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Measuring Credit Risk in a Quantitative way for Countryside Microfinance Institutions: Case study of China

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Keywords:

Direct method, Credit scoring models, Shandong, Credit Risk, MFI

ABSTRACT

Credit scoring models (CSM) are very common in various financial institutions to assess the credit risk. Microfinance institutions' contribution to reduce default risk efficiency is to improve their competitiveness in an increasingly constrained environment while lowering their costs. Now, microfinance institutions assess and estimate the credit risk for effective policy making using the quantitative way to improve competitiveness. Microfinance institutions (MFIs) choose models to form a CSM with good predictive capabilities to recognize and categorize thee variables, and to allocate values to variables and narrow the scope of variables in a suitable manner. A CSM model with a good classifying effect has been created based on data from MFIs in Shandong province, and it shows that bank credit, old customer and interest rate play important roles in classification. The article illustrates the important technical elements for developing a credit scoring model based on a practical application, which can be used by Chinese microfinance institutions to objectively monitor and manage credit risk.

INTRODUCTION

Credit risk is the risk that a bank borrower or counterparty may fail to satisfy its commitments in line with the terms of the agreement. Credit risk management aims to increase a bank's risk-adjusted rate of return while keeping credit risk exposure below permissible limits. Banks must manage both the overall credit risk and the risk associated with individual loans or transactions. Banks should also think about how credit risk interacts with other hazards. Credit risk management is a vital component of a complete risk management strategy and is crucial to any financial organization's long-term performance. Loans are the greatest and most visible source of credit risk for most banks; nevertheless, additional sources of credit risk occur throughout a bank's operations, including in the banking and trading books, as well as on and off the balance sheet. Acceptances, interbank transactions, trade financing, foreign

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exchange transactions, financial futures, swaps, bonds, equities, options, and the extension of commitments and guarantees, as well as the settlement of transactions, are all examples of financial instruments where banks are increasingly exposed to credit risk (or counterparty risk).

When Client applies for a loan, the financial institutions predict its repaying creditability and also guesstimate the risk level associated with new loan applicant. For new as well as existing clients, a credit risk scoring cards are conducted to measure the creditability of clients (Twesige et al., 2021). Financial institutions use credit scorecards to approximate the probability that a client will demonstrate a definite behavior (loan default) with respect to its current position, education, age, income status, credit history, loan utilization, living standards and other related factors (Li & Sheng, 2018), (Emekter, Tu, Jirasakuldech, & Lu, 2015) and (Bordo, Duca, & Koch, 2016). Evaluation of overall default prediction capability and credit credibility is very common in financial institutions to develop models and the prior probabilities so that the misclassification costs should also be considered for ultimate objective (Iqbal & Mohsin, 2019) and (Ntwiga, 2020).

Credit score card for microfinance institutions should be used as institutional arrangements for financial innovation to quantitatively measure and manage credit risk. In recent years, microfinance institutions have developed the assessment techniques rapidly. At the end of 2005, the Central Bank of China approved the establishment of pilot commercial microfinance companies (Raju, 2015). In May 2008, the Central Bank and Chinese banking of supervisory instruction mutually give out the "regulatory framework on Microfinance Pilot Institutions", and formally signed the formal financial system arrangement for specialized microfinance institutions to join the Chinese financial system

. Currently, the industry of microfinance sector has rapidly established which is considered as a rising industry having enormous market share. Beginning from June 2018, various microfinance institutions in China touched the new height of loan distribution and outreach of poor and other clients in china, while loan balance reached at the level of 881.1 billion Yuan and the commercial microfinance institutions are increasing rapidly and enhancing the income of their clients (Iqbal & Mohsin, 2019).

