REFEREED ARTICLE

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# A Credit Scoring Model for Farmer Lending Decisions in Rural China

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**ABSTRACT**

A cooperative mutual fund is an important cooperative-based financing option for farmers in China. As its farmer-borrowers often do not have formal records, a lending decision generally relies heavily on subjective evaluation. This experienced-based judgment has been relatively accurate but is less useful as seasoned loan officers retire or as growth necessitates hiring novice lenders. A credit scoring model was developed to capture the knowledge of experienced loan officers and thereby assist those more novice. The model evaluates a farmer's credit standing based on family background, willingness to repay, repayment capacity, and relationships. The analytic hierarchy process is used to determine factor weighting and the model is empirically tested. The model's predictive accuracy is high, with most error attributed to core indicators in the model that have strong veto power. Therefore, we suggest supplementing the credit scoring model with a crucial indicator negation system.

**KEYWORDS:** Rural mutual fund; cooperative lending; credit; analytic hierarchy process

''In microfinance, computer models will not replace loan officers, but they can flag the highest risks and act as a cross-check on human judgement.'' Schreiner, 1999, p.1

## 1. Introduction

The People's Republic of China's Rural Financial Reformation was launched in 2006. Since this time, the China Banking Regulatory Commission (CBRC) has been steadily loosening policy governing market access for rural financial institutions in an attempt to mitigate the problems of low network coverage, insufficient financial supply, and incomplete competition in rural areas. The goal is an inclusive financial system.

The 2014 Document No.1 of the Central Government, the leading annual policy document of the People's Republic of China (PRC), encouraged the development of new-type rural financial institutions, putting forth the clear guidance to foster and develop rural credit funds within cooperatives that are democratically managed and legally operated. These cooperative mutual funds (CMF) are allowed only to absorb shares rather than savings, and the mutual fund services are limited to cooperative members. They are regulated by the local Administration for Industry and Commerce (AIC) rather than the CBRC.

The 2015 Document No.1 carried forward the exploration of CMF, leading to a cooperative boom during the year. At the end of 2015, 1.53 million specialized farmers' cooperatives were registered. They have become prominent as a driving force in solving the problem of insufficient financial supply in rural areas.

The target of CMF services are farmers rejected by commercial financial institutions; those without sufficient collateral, a steady source of income, and / or complete credit information; and those who are scattered in remote rural areas. It would be prohibitively expensive for commercial finance institutions located in cities to collect farmers' information and evaluate their creditworthiness. And, farmers are generally unable to provide complete and accurate financial information. Further, the credit scoring model used by commercial banks cannot be completely applied to farmers even when farmer recordkeeping practices otherwise would support its use because of different lending standards such as reliance on collateral. In contrast, the CMF enjoys a special information advantage as people in a cooperative live together in the same community and know each other well. This ''acquaintance society'' has been important in solving the information asymmetry problem and saving on regulatory costs. It also results in a relatively quick and simple lending process.

The loan decisions are made based on the soft information generated in the well-established relationship

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between the cooperative and the farmer (such as the borrower's personality, reputation and social status). Pre-existing relationships or stable transaction relationships between borrowers and financial institutions can generate valuable private information, which can in turn increase the loan availability for those borrowers without clear credit information, as well as have the potential to decrease interest rate (Cole, 1998). Loan availability and lending conditions improve with the deepening of these bank-customer relationships (Petersen and Rajan, 1995; Van Gool et al., 2012).

Yet, as the CMF concept is still relatively new, there remain a number of potential risks not effectively mitigated including credit risk. Since CMF's information advantage originates from acquaintance relationships, determining credit risk relies heavily on qualitative information about potential borrowers and a loan officer's subjective judgment. While the process can be predictively accurate, it is a success that is difficult to pass on. Novice loan officers face a steep learning curve as they must acquire applicant information, often through informal processes, and master its relevance to creditworthiness.

