Credit rating and microfinance lending decisions based on loss given default (LGD)

Citation for published version:
Shi, B, Zhao, X, Wu, B & Dong, Y 2019, 'Credit rating and microfinance lending decisions based on loss given default (LGD)', *Finance Research Letters*, vol. 30, pp. 124-129.
https://doi.org/10.1016/j.frl.2019.03.033

Digital Object Identifier (DOI):
10.1016/j.frl.2019.03.033

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
Finance Research Letters

Credit rating and microfinance lending decisions based on loss given default (LGD)

Baofeng Shi[a,*], Xue Zhao[a], Bi Wu[b], Yizhe Dong[c]

[a] *College of Economic and Management, Northwest A&F University, Yangling, Shaanxi 712100, P.R. China;*

[b] *Research Center for Rural Economy, Ministry of Agriculture and Rural Affairs, Beijing, 100810, P.R. China*;

[c] *University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh EH8 9JS, UK.*

Abstract: This paper proposes a credit rating model that considers the impact of key macroeconomic variables on commercial banks' credit decisions and loss given default (LGD). The findings provide additional insight into the phenomena that under some circumstances a higher credit rating may lead to a higher LGD. The empirical analysis is based on actual bank data from 2,044 farmers in China. The theoretical analysis and empirical verification provides key insights into regulatory and commercial bank credit policy in a developing country setting, while helping to alleviate financing problems of small and micro credit entities.

Keywords: China; credit rating; lending decision; credit risk; loss given default (LGD)

JEL classification: C51, C58, G21, G32

Acknowledgments: The study was supported by the National Natural Science Foundation of China (Nos. 71873103, 71503199, 71603141), the Key Project of National Natural Science Foundation of China (No. 71731003), the Social Science Foundation of Shaanxi Province (No. 2018D51). The first author special thanks go to the Youth Talent Cultivation Program of Northwest A&F University (No. Z109021717).

* Corresponding author at: College of Economic and Management, Northwest A&F University, Yangling, Shaanxi 712100, P.R. China; Tel.: +86-29-8708-1293; Fax: +86-29-8708-1209.

E-mail addresses: shibaofeng@nwsuaf.edu.cn (B. Shi), xuerzhao@126.com (X. Zhao), wubi55555@163.com (B. Wu), Yizhe.Dong@ed.ac.uk (Y. Dong).

Credit rating and microfinance lending decisions based on loss given default (LGD)

Abstract: This paper proposes a credit rating model that considers the impact of key macroeconomic variables on commercial banks' credit decisions and loss given default (LGD). The findings provide additional insight into the phenomena that under some circumstances a higher credit rating may lead to a higher LGD. The empirical analysis is based on actual bank data from 2,044 farmers in China. The theoretical analysis and empirical verification provides key insights into regulatory and commercial bank credit policy in a developing country setting, while helping to alleviate financing problems of small and micro credit entities.

Keywords: China; credit rating; lending decision; credit risk; loss given default (LGD)

JEL classification: C51, C58, G21, G32

Credit rating and microfinance lending decisions based on loss given default (LGD)

1 Introduction

The published credit rating plays a crucial role for investors in deciding investment quality. Accurate credit ratings also help financial regulators manage systemic risk, since aggregated loan portfolios convey crucial information about credit risk. To measure the credit risk of loan applicants, many theoretical and empirical analyses have been conducted (Altman et al., 1977; Karlan et al., 2011; Castilloa et al., 2018). Simply stated credit risk assessment should be able to differentiate between good and bad credit applicants. With the former being those that are able to make timely and complete repayments, while those who fail to repay are treated as 'bad credit applicants' (Bai et al., 2019). In addition, lending institutions, such as commercial banks, may decide whether it is appropriate to issue new loans to applicants with reference to existing ratings and credit scores.

