Supply Chain Financing Risk Measurement of Small and Micro Enterprises Based on Logistic-Copula Model

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Abstract: The financing risk measurement and monitoring of small and micro enterprises (SME) is one of the key problems that plague SME, The main reasons for the difficulty of measuring and monitoring the financing risk of SME are as following: (1) Construction of risk measurement index system, (2) Risk measurement Model building. Firstly, establish SMEs supply chain financing risk index database, by the F-value method and logistic regression model based on partial correlation analysis, the indexes with larger correlation and lower significant correlation were eliminated, the risk measurement index system was constructed. Then, the Logistic regression model is used to construct the financing risk measurement model of a single enterprise and calculates the default probability value. Finally, the Copula related structure model of the supply chain is used to calculate the probability of financing default risk. The research shows that the probability of financing default risk of SME is much smaller than the probability of financing default risk of single enterprise. The overall correlation of supply chain financing can effectively reduce the default risk of single enterprise financing. The financial institutions can measure and monitor the financing risks of a single enterprise in light of the overall operation of the supply chain.

1. Introduction

At present, China's economic operation, corporate finance is difficult, especially SME financing difficult to become one of the key issues to be solved urgently, financing is difficult to show the proportion of regional loans imbalance, bank small loans urgent force and policy enforcement needs to be strengthened, The underlying cause of this situation is that the SME financing risk is difficult to measure, the financing risk is difficult to monitor and the enterprise credit qualification is insufficient. The supply chain financing is financed by the current assets. The object of service is mainly in the supply chain upstream and downstream enterprises, especially the SME, in the process of financing, achieve credit bundling with the core enterprises in the supply chain. The risk
is the overall correlation.

Supply chain financing business characteristics can effectively solve the problem of lack of credit qualification, so that the SME supply chain financing risk measurement and risk monitoring has become the core issue to solve the financing of SME. On the one hand, the financial system and operating system of SME are not perfect, so that the relative lack of accurate financial data and real-time operating data, a direct result of SME supply chain financing risk index data is limited, difficult to collect index data; On the other hand, the attention of the existing risk measurement model research on SME is limited, the accuracy that the traditional risk measurement model is applied directly to the SME is limited. Therefore, it is necessary to construct a new index system for the risk measurement of SME, and to construct a risk measurement model suitable for SME according to the characteristics of supply chain financing business, and provide a financing decision reference for financial institutions.

The construction of risk index system is the key to the risk measurement model of SME supply chain financing, The index system of the credit risk assessment system mainly includes five aspects: moral character, capital, ability, guarantee, business environment, that is, often say "5C". Criteria, Moody's, S & P, Fitch, Dagong International and other major credit rating companies in the "5C" based on the different focus, but generally speaking, it is the two aspects of the enterprise's repayment ability and repayment intention. Chi guotai [1] (2016) Based on the index selection system of the discriminatory ability of the default state, the index system of the SME creditor's credit rating is established by using the Probit model. However, because of the confidentiality of the research results, the article only obtains general situation of the index system, can't obtain details of the specific indicator system[2]. Xiao Binqing et al. (2016) constructs the index system from the credit information of the rural commercial banks as the empirical sample. Seven indicators are selected as the input variables from the 19 credit rating indicators. In the input variables, four variables belong to the qualitative variables. Based on the establishment of neural network model for small enterprises and micro-enterprise credit rating test [3]. Gao Lijun (2012) By using the data of the credit risk database of SME in Germany, the quantitative indicators that are the profitability ratio, the total assets ratio, the property right ratio and the debt ratio were significant, the profitability and the total assets ratio were the most influential. In qualitative indicators, Experts on the SME in the past to repay the history of judgments have a significant impact[4].

