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Research Article

Credit Risk Assessment of Small and Medium-Sized Enterprises under the Financial Model of Online Supply Chain

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The rapid development of Internet technology meant that online supply chain finance has become an important source of small- and medium-sized enterprise (SME) finance. From a review of associated studies, this study constructed an online supply chain financial credit risk evaluation index system that had eleven level 2 indicators and 28 level 3 indicators for the four dimensions of financing enterprise qualification, core enterprise qualification, supply chain operations, and the macroenvironment. To assess the viability of this indicator system, data on 368 SMEs in four industries, clothing, home appliances, pharmaceutical, and construction, were selected as research samples. An online supply chain financial credit risk evaluation model for the different industries was then constructed using principal component analysis (PCA) and logistic regression methods. It was concluded that when evaluating online supply chain financial credit risk, it is necessary to focus on the solvency, profitability, and asset structure efficiencies of the financing enterprises. Due to the different production and operating characteristics of industries, significant variations in the degree and direction of the credit risk factors between industries were found; therefore, evaluating credit risks by industry significantly improved the accuracy of the model's credit risk predictions. For example, home appliance SMEs need to pay greater attention to their inventory turnover and construction industry SMEs should pay greater attention to their sales growth rate, return on common stockholders' equity, and GDP growth rate. Based on these results, some suggestions for commercial banks, supply chain core enterprises, and SMEs are given to improve supply chain financing. The conclusion of this study enriches the related research on credit risk assessment of SMEs and also provides decision support for improving SMEs to prevent credit risk.

1. Introduction

China's SMEs play an important role in promoting national scientific and technological innovation and enhancing national competitiveness. Since the introduction of government guidance in 2017, supply chain finance has become increasingly important in resolving SME financing difficulties, with its market scale growing rapidly to reach 22 trillion CNY in 2019. In addition to Ping An Bank and CITIC Bank, many third-party operating platforms and e-commerce platforms have been harvesting credit data to actively provide online supply chain financing services. However, a 2020 China Institute of Fiscal Science survey on more than 17,000 enterprises found that 50.2% of enterprises believed that "financing channels were reduced, and financing was unavailable and difficult" and 28.3% believed that "lending rates increased, interest expense increased, and financing were expensive." The "financing difficulties and financing expense" problems SMEs are facing are therefore very prominent and supply chain financial scandals are common, such as Noah's wealth of 3.4 billion and the Yixing Pharmaceuticals's 2.2 billion CNY incidents. Therefore, examining targeted indicator selection and more accurately developing online supply chain financial financing SME credit risk evaluation methods can reduce bank lending risks, improve lender willingness, and assist SMEs to identify their potential production and operation risk points and improve their management and credit conditions.

The concept of supply chain finance originated in the 1980s, and it was Stemler and Securing's proposal of "supply

chain finance" that first attracted academic attention [1]. Berger and Udall and others put forward the idea of supply chain finance earlier. Hofmann made a theoretical definition of supply chain finance [2]. He believes that supply chain finance is a new interdisciplinary combining finance, logistics, and supply chain management. More recently, in a related development, Blackman et al. [3] proposed a formal definition that a "supply chain financial" is the network of organizations and banks that coordinate the flow of financial transactions through shared information systems to facilitate a product supply chain between trading partners.