In this paper we investigate the microfinance credit rating of farmers. Understanding this process is critical for boosting rural economic development. In China, it is difficult for farmers to receive financial support and high interest rates on loans are widespread. The reason is that banks may be unable to accurately measure the credit risk of high risk agriculture-related enterprises and farmers. This is largely due inaccurate or incomplete information on the credit history of agriculture-related enterprises (or farmers), and the lack of collateral for a mortgage. Thus, credit risk is difficult to measure and requires unsecured lending. Internationally, one explanation for commercial banks' participation in small and medium-sized microfinance activities is that the loans are part of a program of Corporate Social Responsibility (CSR): treating loans to agriculture-related enterprises or farmers as a charity (Scott, 2014). To address these difficulties, China established the development of inclusive finance as a national strategy as early as 2013. In 2015, the State Council of the Peoples Republic of China (SCPRC) issued the Promoting Inclusive Financial Development Plan (2016-2020). However, further efforts to implement the inclusive financial development strategy are required. One key component is for banks to expand lending and financial support for vulnerable groups.

This paper makes three important contributions. First, it provides a model where the credit rating of the loan customers is classified by a risk rating matching standard, which ensures the higher credit rating, the lower the LGD and loan interest rate. The second is creating a credit decision model suitable for both economic tightening and boom periods, by setting the objective function to maximizing the number of loan customers who are above a critical point of target profit (or reaching breakeven). In other words, when the macro economy is in a tightening period, regulators can introduce policies to encourage commercial banks to increase the credit availability of loan customers on the basis of break-even and increase the amount of credit to stimulate economic development. When the macro economy is in a prosperous period, commercial banks can select credit customers based on target profits and maximize their profits. Third, the theoretical analysis and empirical verification of this paper can provide new ideas and useful references for regulators and commercial banks to formulate credit policies and alleviate the financing problems of small and micro credit entities.

The rest of the paper is organized as follows. Section 2 is the literature review. Section 3 introduces the data and credit lending decision-making methodology. Section 4 uses the proposed method to analyze 2,044 farmers' credit data. The paper concludes with Section 5.

2 Literature review

Historically, researchers have mainly used the probability of default (PD) and the LGD to depict the credit risk of a loan applicant (Loterman et al., 2012). This literature can be divided into three categories: Structural Models, Reduced Form Models and Average Historical Default Rate Models. These methods divide the credit rating combining the PD of the loan applicant with the given threshold of PD (Raquel, 2007). The structural model used to measure credit risk was first proposed by Merton (1974). This method uses the financial data of the listed company to determine the PD that is the probability that the assets are greater than the liabilities at a certain point in time. If the company's assets are less than its liabilities, there is a risk of default. Based on the Merton structural model, the KMV Corporation, now part of Moody's Analytics[1], developed the Credit Monitor Model (Vasicek, 2001). The second category of studies focuses on reduced form models. This type of model treats default as a stochastic process, solving applicant's credit score through exogenous default parameters (Jarrow and Turnbull, 1995). Because the above two models rely on

[1] https://www.moodysanalytics.com/request-more-information.

the financial data of enterprises, these approaches are not applicable to the measurement of default risk of SMEs. To this end, commercial banks and rating companies use the Long-Run-Average Values of PDs to approximate the default risk of loan customers based on long-running credit rating data, and propose the Average Historical Default Rate Models (Araujo et al., 2016). Such models usually use historical observation data of more than 5 years and use the measured average value of PD of certain industries as the PD of the loan enterprise. Although this method is simple, the derivation and parameter settings are typically based on the assumptions of developed financial markets.

Compared with the studies of PD, only a limited number of papers investigate LGD. As for how to describe credit risk of loan applicants by using LGD, the existing literature mainly concentrates on the estimation and prediction of the LGD parameter. By comparing six prediction methods of LGD, Qi and Zhao (2011) find that non-parametric models perform better than parametric approaches. Leow and Mues (2012) proposed a novel two-stage LGD prediction model combining the Probability of Repossession Model and the Haircut Model. Data analysis showed that the proposed method performed better than the existing single-stage LGD model. Yao et al. (2015) predicted loss given default of corporate bonds using support vector regression (SVR) technique. Their analysis shows that the proposed SVR method outperforms thirteen other methods.