Default risk of supply chain financing has overall correlation, the existing research shows that using Copula function to measure the correlation has obviously advantages, Lujing(2013) based on operational risk is fat-tailed distribution characteristics, used POT extremum model respectively to estimate the edge of the multiple unit operation risk distribution, and then used multivariate copulas connect function to depict the correlation between operating risk unit and calculate the risk value [5]. Xie chi(2016) used the dual-power fluctuation to match the marginal distribution of the futures price of the CSI 300 stock index, Construction of time-varying mixed Copula function related structure model measure CSI 300 stock market spot high frequency price dependent structure[6].Guo-Fu Zhang (2016) build industry-based and market-based R, to derive the relevant structure between stocks, industry and markets to predict the systemic and non-systemic risks of stocks [7], Use vine Copula- Bayesian network model of Chinese - American stock and bond market nonlinear dependence structure [8]. Ling-Bing Tang (2016) select 30 companies from China stock market list fraud as samples, using logistic regression model to formula sheet accounting fraud Chinese listed in detail, and arrive at debt paying ability, operation ability and capital constitute a significant effect on off-balance sheet accounting fraud, profitability influence was not significant[9].

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The limitations of the existing research is: 1. the index system of financing risk existing measures are not suitable for SME, small and micro businesses financial information and business information is relatively complete, but also in terms of the index screening of default risk, the subjective factors are larger, lack of SME default risk effects whether a significant considerations; 2. The existing SME financing risk measurement only considers the single enterprise default state, lacks the integrity attention, enterprise financing risk focused on credit rating methods, lacked the quantification of the enterprise financing risk of default probability test; 3. One of the advantages of rule based learning algorithms is that they generate easily understood rules, So rule learning algorithms seem to be good for this sort of task, but rules are useful only when they're accurate.

Aiming at the above problems, this text screening SME financing risk index system by logistic regression model, remove no significant effect on default index, through the construction of SME supply chain financing risk Logistic regression model to obtain the default probability of SME supply chain financing. The Copula correlation structure model is used to fit the risk of SME supply chain financing risk, measure the default loss probability of SME. JörgSchwiebert (2016) It is considered that the Copula-based double-span barrier model has a flexible marginal distribution, even if the selected Copula is incorrectly specified, the Copula-based double-hulle model with flexible margins can run well[10]. Xing Yang (2017) The optimal combination of target models is analyzed by using design risk thresholds and Copula-based conditional probability methods, and give the preferred proof of this method[11].

2. Construction method of SME supply chain financing risk measurement index system

Based on the foreign relevant research materials and the research achievements of domestic scholars, combining the reality index data that the financial institutions can be provide ,screening the risk metrics, the principle of screening depends on whether the index data is available and the index data can be quantified.

Data of risk observation indicators are dimensionally processed, because the numerical value of quantitative risk index is different, standardized treatment is carried out in this paper, for qualitative indicators, quantitative processing is carried out. Research groups and joint units provide the supply chain financing business data of four industrial park pilot areas.

2.1 Standardization of indicator data

The dimensionless method of indicator data is mainly selected by the threshold method in the linear dimensionless method. If the selected evaluation indicators are positive indicators (or are inverse indicators), in the first comprehensive evaluation, the same dimensionless formula should be adopted for all indexes. If there are both positive and negative indicators in the evaluation, and do not make inverse index transformation processing, two kinds of dimensionless formulas corresponding to the positive and negative indexes are adopted respectively. The so-called reciprocal formula means that the range of values obtained by the two formulas should be consistent, so that we can conduct a comprehensive evaluation.

Broken line type dimensionless method is suitable for the development of things, the change of index value at different stages is not the same as the general level of things. The structure of the broken line type dimensionless method differs from the straight line in that it is necessary to find out the index value of the turning point of the development of things and determine its evaluation
value. Such as Equation (1), Here \( x_m \) is the turning point index value, \( y_m \) is the evaluation value of \( x_m \).

\[
\begin{align*}
    y_j &= \begin{cases} 
        \frac{x_j - y_m}{x_m}, & 0 \leq x_j \leq x_m \\
        y_m + \frac{x_j - x_m}{\max_i x_i - x_m}(1 - y_m), & x_j > x_m
    \end{cases}
\end{align*}
\] (1)

Quantification of qualitative indicators, where the quantification of the main order of the specified indicators, sequential indicators refer to excellent, good, medium and poor. Processing this level of data quantification, according to the actual observation of the index data should be accounted for, consider the probability distribution, the simpler method is to select the number of digits. The index proportion conforms to the standard normal distribution, use the normal probability distribution table to find out the corresponding data values corresponding to each qualitative index, in this way, the qualitative indexes are quantified. Suppose if there is \( k \) class \( a_1, a_2, \ldots, a_k \), the worst is \( a_1 \), followed by ascending, the best is \( a_k \). The proportion of each class and the cumulative proportion are shown in Table 1.