There would be considerable value to a model that can capture the heuristic decision-making behaviors of experienced loan officers. In this context, we propose a credit scoring model built using the analytical hierarchy process (AHP) and with information provided by experienced loan officers. The model evaluates a loan applicant's family background, ability to repay, willingness to repay, and relationship with the cooperative supporting the CMF. Credit information samples are gathered from 211 farmers applying for loans from the Hejian Sannong Cooperative (Hebei Province, China) CMF to test the predictive accuracy of the model, namely how well the model captures the behavior of experienced loan officers.

The Hejian Sannong Cooperative is chosen for this study because, due to its growth and the resulting increasing loan demand, experienced loan officers are no longer able to effectively reach loan decisions for all applicants. Moreover, they have confirmed the steep learning curve faced by novice loan officers to gain adequate default prediction experience. This model will help mitigate the CMF's credit risk and promote the establishment of an inclusive financial system. Use of this model provides a unique opportunity for CMFs to combine experienced loan officers' subjective judgments and the soft information originating from an acquaintance society to form a standardized farmers' credit scoring model that can be effectively applied, by even a novice loan officer.

## 2. Background

The objective of credit models is to link borrower traits to credit risk (Hand and Henley, 1997; Sharma and Zeller, 1997; Sánchez and Lechuga, 2016; Xiao, Xiao and Wang, 2016). Advantages of statistics-based credit models are that outcomes are easy to calculate and are independent of the lender using the model. An important disadvantage is that use of such models requires high quality data. As such, in spite of their power in identifying high risk applicants, quantitative models cannot replace the judgment of the loan officer in making micro-credit decisions in less developed areas (Schreiner, 1999). Due to a lack of data, these decisions often rely more on experts' experiences (Serrano-Cinca, Gutierrez-Nieto, and Reyes, 2016). This is the case for CMF credit evaluations, which are mostly subjective judgments using discrete observations. For example, loan officers might provide their general impression of a borrower as "good", "fair", or "bad".

For CMFs, and more generally throughout the domain of microfinance, the search for viable credit scoring models useful even when records are not offered by the applicant or are not complete continues. A benchmark-based analytical hierarchy process (AHP) has been tested as a loan applicant disqualifier (Aouam et al., 2009) and as a means to include both qualitative and quantitative data in microfinance evaluations (e.g., see Serrano-Cinca and Carlos, 2016). It is the model adopted in this paper.

### Selection of indicators

The pivotal challenge in credit model development is selecting indicators for inclusion that are both available and useful to predict creditworthiness. Factors found most important in determining credit risk include borrowers' family background, ability to generate income, production and management conditions, social capital, and credit cognition. In some cases, the directionality of these factors is clear. For example, a farmer with a better reputation is less likely to default (Zhao and He, 2008); a farmer with deeper credit awareness has a lower probability of delinquency (Niu, Wang, and Ma, 2014); and higher interest rates and shorter repayment periods are associated with a higher default rate (Li, Gao and Cui, 2006). For other factors, the directionality of influence is less clear. Normally, households with more workers generate higher incomes, and thus have higher repayment capacity. Yet some researchers have found that families with more workers are more likely to default since those workers may go to the city as migrant workers, and people who stay at home are left with higher risk (Huang, 2010). Although income has a positive effect on repayment, its influence decreases with higher income levels (Wang and De-Hong, 2013).

The existing literature that evaluates or develops credit scoring models for farmers usually uses the 5 Cs principle to select indicators (Sun and Tang, 2009; Li, 2009; Yang, Xia, and Zhang, 2012), and lacks indicators that reflect the subtler characteristics available in an acquaintance society. Also, as an increasing number of farmers are taking part in the specialized cooperatives and rural industry associations, their management ability and risk bearing capacity has improved (Hou, 2007). Therefore, farmers' participation in these associations has good potential as a predictive indicator.