In addition, with the development of mathematical statistics and artificial intelligence, new methods such as neural networks, support vector machine, fuzzy decision and hybrid methods have been applied to the determination of credit rating and credit scoring (Boudreault et al., 2014; Moula et al., 2017; Shi et al., 2018). Generally financial intermediaries use customers' credit scores to rate their credit ratings. For example, in China, the Bank of China (2016) divides loan customers into 15 credit grades, four categories i.e. A rating, B rating, C rating and D rating. Shi et al. (2016) constructed a credit classification model with the largest difference in classification results using fuzzy clustering method. Zhang & Chi (2018) show this approach is consistent with expected bell-shaped distribution characteristics according to the number of loan customers, and provides quantiles corresponding to each level of loan customers. This approach then establishes a credit score threshold for the different grades of loan customers, and divides customers into nine ratings from AAA to C.

These studies highlight the estimation, prediction and validation of the PD, LGD and credit score. However, the existing credit rating approach often has two problems. The first is outcome that often the credit rating is high and the LGD is not low. The reason is that the existing classification method does not link the rating result with the LGD, which leads to the failure of the credit rating to meet the basic principle of a higher credit rating with a lower default loss rate. The second is that the credit rating results are often not linked to the state of economic development, that is whether the economy is booming or in recession. This can lead unfavorable bank loan decisions. Importantly, the empirical evidence suggests that credit rating agencies (CRAs) are more likely to exaggerate ratings during boom times (Bolton et al., 2012).

3 Data and Methodology

3.1 Data

The study is based on microfinance data from 2,044 farmers' collected from 28 provinces of a state-owned commercial bank in China (PSBC and DUT, 2014), as shown in Table 1. The sample involves 28 provincial-level administrative regions except for Beijing, Tibet, Yunnan, Taiwan, Hong Kong and Macau among the 34 provinces of China. In Table 1, the second Column is the result of the credit scores obtained according to the evaluation equation in descending order (Selection of the indicators and the solution of the credit scoring are not included in this study). The third Column is sample ratio of each credit rating obtained by summarizing the characteristics of samples assuming a normal distribution. The fourth Column is the sample size of each credit rating. The fifth Column is the credit ratings. The sixth Column is the credit score intervals of different credit ratings. The seventh and eighth Columns are the loan capital and the interest data. The ninth Column is the LGD of nine credit ratings which is obtained based on the normal distribution approach.

(Insert Table 1 here)

Table 1 Data of farmers' microfinance credit rating.

3.2 Model establishing

In this subsection, we introduce a lending decision-making method that combines the credit risk-rating match-up principle with the critical point of a bank's target profit (or the critical point of a bank's breakeven).

Objective function 1: A bank has the largest number of customers when it reaches its target profit. Let N_k denote the number of customers in the k-th credit rating, and k = 1, 2, ..., 9 respectively represent the nine credit ratings, that is, AAA, AA, ..., C. l denote the credit rating which cumulative LGD is less than and closest to a_0. N denote total number of customers. a_0 denote target profit critical point. We have

$$obj\text{: } max\, f=\frac{N_1+N_2+\cdots+N_l}{N} \tag{1}$$

Objective function 2: A bank has the largest number of customers at the break-even point. Let j denote the credit rating which cumulative LGD is less than and closest to b_0. b_0 denote the break-even point. We have

$$obj\text{: } max\, g=\frac{N_1+N_2+\cdots+N_j}{N} \tag{2}$$

Constraint 1: The higher the credit rating is, the lower the LGD is. It means that the LGDs increase strictly. Namely,

$$0<LGD_1<LGD_2<\ldots<LGD_9\leq 1 \tag{3}$$

where LGD_k denote the loss given default of the k-th credit rating.