At the same time, competition among microfinance institutions is becoming increasingly fierce. Township banks, commercial banks, NGOs, MFIs and other community banks have also been acknowledged through supplying the loan to their client. Additionally, policy banks small and medium-sized commercial banks, National banks, foreign banks and other large commercial banks of country have also shown prodigious interest in microfinance investment sector(Iqbal & Akhtar, 2015). Financial Holdings Limited, wholly-owned by Temasek, has capitalized hundreds of millions of Yuan, and has established many microfinance companies, rural banks and other organizations in many places to distribute nationwide to seize the SME loan market (D'Espallier, Goedecke, Hudon, & Mersland, 2017). Therefore, in order to survive and improve in the ferocious competition, microfinance institutions must improve efficiency, reduce costs and effectively control risks (Ahmed & Khoso, 2020) and (Chen, 2016). Based on foreign experience, microfinance institutions measure the size credit risk in a measurable way so that a competitive advantage may be achieved.

Currently, a lot of microfinance institutions are functioning without introducing CSM model in the market. Additionally in the absence of the importance of CSM, there are also worries about the weak data base of microfinance institutions, which may make it difficult to establish models or models established have poor prediction effect for policy maker and planner (Cuéllar-Fernández, Fuertes-Callén, Serrano-Cinca, & Gutiérrez-Nieto, 2016). It is true that with larger sample size, a sufficient data, developing a model doing better in predictive power, stability, and shock resistance is easier. Currently, customer data of the microfinance institutions' are ensured to be authentic which are considered as a qualitative data but the sample accumulation is less which is not a hurdle to develop a CSM. On the one hand, contemporary organization and assessment tools can efficiently assimilate qualitative data into the empirical model. From an international perspective, in the field of microfinance institutions, qualitative data dominates the CSM model. On the other hand, more importantly, any robust empirical model cannot be immediate, nevertheless it requires to be continually efficient and updated.

This article evaluates the experience of some microfinance institutions in Shandong Province to establish CSM, discusses the modeling techniques of establishing CSM. The study also discusses to pool CSM with corporate risk management effectively and provides reference for microfinance organizations to assess and accomplish credit risk management strategies. This study also provides the outline for policy maker to measure the credit risk in quantitative way and also guide them to tackle the credit risk and to minimize the credit risk and to maximize the loan distribution for their clients in sensible way.

Literature review

Some advanced models are constructed depending upon the default database or equity and common stock prices, like as the KMV but this model is not applicable to microfinance institution. The characteristic of loan risk is that it provides default possibilities, usually be more than 2,000 sample data. Domestic microfinance institutions can choose appropriate models based on their data characteristics and model classification effects (Lopatta, Tchikov, Jaeschke, & Lodhia, 2017). Appropriate identification of initial variables also has a large impact on the proposed technology's assessment of default risk. There are many ways to choose the type and number of CSM initial variables (Wijesiri, Yaron, & Meoli, 2017). The credit score model uses 48 initial underlying factors and the model with the highest Fair Isaac credit score uses 50 to 60 initial variables (Etongo et al., 2015) and other model uses 53 initial variables. A researcher (Widiarto & Emrouznejad, 2015) established the mathematical model by using the data of microfinance organizations in Bolivia, by using the case study of 9 preliminary factors and other researcher (Ngo & Nguyen, 2016) proposed a model by using the Vietnamese retail banking business data, which used 22 preliminary factors . When domestic microfinance institutions formulate models, they can learn from the above-mentioned classic models and then adjust them according to actual conditions. The most significant factors is to confirm the genuineness and consistency of the data which is provided for analysis. Various experts and model designer and developers favor financial data for reliable analysis, however in the experience of researchers of the study, the reliability of most microfinance institution's customer financial data is questionable.

Many researchers have concluded that by developing models, how to assign values to variables is indeed a careful consideration. From the perspective of international experience for CSM, variable assignment which need to be divided the variables into groups, and then assign values based on the distribution of quality samples in each group (Liu, Ji, Zhang, An, & Sun, 2021) and (Airong & Yong, 2021). When establishing CSM, there is no clear standard to use the direct method or grouping method, which mainly depends on the sample size and prediction effect (Hansen, Monllor, & Shrader, 2016) and (Mehmood, Lace, & Danilevičienė, 2020). It is also observed that when local microfinance institution establishes a CSM, it can choose a method based on its own data characteristics. According to practice and understanding of researcher, larger sample size is associated with higher default recording rate by applying grouping method. By developing the method and model, researcher finally used the direct allocation method after analyzing the prediction effect.