A credit scoring model for farmers has both theoretical and practical significance. Most of the existing models are based on complicated statistical models which are not suitable for use in part because indicator data cannot be obtained for rural farmers. On the other hand, models built with non-statistical techniques tend to rely too heavily on commercial bank precedents. For example, during field research for the current study, it became known that that educational background is not emphasized in the CMF, whereas great importance is attached to a borrower's identity. A borrower will only be considered trustworthy if he or she has lived in the community for a long time. The CMF is in urgent need of a simple credit scoring model that takes farmers' special credit characteristics into account and employs the experience of experts and the ''rules of thumb'' they have developed. This paper empirically considers the Hejian Sannong Cooperative and constructs a credit scoring model for farmers based on in-depth interviews with the CMF's presidents (i.e., the experienced loan officers who make loan decisions), designed to capture their subjective judgment. We also use farmers' real credit information to test the validity of the model.

### Hejian Sannong Cooperative

Hejian Sannong Cooperative, registered in March 2009, is located in Hejian in Hebei Province. Cooperative leadership investigated options to provide farmer credit. A large layoff of the local rural credit union allowed for the employ of traveling agents with local experience.

Local farmers initially faced cumbersome loan application procedures, and their lack of education at times generated frustration and impatience within the lending staff. Further, a number of farmers had been sold on a credit product with terms that were later altered. Some retaliated by refusing to pay the resultant debts. This exasperated the problem as financial institutions found themselves spending time and money handling the defaults, and farmers lost their creditworthiness.

To serve farmers, the Hejian Sannong Cooperative reorganized as a credit cooperative. On January 11, 2011, the cooperative assimilated the first sum of money paid for shares. Prior to July 2015 (the period of field research), the cooperative had developed 39 branches in towns and villages; had 3,356 members and a share balance of 41 million ¥[5]; and had issued 35 million ¥ in loans, all of which were small loans with no bad debt record. The microfinance loan service has now become Hejian Sannong Cooperative's signature product and has helped thousands of farmers obtain needed financing.

## 3. Methods

The credit scoring model constructed in this paper shares the common development objectives of other credit models including determining predictive indicators and estimating the weight and direction of their influence on credit risk; that is, defining and estimating the influence of decision criteria used by lenders. The analytic hierarchy process (AHP) is a method introduced by Saaty (2008) wherein a complex problem such as the lending decision is deconstructed. Pairwise selections of subject matter experts are used to estimate priority rankings of indicators such as credit history and family income in lending decisions. The AHP works well for a farmer-controlled cooperative wherein qualitative indicators such as those associated with an acquaintance society heavily influence the lending decision. Detailed procedures using AHP to weigh each indicator are as follows:

Step 1: Construct the decision hierarchy. The highest level is the lending decision. The next level consists of criteria on which subsequent elements depend. The lowest level is the indicator level, containing specific indicators relevant to the decision.

Step 2: Construct the pairwise comparison matrix. Each indicator in the upper level is compared with indicators in the level below using Saaty's comparison scale. Saaty's scale factor ranges from 1 (i and j are of equal importance) to 9 (i is much more important than j). The pairwise matrix is defined as:

$$A = (A_{ij})_{n\times n}, A_{ij} > 0$$

where A is an n x n matrix, and $A_{ij}$ denotes the element in row i and column j of matrix A, which is the scale factor comparing the influence of indicator i and indicator j on the lending decision.

Step 3: Calculate the weights as follows:

1. Normalize elements in the matrix $A = (A_{ij})_{n\times n}$ by column, resulting in $\overline{A} = (\overline{A_{ij}})_{n\times n}$, where $\overline{A_{ij}} = A_{ij} / \sum_{k=1}^{n} A_{kj}, (i = 1, 2, \cdots, n)$
2. Sum elements in the matrix $\bar{A}$ by row to obtain vector $W = (\omega_1, \omega_2, ..., \omega_n)$
$$\omega_i = \sum_{j=1}^{n} A_{ij}, (i, j = 1, 2, \cdots, n)$$
where $\omega_i$ is the sum of values in each row of $\bar{A}$.
3. Normalize vector W to obtain eigenvector $\overline{W} = (\overline{\omega_1}, \overline{\omega_2}, \cdots, \overline{\omega_n})$:
$$\overline{\omega_i} = \omega_i / \sum_{i=1}^{n} \omega_i, (i, j = 1, 2, \cdots, n)$$
where $\overline{\omega_i}$ is the normalized $\omega_i$ in the W matrix.
4. Calculate the maximum eigenvalue of the matrix:
$$\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n}\frac{(AW)_i}{\omega_i}$$
where $\lambda_{max}$ is the largest eigenvalue of a matrix and $(AW)_i$ is the sum of product of elements in row i of matrices A and W.
5. Employ the consistency test to validate the consistency of the comparison. The consistency index is calculated as $CI = \frac{\lambda_{max} - n}{n - 1}$ and the random consistency index (RI) is referenced from Saaty and Vargas (2012). The consistency ratio (CR) is calculated as. $CR = \frac{CI}{RI}$ If CR is $\leqslant$ 0.1, the matrix passes the consistency test; otherwise the matrix has to be revised. An eigenvector $\overline{W} = (\overline{\omega_1}, \overline{\omega_2}, \cdots, \overline{\omega_n})$ that has passed the consistency test represents the weights for the indicator variables.

### Model data

Nine experienced loan officers participated in a focus group discussion to select the indicators and to complete the pairwise comparisons. Hejian Sannong Cooperative was chosen because it operates on a large scale with thousands of rural household members, and its loan officers have a relatively long history of experience. Most of the loan officers are middle-aged, have several years of post-secondary education, and have been loan officers for at least three years. Seventy percent were travelling agents of the local rural credit union, and thus can be considered experienced loan decision-makers familiar with local people. The final loan decision is closely

[5] At the time of writing, 1 Chinese ¥ was approximately equal to 0.13€, 0.14$ U.S., and 0.11£.

 

related to these loan officers' personal judgments. Eight of the nine loan officers were classified as risk averters.

Loan officers were asked to grade cooperative members who had submitted loan applications using indicators determined by consensus during the focus group and from the literature. The sample covered nine villages and 211 members. Of the members, 90 were granted loans. Indicators are classified into four groups including family background, willingness to repay, ability to repay, and relationship with the cooperative.

1. Family background: Seven indicators represent family background including: Age (A1), Number of farm workers (A2), Identity as born and raised locally or not (A3), Marital status (A4), Lifestyle (A5), Family member health conditions (A6), and Mastery of professional skills (A7). Identity is an indicator used by local cooperatives. Loan officers make decisions according to their knowledge of the borrowers and they generally have more knowledge about those born and raised locally. Generally, local applicants have a higher chance of being granted a loan than newcomers. Educational background is a common indicator in credit scoring models but is not included here. The field research revealed that loan officers pay little attention to the formal education level of borrowers. As long as the borrowers are trustworthy and diligent, with a steady source of income and proper loan purpose, low education level is generally not considered against them.
2. Wiliness to repay: Four indicators representing willingness to repay include: Credit record (B1), Social reputation (B2), Social relations (B3), and Sense of family responsibility (B4). Generally speaking, farmers with higher social reputation are less likely to default (Zhao and He, 2008).
3. Ability to repay: The seven indicators for repayment ability include Family income per capita (C1), Condition of assets (C2), Living standard (C3), Production and management condition (C4), Main business stability (C5), Own capital ratio (C6), and Insurance condition (C7). The loan officers place considerable emphasis on the stability of a household's main business. A stable business operated for years with steady source of income is considered relatively low risk. Farmers who frequently change their main business are prone to loss and are more likely to default.
4. Relationship with the cooperative: Three indicators representing the borrower's relationship with the cooperative include: Participation in professional associations (D1), Business contact (D2), and General impression (D3). These indicators reveal the characteristics of the acquaintance society. Borrowers who maintain close business contacts with the cooperative, e.g., have savings in the cooperative and have a history of loan repayment, built their direct credit records in the cooperative and these are available to the lender making the decision. The indicator of loan officers' general impression of the borrowers is subjective.

