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Risk Evaluation and Control of Supply Chain Finance

Ying-Yu Du[1], Jun-Bin Zhong[2], Zi-Yue Su[1], Xin-Peng Yang[1] & Yi-Lan Yao[3]

[1] Financial Management, International Business School, Jinan University, Zhuhai, China

[2] Finance Department, International Business School, Jinan University, Zhuhai, China

[3]Translation Department, School of Translation Studies, Jinan University, Zhuhai, China

Correspondence: Ying-Yu Du, Financial Management of International Business School, Jinan University, Qianshan Road 206#, Zhuhai City, Guangdong Province, Post No. 519070, China.

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Abstract

As an effective way of enterprises financing, supply chain finance has attracted much attention in recent years. However, since supply chain finance has some problems like long financing period, numerous stakeholders and complex effects, banks are at a higher risk carrying out this kind of service. The purpose of this paper is to explore the key factors in supply chain finance risk assessment and study the effective mode of risk elevation. Based on the existing literature and research, this paper uses Z-score to standardize the financial index of 344 medium-sized enterprises in automotive industry chain from October, 2016 to October, 2017 and build a model of supply chain risk assessment and control basing on analytic hierarchy process, principal components analysis and logistic regression analysis. Finally, we summarize how each index affects risk assessment and then analyze the reasons.

Keywords: supply chain finance, risk evaluation and control, principal component analysis, logistic regression

1. Introduction

1.1 Background Description

For a long time, small and medium-sized enterprises (SMES) have occupied an important position in China's national economy and played an important role in promoting economic and social progress. Financing difficulties and expensive financing have become the biggest bottle neck that restricts the development of smes. Supply chain finance is a new financing mode specially tailored by commercial Banks for smes. Risk management is the unchanging focus in the application process of all financial industries. At present, China's supply chain financing has just entered the 2.0 mode of Internet financing from the traditional offline financing mode. The stage of supply chain financing 3.0 in the iot financial mode is internet-based supply chain financing, which will profoundly change the traditional risk return matrix, financial market equilibrium mode, risk management mode, social credit system and financial supervision system, and become an inexorable trend of development.

1.2 Aim of Research

The research goal of this project is to evaluate the default risk of medium-sized and small enterprises under different modes, try to find the key factors affecting the probability of default, and provide more clear direction guidance for risk control. Risk management is the constant focus of all financial industry applications. At present, China's supply chain financing has just entered the 2.0 model of Internet financing from the traditional offline financing 1.0 model, which will profoundly change the traditional risk-return matrix, financial market equilibrium model, risk management model, social credit system and financial supervision system, become an unstoppable development trend. The main idea of the project is to establish an enterprise risk assessment system of Supply Chain Finance. The financial report of the listed company is used as the data source. The PCA-Logit model is used to obtain the default probability of the enterprise, which provides a clearer direction for risk control.

1.3 Research Design

1.3.1 Literature Research Method

Literature research method is adopted to collect, sort out, summarize and extract the domestic and foreign literature on supply chain finance. In the process of analysis, the development model, development characteristics, current limitations of supply chain finance, combination of Internet finance model and new risks in the future iot financial model are elaborated in detail.

1.3.2 Comparative Analysis

Comparing traditional supply chain finance with Internet finance and supply chain finance with Internet finance, analyzes the similarities and differences as well as their respective characteristics, and compares the credit risk evaluation method of supply chain finance and selects the most appropriate measurement method.

1.3.3 Model Analysis

Model analysis method was adopted to establish the regression model with the selected variables through the pca-logit model, and the prediction model of the correlation between financial ratio and enterprise default probability was obtained, and the future default probability of the evaluation object was measured according to the model.

1.3.4 Combination of Quantitative Analysis and Qualitative Analysis

The qualitative research mainly aims to build a credit risk assessment system through financial statement collation and analysis, so as to make a comprehensive and systematic analysis and comparison on risk control and management of supply chain finance in theory.

2. Related Literature Review

2.1 Supply Chain Finance

Among foreign scholars, Timme and Williamstimme have the earliest mention of Supply Chain Finance (SCF). Timme and Williamstimme (2000) believe that SCF is a new business arising from the cooperation between supply chain participants and external financial organizations, which aims to promote the flow of upstream and downstream enterprises in the supply chain smoothly, while to implement the combination of flow, consisting of capital, information and commodity. Accordingly, further research by Hoffmann (2005) pointed out that SCF has the essential functions of tracking, applying and financing the flow of funds. Simultaneously proposed its components and fundamental processes. Wuttke (2013) and others defined the functions of SCF as real-time monitoring, control approaches and optimization of cash flow; and reduced the capital cost of suppliers through the provision of funds and settlement between supply and demand sides.