<table>
<thead>
<tr>
<th>classify</th>
<th>( a_1 )</th>
<th>( a_2 )</th>
<th>\ldots</th>
<th>( a_k )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Various proportion</td>
<td>( p_1 )</td>
<td>( p_2 )</td>
<td>\ldots</td>
<td>( p_k )</td>
</tr>
<tr>
<td>Cumulative proportion</td>
<td>( p_1 )</td>
<td>( p_1 + p_2 )</td>
<td>\ldots</td>
<td>1</td>
</tr>
</tbody>
</table>

Accordingly, the \( a_i \) corresponding to the \( x_j \) should have nature:

\[
    P(x < x_j) = \sum_{j=1}^{i-1} p_j + \frac{1}{2} p_i, i = 1, 2, \ldots, k,
\]

with the \( \alpha \) quantile \( u_\alpha \) of \( N(0,1) \) is used to represent, would have

\[
    x_1 = u_{\frac{\alpha}{2}}, x_2 = u_{\frac{1}{2}p_1}, \ldots, x_k = u_{\frac{1}{2}p_1 + \frac{1}{2}p_2} + \sum_{j=1}^{i-1} \frac{1}{2} p_j, \quad i = 1, 2, \ldots, k,
\]

this gives a general expression.

### 2.2 Filtering index data

Correlation analysis and Logistic regression model were used to filter the index data. The partial correlation analysis method selected in Chi guotai group is used to screen the index data. Test the correlation between multiple indicators, eliminate redundant indicators, avoiding multiple indicators repeated reaction to enterprise default risk information. Failure to eliminate the relevance will cause the risk measurement model to be too complex to cause the accuracy of the SME supply chain financing risk measurement.

Due to the large number of risk measurement indicators, if the correlation between the indicators is verified, the number of related indicators will be more, some indicators are only numerical correlations, not real correlations. Therefore, it is necessary to classify the indexes in advance, and test the correlation of the indexes in each classification, so as to avoid false deletion of false correlation index.

In theory, Pearson's correlation coefficient is between -1 and 1. However, for some random
variables, the actual scope of the coefficient is relatively small, and other measures of correlation are also given in the literature, the two most popular are the Spelman correlation coefficient and Kendall correlation coefficient, the Kendall correlation coefficient reflects the difference between the congruent pairs and the incongruent pairs. So let's say that \((X_i, X_j)\) and \((Y_i, Y_k)\) are two independent binary continuous random variables, \(i\) and \(j\) are the \(i\) and \(j\) indicators of risk measurement. \(k\) and \(t\) represent two different companies, and the Kendall correlation coefficients are defined.

\[
\tau_{ij} = P[(X_{ik} - Y_{jk})(X_{it} - Y_{jt}) > 0] - P[(X_{ik} - Y_{jk})(X_{it} - Y_{jt}) < 0]
\]

Then the correlation coefficient matrix \(R\) is obtained, \(R = \begin{bmatrix} \tau_{11} & \tau_{12} & \cdots & \tau_{1n} \\ \tau_{21} & \tau_{22} & \cdots & \tau_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tau_{n1} & \tau_{n2} & \cdots & \tau_{nn} \end{bmatrix}\), Its inverse matrix is \(R^{-1} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix}\), The coefficient of partial correlation obtained is \(\rho_{ik} = \frac{-r_{ik}}{\sqrt{r_{ii}r_{kk}}}\).

The partial correlation coefficient is greater, the correlation is stronger between the two indicators. However, when the index is deleted by partial correlation coefficient, which one should be deleted between the two indexes with partial correlation coefficient? Here refer to the F value method of the Chi guotai group, shown in Equation (2), by calculating the F value of high correlation index, to select the index variable to delete.

\[
F = \frac{1}{n^{(0)} - 1} \sum_{j, y = 0} \left( \frac{\bar{x}_{ij} - \bar{x}_{ij}^{(0)}}{\bar{x}_{ij}^{(0)} + \bar{x}_{ij}} \right)^2 + \frac{1}{n^{(1)} - 1} \sum_{j, y = 1} \left( \frac{x_{ij} - \bar{x}_{ij}^{(1)}}{\bar{x}_{ij}^{(0)} + \bar{x}_{ij}} \right)^2
\]  \(\text{(2)}\)

