Research on Credit Decision-making for SMEs Based on the Entropy Weight TOPSIS Method

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Abstract. In the context of the rapid development of big data, small and medium-sized micro-enterprises (SMEs) hold an indispensable position in contributing to the national economy. To tackle the challenges encountered by banks in extending credit to SMEs, this research develops a credit decision-making model grounded in risk assessment. This model utilizes linear programming to ascertain the loan amounts for SMEs across various credit ratings and adopts the entropy weight method to define risk assessment metrics. Moreover, it takes into account the potential influence of sudden events on credit risks for both financial institutions and enterprises. Through the application of the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for integrated evaluation and scoring, this study delineates credit risk management strategies specifically aimed at SMEs.

Keywords: SMEs, Linear Programming, Entropy Weight Method, TOPSIS, Credit Decision-Making

1   Introduction

In the era of big data, with the diversification of information sources and acquisition methods, the credit risk data faced by commercial banks exhibit complex and varied characteristics. Leveraging big data sharing enables banks to gain deeper insights into the essence of credit risks. As a cornerstone for the stable development of bank lending operations, the importance of risk management cannot be overstated, especially in the current environment where credit risk management has become a core issue in the operation of commercial banks. Historically, China's commercial banks have inclined their financing services towards large enterprises. However, in recent years, SMEs have played an increasingly significant role in the national economy, receiving high attention and support from society and the government alike. Consequently, under this new scenario, banks are gradually increasing investment support for SMEs[1][2][3] to facilitate rapid financing and development.

Nevertheless, due to their typically smaller scale, limited risk resistance capabilities, and insufficient collateral assets, SMEs present higher risks and costs when banks provide financing. Facing such challenges, commercial banks need to find a balance

between supporting SME development and maximizing their own interests. In practice, banks consider multiple factors, including the policy environment for credit, enterprises' bill transaction information, competitive dynamics within supply chains, and more, to offer higher credit limits to those enterprises demonstrating stronger capabilities and stable supply-demand relationships. Banks may also provide interest rate discounts to enterprises with good credit ratings and lower credit risks.

To address these issues, this study proposes using linear programming to set condition constraints for evaluating credit risks in commercial banks. This method integrates the actual capabilities and credit status of SMEs to assess their credit risk levels. Additionally, we introduce quantitative indicators such as loss intensity, profit intensity, differences in profit risk, and tax ratios, calculating the weights for each risk indicator. By employing the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [4][5][6]comprehensive evaluation method and considering the impact of sudden factors, we have developed credit risk decision-making strategies specifically aimed at SMEs. The goal is to provide a scientific and rational framework for credit risk management to banks, thereby ensuring that they can effectively manage risks while supporting the development of SMEs.

2   Establishment of a Bank Credit Decision Model

2.1   Entropy Weight Method

Establish Evaluation Indicators.
In managing bank credit operations, risk identification should focus not only on reducing losses but also on enhancing profitability. Traditional risk concepts emphasize the losses caused by uncertainty, yet concentrating solely on negative impacts can limit long-term credit operation development. To foster healthy growth, it's important to consider the opportunities within risks and the potential for profit.

To this end, risk assessment should establish two indicators: "probability of loss" and "probability of profit," reflecting the dual nature of risk. By introducing quantifiable metrics such as loss intensity, profit intensity, profit-risk difference, and tax ratio, these assessments describe the relationship between risk levels and factors like loan amounts and interest rates. The goal is to build a balanced risk assessment framework that considers both potential losses and possible profit opportunities.

Incorporation of Input and Output Invoice Information into Evaluation Indicator Calculation.
Based on the available input and output invoice information[7], let the input amount for the i-th company be A_i, the input tax amount be B_i, the output amount be C_i, and the output tax amount be D_i. Then, the loss intensity is denoted as Y_1, the profit intensity as Y_2, and the profit-risk difference as Y_3:

$$Y_1 = \frac{\sum\limits_{i=1}^{n} A_i}{\sum\limits_{i=1}^{n} A_i + B_i}, Y_2 = \frac{\sum\limits_{i=1}^{n} C_i}{\sum\limits_{i=1}^{n} C_i + D_i}, Y_3 = \frac{\sum\limits_{i=1}^{n} \sqrt{(C_i - A_1)^2}}{\sum\limits_{i=1}^{n} A_i + B_i + C_i + D_i} \tag{1}$$

Where n represents the number of companies.

Establish Indicator Weights.