Constraint 2: It is the equality constraint to caculate LGD_k of the k-th credit rating. Let L_{ik} denote the annual owed loan capital and the interest of the j-th credit rating on the i-th customer, let R_{ik} denote the annual receivable loan capital and interest of the j-th credit rating on the i-th customer. Then the LGD of the k-th credit rating is given by

$$LGD_k=\frac{\sum_i L_{ik}}{\sum_i R_{ik}} \tag{4}$$

Constraint 3: The cumulative LGD of the j-th credit rating ≤ target profit threshold a_0. Namely

$$\sum_{k=1}^{j} LGD_k \leq a_0 \leq \sum_{k=1}^{j+1} LGD_k \tag{5}$$

where, a_0 denote the bank's maximum acceptable loss given default when it reach the target profit, j denote the rating which cumulative LGD is less than and closest to a_0.

Constraint 4: The cumulative LGD of the l-th credit rating ≤ break-even point b_0. Namely

$$\sum_{k=1}^{l} LGD_k \leq b_0 \leq \sum_{k=1}^{l+1} LGD_k \tag{6}$$

where, b_0 denote the bank's maximum acceptable loss given default when in break-even point, l

denote the rating which cumulative LGD is less than and closest to b_0.

3.3 Model solving

In order to solve the multi-objective programming model established as shown in 3.2 above, we use the weight coefficient method to transform multi-objective planning into single-objective planning (Chiclana et al., 2004). Let f_0=max f, g_0=max g, then the double objective functions consisting of Equations (1) and (2) are equivalent to Equation (7).

$$min\ F= c|f\text{-}f_0|+ (1\text{-}c)|g\text{-}g_0| \tag{7}$$

where the weight coefficient $c \in [0, 1]$.

In Equation (7), the decision makers can determine the value of the parameter c according to their own situation. A different value of parameter c is applicable to the bank's credit policy in different economic environments. The selection of parameters reflects the degree of preference of the decision makers to the target. (*i*) When c=0, Equation (7) is equivalent to Equation (2), reflecting the decision maker expects to find the credit rating result that ensure the number of customers who above the break-even point is the largest. In a period when the macro economy is tightening, regulators hope to stimulate economic development by increasing the amount of credit. Under this setting, regulators encourage commercial banks and other financial institutions to choose this plan. It will improve the credit of loan customers while ensuring business sustainability. (*ii*) When c=1, Equation (7) is equivalent to Equation (1), reflecting the decision maker expects to find the credit rating result that ensure the number of customers who above the target profit threshold is the largest. When the macro economy is in a prosperous period, financial institutions such as commercial banks can use this credit decision-making plan to maximize their profits. (*iii*) In the case of stable economic operation, decision makers can flexibly choose parameter values within the range of $c \in (0, 1)$ according to their own needs. The basic framework of credit decision can be illustrated by Fig. 1.

(Insert Fig. 1 here)

Fig. 1. A basic framework of credit decision.

From the above analysis, we can conclude that the multi-objective programming credit decision model composed of Equation (1) to Equation (6) is equivalent to Equation (8).

$$\min \quad F = c|f - f_0| + (1-c)|g - g_0|$$

$$s.t. \quad \begin{cases} 0 < LGD_1 < LGD_2 < \ldots < LGD_9 \le 1 \\ LGD_k = \dfrac{\sum_i L_{ik}}{\sum_i R_{ik}} \\ \sum_{k=1}^{j} LGD_k \le a_0 \le \sum_{k=1}^{j+1} LGD_k \\ \sum_{k=1}^{l} LGD_k \le b_0 \le \sum_{k=1}^{l+1} LGD_k \\ k = 1, 2, \ldots, 9 \end{cases} \tag{8}$$

4 Empirical study

4.1 Divide the farmers' credit ratings

When the large state-owned commercial bank reaches its target profit, the bank's maximum acceptable loss given default a_0 equal equals to 3.74%. When the commercial bank reaches break-even point, the bank's maximum acceptable loss given default b_0 equals to 9.03% (PSBC and DUT, 2014). If the decision maker is risk neutral and the macroeconomic operation is stable, it is possible to assume the parameter c=0.5 in Equation (8).

