A Multi-Criteria Group Decision Making Model for Credit Risk Analysis

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Citation

Abstract
This paper introduces multi-criteria decision making (MCDM) into group decision making to propose a multi-criteria group decision making model for credit risk analysis. This model can not only deal with multi-criteria and complicated practical problems, but also reduce individual subjective preference to support group decision-making. In this model, experts' opinion is integrated by post-expert information, and grey relational analysis method is applied to extend the aggregation method for group decision making. The empirical results on credit risk analysis demonstrate the feasibility and effectiveness of the proposed model, which can process complicated practical problems.

1. Introduction
Credit risk analysis is one of the key problems in modern financial institutions. Since the 1980s, with the development of credit market, there have been many new methods of quantitative analysis models in risk analysis (Jarrow, 1997; Peng et al. 2008; Yang and Zhou, 2013; Kou and Wu, 2014). As a classical MCDM method, TOPSIS (Hwang & Yoon 1981) has been used to assess financial risk along with the integration of data mining, machine learning and so on (Wu and Olson, 2006). In this research, TOPSIS method is applied to assess credit risk, and the weights of attributes are determined by AHP (Saaty, 1980; Peng et al., 2011; Wu et al., 2012).

However, decision-making is a comprehensive interdisciplinary process. In order to make decisions more accuracy and efficiency, decision mistakes caused by a single decision-maker should be reduced. Group decision making (Hwang and Lin, 1987; Xia and Chen, 2015) can synthesize views and information of policy makers, such as brainstorming, to form a common wisdom for making a reasonable choice or sorting and focus on decision-making by post-expert information which can better ensure a good consistency matrix (Ishizaka and Labib, 2011). In this paper, grey relational analysis (Deng, 1982) method is introduced to gather different experts’ opinion by post-expert information.

The remaining parts of this paper are structured as follows: In section 2, a credit risk assessment model is proposed based on qualitative and quantitative analysis, multi-criteria decision making and group decision making. In section 3, the proposed model is verified by an empirical credit risk analysis case. Finally, Section 4 concludes the paper.

2. Proposed Model
Based on the company's financial ratio data (Altman, 1968), MCDM are increasingly applied for risk analysis and management (Steuer and Na, 2003). With the social
development, decision-making process has also becoming more and more complex. It is difficult to make a scientific and accurate evaluation only by one decision maker on complicated practical problems. Thus, it is necessary to gather all the views and preferences of the group members to form a unified view or preference to sort the program and select the most preferred solution. In this paper, grey relational analysis (GRA) method is introduced to gather different experts’ opinion in credit risk analysis in order to extend the aggregation method for group decision making. The group decision making process includes the following steps:

Step 1: Determine attribute weights. The weights are determined by AHP method combined with qualitative analysis and quantitative analysis.

Step 2: Rank the alternative. TOPSIS is used to determine the ranking of each alternative.

Step 3: Gather post-expert information. Ishizaka and Labib (2011) indicated that group decision making should focus on decision-making by post-expert information, which can better ensure a good consistency matrix.

Step 4: Determine the expert weight. As different experts have different prestige, knowledge, experience, expectations, decision power, and risk preferences, different experts should be assigned with different weights.

Step 5: Gather experts’ opinion. This paper applies GRA method to gather different experts’ opinion.

Step 6: Determine the priorities of alternative. Determine the priorities of alternative by the grey relational degree in group decision making. The larger the grey relational degree, the larger the values of credit risk.

The assessment flow chart is presented in Figure 1.

3. Empirical Analysis

In this section, an empirical credit risk analysis case is tested to verify the proposed model for credit risk analysis.

3.1. Index System and Data Sample

The selected data and indicators are collected from the public-listed company's financial data in the first half year of 2008 (Lu and Wu, 2010). Four companies A, B, C and D are selected as the assessment object. The data of financial indicators are obtained and further to be pre-processed to get the standardized data, as shown in Table 1.

Table 1. Index system and data sample

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Company A</th>
<th>Company B</th>
<th>Company C</th>
<th>Company D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quick ratio</td>
<td>0.0013</td>
<td>0.1872</td>
<td>0.2054</td>
<td>0.6061</td>
</tr>
<tr>
<td>Current ratio</td>
<td>0.1228</td>
<td>0.4122</td>
<td>0.0350</td>
<td>0.4300</td>
</tr>
<tr>
<td>Asset-liability ratio</td>
<td>0.1714</td>
<td>0.5889</td>
<td>0.2375</td>
<td>0.0022</td>
</tr>
<tr>
<td>Property net profit ratio</td>
<td>0.2267</td>
<td>0.0420</td>
<td>0.0560</td>
<td>0.6754</td>
</tr>
<tr>
<td>Net assets returns ratio</td>
<td>0.2502</td>
<td>0.0191</td>
<td>0.0764</td>
<td>0.6542</td>
</tr>
<tr>
<td>Net profit ratio</td>
<td>0.2309</td>
<td>0.0400</td>
<td>0.0909</td>
<td>0.6382</td>
</tr>
<tr>
<td>Account receivable ratio</td>
<td>0.1967</td>
<td>0.0211</td>
<td>0.2013</td>
<td>0.5809</td>
</tr>
<tr>
<td>Total assets return ratio</td>
<td>0.1293</td>
<td>0.0155</td>
<td>0.0546</td>
<td>0.8005</td>
</tr>
<tr>
<td>Total assets increasing ratio</td>
<td>0.3309</td>
<td>0.0104</td>
<td>0.0007</td>
<td>0.6580</td>
</tr>
<tr>
<td>Net capital increasing ratio</td>
<td>0.7183</td>
<td>0.0936</td>
<td>0.1872</td>
<td>0.0009</td>
</tr>
</tbody>
</table>
3.2. Empirical Process