The study on SCF started late in China. From the perspective of commercial banks, Yang (2005) pointed out that supply chain finance is a financing model tailored for small and medium-size enterprise (SMEs). It can provide new loans to disadvantaged enterprises when resources are integrated effectively. Through the research on the operating capital management model of SMEs and the core concepts and related theories of SCF, Yan and Xu (2007) proposed three basic financing patterns, accounts receivable financing, inventory financing and prepayments financing, respectively.

2.2 Risk Identification of Supply Chain Financial Risk

Foreign scholars have studied price risk, management risk and information risk. About price risk: Chih-Yang Tsai (2011) starts with price risk and points out that one of the major risks of supply chain finance is the risk of collateral impairment. Because of this, many scholars regard the mortgage rate issue as one of the key research directions of supply chain finance. About Management Risk: Shashank Pao, Thomas J. Coldsby (2009) reviewed the literature on supply chain financial risk. They believe that supply chain finance research involves less risk issues and supply chain financial risk sources are complex, including Environmental factors, industrial factors, organizational factors, and other specific issues. Regarding information risk: Liu Xiang (2008) believes that the growth of supply chain financial data makes commercial banks more difficult to mine useful information, it is necessary to introduce DDM system to deal with this. Multi-media systems provide a channel for supply chain financial heterogeneity solutions.

Chinese scholars have the following research findings of Risk Identification. Yan-Zhong Yang (2007) believes that supply chain finance mainly has risks in seven aspects: market, credit, law, natural environment, policy, corporate culture differences, information transmission and behavior. Jing-Sheng Feng (2009) thinks that the supply chain financial risk is divided into supply chain's own risk, corporate credit risk, operational risk and exchange rate risk. Yi-Xue Li (2011) further attributed logistics financial risks to systemic and non-systemic risks. Among them, system risks include supply chain system risks, macro risks and industry risks; non-system risks include inventory risks, operational risks and credit risks.

2.3 Controlling Approaches & Evaluation of Supply Chain Financial Risk

Risk assessment refers to the process of using quantitative analysis methods to estimate and measure the possibility of occurrence of financial risks in the supply chain and the degree of damage in the event of the loss. Altman (1968) used discriminant analysis to study the linear discriminant model of bankruptcy prediction and creatively proposed the Z-Score model to measure the credit risk of enterprises. Messier and Hansen (1998) analyzed the expert system approach in credit risk assessment. Cramer (2004) constructed the Boundary Logistic model to compensate for the defects of the ordinary logistic model when the bad debts exist. Rosenberg and Schuermann (2006) and others proposed a comprehensive VAR method for market risk, operational risk and credit risk from the perspective of financial risk management. Xiong (2009) took the superior and debt rating into consideration and innovatively construct a credit risk evaluation model.

Risk control refers to controlling the impact of risk on the participants in the supply chain by strengthening the understanding of risk information in a minimum cost and optimal manner. Yan and Xu (2007) constructed the credit risk index evaluating system of the enterprises in the supply chain, and the multi-level grey comprehensive evaluation method is used to evaluate its credit risk. Wan (2008) point out that due to the existence of moral hazard, the risk aversion mechanism that SCF relies on may fail, and it requires banks and core firms in the supply chain to work together to solve such problems. Hu and Huang (2009) believe that the core of SCF is risk monitoring of the entire supply chain. Moreover, because of the need to identify the risk of each node, the risk control of SCF is more complicated than traditional financing.

3. Theoretical Models

Firstly, the preliminary evaluation of AHP analytic hierarchy process is carried out. The PCA-LOGIT model is used to take the financial indicators of listed companies as the main data source, and the index system is analyzed by dimensionality reduction. The LOGIT regression is performed with the selected indicators to determine the probability of default. A more accurate assessment of the company's financing credit.

3.1 Analytic Hierarchy Process

Analytic Hierarchy Process refers to the decomposing of elements that are always related to decision-making into goals, criteria, and programs. On this basis, qualitative and quantitative analysis methods are used. Specific implementation steps for solving the Analytic Hierarchy Process are as follows.