Another factor that also plays a key role is to pay attention is how to reduce the size of the variable in model to estimate the results. According to international experience, when establishing a CSM, one should reduce the size or directly use all variables to enrich the feasible results. Whether the dimensionality reduction process is mostly by using the various underlying factors, model association and likelihood correctness (Xu, 2021). There are many ways to reduce the dimension of variables, including association examination, factor analysis, cluster analysis, principal component analysis and forward or backward stepping methods. For international classic models ((Iqbal & Akhtar, 2015), correlation analysis and factor analysis (Torero et al., 2020) use the back-off method. Evidence from the past decade clearly shows that the microfinance industry is growing rapidly and is now considered to be a prosperous global industry. During the periods of 1998 to 2008, the micro financial institutions have grown by 474% and at the same time the number of customers increased by 1048% (Khan & Malik, 2020). The rapid growth of these institutions attracts a large number of international commercial banks. So, there is an increasing trend to use CSM by MFI's to judge, hedge and mitigate the credit risk. They viewed as there is a potential for profitable investment in the microfinance scheme of the banking sector. Therefore, the injection of interest has expanded competition among organizations in the beauty industry (Iqbal & Mohsin, 2019). It is suggested that credit score is the most important use of this skill. which might be strongly affected microfinance sector (Serrano-Cinca, Gutiérrez-Nieto, & Reyes, 2016) and confirms that experimentations conclusions conducted in Bolivia and Colombia which show that the implementation of credit scoring improves the judgment of credit risk and it's decreased by more than $75,000 per year which is the cost of microfinance institutions. In this context CSM is proved as a cost saver here for microfinance institutions. So it is concluded that two basic assumptions of linear discriminant analysis (LDA) are often violated by researchers during the application of credit scoring problems and also from authorities of the financial institutions (Van Gestel & Baesens, 2009). The variables of the independent model are multivariate for evaluation of data and are normally distributed. The variance and covariance matrix (group discrete matrix) between the failed and non-failed groups are equal (for detailed analysis. The problem of applying discriminant analysis to the credit scoring model is the same as linear discriminant analysis (LDA). Assuming a multivariate normal distribution, the LR model is also optimal. It also remains optimum with respect to a broader variety of situations for the measurement of credit risk or default risk of microfinance institutions. Larger data sets are required in logistic regression to get more effective and efficient results interactions between predictor variables, complex nonlinearities and dependent variables so for non-parametric statistical algorithm and vector machines have been proposed by (Tisdell, Ahmad, Agha, Steen, & Verreynne, 2020). For stable measurement of credit risk of financial institutions literature concludes that some others models like decision tree models, and neural network models successfully applied toward (CSM) problems of credit scoring. Adaptive-learning characteristics of properties nonlinear and non-parametric of artificial neural networks (ANNs) and their major tool for pattern classification, is considered as a major tool. Some researchers suggest to financial institutions, some other types of methods that can be used are based on neural networks and fuzzy logic approach and in many cases results show that LDA accuracy performance is preferable as compared to QDA MP and LR model (Ju, Chen, Li, Wang, & Tong, 2021) and (Blanco, Pino-Mejías, Lara, & Rayo, 2013).

METHODOLOGY AND DATA

In this case, this research uses additional and supplementary qualitative data before conducting quantitative analysis, such as education, housing status, etc. There are few qualitative variables are used in the model, with a total of 16 variables.

The model uses linear discriminant analysis (LDA) method (Pouplier, Cederbaum, Hoole, Marin, & Greven, 2017) and regression by using the data. Specifically, if the two sets of samples are S1 and S2, then the observations of n1 and n2 will also be recorded, and each observation contains p-dimensional variables, then the LDA model assumes that these two samples are usually multivariate distributed, and the average values are μ1 and μ2, respectively, and the covariance matrix is Σ. For the record X of the p-dimensional variable, if the following conditions are met, the LDA classification principle will divide them into the second group (Todorov, 2007)

$$X^t \sum^{-1}(\hat{\mu}_2 - \hat{\mu}_1) > \frac{1}{2}\hat{\mu}_2^t \sum^{-1}\hat{\mu}_2 - \frac{1}{2}\hat{\mu}_1^t \sum^{-1}\hat{\mu}_1 + \log\hat{\pi}_1 - \log\hat{\pi}_2 \quad (1)$$

Here, π_1 and π_2 are the prior probability of the first and the second group, estimated by the two groups' sample proportion. In this paper, the CSM model employs this method by SPSS.