Substitute a_0=3.74%, b_0=9.03%, c=0.5, and the 7th and 8th Columns of Table 1 into the Equation (8), we can obtain the corresponding credit rating results as shown in Table 2. This process can be easily implemented using C++ software programming.

(Insert Table 2 here)

Table 2 Results of farmers' microfinance credit rating.

4.2 Comparative analysis

To illustrate the rationality and effectiveness of the proposed model, we compare the credit rating results obtained from this model with the existing results. It is known from the third Column of Table 2 that the LGD of each rating is increasing, and meets the credit risk-rating match-up principle that the higher the credit rating is and the lower the LGD would be. Since existing credit rating methods often calculate the applicants' credit scores (Raquel, 2007; Boudreault et al., 2014; Shi et al., 2016; Bank of China, 2016; Moula et al., 2017; Zhang & Chi, 2018; Chai et al., 2019), do not consider the real default loss of loan customers, these results in the rating result not meeting the credit risk-rating match-up principle. As shown in the last Column of Table 1, the LGD of the A rating is 0.236%, while the LGD of the BBB rating is 0.022%, i.e. LGD_{A}=0.236%>LGD_{BBB}=0.022%. It is an unreasonable phenomenon that the LGD of a higher credit rating is more than of a lower one, not meeting the credit risk-rating match-up principle.

As can be seen from Table 2, the target profit of the bank can be insured when the bank issues loans to the farmers in ratings AAA, AA, A, BBB and BB. When the bank issues loans to the farmers in ratings AAA, AA, A, ..., CCC, CC, the bank can achieve its break-even point. In addition, in the credit decision-making process, setting an objective function of maximizing the loan customer above the critical point, reflects the inclusive financial concept that the credit fund benefits more farmers under the principle of sustainable commercial development. This kind of loan decision-making method can provide new ideas and references for the implementation of inclusive finance by regulators, commercial banks and small loan companies and helps solve the financing problems of agriculture-related enterprises and farmers.

5 Conclusions

This article presents a unique credit rating model that matches the credit ratings of microfinance borrowers with the corresponding LGD using a nonlinear programming approach. Furthermore, we study the impact of the state of economic development on commercial banks' credit decisions. More specifically, when the macro economy is in a tightening period, regulators can introduce policies to encourage commercial banks to increase the credit availability of loan customers on the basis of break-even and increase the amount of credit to stimulate economic development. When the macro economy is in a prosperous period, commercial banks can select credit applicants based on target profits and maximize their profits. This empirical work is developed using actual bank data from 2,044 farmers in China. The results show that the proposed credit rating model is effective.

This article contributes to the literature in two aspects. First, the theoretical analysis and empirical verification of the credit rating and lending decision based on LGD can provide new ideas and useful references for regulators and commercial banks to formulate credit policies. Second, the credit decision-making model, after considering macroeconomic impacts, is able to increase the availability of credit to farmers thereby addressing a critical issue in development finance.

Acknowledgments

References

Altman, E.I., Haldeman, R.G. and Narayanan P., 1977. ZETATM analysis: A new model to identify bankruptcy risk of corporations. Journal of Banking & Finance 1(1), 29-54.

Araujo, A., da Silva, P., Faro, J.H., 2016. Ambiguity aversion in the long run: "To disagree, we must also agree". Journal of Economic Theory 165, 242-256.

Bai, C., Shi, B., Liu, F. and Sarkis, J., 2019. Banking credit worthiness: evaluating the complex relationships. Omega 83, 26-38.

Bank of China. Management measures for credit rating of Chinese institutional and corporate customers. Bank of China Limited, 2016.

Bolton, P., Freixas, X., Shapiro, J., 2012. The Credit Ratings Game. The Journal of Finance 67(1):85-112.