Step 1 Construction of measurement index system

We intend to tell the experts such data after determining the preliminary set of predictive indicators and ask them to add indicators that are considered important. After collecting the opinions of the expert group, we will merge the existing overlapping indicators, delete the unimportant indicators, integrate into the thinking and organize them, and construct a measurement index system.

Step 2 Construction of pairwise comparison matrix

According to the Saaty 1-9 scale method, using 1-9 and its reciprocal as the scale, the fuzzy judgment matrix ($A=(a_{ij}), i=1,2,...,n, j=1,2,...,n$)is obtained by comparing the two factors of the measurement factors.

$$A=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}$$

Compare the indicators of the measurement factors to determine the importance and intensity of the measurement factors, and assign 9, 7, 5, 3, 1 to the strength of the two measurement factors (very important, very important, obviously important, slightly important and equivalent important), where 8, 6, 4, 2 are the median of the intensity.

Step 3 Determining the measure factor set

The specific steps of determining the measure factor set are as follows.

(1) Calculate the geometric mean A_i of each row a_{ij} in the judgment matrix A.

$$A_i=\sqrt[n]{\prod_{i=1}^{n} a_i}$$

(2) Normalize the geometric mean A_i.

$$W_i=\frac{A_i}{(\sum_{i=1}^{n} A_i)}, \sum_{i=1}^{n} W_i=1$$

(3) Calculate the maximum eigenvalue $L_{\max}$ of the judgment matrix A.

$$L_{\max}=\frac{1}{n}\sum_{i=1}^{n}\frac{A_i W_i}{W_i}$$

(4) Calculate consistency indicator CI, accept the matrix A when $CI<0.1$

$$CI = \frac{L_{\max} - n}{n-1}$$

(5) Calculate consistency ratio CR.

$$CR = \frac{CI}{RI}$$

RI is the average random number indicator. Determine the value of RI according to the order of the measure factor matrix. If $CR < 0.1$ at this time, accept the matrix A .Otherwise, return the expert to re-compile the judgment matrix, and then perform the above steps; if the condition is still not met, then the expert's judgment matrix is rejected.

Calculate the eigenvectors of the expert judgment matrix. The column vector is normalized first, and then the sum of the row vectors is used to perform normalization processing to obtain the feature vector of the judgment matrix. The vector weights are obtained by normalizing the feature vectors of all the experts and normalizing them.

Step 4 Determining the measure level and fuzzy measure matrix

The level composition of the measurement index is obtained by the expert through the pairwise comparison measure, thereby obtaining the measurement set $V=\{V_1, V_2, ..., V_n\}$. By determining the weight of the indicator and normalizing it, the fuzzy measure matrix R can be obtained.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix}$$

Where r_{ij} is the j^{th} grade rating or the j^{th} level of experts as a percentage of the total number of experts, indicating the membership of the j^{th} level of the i^{th} indicator.

Step 5 Determine the comprehensive membership and measurement level of the indicator system

On the basis of determining the set of measurement factors $U = \{\mathrm{u}_1, ..., \mathrm{u}_n\}$, the comprehensive membership degree of the measure index system can be obtained by multiplying the index comprehensive weight vector and the fuzzy measure measure matrix. Then the measure level is determined based on the position of the largest number of the comprehensive membership degrees.

3.2 Principal Component Analysis

Principal component analysis is a mathematical transformation method that converts a given set of related variables into another set of unrelated variables by linear transformation. The steps of principal component analysis are as follows.

Step 1 Data standardization

Before the data analysis, the data is usually standardized. Commonly used methods are Min-Max labeling method, decimal scale standardization method and Z-score standardization method. This paper adopts SPSS default Z-score standardization method. The mathematical principle of the Z-score standardization method is as follows.

$$Z = \frac{x-\mu}{\sigma}$$

In the above formula, x is a specific fraction, μ is the average, σ is standard deviation.

Step 2 KMO test and Bartlett sphericity test

Bartlett sphericity testing and KMO testing are required prior to factor analysis. The larger the KMO value, the more common the factors in the variable are for factor analysis. If the value of KMO is greater than 0.5 and the value of the Bartlett sphericity test sig (P value) is less than 0.05, then the data can be used for principal component analysis.

Step 3 Calculate correlation coefficient matrix

Based on this idea, the factor analysis of the remaining financial indicators is performed before the financial indicators selected by the AHP are tested for principal component analysis. Determine whether there is a strong correlation between the indicators. The normalized correlation coefficient is as follows.

$$R = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1j} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ \gamma_{i1} & \gamma_{i2} & \cdots & \gamma_{ij} \end{bmatrix}$$

γ_{ij} is the correlation coefficient between the j^{th} indicator and the i^{th} indicator.