### Descriptive statistics

A contingency table shows the 211 farmers' credit information (table 1). The samples are divided into two groups: farmers who were granted loans and farmers whose loan applications were declined. The performance of the two groups is compared on each indicator using a chi-square test.

Borrowers' age, identity, family members' health conditions, main business stability, own capital ratio, and business contact with the cooperative are different between those who were offered loans and those who were not. Just over half of farmers who were offered loans are between 31 and 45 years old. No farmers in the group offered loans belong to the ''other'' age sector (over 60 or below 20 years old) whereas 13.2% of the farmers who failed to obtain a loan are in the ''other'' age group. Since few loan applicants are below 20 years old, it can be inferred that older farmers tend to be refused more often.

The identity indicator shows that although most of the sampled farmers are native residents, those who were granted loans were *all* born and raised locally while 10% of those who failed to get a loan were not. The own capital ratio indicator shows that 34.4% of farmers who obtained a loan have an own capital ratio over 50%, in contrast to only 11.6% of the farmers that were denied. Moreover, 51.2% of those not offered a loan have an own capital ratio below 30% as compared to only 10% of those who received a loan. The relationship with the cooperative indicator shows that farmers who received loans had more frequent contact with the cooperative than those who did not. Sixty-two percent of farmers granted loans have close contact with the cooperative versus only 24% of the farmers who failed to get the loan; 38.8% of the farmers who failed to get a loan have little or no contact as compared to only 76.7% of those granted a loan.

## 4. Results and Discussion

### Pairwise comparison matrix

Pairwise comparisons were made by the loan officers using the one to nine scale proposed by Saaty (2008). The results of M-U and U1-A pairwise comparison matrices are shown (tables 2 and 3)[6]. Weights are determined in a four-step process. The process is illustrated using the M-U matrix as an example.

Step 1: Normalize the M-U matrix by column and obtain $\overline{M}$:

$$M_{ij} = \frac{A_{ij}}{\sum_{i=1}^{n} A_{ij}}$$

where $A_{ij}$ is the element in the original matrix M, $M_{ij}$ is the element of the normalized matrix $\overline{M}$, i, j= 1, 2, 3, 4 (table 4).

Step 2: Sum the matrix $\overline{M}$ by row and normalize it to obtain vector. $W = (\omega_1, \omega_2, \omega_3, \omega_4)$

The result $W = (0.088, 0.233, 0.467, 0.213)$ is the vector of weights of indicators (table 5).

Step 3: Calculate the maximum eigenvalue of the matrix, $\lambda_{max} = 4.06$

Step 4: Perform the consistency test:

$$CI = \frac{\lambda_{max} - n}{n - 1} = \frac{4.06 - 4}{4 - 1} = 0.021 < 0.1$$

where CI is the consistency index, $\lambda_{max}$ is the maximum eigenvalue of matrix, $\overline{M}$ and n is the number of factors

[6] The U2-B, U3-C, and U4-D pairwise comparison matrices are included in the related weight calculations and are available from the authors.