To ensure accurate and effective credit assessment, it's important to standardize quantitative indicators, removing invalid or negative invoice information and other anomalies. This helps eliminate the impact of dimensional differences on the assessment results. Greater dispersion means lower entropy, indicating a more significant influence on the evaluation. Equal entropy values across indicators suggest they lack differentiation and are not decisive in the evaluation. Specifically, the calculation of information entropy for a set of data is as follows:

$$E_j = -\ln(n)^{-1} \sum_{i=1}^{n} P_{ij} \ln(P_{ij}) \tag{2}$$

In the context of calculating information entropy for credit assessment, the probability P_{ij} is defined as follows: $P_{ij} = y_{ij} / \sum_{i=1}^{n} y_i$.   To address cases where $P_{ij} = 0$, it is mathematically convenient to define: $\lim\limits_{P_{ij}} P_{ij} ln(P_{ij}) = 0$.

The second step is to calculate the weight of each indicator. According to the information entropy theory, after calculating the entropy values $E_1, \cdots, E_k$ for each indicator, the weights of these indicators can be computed using the following formula:

$$Y_2 = \frac{1 - E_i}{k - \sum E_i}, (i = 1, 2, ..., k) \tag{3}$$

2.2   A Bank Revenue Optimization Model Based on Linear Programming

When constructing a multi-objective optimization model[8], linear programming can be used to impose condition constraints on credit risk, thereby categorizing the credit risk of enterprises into four levels: A, B, C, D. However, in practice, banks typically do not extend loans to high-risk enterprises rated as D. Therefore, we will focus our analysis and calculations on enterprises rated A, B, C. To establish the model, we define the following parameters: let Q represent the annual loan interest rate, P the customer churn rate, M the bank's loan issuance limit, and W the bank's revenue. As shown in Table 1.

Table 1. Decision Variables

Credit Rating	A	B	C
Annual Loan Interest Rate	Q_1	Q_2	Q_3
Customer Attrition Rate or Customer Churn Rate	P_1	P_2	P_3
Loan Disbursement Limit	M_1	M_2	M_3

Secondly, construct the objective function for bank revenue:

$$W_{max} = M_1 * Q_1 * (1-P_1) + M_2 * Q_2 * (1-P_2) + M_3 * Q_3 * (1-P_3)$$

$$s.t. \begin{cases} 0.04 < Q_1 \le 0.08 \\ 0.08 < Q_2 \le 0.12 \\ 0.12 < Q_3 \le 0.15 \\ 0.09 < P_1 \le 0.92 \\ 0.07 < P_2 \le 0.89 \\ 0.07 < P_3 \le 0.88 \\ M_1 + M_2 + M_3 = 10^8 \end{cases} \tag{4}$$

Finally, determine W_{max} the maximum revenue for the bank, and calculate the values of each decision variable that achieve this optimal rating.

2.3   The TOPSIS Method

TOPSIS is a method used to evaluate and rank options based on how closely they match the best (ideal) and worst (anti-ideal) solutions. In TOPSIS, the best choice is the one closest to the ideal solution and farthest from the anti-ideal solution.

Distance of Alternative d_i to the Positive Ideal Solution:

$$S_i^* = \sqrt{\sum_{j=1}^{n}(C_{ij} - C_j^*)}, i = 1, 2, \cdots, m \tag{5}$$

Distance of Alternative d_i to the Negative Ideal Solution:

$$S_i^0 = \sqrt{\sum_{j=1}^{n}(C_{ij} - C_j^0)}, i = 1, 2, \cdots, m \tag{6}$$

To obtain the ranking index values for each alternative, which is also known as the comprehensive evaluation risk:

$$f_i^* = S_i^0 / (S_i^0 + S_i^*), i = 1, 2, \cdots, m \tag{7}$$

Subsequently, the alternatives are ranked according to the magnitude of f_i^*. A larger f_i^* indicates that the evaluation object is closer to the optimal value.

3   Solving the Bank Credit Decision Model

To solve the credit decision model, we first use linear programming to determine if a bank should extend a loan and define key loan parameters such as interest rate, amount, and term. This involves imposing conditional constraints on credit risk and assessing enterprises' creditworthiness to assign credit ratings[9][10].

Next, we apply the entropy weight method to establish two quantitative risk indicators: "probability of risk loss" and "probability of risk profit." These indicators consider factors like the loan amount and annual interest rate, incorporating specific metrics such as loss intensity, profit intensity, differences in profit-risk intensity, and tax ratios to calculate the weights of various risk indicators.