Boudreault, M., Gauthier, G., Thomassin, T., 2014. Contagion effect on bond portfolio risk measures in a hybrid credit risk model. Finance Research Letters 11, 131-139.

Castilloa, J. A., Mora-Valenciab, A., Perote, J., 2018. Moral hazard and default risk of SMEs with collateralized loans. Finance Research Letters 26, 95-99.

Chai, N., Wu, B., Yang, W. and Shi, B., 2019. A multicriteria approach for modeling small enterprise credit rating: Evidence from China. Emerging Markets Finance and Trade, Article in press, 1-21. DOI: 10.1080/1540496X.2019.1577237.

Chiclana, F., Herrera-Viedma, E., Herrera, F., Alonso, S., 2004. Induced ordered weighted geometric operators and their use in the aggregation of multiplicative preference relations. International Journal of Intelligent Systems 19(3), 233-255.

Jarrow, R., Turnbull, S., 1995. Pricing derivatives on financial securities subject to credit risk. Journal of Finance 50(1), 53-86.

Karlan, D., Zinman, J., 2011. Microcredit in theory and practice: Using randomized credit scoring for impact evaluation. Science 332(6035), 1278-1284.

Leow, M., Mues, C., 2012. Predicting loss given default (LGD) for residential mortgage loans: A two-stage model and empirical evidence for UK bank data. International Journal of Forecasting 28(1), 183-195.

Loterman, G., Brown, I., Martens, D., Mues, C., Baesens, B., 2012. Benchmarking regression algorithms for loss given default modeling. International Journal of Forecasting 28(1), 161-170.

Merton, R., 1974. On the pricing of corporate debt: the risk structure of interest rates. Journal of Finance 29, 449-470.

Moula, F.E., Chi, G., Abedin, M., 2017. Credit default prediction modeling: an application of support vector machine. Risk Management 19(2): 158-187.

Postal Savings Bank of China (PSBC), Dalian University of Technology (DUT), 2014. Credit risk lending decision and evaluation report for farmers, Postal Savings Bank of China Co., LTD.

Qi, M., Zhao, X., 2011. Comparison of modeling methods for Loss Given Default. Journal of Banking & Finance 35(11), 2842-2855.

Raquel, F.L., 2007. Modelling of insurers' rating determinants: an application of machine learning techniques and statistical models. European Journal of Operational Research 183(3), 1488 -1512.

Scott, W. R., 2014. Institutions and Organizations: Ideas, Interests, and Identities. Lecture Notes in Computer Science, 3368(2):148-158. Stanford University (Fourth Edition).

Shi, B., Chen, N., Wang, J., 2016. A credit rating model of microfinance based on fuzzy cluster analysis and fuzzy pattern recognition. Journal of Intelligent & Fuzzy Systems 31(6), 3095-3102.

Shi, B., Meng, B., Yang, H., Wang, J. and Shi, W., 2018. A novel approach for reducing attributes and its application to small enterprise financing ability evaluation. Complexity 2018: 1-17.

Vasicek, O., EDF credit measure and corporate bond pricing. KMV Corporation, 2001.

Yao, X., Crook, J., Andreeva, G., 2015. Support vector regression for loss given default modelling. European Journal of Operational Research 240(2), 528-538.

Zhang, Y., Chi, G., 2018. A credit rating model based on a customer number bell-shaped distribution. Management Decision 56(5), 1-22.

Table 1

Data of farmers' microfinance credit rating.

