Research on Credit Risk Assessment of Small and Medium-sized Enterprises by COVID-19 and Supply Chain Finance

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ABSTRACT

The global economy has a huge fluctuation, because there was a big shock to industries by COVID-19. In this context, supply chain financing is becoming a convenient and efficient way to help small and medium-sized enterprises(SMEs) take the next step, which is why it is experiencing rapid development in China. Under the influence of this, the credit risk of different sectors has undergone a large change. The research built a credit risk index system of listed SMEs based on COVID-19 and supply chain finance(SCF). With the principal component analysis and logistic model, the credit risk of 100 listed SMEs in China based on default probability was analyzed. Finally, the paper applied the mode to the instance and got the situation of credit risk for other companies. The results show the reasonability and practicability of the evaluation model. This model can identify key factors affecting the credit risk, providing a basis for the credit risk evaluation and control of SMEs in the period of returning to production. The researcher found that this is also a great way to improve the choice of financing for banks and other financial institutions to further cut losses in implementing projects of SCF.

Keywords: *Credit Risk, small and medium-sized enterprises, COVID-19, Supply Chain Finance, Principal Component Analysis, Logistic Regression*

1. INTRODUCTION

Since outbreak of COVID-19 in 2019 world economy has a deep recession, especially different industries of SMEs sale and profit of industry chains exist uncertainty. In terms of, SCF is a great way to solve problems,like funding, longer recovery period of the receivable[1]. It makes risk of single company into risk of entire supply chain based core enterprise to reduce the funding gap[2,3].

Credit risk assessment of core companies is the key point of SCF with dynamic development. Despite the fact that credit risk assessment methods are constantly evolving, some research indicates that there are still selection indicators that are subjective and construction models that are non-objective[4]. In the past, academic papers about credit risk mainly adopted data before COVID-19. From the actual situation the judgement of previous studies will be unscientific and indeterminate, if we still use the old method. Therefore, this article sets up an index system of credit risk by SCF and COVID-19. Principal component analysis and logistic regression method are used to establish a proper credit risk assessment model based on the data of 100 listed SMEs between 2020 and 2021, which reduces the current limitations of subjective evaluation dependence. The principal component analysis and logistic regression model were used to give a score to SMEs' credit[5]. By comparing the difference, this paper can identify the credit risk of listed SMEs in the production phase in China and measure probability of credit risk occurrence. Meanwhile, key factors of credit risk can be obtained, banks and other financial institutions would make correct decision of financing to relevant industry. SMEs can forecast and judge credit risk for themselves scientific, which could better control and supervisory risk.

2. CONSTRUCTION OF A CREDIT RISK EVALUATION INDEX SYSTEM FOR SMES

For index system construction, this index system learns from credit rating agency and literature[4,6,7], then selects indicators linked with the development of

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SMEs in various impact to improve explanatory power, standing on broad and comprehensive, high data availability and reliability principles. Finally, it build the index system as shown in Table 1.

Table 1. Credit risk assessment index system of small and medium-sized enterprises by supply chain finance and COVID-19

Level indicators	The secondary indicators	Index description
Short-term liquidity	Current ratio	A ratio shows a company's ability to pay its current bills from its current assets.
	Quick ratio	The ratio analyzes the ability of immediate debt paying.
	Cash ratio	The ratio evaluates the immediate solvency.
Long-term liquidity	Debt to asset ratio	The percentage is a measure of a business firm's financial leverage or solvency.
	Interest coverage ratio	The ratio used to determine the ability of a company to pay its interest expense on outstanding debt..
Operating capacity	Rate of stock turnover	The times of a corporation’s selling its inventory during a year.
	Accounts receivable turnover	The times of a corporation’s accounts receivable into cash during a year.
	Total assets turnover	The ratio measures the ability of a company to use its assets to generate sales.
Profitability	Operating margin	The ratio measures the ratio of a business’s operating income to its return on sales.
	Return on assets(ROA)	The ratio reflects a company's profitability in relation to its total assets.
	Return on equity(ROE)	The ratio reflects a company's profitability in relation to its equity.
	Total return on assets	The ratio compares the earnings of a business to the total assets invested in its.
Marketable value	Price-to-sales(PS)	The ratio compares a company’s stock price to its revenues
	Price-to-book ratio(PB)	The ratio compares a firm's market capitalization to its book value.
	Enterprise value(EV)	The cash flow created by a firm.
Growth	Rate of capital accumulation	The ratio of an accumulated sum of surplus value to operating capital or to the mass of surplus value.
	Growth rate of total assets	The ratio changes in assets between two years in a row.
	Increase rate of business revenue (REVINR)	The ratio reflects total revenue growth.
Financial structure	Fixed assets ratio	The ratio shows the amount of fixed assets being financed by each unit of long-term funds.
	Current-debt ratio	The ratio degree of dependence on short-term creditors.
	Debt equity ratio	The ratio of financial liabilities against total shareholders’ equity.