Some scholars have assessed supply chain finance risks in specific industries. Based on the interest rate term structures, Gordy [4] applied a credit metrics model to calculate the financing enterprises' default rates. Basu and Nair [5] analyzed online supply chain finance feasibility and developed a stochastic dynamic programming model that analyzed the Internet supply chain finance prepayment business model on B2B platforms, finding that incomplete SME financial information increased credit risks. After examining SME financial data performances, Rice and Weber [6] found that multilayer neural network models were unable to accurately identify the credit risks faced by commercial banks. Zhu et al. [7] proposed an SME credit risk evaluation index system specifically designed for SCF. This system is used to evaluate the credit risks from different points of view, which not only consist of financial and nonfinancial conditions of SMEs but also contain the financial and nonfinancial conditions of CEs, the operational status of the entire supply chain, and the transactional relationship between SMEs and CEs. In Chen et al's study [8], the fuzzy analytical hierarchy process was applied for risk evaluation in model building of logistics financial business for banks. Evaluating the risks across the whole supply chain is also important. Silvestro and Lustrato [9] argued that the factors that could affect the risk of SCF include supply chain coordination, cooperation, and information sharing. Mou et al. [10] stated that measuring and evaluating the credit level of core enterprises, and controlling the credit risk of core enterprises, are the keys to using supply chain finance in an efficient manner. Nehrebecka [11] built a general model with microeconomic model and macro-economic module and studied the impact of COVID-19 on the default probability of non-financial enterprises. It was found that under the negative test scenario, the default probability of large and medium-sized enterprises increased by 15 times, while that of small enterprises increased by 3 times. The probability of default for corporations increased by 1.5 times, while the probability of default for small companies increased by a factor of 3. Nehrebecka [12] used the multifactor model to track the evolution of tail risk in banks' NPL portfolios present under normal and worst conditions (before and during the pandemic of COVID-19) and to estimate the impact of sector concentration risk on amounts of economic capital.

The literature review revealed that although there have been many risk assessment methods, with most analyses only focusing on single industry sample data for model validation; however, the applicability of these index systems and evaluation models need to be further verified in different industries.

Therefore, this study selected 368 SMEs in four industries, clothing, household appliances, pharmaceutical, and construction, as the research samples to broaden the research object scope. A reasonable evaluation indicator system was established, and using the relatively stable and simple PCA and logistic regression methods, a credit risk evaluation model was built for the different industries, with the aim of providing banks and other financial institutions with suggestions and reference on core enterprises to prevent risks and improve SME credit conditions.

This study constructs the online supply chain finance credit risk assessment indicator system from the four dimensions of financing enterprise qualifications, core enterprise qualifications, supply chain operation, and macro environment, uses the PCA method to measure the financial risk of small and medium-sized enterprises, and uses the logistic model to reveal the driving factors of the financial risk of small and medium-sized enterprises. The study found a significant positive correlation between the enterprise's asset structures and credit risk. There was a significant negative correlation found between solvency, profitability, enterprise capital efficiency, and credit risk. For SMEs in the pharmaceutical and construction industries, a significant negative correlation was found between revenue quality and credit risk. For the SMEs in the construction industry, a significant negative correlation was found between enterprise development capability and credit risk; however, the macroeconomic environment was found to have an opposite effect. The impact of external guarantees and the supply chain information sharing degree on SME credit risk needs to be further determined. Overall, there were significant differences found in the SME credit risk evaluation indicators in different industries.

The rest of this study is structured as follows: Section 2 introduces the indicator system establishment. Section 3 presents the risk assessment study design, while Section 4 and Section 5 present the empirical results, conclusions, and policy implications.

2. Indicator System Establishment

The evaluation indicator system development was informed by the literature review, with the main sources being existing online supply chain finance credit risk indexes, the supply chain finance credit risk indexes, and traditional enterprise subject rating and debt rating indexes. The online supply chain financial credit risk evaluation indicator system was established based on the four main aspects, financing enterprise qualifications, core enterprise qualifications, supply chain operations, and the macro environment, and included 11 level 2 indicators and 28 level 3 indicators, each of which are further explained in Table 1.

3. Risk Assessment

3.1. Sample Selection

3.1.1. Clothing Industry. With an industrial scale of several trillion CNY, China is the world's largest textile producer and exporter. However, due to the inherent problems in the

Table 1: Online supply chain finance credit risk assessment indicator system.