(1) No.	(2) Credit score	(3) Sample ratio	(4) Number of samples in the interval m_k	(5) Credit rating k	(6) Scoring interval S_i	(7) Owed loan capital and the interest L_{ik}	(8) Receivable loan capital and interest R_{ik}	(9) Loss given default LGD_k
1	99.99					0	51725.00	
…	…	8%	164	1 AAA	$72.30 \le S_i \le 100$	…	…	0.002%
164	72.30					0	52653.50	
165	72.29					0	51955.00	
…	…	16%	327	2 AA	$62.68 \le S_i < 72.30$	…	…	0.003%
491	61.68					0	51979.28	
492	61.66					0	52618.00	
…	…	30%	613	3 A	$51.19 \le S_i < 62.68$	…	…	**0.236%**
1104	51.19					0	55015.00	
1105	51.18					0	52610.00	
…	…	16%	327	4 BBB	$46.19 \le S_i < 51.19$	…	…	**0.022%**
1431	46.19					0	52600.00	
1432	46.16					0	52588.25	
…	…	10%	204	5 BB	$42.13 \le S_i < 46.19$	…	…	0.959%
1635	42.13					0	30956.25	
1636	42.12					0	53849.75	
…	…	8%	164	6 B	$36.10 \le S_i < 42.13$	…	…	2.056%
1799	36.10					22.35	52613.75	
1800	36.07					54567.50	54567.50	
…	…	6%	122	7 CCC	$26.87 \le S_i < 36.10$	…	…	3.598%
1921	26.87					0	31568.25	
1922	26.73					9.16	21070.10	
…	…	4%	82	8 CC	$16.83 \le S_i < 26.87$	…	…	7.697%
2004	16.83					146.38	41724.80	
2005	16.69					623.80	21383.30	
…	…	2%	41	9 C	$0 \le S_i < 16.83$	…	…	11.474%
2044	3.920					45.81	52697.00	

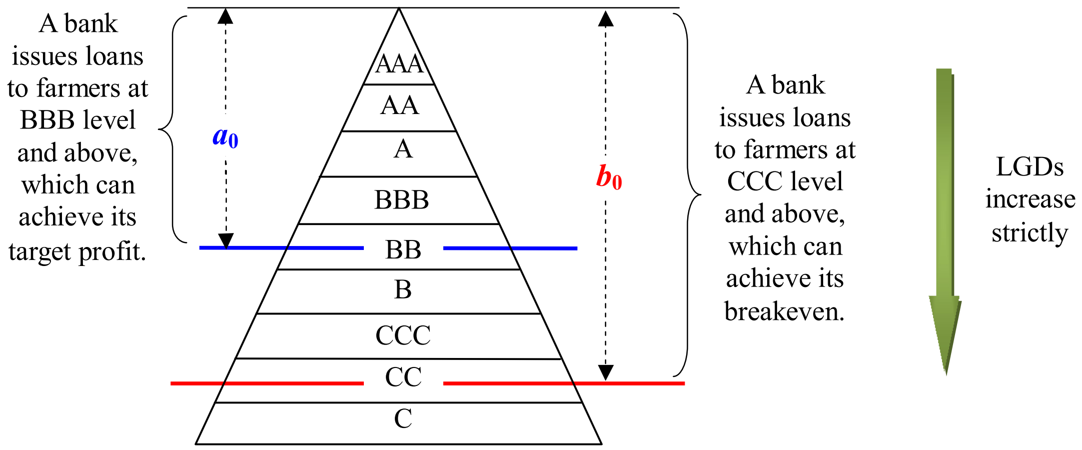

Fig. 1. A basic framework of credit decision.

Table 2

Results of farmers' microfinance credit rating.

(1) Credit rating		(2) Number of samples	(3) LGD_k	(4) Cumulative LGD_k	(5) Critical point	(6) The trend of *LGDk*
1	AAA	117	0.0073%	0.0073%		
2	AA	55	0.3041%	0.3113%		
3	A	429	0.5471%	0.8584%	a_0=3.74%	Increase strictly
4	BBB	413	0.7526%	1.6110%		
5	BB	337	0.9550%	2.5660%		
6	B	35	1.1829%	3.7490%		
7	CCC	61	1.4703%	5.2193%	b_0=9.03%	
8	CC	101	1.8295%	7.0488%		
9	C	496	2.2720%	9.3208%	-	
10	Objective function value: F=70.91%，f=(117+55+429+413+337)/2044=66.10%, g=(117+55+429+413+337+35+61+101)/2044=75.73%。					