The sample for the study is taken form MFIs working in Shandong province, China. It was established from January 2014 to November 2018 which is consisted for a period of four years and 11 months for this study. The size of samples is 250, including 35 default records from MFIs record having 3 months overdue as compared to 215 clients having normal records. The company's clients and customers have significance and priority over small businesses, and its industries covering manufacturing sector, agricultural industry, wholesale business, building materials industry, trade, service industries and commerce. Basic information for data set is included in data and relevant certificates and documents provided by the borrower, bank card transactions, field studies by credit managers, financial management data records and other copies submitted after the report. Micro credit is supplied by different institution in the country which are summarized in table 1.

Table 1. ***comparison of microcredit provider-Client and products***

Type of Institution	Since	Regions	Target Clients	traditional Collateral	Average Loan Size	Annual Interest Rate*	Savings	Remittances
NGO MFIs	1993	Country-wide	Mid/low income and poor clients	No	Several thousand	3-18%	No	No
ABC	1997	Country-wide	Mid/low income and poor clients	No	Several thousand	2-3%	No	No
RCCs	2000	Country-wide	All kinds of farm households	No, but yes for large loans	Several thousand —ten thousand	0.9-2.3 times basic rate	Yes	Yes
Urban Commercial Banks	2002	Urban Areas	Laid-off workers	Guarantee companies	Several thousand	Basic rate but subsidized	Yes	Yes
MCCs	2005	5 provinces	Farmers and microenterprises	Yes	Several thousand —hundred thousand	Around 20%	No	No
Village Banks	2006	6 provinces	Farmers and microenterprises	Yes	Several thousand —hundred thousand	0.9-2.3 times basic rate	Yes	No
RMCCs	2006	6 provinces	Member farmers and enterprises	No	Several thousand	0.9-2.3 times basic rate	Yes	No
Lending Companies Companies	2006	6 provinces	Farmers and microenterprises	Yes	Several thousand —hundred thousand	0.9-2.3 times basic rate	No	No
Poverty Alleviation Loans	2004	Country-wide	Mid/low income and poor clients	No	Several thousand	Less than basic rate	Yes	Yes
Postal Savings Banks	2007	Country-wide	All kinds of farm households	Yes	Several thousand —hundred thousand	0.9-2.3 times basic rate	Yes	Yes
Microcredit Pilot Project of Commercial Banks	2005	More than 10 regions	Microenterprises and disadvan-taged people	No	Several tens of thousands	Around 20%	Yes	Yes

Source. The information in this summary table is extracted from relevant documents and sources

For the meaningful results, this study uses the dataset which contains customer information during the period of January 2014 to November 2018 which explain as: (a) personal characteristics such as age， gender，marital，education; (b) Related to business and financial situation (bank credit，home，exist year) (c) Related to past history of corporation (old client) (d) Related to Borrowing situation (loan purpose loan amount loan period，rate，collateral，pledge, guarantee full). In this scenario of our (specific) case there are two types of clients, one those who will repay the loan and those who will not repay the loan as per defined criteria (number of days) of our loan default pattern. On the basis of our definition we classify all the clients at the term of two ways (defined number of days as per definition) (Lee Rodgers & Alan Nice Wander, 1988).

RESULTS and DISCUSSION

In order to analyze and measured the performance under different and alter conditions, there are three different experimental samples (the original sample and two large-scale default samples) which were established. By adopting and applying the direct method to assign and allocate values separately and different tables are extracted from the data set. Lastly, for the different data tables, using the full variable method and the stepwise method, 12 discriminant functions (scoring models) were received. While comparing and equating the classification impacts of the model, this study rely on 2 widely used indicators: the percentage of correctly classified nonperforming loans PCCbad (PCC, the percentage of correctly classified loans) and the percentage of correctly classified nonperforming loans PCCgood. The calculation methods of these two indicators are shown in Tables which is inserted under below.