The mean of the \(i\) index in the non-default sample is \(\bar{x}_{ij}^{(0)} = \frac{1}{n^{(0)}} \sum_{j, y = 0} x_{ij}\), the mean of the \(i\)-th index in the default sample is \(\bar{x}_i = \frac{1}{n} \sum_{j, y = 0} x_{ij}\). The mean of the \(i\)-th index is \(\bar{x}_i = \frac{1}{n} \sum_{j, y = 1} x_{ij}\), \(x_{ij}\) is the value of the \(i\)-th index of the \(j\)-th sample, \(n^{(0)}\) is total number of the non-default samples, \(n^{(1)}\) is the total number of the default samples, \(n\) is the total number of the samples. The F value represents the sum of the distance between the mean of the default, non-default samples of the \(i\)-th index and the mean of the population sample, reflect the difference between the default sample and the non-default sample, if the difference is greater, the index is more able to distinguish the default state of the enterprise, the denominator is the sum of the variance of the default sample and the variance of the non-default sample in the \(i\)-th index, it reflects the degree of discreteness between default samples and non-default samples. If the degree of discrepancy is smaller, the characteristics of the indicators within the default and non-default samples is more concentrated, the \(F\) value reflects the discrimination ability of the \(i\)-th index to the enterprise default, if the \(F\) value is greater, the identification ability is stronger, the effect of indicators on the default state is more significant. On
the contrary, the effect of the index on the default state is smaller.

In the selection of index variables, usually select the indicators that partial correlation coefficient is more than 0.7, then delete the indicators that the \(F\) value is smaller and construct risk index system.

3. Construct SME supply chain financing risk measurement model

3.1 Measurement of enterprise default risk based on Logistic regression model

First, choose the logistic model to select significant variables, Instead of using traditional principal component analysis and factor analysis to explain variables. Further screening out the default risk measurement index system, logistic regression model was used to analyze the sample data. Here, use the method of gradual optimization, Gradually eliminate the least significant dependent variable, refers to delete one of the least significant indicators and then make a Logistic regression again, some of the less significant variables can become significant, the process of index deletion is repeated step by step until all indicator variables become significant. The final model only retains important variables. Part of the model analysis results are shown in Table 2, and the model is shown in Equation (3).

|                  | Estimate | Std.Error | z value | Pr(>|z|) |
|------------------|----------|-----------|---------|---------|
| intercept        | -1.4573  | 0.3602    | -4.046  | 5.22e-05|
| Tax Control      | 381.6093 | 70.0763   | 5.446   | 5.16e-08|
| Running Rate     | -2.8562  | 1.4059    | -2.032  | 0.0422  |
| Agency           | 2.7063   | 1.2931    | 2.093   | 0.0364  |
| Insurance Rate   |          |           |         |          |

\[
\ln\left(\frac{p}{1-p}\right) = -1.4573 + 381.6093x_1 - 2.8562x_2 - 2.7063x_3 + \cdots \quad (3)
\]

Through the analysis of the model, it is found that the significant value of the indicator variable provided by the enterprise is not obvious when the data of the operational risk are analyzed. It shows that the reliability of the index data provided by the enterprise is relatively poor, and the index data from the tax section and the business data of the affiliated enterprise are relatively more credible. The confusion matrix is shown in Table 3. It is shown that the regression analysis model of Logistic model is good.

<table>
<thead>
<tr>
<th></th>
<th>abnormal</th>
<th>normal</th>
</tr>
</thead>
<tbody>
<tr>
<td>abnormal</td>
<td>244</td>
<td>14</td>
</tr>
<tr>
<td>normal</td>
<td>25</td>
<td>357</td>
</tr>
</tbody>
</table>

3.2 Supply chain financing risk correlation measurement based on copula correlation function

The Copula related structure model is established, and the operation information of the enterprises in the supply chain is taken as the index data, such as the logistics information of
third-party logistics warehouse, establish the correlation structure model of inter firm yield. Here we need to show that some enterprises in the sample data of the screening risk index lack the third party logistics information, therefore, the relevant structural model is established only for the enterprises with third party logistics information in the supply chain, and the risk measurement is studied.