Recognizing that industries are affected differently by sudden factors, we developed a multi-criteria evaluation model based on TOPSIS. This model analyzes each company's decision matrix to evaluate overall strengths and weaknesses comprehensively. Companies are ranked by their performance index, with higher-ranked firms deemed closer to the optimal solution. This approach helps banks develop more reasonable credit risk strategies for SMEs.

4   Case Study Analysis

This study is based on the data provided for the 2020 College Student Mathematical Modeling Contest, conducting a case analysis. Using Lingo software to solve for the decision variables, we obtained the results shown in Table 2:

Table 2. Results of the Decision Variables

Q_1	Q_2	Q_3
0.08	0.10	0.13
P_1	P_2	P_3
0.09	0.07	0.06
M_1	M_2	M_3
52364000	32415000	15221000

As shown in the table, it can be determined that the total investments for enterprises with credit risk ratings of A, B, and C are 5236.4 million yuan, 3241.5 million yuan, and 1522.1 million yuan, respectively.

Using SPSS software for analysis and calculation, we determined the proportions of six key risk indicators: loss intensity, risk loss rate, input tax proportion, difference in profit risk intensity, risk return rate, and profit intensity (the weights of these risk indicators are shown in Figure 1).
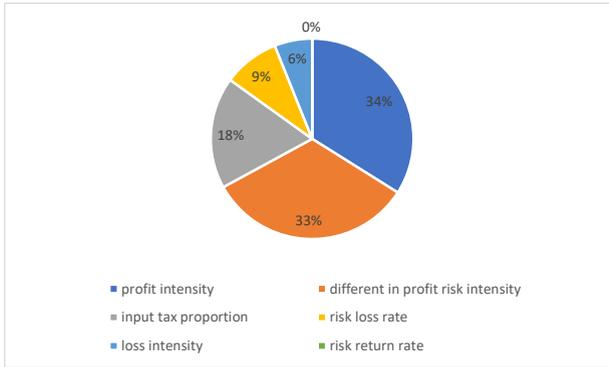
Fig. 1. weights of the risk indicators

As shown in the figure, the proportions of the six key risk indicators are as follows: profit intensity accounts for 34%, difference in profit risk intensity accounts for 33%, input tax proportion accounts for 18%, risk loss rate accounts for 9%, loss intensity accounts for 6%, and risk return rate accounts for 0%.

Based on the established credit risk assessment model, the credit investment amounts for 96 enterprises (excluding those rated D) are obtained as follows in Table 3:

Table 3. the investment amounts for the 96 companies

Company Code	Annual Interest Rate	Loan Amount	Company Code	Annual Interest Rate	Loan Amount
E1	0.118049	33.88416	E87	0.045727	87.47543
E2	0.053834	74.30281	E88	0.045563	87.79117
E3	0.100711	39.71752	E89	0.043521	91.90873
E4	0.12466	32.08772	E90	0.043692	91.55025
E5	0.12249	32.65581	E91	0.043522	91.90827
E6	0.056241	71.12283	E92	0.04457	89.74594
E7	0.096967	41.25119	E93	0.043521	91.90909
E8	0.052937	75.56142	E94	0.045385	88.13389
E9	0.095334	41.95773	E95	0.043277	92.42794
E10	0.044526	89.83559	E96	0.044498	89.89174

5   Conclusion

Compared to traditional credit decision-making methods, the proposed model selects a more comprehensive set of indicators that influence credit risk. By analyzing six key indicators, it provides extensive coverage of factors affecting the credit risk of small and medium-sized micro-enterprises (SMEs), thereby reducing the subjectivity in credit risk assessment and enhancing objectivity. The model employs the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) algorithm to preprocess and quantitatively transform both qualitative and quantitative data collected. This

process eliminates dimensional differences and correlations among indicators, resulting in normalized first-level decision indicators known as the Credit Risk Stability Coefficient. Based on variations in the Credit Risk Stability Coefficient of SMEs, financial institutions can provide differentiated loan decisions.

However, there are areas for improvement, notably through integration with big data technologies. Leveraging big data technology can address issues such as data distortion and information opacity in SMEs. Moreover, utilizing big data mining and analysis techniques enables real-time data processing and dynamic adjustment of the Credit Risk Stability Coefficient for SMEs. Additionally, introducing decision indicators related to the industry structure and supply chain conditions of SMEs is recommended. Classifying SMEs based on their primary economic activities and considering their position within the supply chain, along with the importance of their status within the industry, can lead to the development of industry-specific credit risk evaluation models for SMEs.

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