Table 2 ***Results of discriminant effects by applying direct method***

		all variable method	step-by-step method
Original sample	PCCbad	58.22	58.22
	PCCgood	98.64	98.27
Sample one	PCCbad	70.82	62.5
	PCCgood	95.25	97.67
Sample two	PCCbad	75	62.5
	PCCgood	98.59	98.59
synthesis	PCCbad	68.06	61.11
	PCCgood	97.52	97.96

Author calculation

The overall impact of the all variable technique is somewhat better than the step-by-step technique when the direct technique is applied (see table 2). PCC indices using the all variable technique are greater than or equivalent to those using the step-by-step technique in both the original sample and sample two. Both strategies have their own advantages in sample one. PCCbad is clearly greater when using the all variable technique than when using the step-by-step technique, while PCCgood is the inverse. In summary, PCCbad is substantially higher under the all variable technique than under the step-by-step technique, whereas PCCgood is somewhat higher under the step-by-step technique than under the all variable technique.

Table 3 ***Discriminant effects of all variable by applying grouping method***

		all variable method	step-by-step method
Original sample	PCCbad	78.33	78.33
	PCCgood	87.21	87.83
Sample one	PCCbad	72.7	58.33
	PCCgood	88.84	87.51
Sample two	PCCbad	77.77	58.33
	PCCgood	87.18	88.58
synthesis	PCCbad	62.5	58.33
	PCCgood	87.41	97.01

Author calculation

When using the grouping approach, the findings demonstrate that the all variable technique outperforms the step-by-step technique. Except for PCCgood in sample two, all indices under the all variable technique are greater than or equal to those using the step-by-step technique in all three samples and the synthesis in table 3.

By applying model (LDA) performance and efficiency include to discuss and compare the different results for meaningful conclusion to develop benchmark with respect to the classic techniques and statistical physiognomies of the best credit scoring models which are defined for purpose results. Synthesizing the effect of all the models, when developing a CSM measuring depending on the data of this microfinance institution, the variable assignment should employ direct method. As for determining the variable, not reducing the dimensions and using all variable method.

Table. 4 ***coefficients of variables***

Variables	Coefficient I	Coefficient II
Y	*+ 0.727 **	*-0.480 **
Age	*+ 0.310 **	*+ 0.180 **
Gender	*+ 0.738 **	*+ 0.124 **
Education level	*+ 0.017 **	*+ 0.207 **
Bank Loan	*-0.321 **	*+ 0.703 **
Marriage	*+ 0.013 **	*-0.170 **
Family	*+ 1.101 **	*+ 2.67 **
Old customer	*+ 0.018 **	*-0.327 **

Existing year	*-0.001 **	*-0.08 **
Loan amount	*+ 0.712 **	*+ 0.53 **
Guarantee	*-0.131 **	*-0.180 **
Collateral	*-0.771 **	*+ 0.044 **
Loan purpose	*+ 0.011 **	*-0.047 **
Interest rate	*-0.471 **	*+ 0.781 **
Mortgage	*-0.734 **	*+ 0.131 **

It is observed that education, bank credit, old customer and interest rate have greater impact on discrimination effect in the model which is used to measure the impact (see table 4). Customers with a history of defaulting at the bank, as well as those with low educational levels and who are new, are more likely to fail and need special attention, according to loan officers' experience. Customers who have high loan rates are also more prone to default. The lending rate is determined by the company's financial situation. Customers who have high loan rates are also more prone to default. The loan rate is determined by the company's credit assessment of the customer, therefore this variable indicates that the company's credit assessment of the client is pretty correct; nevertheless, it also implies that the loan rate has an impact on the client's repayment capacity and willingness. .In order to further compare the contribution and influence of each variable and determine the variables that need attention, a standardized discriminant function must be used:

It is concluded from the result that the four variables that have the greater influence and impact on discrimination which included bank credit, education, fixed customers, and interest rates. With the bank’s default records, low-education and new customers are more likely to default, which are needed more attention, that is stable and consistent with the loan staff’s experience assessment. Additionally, customers having high loan interest rates are more likely to default. The loan interest rate is determined based on the company's credit evaluation of customers. Therefore, this indicator reflects the company's relatively accurate credit evaluation of customers on the one hand; it also shows that the loan interest rate itself will affect the customer's repayment ability and willingness on the other hand. In this case, the company should further study interest rate policy.