**Table 1:** Contingency table of indicators and loan availability

| Indicator | Level | Loan granted | | Chi-square P value |
|---|---|---|---|---|
| | | Yes | No | |
| Age | 20-30 | 11.1 | 9.9 | 0.001 |
| | 31-45 | 51.1 | 34.7 | |
| | 46-60 | 37.8 | 42.1 | |
| | Other | 0 | 13.2 | |
| Identity | Borrower was born and raised locally. | 100.0 | 89.2 | 0.006 |
| | Borrower settled in the village due to marriage. | 0 | 6.7 | |
| | Borrower is non-native but a long time resident in the village. | 0 | 4.2 | |
| Family member health conditions | Borrower is in good health condition; family members have no critical disease. | 82.2 | 58.7 | 0.001 |
| | Borrower is of general health; family members have no critical disease. | 15.6 | 27.3 | |
| | Borrower is of general health; family members have critical disease. | 2.2 | 11.6 | |
| | Borrower is in bad heath condition. | 0 | 2.5 | |
| Main business stability | Main business operated for over 5 years. | 24.4 | 15.7 | $<0.001$ |
| | Main business operated for 3-5 years. | 34.4 | 7.4 | |
| | Main business operated for 1-3 years. | 37.8 | 43.0 | |
| | Main business operated for less than 1 year, with prominent future income. | 3.3 | 13.2 | |
| | Main business operated for less than 1 year, with no obvious benefits. | 0 | 20.7 | |
| Own capital ratio | Over 70% | 1.1 | 0 | $<0.001$ |
| | 50%-70% | 33.3 | 11.6 | |
| | 30%-50% | 55.6 | 37.2 | |
| | Below 30% | 10.0 | 51.2 | |
| Business contact | Have opened account in cooperative and repaid more than 2 loans on time. | 62.2 | 24.0 | $<0.001$ |
| | Have opened account in cooperative and put idle money in the account. | 5.6 | 15.7 | |
| | Have opened account in cooperative but put little money in the account or borrowed from the cooperative. | 25.6 | 21.5 | |
| | Have no account in the cooperative. | 6.7 | 38.8 | |

**Table 2:** M-U pairwise comparison matrix

| M | U1 | U2 | U3 | U4 |
|---|---|---|---|---|
| U1 | 1 | 1/3 | 1/4 | 1/3 |
| U2 | 3 | 1 | 1/2 | 1 |
| U3 | 4 | 2 | 1 | 3 |
| U4 | 3 | 1 | 1/3 | 1 |

**Table 3:** U1-A pairwise comparison matrix

| U1 | A1 | A2 | A3 | A4 | A5 | A6 | A7 |
|---|---|---|---|---|---|---|---|
| A1 | 1 | 3 | 1/3 | 5 | 1/2 | 1/2 | 1/3 |
| A2 | 1/3 | 1 | 1/5 | 2 | 1/4 | 1/5 | 1/4 |
| A3 | 3 | 5 | 1 | 4 | 2 | 2 | 1 |
| A4 | 1/5 | 1/2 | 1/4 | 1 | 1/5 | 1/5 | 1/5 |
| A5 | 2 | 4 | 1/2 | 5 | 1 | 1/4 | 1/2 |
| A6 | 2 | 5 | 1/2 | 5 | 4 | 1 | 1/2 |
| A7 | 3 | 4 | 1 | 5 | 2 | 2 | 1 |

being compared in a matrix. RI = 0.89 when n = 4 (Saaty and Vargas, 2012).

$CR = \frac{CI}{RI} = \frac{0.021}{0.89} = 0.023 < 0.1$ indicating the matrix passes the consistency test.

This weight calculation and consistency test are performed for the remaining matrices. For each, CR $<0.1$, passing the consistency test. The weighted results of each matrix are combined and the result is the weight of each indicator relative to level M (table 6).

The indicator with the highest weight is Main business stability (0.166), followed by Credit record (0.128),

**Table 4:** Normalized M-U matrix $\overline{M}$

| $\overline{M}$ | U1 | U2 | U3 | U4 |
|---|---|---|---|---|
| U1 | 0.091 | 0.077 | 0.120 | 0.062 |
| U2 | 0.273 | 0.231 | 0.240 | 0.188 |
| U3 | 0.364 | 0.462 | 0.480 | 0.563 |
| U4 | 0.273 | 0.231 | 0.160 | 0.188 |

**Table 5:** M-U pairwise matrix, the weigh calculation and consistency test

| M | U1 | U2 | U3 | U4 | W | CI | CR |
|---|---|---|---|---|---|---|---|
| U1 | 1 | 1/3 | 1/4 | 1/3 | 0.088 | 0.021 | 0.023 |
| U2 | 3 | 1 | 1/2 | 1 | 0.233 | | |
| U3 | 4 | 2 | 1 | 3 | 0.467 | | |
| U4 | 3 | 1 | 1/3 | 1 | 0.213 | | |

Business contacts (0.124) and Own capital ratio (0.101). Other indicators that have a weight over 0.05 are Production and management condition, General impression and Social reputation.