Multivariate mixed Copula correlation structure model is chosen, because the logistics information is dynamic, so the parameters of the multivariate mixed Copula correlation structure model are also time-varying. In order to illustrate the simple principle of the model, we construct multivariate mixed time-varying copula correlation structure model based on three enterprises, the three enterprises are Zhonglian**B, Xinlong**A and Hexing**C in the supply chain.

When constructing the Copula correlation structure between three enterprises, the Archimedes Copula correlation function is selected. Gumbel, Clayton, and Frank have different characteristics for the relevant structure, but in general they can describe the structure of the upper tail, the lower tail, and the symmetry, this determines that the Archimedes Copula function is widely used in related structural risk analysis. Three common Archimedes Copula correlation functions have advantages in measuring the correlation of enterprises, so we need to mix these three Copula related structures in the measurement of enterprise correlation structures, construct a hybrid Copula correlation structure to measure the correlation between enterprises. Part of the specific estimates of the enterprise are shown in Table 4.

Table 4 Parameters of model, Kendall rank correlation coefficient and tail correlation coefficient.

<table>
<thead>
<tr>
<th></th>
<th>Xinlong**A &amp; Zhonglian **B</th>
<th>Xinlong**A &amp; Hexing **C</th>
<th>Zhonglian **B &amp; Hexing **C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gumbel-copula parameter</td>
<td>1.5970</td>
<td>1.3170</td>
<td>1.3255</td>
</tr>
<tr>
<td>Kendall rank correlation coefficient $\tau$</td>
<td>0.373826</td>
<td>0.240699</td>
<td>0.245568</td>
</tr>
<tr>
<td>Upper tail correlation coefficient $\lambda_u$</td>
<td>0.456534</td>
<td>0.307329</td>
<td>0.313032</td>
</tr>
<tr>
<td>Clayton-copula parameter</td>
<td>1.0991</td>
<td>0.6134</td>
<td>0.6973</td>
</tr>
<tr>
<td>Kendall rank correlation coefficient $\tau$</td>
<td>0.354651</td>
<td>0.234713</td>
<td>0.258518</td>
</tr>
<tr>
<td>Lower tail correlation coefficient $\lambda_l$</td>
<td>0.532246</td>
<td>0.323031</td>
<td>0.370077</td>
</tr>
<tr>
<td>Frank-copula parameter</td>
<td>4.3495</td>
<td>2.8493</td>
<td>2.9939</td>
</tr>
<tr>
<td>Kendall rank correlation coefficient $\tau$</td>
<td>0.4135</td>
<td>0.2940</td>
<td>0.3067</td>
</tr>
</tbody>
</table>

We constructed three binary Gumbel Copula models, three binary Clayton models and three binary Frank models. In order to evaluate the merits of the model, introduce the empirical Copula function. For the three companies operating information observation data, respectively, to construct a binary Gumbel, Clayton and Frank Archimede Copula function model. In order to evaluate the merits of the model, introduce the concept of empirical Copula.

The sample of two-dimensional random variable $(X,Y)$ is $(x_i, y_i), (i = 1, 2, \ldots, n)$, If the
empirical distribution function of random variables $X$ is $F_n(x)$, the empirical distribution function of the random variable $Y$ is $G_n(y)$, then the empirical Copula function is presented.

$$
\hat{C}_n(u, v) = \frac{1}{n} \sum_{i=1}^{n} I[F_n(x_i) \leq u, G_n(y_i) \leq v], u, v \in [0,1]
$$

Among them, $I[\cdot]$ is indicative function, when $F_n(x_i) \leq u$, $I[F_n(x_i) \leq u] = 1$, otherwise $I[F_n(x_i) \leq u] = 0$. Compare empirical copula function and estimated three copula function model square Euclidean distance.