Level 1 indicator	Level 2 indicator	Level 3 indicator	Indicator explanation
Financing enterprise qualifications	Solvency	Current ratio $X1$	Current assets/current liabilities
		Quick ratio $X2$	Quick assets/current liabilities
		Asset-liability ratio $X3$	Total liabilities/total assets
		Interest coverage ratio $X4$	EBIT/interest expense
	Capital efficiency	Rate of return on common stockholders' Equity(ROE) $X5$	Net profit/net assets
		Return on total Assets(ROTA) $X6$	Net sales revenue/average total assets
		Accounts receivable turnover ratio $X7$	Net income/average accounts receivable balance on credit
		Current assets turnover $X8$	Total net/average current assets from main operating income
		Inventory turnover (ITO) $X9$	Operating costs/average inventory balance
	Profitability	Profit growth rate $X10$	Profit growth/total operating profit
		Net profit growth rate $X11$	Net profit growth/previous year's net profit
		Net profit margin $X12$	Net profit/sales revenue
	Development capacity	Total assets growth rate $X13$	Growth of total assets at the end of the year/total assets at the beginning of the year
		Sales growth rate $X14$	Sales revenue growth for the current year/total sales revenue for the previous year
		Leadership qualities $X15$	Educational status of the main enterprise managers
	Credit status	Quality of financial information disclosure $X16$	Audit of financial statements and disclosure of information
		Past performance $X17$	Performance of past contracts, loans, etc
Core enterprise qualifications	Solvency	Current ratio $X18$	Current assets/current liabilities
		Interest coverage ratio $X19$	EBIT/interest expense
	Capital efficiency	ROE $X20$	Net profit/net assets
		ROTA $X21$	Net sales revenue/average total assets
	Enterprise quality	Industry status $X22$	Order and influence of companies in the respective industries
		Enterprise size $X23$	Log (main business income)
		External guarantees $X24$	Size and degree of dispersion of the guaranteed amount
Supply chain operation	Informatization level	Information sharing degree of supply chain $X25$	Degree of information open sharing and system compatibility in the overall supply chain
	Cooperation degree	Product substitutability $X26$	Alternative to comparable goods bought or sold by a financing enterprise
		Years of cooperation $X27$	Number of years that the financing enterprise has cooperated with the core enterprise
Macro environment	Macroeconomic environment	GDP growth rate $X28$	GDP growth rate in the region the financing enterprise is located

textile industry, such as high labor intensity, lack of innovation and core competitiveness, low informatization, backward enterprise management, and poor rapid market response mechanism, the upstream and downstream supply chain enterprises have serious information asymmetry. An online supply chain financial financing model based on big data technology could effectively alleviate these information asymmetry problems and assist the banks to obtain business data and make reasonable credit decisions. Therefore, China's textile garment manufacturing industry is in an active exploration stage for the development of reliable online supply chain finance options. For example, to assist the upstream silkworm farmers and the downstream garment processing SMEs to obtain financing, Jiaxin silk corporation and esilk.net have cooperated to set up an online supply chain finance business. However, to properly evaluate the credit risks, the actual clothing industry supply chain finance textile and garment industry demand and the industry characteristics need to be considered.

3.1.2. Home Appliance Industry. China's home appliance industry is an important part of the national economy and is one of the pillar manufacturing industries. Because of industry upgrading, industrial product homogenization has become more serious, overall profitability is poor, and the home appliance competition has become increasingly fierce, which has put in doubt the survival and development of many SMEs. Because of the weak supply chain relationship positions and the intense competition, the profit space is being weakened, with the overall depression in the industry aggravating the poor finance conditions. Therefore, the development of the home appliance industry's online supply

chain finance could be an effective method for improving these poor conditions. Core enterprises play an important role in the home appliance industry's industrial chain. The upstream suppliers are mainly manufacturers of raw materials, compressors, motors, panels, integrated circuits, and other parts, while the downstream enterprises are multilevel distributors or directly connected to the terminal sales channels, with other auxiliary enterprises providing support services, such as transportation and warehousing. As China's Supply Chain Finance Research Report identified the electronics and associated industries as the main target supply chain finance customers in the future, this study selected the home appliance industry as one of the research objects.