In the M-U matrix, U3 has the highest weight (0.467) and U1 has the lowest. Thus, for the loan officers, the relative importance of the four indicator categories are, in order from most to least important, Ability to repay, Willingness to repay, Relationship with the cooperative, and Family background. Having a certain level of income and family assets are primary factors considered by loan officers. Reputation and personality are also crucial, which was expected because of the tradition of using acquaintance society indicators.

 

**Table 6:** Weight of indicators relative to U and M

| Indicator | Likert Scale Measure* | Weight relative to $U_i$ | Weight relative to M ($W_i$) |
|---|---|---|---|
| U1 Family background | | | 0.088 |
| A1 Age | 1 to 4 | 0.101 | 0.009 |
| A2 Number of laborers | 1 to 4 | 0.046 | 0.004 |
| A3 Identity | 1 to 3 | 0.240 | 0.021 |
| A4 Marital status | 1 to 3 | 0.035 | 0.003 |
| A5 Lifestyle | 1 to 3 | 0.134 | 0.012 |
| A6 Family members' health condition | 1 to 3 | 0.206 | 0.018 |
| A7 Mastery of skills | 1 to 3 | 0.239 | 0.021 |
| U2 Willingness to repay | | | 0.233 |
| B1 Credit record | 1 to 3 | 0.550 | 0.128 |
| B2 Social reputation | | 0.225 | 0.052 |
| B3 Social relations | 1 to 3 | 0.153 | 0.036 |
| B4 Sense of family responsibility | 1 to 3 | 0.072 | 0.017 |
| U3 Ability to repay | | | 0.467 |
| C1 Family income per capita | 1 to 5 | 0.102 | 0.048 |
| C2 Assets condition | 1 to 5 | 0.088 | 0.041 |
| C3 Living standard | 1 to 5 | 0.065 | 0.031 |
| C4 Production and management condition | 1 to 5 | 0.142 | 0.066 |
| C5 Main business stability | 1 to 5 | 0.354 | 0.166 |
| C6 Own capital ratio | 1 to 3 | 0.215 | 0.101 |
| C7 Insurance condition | 1 to 5 | 0.033 | 0.015 |
| U4 Relationship with the cooperative | | | 0.213 |
| D1 Participation in professional associations | 1 to 3 | 0.110 | 0.023 |
| D2 Business contacts | 1 to 4 | 0.581 | 0.124 |
| D3 General impression | 1 to 3 | 0.309 | 0.066 |

*One is the lowest rating and the highest score is the highest rating.

In the U1-A matrix, within Family background, Family members' health conditions and Identity are principle indicators. The importance of these indicators was reinforced by field research; experiences and precedents appear to shape the judgment of loan officers. Lenders shared stories of the cooperative granting loans to households with a family member suffering from serious illness, and the financial drain for the treatment resulted in loan default. Defaults have also occurred among newcomers in the villages.

In the U2-B matrix, Credit record is the leading factor in repayment willingness. In practice, a borrower with default record is rarely granted another loan. In the U3-C matrix, Main business stability and Own capital ratio are the dominating indicators, together accounting for over 50% of predictive influence within Repayment capacity, indicating that a steady source of income and accumulation of assets are favorable indicators for loan attainment. In the U4-D matrix, Business contact takes the largest proportion. The core of the cooperative is the bonds of acquaintance society.