3. DATA COLLECTION

This article selects 100 SMEs listed on Shenzhen and Shanghai stock exchanges as research objects. In terms of regulations on the stock exchange, shares are divided into special treatment shares(ST shares) and non-special treatment shares. ST shares mean that the operations of this company have lost for the sequence of two years, and stock exchange gave it special treatment. This kind of corporations have financial problems and cash flow difficulties commonly, and these firms are bearing lots of debt, more or less, which is the high incidence area of credit risk.

For the combination effects of COVID-19 on SMEs, researchers chose 10 ST shares and 90 non ST shares in the China Stock Market & Accounting Research Database between 2020 and 2021 as study samples. In order to quantify credit risk to different kinds of corporations, setting a value of F is an efficient method, which supposes that if the credit rating of this company is high and the credit risk is low, the company will be creditworthy and the value of F will be 0. On the contrary, it will be 1. After that, data preprocessing to obtain dimensionless quantity finally by SPSS is a significant step, which includes the process of data cleaning, data integration, data transformation, and data reduction.

4. CREDIT RISK ASSESSMENT INDEX SYSTEM PROCESS BASED ON PRINCIPAL COMPONENT ANALYSIS

The nature of principal component analysis is to group data according to relevance. Data in the same group have high relevance, vice versa. This step could find the main factors to explain complex issues. Then, the work of analysis of representative and incoherent main factors by logistic regression method would be simple.

4.1 KMO and Bartlett test

The KMO and Bartlett sphericity test could inspect the feasibility of factors[8]. In the following table, the results are shown. The number of KMO more than 0.5 means data can be used to make factorial analysis. And the P value of Bartlett sphericity test equal to 0, the project rejects the original hypothesis, which means the original indicators with correlation could be further analyzed.

Table 2. The results of KMO and Bartlett sphericity test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.681
Bartlett's Test of Sphericity	Approx. Chi-Square	54143.758
	df	210
	Sig.(P value)	0.000

4.2 Principal component analysis

Depending on the maximum variance method of rotating components of the matrix, results are shown in Table 3. It is obvious that the first eight common factors could explain all 21 indicators with characteristic roots above 1. The explanatory ability of these is 16.023%, 15.798%, 9.703%, 8.377%, 6.978%, 5.713%, 5.001%, and 4.935% respectively. The general features can be reflected by the first eight common factors with 72.528% of accountability.

Table 3. Results reflect the explanation of total variance

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.370	20.811	20.811	4.370	20.811	20.811	3.365	16.023	16.023
2	3.208	15.278	36.089	3.208	15.278	36.089	3.318	15.798	31.821
3	1.770	8.428	44.517	1.770	8.428	44.517	2.038	9.704	41.524
4	1.440	6.855	51.372	1.440	6.855	51.372	1.759	8.377	49.901
5	1.324	6.303	57.675	1.324	6.303	57.675	1.465	6.978	56.879
6	1.105	5.262	62.937	1.105	5.262	62.937	1.200	5.713	62.592

7	1.009	4.806	67.743	1.009	4.806	67.743	1.050	5.001	67.593
8	1.005	4.785	72.528	1.005	4.785	72.528	1.036	4.935	72.528

Creating insights into data and finding significant subsets could help understand the implications of data, and find hidden information. In terms of the rotated component matrix, each detailed indicator of common factor is analyzed, as shown in Table 4. Indicators of accounts receivable turnover, total assets turnover, REVINR and current-debt ratio are found in FAC 1, so FAC 1 reflects the ability of operations and growth in a company. EV, growth rate of total assets and fixed assets ratio are obvious in FAC 2, reflecting the corporation's comprehensive capacity. FAC 3 mirrors quick ratio, cash ratio and ROA, which is also known as short-term liquidity. Similarly, FAC 6 is named long-term liquidity, because it contains an interest coverage ratio and operating margin. FAC 4 is defined as a company's liabilities and profitability, which includes the current ratio, debt-to-asset ratio, stock turnover rate, and total return on assets. For shareholders' return, FAC 5 could be expressed with indicators of ROE, PS and debt equity ratio. FAC 7 and FAC 8 each reflects only one element directly, rate of capital accumulation and PB separately.