3.1.3. Pharmaceutical Industry. With the rapid development of China's economy, the continuous improvement of Chinese resident living standards over the past decade, and the implementation of the "two-vote system," "zero bonus" and "4 + 7" procurement policies, China's pharmaceutical circulation market has been reshaped, with the pharmaceutical market about to enter a rapid development stage. Data released by intelligent research consulting indicated that the scale of China's pharmaceutical market exceeded 1.1 trillion CNY in 2014 and reached about 1.64 trillion CNY in 2019, with the associated growth forecasts being 2.13 trillion CNY in 2023. As large pharmaceutical manufacturing and circulation enterprises occupy key positions in the supply chain, there are significant transaction data between the upstream and downstream enterprises. Therefore, an online supply chain service platform based on these could resolve the SME financing problems in this industry. Based on the huge demand and supply chain financial market development potential in the pharmaceutical field, it is very important to effectively evaluate and prevent credit risks; therefore, this study selected the pharmaceutical industry as one of the research objects.

3.1.4. Construction Industry. The National Development and Reform Commission report on 16 provinces and cities in early 2020 estimated that the annual total infrastructure investment was planned to reach 34.4 trillion CNY. The huge capital demand resulting from infrastructure construction as well as the construction industry characteristics, such as a long supply chain, large advance payment scale, long-term projects, and contract settlements based on project progress, means that the urgency to develop the construction industry supply chain finance has grown. Relying on their industrial cluster advantages, central construction enterprises have built mutually beneficial and win-win industrial chain financial ecosystems on supply chain financial platforms, with supply chain financing being the foothold. The analysis of the construction industry characteristics revealed that as there are many large construction industry enterprise groups, the construction industry process is fairly complex because there are many types of supply goods and a wide range of SMEs and core enterprises. Because of the rapid development of supply chain finance in the construction industry, the focus of banks' work is expected to be focused on the reasonable and effective assessment and control of risks; therefore, this study selected the construction industry as one of the research objects.

To ensure data availability, only core enterprises listed in Shanghai and Shenzhen stock markets and the SMEs listed on the SME Board, GEM, STAR Market, and the NEEQ were selected, with the sample selection method being as follows. First, the clothing, household appliance, pharmaceutical, and construction industry enterprise lists were extracted from the Shanghai and Shenzhen Stock Exchange official companies' stock list website. Then, the relevant enterprise information was collected from tianyancha.net and other websites, and the supply chain relationships between enterprises were matched from the supply chain and customer information lists. SMEs were defined based on whether the enterprise website was labeled "SME" or "small and microenterprise." Finally, 368 groups of sample data for the SMEs and core enterprises were collected, 41 groups from the clothing industry, 83 groups from the home appliance industry, 116 groups from the pharmaceutical industry, and 128 groups from the construction industry, with a further 368 data groups gathered as the control group for the comparative analysis.

3.2. Data Sources

(1) Quantitative indicator data: 19 quantitative mainly corporate financial indicators were obtained by querying the forward-looking network database and the enterprise annual reports, with the data deadline being 31/12/2018.

(2) Determinative indicator data: 9 determinative indicators were graded. The specific assignment method is shown in Table 2.

3.3. PCA Process

3.3.1. Feasibility and Reliability Tests. In the study, the existing domestic research literature was used for reference. In order to solve the limitations of the previous scoring methods, the logistic regression model and the principal component analysis method were used to analyze the various indicators in this study. Before this, the analysis had to be carried out using Bartlett's sphericity test and the Kaiser–Meyer–Olkin test. Generally, KMO and Bartlett's tests were used to test whether a sample was suitable for PCA. As shown in Table 3, the KMO test values for the five sample types were more than 0.5 and Bartlett's test significances were 0, which indicated that the correlations for the original index variables for the five sample types were relatively significant and therefore suitable for the PCA. Table 4 shows that most of the initial index communalities for the five sample types were above 60%, and only the individual index communalities were between 50% and 60%, which was not seen to affect the overall model quality. In general, the index extraction for the five sample groups had high reliability.

