Andhra Pradesh became a central narrative of for-profit microcredit, leading to the formation of regulatory bodies and a general distrust in the industry. Default rates skyrocketed, and loans made fell sharply, as people refused to associate with for-profit MFIs.

For-profit MFIs can provide a natural way of increasing financial inclusion, but it is necessary that stricter regulations are imposed. History tells us that controlled growth is necessary for the financial sustainability of microcredit at scale and that regulating the methods of collecting repayment is necessary in building trust in the institutions. Without regulation, the poor may be left at the hands of exploitative lenders, which can reinforce poverty rather than alleviating it.

5. Conclusion

Through feature analysis, this paper finds that for-profit models of microcredit can aid in bringing down the cost of borrowing and expanding the reach of microcredit through economies of scale. Analysis points towards the need for greater emphasis on risk aversion in for-profit models due to poor evaluation of high-ticket loans, which can potentially lead to the expansion of financial services offered to the poor but may also contribute to a “Mission drift” in the poverty alleviation function of microcredit, which will fail to reach the poorest sections of society. Though, analysis does suggest that for-profit institutions may allocate capital more efficiently to more capable borrowers, which can help spur financial inclusion and reduce credit risk in the industry.

Overall, for-profit microcredit is a beneficial and plausible model, allowing for organic growth of the microcredit industry while improving accessibility, cost, and risk for borrowers. However, policies that encourage growth of microcredit are insufficient alone; history tells us that regulating this growth is necessary, and strict checks on the practices of MFIs must be conducted to ensure trust of the poor in MFIs. Moreover, the poverty alleviation function of microcredit provided by profit-driven MFIs will only be seen in higher-strata of the poor. Though the financial situation of this strata can be improved significantly by for-profit models, not-for-profit models of microcredit are necessary for reaching the poorest sections of society.

This paper adds to a growing body of literature in microfinance by combining existing problems identified in literature with original empirical analysis to provide an informed view of whether for-profit models of microcredit can be conducive to sustainable financial inclusion. Future works may hope to assess this problem on a case-study level basis, such that the practical applications of the results of this paper can be tested.

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