$$
\begin{align*}
\hat{d}^2_{Gumbel} &= \sum_{i=1}^{n} |\hat{C}_n(u_i, v_i) - \hat{C}_{Gumbel}(u_i, v_i)|^2 \\
\hat{d}^2_{Clayton} &= \sum_{i=1}^{n} |\hat{C}_n(u_i, v_i) - \hat{C}_{Clayton}(u_i, v_i)|^2 \\
\hat{d}^2_{Frank} &= \sum_{i=1}^{n} |\hat{C}_n(u_i, v_i) - \hat{C}_{Frank}(u_i, v_i)|^2
\end{align*}
$$

Here, $u_i = F_n(x_i), v_i = G_n(y_i), (i = 1, 2, \cdots, n)$. The distance is smaller, the model fit the original data better. Data fitting results are shown in table 4, by data confidentiality restrictions, the study did not give the full name of the enterprise, here, Zhonglian**B is the core enterprise, Xinlong **A is upstream enterprises and Hexing **C is downstream enterprises.

<table>
<thead>
<tr>
<th>Table 5 Euclidean Euclidean distance of model.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td><strong>Model</strong></td>
</tr>
<tr>
<td>Euclidean Euclidean distance of gumbel-copula</td>
</tr>
<tr>
<td>Euclidean Euclidean distance of clayton-copula</td>
</tr>
<tr>
<td>Euclidean Euclidean distance of frank-copula</td>
</tr>
</tbody>
</table>

By comparing the square Euclidean distance, the smaller value is better for the fitting effect, for each business combination, the squared Euclidean distance of Clayton copula function is relatively smaller, so the description of Clayton copula function to the correlation structure between the three enterprises is more appropriate, and then select the Clayton Copula function to measure the overall relevance of the three enterprises.

The expression of the $n$-dimensional Clayton Copula function is presented.

$$
C(u_1, u_2, \cdots, u_N; \theta) = \left( \sum_{n=1}^{N} u_n^{-\theta} - N + 1 \right)^{-\frac{1}{\theta}}, \theta \in (0, \infty)
$$

For multivariate Archimedes Copula Functions, there is,

$$
C(u_1, u_2, u_3) = C(C(u_1, u_2), u_3)
$$
According to the above method, we construct a ternary Clayton copula dependent structure model.

\[ C(u_1, u_2, u_3, u_4) = C(C(u_1, u_2, u_3), u_4) \]

\[ \vdots \]

\[ C(u_1, u_2, \ldots, u_{N-1}, u_N) = C(C(u_1, u_2, \ldots, u_{N-1}), u_N) \]

3.3 Supply chain financing default risk measurement based on Logistic-Copula model

Based on the significant indicators selecting by the correlation analysis and Logistic model, the study construct Logistic model, shown in Equation (3), measure the single risk default probability value of the enterprise in the supply chain. It should be noted here is not the result of the status of default, but the specific default probability value, as shown in Table 6, then, the results are brought into the Copula-related structural model, shown in Equation (4) obtained previously.

Table 6 Probability of default of a single enterprise in supply chain.

<table>
<thead>
<tr>
<th>Default probability value</th>
<th>Xinlong **A</th>
<th>Zhonglian * * B</th>
<th>Hexing **C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Default probability</td>
<td>0.5127</td>
<td>0.3764</td>
<td>0.6812</td>
</tr>
</tbody>
</table>

The overall default probability of supply chain financing is 0.2332294 calculated by the model, the default probability value is lower than any single enterprise, which shows that the integrity of supply chain financing reduces the default risk of enterprise financing.

4. Conclusion

Firstly, the research establishes the risk index database of SME supply chain financing, by F-value method based on partial correlation analysis and Logistic regression model, screen risk indicators in the risk index database, remove the more relevant and less significant indicators, construct risk measurement index system, Then use the Logistic regression model to build a single enterprise financing risk measurement model and calculate the default probability value, finally use the copula correlation structure model of the enterprise in the supply chain to calculate the default risk probability value of the SME supply chain financing.

Research shows that the Logistic-Copula measurement model verifies that the supply chain financing integrity can effectively reduce the single enterprise's financing default risk, the default risk probability value of the SME supply chain financing is far less than that of a single enterprise. On the other hand, it can also measure the default risk of the SMEs supply chain financing through the measurement model, which is different from the previous measurement models of risk only consider the data of single enterprise, pay more attention to the overall relevance of the supply chain. Financial institutions can measure and monitor the financing risk of a single company based on the overall operation of the supply chain.
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