The final scores are estimated as follows:

$$\begin{aligned} Z = {} & 0.009a_1 + 0.004a_2 + 0.021a_3 + 0.003a_4 + 0.012a_5 \\ & + 0.018a_6 + 0.021a_7 + 0.128b_1 + 0.052b_2 \\ & + 0.036b_3 + 0.017b_4 + 0.048c_1 + 0.041c_2 \\ & + 0.031c_3 + 0.066c_4 + 0.166c_5 + 0.101c_6 \\ & + 0.015c_7 + 0.023d_1 + 0.124d_2 + 0.066d_3 \end{aligned}$$

where Z is the total score for a borrower, $Z = \sum (T_i \times W_i)$ is the sum of product of each indicator and the corresponding weight, and $a_1, a_2, \ldots d_3$ are the scores of borrowers for indicators graded by loan officers. The credit score is then standardized to $H = \frac{Z}{u}$ x 100% where u is the output of the model when all indicators are graded with their highest scores. We define farmers with $H \geqslant 70\%$ to be a good credit risk and those with $H < 70\%$ to be a bad credit risk.

## Predictive accuracy of the model

Credit information of 211 farmers graded by loan officers were put into the model to test its predictive accuracy. First, credit scores for individual farmers are calculated. Next, the credit scores are divided by u to get the ratio H. According to the defined criteria, the 90 farmers who received a loan should have $H \geqslant 70\%$, and the 121 failed farmers should have $H < 70\%$. Eighty-three of the 90 farmers who successfully received the loan have $H \geqslant 70\%$ and 89 of the 121 farmers denied a loan have $H < 70\%$. Therefore, predictive accuracy for farmers who received loans is 92%. It is 74% for the farmers who were denied a loan. The combined predictive accuracy of the model is 82%.

Predictive accuracy for farmers denied a loan is relatively low, which calls for further investigation. The files for the 32 samples that earned $H \geqslant 70\%$ but were denied a loan were revisited. Among the 32 farmers, eight were relatively older (older than 60 years), eight had a low own capital ratio (less than 30%), thirteen had no business contact with the cooperative, and three had a low level of skill mastery. Despite these defects, they all performed reasonably well on other indicators. We conclude that some core indicators have veto power, which was confirmed by the loan officers during our return visit to the cooperative. A low score on any of the core indicators would effectively counter good performance on the other indicators, and thus prevent the borrower from getting the loan. Therefore, we propose adding a crucial indicator negation system as a supplement to the credit scoring model. In rural China, we suggest that in any credit model, extra attention should be paid to those crucial indicators such as age, own capital ratio and business contacts before making a loan decision. This may not hold as the case in other countries where such activities may be considered discriminatory and even illegal.

## 5. Conclusion

This paper validates AHP as a viable tool in constructing a credit scoring model for farmers taking part in CMF. The model is the quantification and standardization of experienced loan officers' expert opinions that aims at improving the efficiency of loan decision making. This information can be directly applied in building a model that will help support credit decisions, particularly by novice lenders, at any institution. While there are no claims that use of this model would mitigate financial exclusion in rural China, its use would indirectly help the effort by reducing loan default and credit evaluation costs for lenders This may be especially true for institutions employing novice loan officers or those with officers not indigenous to the particular region of their employ.

Credit scoring models like the one described in this paper also offer a context against which loan officers can compare their own judgments and preferences with one another and with themselves over time. This self-reflection would serve to encourage professional growth for experienced loan officers that have long-held decision-making habits. In addition, discussions stemming from model results may create greater consistency in decisions made by an institution's many employees. Although this paper analyzes microfinance decisions in rural China, the aforementioned learning opportunities are also applicable to larger financial institutions that possess better data on borrowers and have greater in-house capabilities for analyzing those data.

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## Abbreviations

AIC: Administration for Industry and Commerce
CBRC: China Banking Regulatory Committee
CMF: Cooperative Mutual Fund
PRC: People's Republic of China

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