Step 4 Calculate eigenvalues and eigenvectors

Solute characteristic equation $|\lambda I - R| = 0$, we often use the Jacobian method to find the eigenvalues and sort them by size $\lambda_1 \geq \lambda_2 \geq \ldots, \geq \lambda_p \geq 0$. Then we need to find the eigenvectors of the corresponding $e_i (i = 1, 2, \ldots, p)$ and eigenvalues separately. It claims $\|e_i\| = 1$, which also means $\sum_{j=1}^{p} e_{ij}^2 = 1$. In the meantime, e_{ij} represents the j^{th} component of the vector e_i.

Step 5 Calculate variance contribution rate and cumulative variance contribution rate

The variance contribution rate of the i^{th} principal component is defined as:

$$\alpha_k = \frac{\lambda_k}{\sum_{i-1}^{P} \lambda_i}$$

The contribution rate is as follows:

$$\beta_k = \frac{\sum_{i-1}^{k} \lambda_i}{\sum_{i-1}^{P} \lambda_i}$$

Step 6 Factor selection

Generally, the principal component ($F_1, F_2, \ldots, F_m$) corresponding to the eigenvalue ($\lambda_1, \lambda_2, \ldots, \lambda_m$) of the cumulative contribution rate of 80% or more is taken, and the selected principal component eigenvalue is preferably not less than 1.

Step 7 Factor rotation

In the principal component analysis, when the principal component factor and its factor load matrix are obtained, a reasonable explanation for the principal component is given. If the principal component is difficult to correspond to the actual problem, the principal component can be rotated so that the principal component after the rotation has practical significance.

3.3 Logistic regression

Logistic regression analysis is a generalized linear regression analysis model, which is often used in data mining, automatic disease diagnosis, economic forecasting and other fields. The reason for the wide application of the Logit model is mainly because of the dominant characteristics of its probability expressions. Through the above-mentioned analytic hierarchy process, the financial indicators of the enterprise are eliminated, and then the principal component analysis is used to classify the financial indicators of the enterprise into four principle components. The situation of various financial indicators of a company has a certain relationship with the probability of default of the enterprise. To further quantify the relationship between them, we combine the logical model with the financial indicators of the enterprise and establish a new logical model as follows.

$$\ln(Y) = \ln(\frac{P}{1-P}) = \alpha_0 + \alpha_1 F_1 + \alpha_2 F_2 + \alpha_3 F_3 + \alpha_4 F_4$$

Substituting the relevant financial data of each sample into the equation, the probability value of the company default is obtained. When P=1, the probability of default of the company is large, and the company is a financial distress company; otherwise, when P=0, the company defaults. The possibility is small and the company's finances are normal.

4. Empirical Analysis

4.1 Data Resources

According to the industry classification of the CSRC 2012 edition, this paper considers the industries that may be involved in the entire supply chain, and selects the automobile manufacturing industry, electrical machinery and equipment manufacturing industry, metal products, equipment and metal repair industry among the listed companies in China as the sample enterprises. The company is a large-scale automobile manufacturer, choosing upstream parts suppliers and auto parts and downstream auto distributors as financing companies. The sample data of this paper comes from the financial indicators report data of 344 SMEs in the automotive industry industry chain from October 2016 to October 2017. The quantitative data are from CSMAR Guotaian Database and Wande information..

4.2 Results of Analytic Hierarchy Process

Analyze the 30 financial indicators and obtain their weights as shown in Table 1

Table 1. 30 indicators corresponding weights

	Vector weight		Vector weight		Vector weight
X1	0.052247835	X11	0.042835291	X21	0.028108182
X2	0.053994141	X12	0.032360642	X22	0.020807497
X3	0.059660213	X13	0.024315016	X23	0.029468226
X4	0.050257729	X14	0.035862232	X24	0.011448917
X5	0.049074917	X15	0.026140163	X25	0.015646252
X6	0.043217174	X16	0.024066472	X26	0.021714283
X7	0.048914737	X17	0.024563854	X27	0.027171029
X8	0.041170078	X18	0.028636828	X28	0.027033864
X9	0.041692231	X19	0.028591873	X29	0.018055682
X10	0.041947212	X20	0.037052939	X30	0.013944488

The weights corresponding to the 30 indicators are sorted from large to small in order, and the first 14 indicators with larger weights are selected for analysis. The 14 indicators selected are shown in Table 2.