These results propose that one should not explain the data as good as possible rather one should focus on the high accuracy of characteristics description. There is a significant difference in default among different clients and their nature and default nature depends upon their education and life pattern which significantly depends upon the utilization of loan (loan purpose).

Recommendation and Further Research

Analyzing the past literature about microfinance institutions, it is resulted and recognized the credit risk as a main and major risk. Commonweal or commercial MFIs, both should place credit risk prevention in an important position (Iqbal & Mohsin, 2019)

Irrespective of whether a MFI is agreed for acceptance it or not, quantitative measurement and management of credit risk will become a trend. Back in 1996, nearly 97.00% of US banks applied and used CSM for development of credit card loan to scrutiny for applications, while 70% of US banks used CSM to evaluate small business loans. Practices in developing countries such as Bolivia and Colombia have resulted from evidences that the use and application of CSM can impressively improve the decision and judgment of microfinance institutions on the risk of default. Introducing CSM to quantitatively measure and manage credit risk can significantly reduce costs, shorten loan evaluation time and reduce costs. In the long run, the efforts of loan officials will undoubtedly become a powerful tool and instruments which is used by MFIs to improve and increase efficiency of institution and its competitiveness.

In credit risk management, MFIs may lack the essential expertise, risk management tools, and experienced employees to compete effectively with other commercial banks and other financial institutions (e.g., international banks). Financial control, risk management, accounting, Internet banking, credit card service customer service, and other data processing systems, as well as communication networks between various branches and outlets and main data processing centres, are critical to MFIs' ability to manage credit risk and remain competitive. Establishing a clear framework, allocating duty and accountability, prioritising and disciplining processes, clearly communicating roles, and assigning accountability are all fundamental elements in credit risk management. Organizing and managing the loan function in a competent and proactive way may help to reduce losses, regardless of the level of risk accepted. With technological improvements, NFIs may use more complex measurement approaches to tackle risk management challenges. Technological advancements, notably the increased availability of low-cost computer power and connectivity, have played and will continue to play a significant supportive role in allowing MFIs to adopt more rigorous credit risk assessments. The likely acceleration of change in MFIs credit risk management should be viewed as an unavoidable response to an environment in which competition in the provision of financial services to rural areas is increasing, and thus the need for MFIs to identify new and profitable business opportunities while properly measuring the associated risks is increasing. To do so, MFIs must collect sufficient information about prospective clients in order to calibrate credit risk exposure. The data acquired will help the bank determine the likelihood of a borrower default and price their goods appropriately. In fact, China's financial sector is growing highly competitive. The microfinance sector in the People's Republic of China is heavily controlled, and changes in policies, rules, and regulations affecting the financial sector in China might have a direct impact on MFIs. The suggested credit risk management framework is expected to assist MFI executives in developing a workable credit risk management model. To summarise, MFIs operate in a unique business environment and face distinct risks, necessitating a distinct credit risk management strategy that considers both quantitative and qualitative aspects. The examination of environmental, operational, financial, and guanxi (relationship) risks of their SMEs and agricultural household clients should be the emphasis of credit risk management in MFIs.

Future research may consider the subset of these variables. There should be a logical reasoning behind credit risk assessment which may attract nonlinear and non-parametric regression to meet heuristic methods of global optimization to secure loan disbursement and minimized cost and why the local economic activity that consequences from the neighborhood association with organizations. It is also evident from the literature that the logistic regression models have been used to measure the risk of customer default from nearly 20 years so some related explanatory variables should be used, like reference file, default history, credit demand, and payment history of credit. Future work expects the link between statistical accuracy and business values which are far from perfect.

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