We consulted three domain experts to assess credit risk. The procedures are as follows:

1. Determine attribute weights and consistency test. The three experts include a risk neutral expert $k_1$, a risk-preference expert $k_2$, and a risk-averse expert $k_3$. The pair-wise comparison matrix of the three experts is collected respectively to determine each attribute weight value by AHP method.

$$w_k = (0.112, 0.041, 0.195, 0.039, 0.066, 0.124, 0.112, 0.097, 0.032, 0.182)$$

$$w_k = (0.072, 0.116, 0.072, 0.161, 0.168, 0.228, 0.072, 0.042, 0.024, 0.045)$$

$$w_k = (0.139, 0.025, 0.025, 0.059, 0.092, 0.038, 0.203, 0.091, 0.038, 0.290)$$

The consistency test results of the three matrices are $CR_{k_1}=0.055<0.1$, $CR_{k_2}=0.023<0.1$ and $CR_{k_3}=0.021<0.1$ respectively. The pair-wise comparison matrices of the three experts are all satisfied the condition of the consistency ratio, indicating that the opinion of each expert is reasonable and effective.

2. Determine the expert weight. The value of the expert weight should reflect consistency of the results between one expert and group experts in the decision activities. That is to say, the more concordant of decision results between one expert with a majority of group experts, the greater the decision power of the expert, and the larger the expert weight. So the weights of three experts are assigned as 0.1, 0.3, 0.6 respectively.

3. Determine the final priorities of alternative according to the Step 2-6. First, TOPSIS method is used to determine the priority of each alternative. The evaluation results are presented in Table 2. Then, experts’ opinions are gathered by grey relational analysis method. Finally, the grey relational degree of group decision making is calculated, as shown in Table 2.

<table>
<thead>
<tr>
<th>Company</th>
<th>Expert 1 relative close degree</th>
<th>Expert 2 relative close degree</th>
<th>Expert 3 relative close degree</th>
<th>Grey relational degree</th>
<th>Credit risk Ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company A</td>
<td>0.4906</td>
<td>0.3294</td>
<td>0.6041</td>
<td>0.9262</td>
<td>2</td>
</tr>
<tr>
<td>Company B</td>
<td>0.3943</td>
<td>0.2276</td>
<td>0.1437</td>
<td>0.7895</td>
<td>4</td>
</tr>
<tr>
<td>Company C</td>
<td>0.2721</td>
<td>0.1339</td>
<td>0.2575</td>
<td>0.7926</td>
<td>3</td>
</tr>
<tr>
<td>Company D</td>
<td>0.4657</td>
<td>0.8033</td>
<td>0.4583</td>
<td>0.9487</td>
<td>1</td>
</tr>
</tbody>
</table>

3.3. Results Analysis

When assessing credit risk, different experts focus on different financial indicators. The analysis of attribute weights presents that the risk neutral expert focuses on the asset-liability ratio, so the asset-liability ratio has the largest weight of 0.195. The risk-preference expert concerns about the net profit ratio, so the net profit ratio has the largest weight of 0.228. The risk-averse expert concerns about net capital increasing ratio, so the net capital increasing ratio has the largest weight of 0.290. There is significant inconsistency among decision makers in the judge of the same decision.

From Table 2, Company D’s credit risk value is the highest, followed by Company A and Company C, and Company B’s credit risk value is the lowest, its credit is best. While Lu and Wu (2010) shows that the credit risk level of the four companies is D>A>C>B. The results of the assessment are consistent, which illustrates that our proposed multi-criteria group decision making model for credit risk analysis is feasible and effective.

According to the weight analysis of AHP, we found that financial institutions should pay more attentions on the impacts of asset-liability ratio, net profit ratio and net capital increasing ratio by the dynamic changes of index value to guide decision-making, adjust business strategy and reduce the credit risk level.

4. Conclusion

This article conducts a multi-criteria group decision making model which combined MCDM and group decision making theory to manage credit risk. The results indicate that the proposed model can be used to support credit risk management and guide business strategy adjustments. In addition, experts’ opinions are integrated based on post-expert information by applying MCDM method, rather than simply applying linear weighted geometric mean or arithmetic mean method. Furthermore, by calculating grey relational degree in group decision making, the views and preferences of decision-makers can be synthesized to form a common wisdom.

Acknowledgements

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References