Table 2. 14 selected corporate financial indicators

Number	Meanings	Number	Meanings
X1	Return on assets	X8	Assets and liabilities
X2	Return on invested capital	X9	Total asset turnover
X3	Current ratio	X10	Equity Multiplier
X4	Quick ratio	X11	Working capital and borrowing ratio
X5	Property ratio	X12	Total net profit margin (ROA)
X6	Net asset growth rate	X13	Integrated lever
X7	Shareholder equity turnover rate	X14	Net asset growth per share

4.3 Results of Principal Component Analysis

Before performing principal component analysis, it is necessary to test whether the data is suitable for principal component analysis. Therefore, KMO and Bartlett spherical test are required., the results are shown in Table 3.

Table 3. KMO and Bartlett's inspection

KMO		0.775
Bartlett sphericity test	Approximate Chi-square	426.474
	Degree of freedom	36
	Significance	0

The KMO and Bartlett spherical tests of the 14 indicators have a KMO value of 0.775, and the Sig. value in the Bartlett test is less than 0.001. The null hypothesis is rejected, indicating that the variables are not independent and have strong correlation. Theaefore, principal component analysis of 14 indicators is necessary and possible.

Table 4. Explanation of variance

Ingredient	Initial eigenvalue			Extract square sum loading		
	Total	Variance%	Accumulation%	Total	Variance%	Accumulation%
F_1	3.938	28.131	28.131	3.938	28.131	28.131
F_2	3.220	22.999	51.130	3.220	22.999	51.130
F_3	2.500	17.860	68.990	2.500	17.860	68.990
F_4	1.237	11.837	80.827	1.237	8.837	77.827

It can be seen from Table 4 that among the numerical values of the initial eigenvalues of the explanatory variables, the largest value is 3.938, the eigenvalues of the first four principal components reach a value greater than 1, and the cumulative contribution rate exceeds 80%, indicating that 4 The main component can represent most of the information of the original data and has a strong explanatory power. Therefore, the extraction of the first four principal component factors replaces the original 14 financial indicators, which reduces the complexity of the model and makes the results more accurate and credible.

Table 5. Component score coefficient matrix

	Ingredients			
	1	2	3	4
X1	-0.004	-0.034	0.300	0.075
X2	0.003	0.006	0.272	0.056
X3	0.307	0.002	-0.016	-0.074
X4	0.305	-0.002	-0.009	-0.079
X5	0.001	0.315	-0.012	-0.069
X6	-0.028	-0.033	-0.062	0.651
X7	-0.006	0.292	0.038	-0.119
X8	-0.058	-0.021	0.248	-0.280
X9	-0.157	0.001	0.021	-0.202
X10	0.001	0.315	-0.012	-0.069
X11	0.302	-0.005	0.010	-0.113
X12	0.022	-0.037	0.299	0.069
X13	-0.032	-0.029	0.027	0.234
X14	0.001	-0.213	0.185	-0.337

In summary, the extracted four principal components are used to construct the independent variables of the Logit model to assess the probability of corporate default probability. According to the Table 5, four principal components are respectively represented by F1, F2, F3, and F4, and four principal components can be linearly represented by each factor. According to the data in the table, each main character can be written by using standardized variables. The expressions of the component are as follows:

$F1=-0.004X1+0.003X2+0.307X3+0.305X4+0.001X5-0.028X6-0.006X7-0.058X8-0.157X9+0.001X10+0.302X11+0.022X12-0.032X13-0.001X14$

$F2=-0.034X1+0.006X2+0.002X3-0.002X4+0.315X5-0.033X6+0.292X7-0.021X8+0.001X9+0.315X10-0.005X11-0.037X12-0.029X13-0.213X14$

$F3=0.300X1+0.272X2-0.016X3-0.009X4-0.012X5-0.062X6+0.038X7+0.248X8+0.021X9-0.012X10+0.010X11+0.299X12+0.027X13+0.185X14$

$F4=0.075X1+0.056X2-0.074X3-0.079X4-0.069X5+0.651X6-0.119X7-0.280X8-0.202X9-0.069X10-0.113X11+0.069X12+0.234X13-0.337X14$

4.4 Results of Logistic regression

The logistic regression model was tested by Hosmer and Lemeshow, and the results are shown in Table 6.