Table 4. Results of principal component analysis

Component		Contains financial indicators	Coefficient
FAC 1	Operation and growth	Accounts receivable turnover, Total assets turnover, REVINR, Current-debt ratio	FAC 1=0.755Accounts receivable turnover +0.927otal assets turnover -0.734REVINR +0.922Current-debt ratio
FAC 2	Comprehensive capacity	EV, Growth rate of total assets, Fixed assets ratio	FAC 2=0.965EV+0.936Growth rate of total assets +0.958Fixed assets ratio
FAC 3	Short-term liquidity	Quick ratio, Cash ratio, ROA	FAC 3=0.842Quick ratio +0.821Cash ratio -0.611ROA
FAC 4	Liabilities and profitability	Current ratio, Debt to asset ratio, Rate of stock turnover, Total return on assets	FAC 4=0.530Current ratio +0.589Debt to asset ratio +0.665Rate of stock turnover +0.541Total return on assets
FAC 5	Shareholders' return	ROE, PS, Debt equity ratio	FAC 5=0.810ROE -0.451PS +0.612Debt equity ratio
FAC 6	Long-term liquidity	Interest coverage ratio, Operating margin	FAC 6=-0.772Interest coverage ratio +0.472Operating margin
FAC 7	Rate of capital accumulation	Rate of capital accumulation	FAC 7=0.909Rate of capital accumulation
FAC 8	PB	PB	FAC 8=0.903PB

5. THE CONSTRUCTION OF THE LOGISTIC MODEL

Regarding the study of scholars in the past, the F value of credit risk is a dependent variable and other common factors are as independent variables to discover the credit risk impact of different indicators in this research[9]. Assuming that each company's default probability follows a logistic distribution, it could be used to predict the default probabilities of the listed SMEs using eight independent variables. The probability has a critical values 0.5 in the range of zero to one. If it is closer to 0, the credit risk is getting smaller. In contrast, a corporation will have higher credit risk and go bankruptcy easily, if probability is close to 1. Financial institutions must consider decision of financing and loan to some companies that have a high probability of default. After wald regression of binary logistic by SPSS, the FAC 7 and FAC 8 are omitted, because the significance of them both are more than 0.05 and there is no obvious difference. According to this table, only FAC 6 have positive influence. Other factors all have a negative impact on the results. And the formula of default probability(DP) obtained by SPSS. It is easy to discover that EV, growth rate of total assets and fixed assets ratio have a great influence on DP.

$$\mathrm{DP} = \frac{1}{1 + e^{-(-4.56-0.936F1-1.754F2-0.184F3-0.937F4-0.405F5+0.186F6)}}$$

Then regression results and goodness of fit need to be tested. In the following Table 6, the significance of the model is less than the statistical level of 1%. This regression has practical implications.

Table 5. Comprehensive test results of model coefficients

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	393.701	8	.000
	Block	393.701	8	.000
	Model	393.701	8	.000

In the end, from the reliability principle, selecting 80 listed SMEs estimates their DP to verify the accuracy of the formula. There are only 4 enterprises' DP that are misjudged. The accuracy of this regression model is 95%. According to the outcome in the Table 7, 72 enterprises have low credit risk and 71 enterprises satisfy the formula, and the accuracy is up to 98%. For high credit risk firms, the accuracy rate is 62.5%.

Table 6. A reality check

Classification Table[a]

Observed		Predicted		
		Credit risk F		Percentage Correct
		0	1	
Credit risk F	0	71	1	98.6
	1	3	5	62.5
Overall Percentage				95.0

a. The cut value is .500

6. CONCLUSION

This article analyzes the credit risk of listed SMEs and the research assessment method by SCF and COVID-19. A credit risk assessment index system of SMEs based on the present social environment has been set, and a credit risk evaluation model has been established using principal component analysis and logistic regression methods. These can provide a more accurate and scientific way to estimate credit risk. There are 21 indicators in the credit risk assessment index system, and they are divided into 7 common factors. After obtaining the formula, only FAC 6 has a positive influence on the DP. EV, growth rate of total assets and fixed assets ratio are found to be the key points for SMEs' DP. Finally, the formula established by logistic regression could achieve 95% accuracy prediction and only 4 out of 80 SMEs are misjudged. This provides a scientific opinion to evaluate core enterprises by SCF. Therefore, SCF could upgrade to improve the situation in Chinese economy for development of SMEs further. Although SCF is a very promising mode for commercial banks and other financial institutions by COVID-19[10,11], this kind of economy in China is still in the exploration stage to look for a suitable development way. Thus, there are some limitations to this paper. Firstly, due to the length of research time being relatively short, only two years of data could be used. Then, the experimental results may be biased due to small sample size. Second, SCF is described as succinctly as possible. Therefore, scholars could strengthen the study of the SCF of China with more useful data analysis in different lights in the future.

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