Table 6. Hosmer and Lemshow inspection

step	Bangla	df	Sig.
1	2.407	8	0.993

The observation value of Hosmer-Lemshow test result is 2.407, and the corresponding probability P value is 0.993, and the significance level α value is 0.05, indicating that the corresponding probability P value is larger than α value, so the original hypothesis cannot be rejected, indicating that the model has The ideal fit. With SPSS regression model, based on the condition parameter estimation using forward stepwise regression to obtain results as shown in Table 7.

Table 7. Variable in the equation

		B	SE	Wals	df	Sig.	Exp(B)
step	FAC1_1	0.372	0.322	0.399	1	0.012	0.000
	FAC2_1	0.628	0.343	2.760	1	0.049	0.000
	FAC3_1	1.323	1.584	4.996	1	0.021	9.056
	FAC4_1	0.988	0.753	0.753	1	0.016	0.000
	constant	-0.439	2.452	1.249	1	0.015	0.000

When the significance level α is 0.05, the four principal components of F1, F2, F3 and F4 pass the significance test. Therefore, the null hypothesis can be rejected. According to the above coefficients, the final Logit model is as follows.

$$\ln(Y) = \ln(\frac{P}{1-P}) = -0.439 + 0.372\mathrm{F}_1 + 0.628\mathrm{F}_2 + 1.323\mathrm{F}_3 + 0.988\mathrm{F}_4$$

Substituting the relevant financial data of each sample into the equation to obtain the probability value of the company's default. When P=1, the company is likely to default, the company is a financial distress company. Conversely, when P=0, the company is less likely to default and the company's finances are normal. Substituting the selected 344 sets of sample company data into the model for testing, and using the estimated model to test the determined samples, part of the test results are shown in Table 8.

Table 8. Partial sample backtest test results

Whether it was originally a breach of contract	P (probability of default)	F1	F2	F3	F4
0	0.18	-0.11756	0.0158	-0.32695	0.30735
0	0.42	-0.1992	0.0249	-0.98301	0.50223
0	0.295	-0.50863	-1.61336	-3.93152	-0.65408
0	0.275	-0.32103	0.57054	-0.78141	-0.16752
0	0.46	-0.2312	0.22719	-0.30081	-0.01024

The results show that 302 of the 344 normal enterprises are correctly predicted, 42 are misdetected, and the prediction accuracy is 87.8%. It can be seen that the prediction effect of the model is very ideal, and the model has certain guiding significance.

5.Conclusion

Through the elevation research of supply chain finance credit risk based on Logistic model, this paper constructs a evaluation index system of supply chain finance credit risk which is helpful in assessing the credit risk of supply chain finance. Four first level index in the evaluation index system: the operation of supply chain, external environment, influence factors of core enterprises and entity qualification in supply chain, play key roles in the elevation of supply chain finance credit risk; four principal components extracted from principal components analysis have a significant impact on supply chain finance credit risk.

This paper shows that return on total assets of core enterprises, return on invested capital and return on net assets are positively correlates with risk assessment, and it is most affected by these three factors, which reveals that the profitability and the strength of enterprises are still the focus of the risk assessment of enterprises. However, owing to the fact that supply chain finance is integrated into business management (includes account receivable financing, inventory financing and prepayment financing mode), which may bring certain endogenous risk to business management and financial situation, so it needs further analysis covering other aspects of financial index.

Net asset grow rate is also the second most important financial index in the risk assessment. Supply chain enterprises generate a great demand for external funding when offer financial services since they sustain the financial business by debt financing. In the concrete process, companies take out loans from banks or other organizations relying on their good credit and the whole supply chain as the potential guarantee. Then they make loans to other small and medium-sized enterprises by means of supply chain trade and financial services. Therefore, the steady growth of net asset ratio is the basic guarantee for debt repayment and shows company’s growth space as well as potential.

Although principal components analysis can extract the notable representatives of the index system, realize data dimension reduction and greatly simplify the index system, it can still be seen through the regression results that liquidity indexes like current ratio and quick ratio are the factors which should not be overlooked in the supply chain finance. Although their coefficients in the regression equation are relatively small, we can draw a conclusion combined with qualitative indexes and practical experience that the increasing outflow of enterprise capital stemmed from a large amount of advance fund and sell on credit, plus deferred recovery period, make it difficult to accumulate liquidity. Moreover, as operating cash flow has low debt coverage ratio, the fund of enterprises operation and debt repayment mainly depend on external financing, which causes great pressure of funding. Once the financing channels are blocked, supply chain enterprises will be at risk of capital chain rupture.

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