Table 2: Quantitative scoring standard.

The name of the indicator	Evaluation criteria	Scoring criteria			
		10	7	4	0
Quality of financial information disclosure	Shenzhen stock exchange evaluation standard of information disclosure	A	B	C	D
External guarantees	Average amount of a single guarantee	0 CNY	<100 million CNY	1–3 billion CNY	>300 million CNY
Industry status	The proportion of the registered capital scale of core enterprise accounts in the same industry in China	≤20%	20%–50%	50%–70%	>70%
Product substitutability	Number of competitive products in the financing enterprises	≥90	50–90	20–50	<20
Information supply chain sharing degree	Use of ERP and PDM system	Both SMEs and core enterprises use	Only SMEs use	Only core enterprises use	Neither SMEs nor core enterprises use
Years of cooperation	Financing enterprises and core enterprises' number of years of cooperation	≥5	3–5	1–3	<1
Past performance	Record of being sued by customers or suppliers	Set the score range from 0 to 10, and query the judicial case records of the company sued by customers or suppliers on the qichacha.net, tianyancha.net, and other websites, each 1 prosecution case deduction of 2 scores, and there are no negative scores			
Enterprise size	Main enterprise business income	LOG (main business income).			
Leadership qualities	Educational background of management personnel	The educational background of management personnel is divided into under technical degree, technical degree, bachelor degree, master's degree, doctoral degree, and professor, respectively, assigned 0, 1, 2, 4, 8, and 16, with the indicator score obtained by summation			

Table 3: KMO and Bartlett's test.

Industries		Clothing	Home appliance	Pharmaceutical	Construction	Control group
Number of indicators		18	24	24	22	23
Kaiser–Meyer–Olkin measure of sampling adequacy		0.526	0.521	0.545	0.63	0.547
Bartlett's test of sphericity	Approx. chi-square	280.976	1075.716	976.569	896.012	1551.488
	df	153	276	276	231	253
	Sig.	0.000	0.000	0.000	0.000	0.000

3.3.2. Common Factor Extraction. The maximum variance method was used to construct the rotated component matrix, and the PCA was used to extract the common factor, with the extraction condition being whether the eigenvalue was more than 1; that is, if the eigenvalue was more than 1, the factor was extracted and included, and if it was less than 1, it was not considered. After the calculation, the total variance interpretation table was obtained; the higher the total variance interpretation value, the higher the interpretation degree of the extracted factor for information. Because each index variable was explained by the multiple principal component factors, it was necessary to rotate the factors to better explain the potential factors. After the calculation, the rotation factor load matrix was obtained. Due to the large number of sample groups in this study, for reading and layout convenience, the following total variance explanation table shows only the explained variance proportions and cumulative addends in the column "sum of squares of extracted load" as well as the variables that had larger loads contained in each factor.

(1) Common Clothing Industry Sample Extraction Factors. Table 5 shows that there are eight common component factors extracted from the clothing industry sample, which are defined as $A1$–$A8$, and a total of 18 variables, with the cumulative variance explained value accounting for 79.631% of the total variance.

(2) Common Home Appliance Industry Sample Extraction Factors. Table 6 shows that there are ten common component factors extracted from the home appliance industry samples, which are defined as $B1$–$B10$, and 24 variables, with the cumulative variance explained value accounting for 78.258% of the total variance.

(3) Common Pharmaceutical Industry Sample Extraction Factors. Table 7 shows that there are eleven common component factors extracted from the pharmaceutical industry samples, which are defined as $C1$–$C11$, and 24 variables, with the cumulative variance explained value accounting for 75.875% of the total variance.

Table 4: Communalities.

Indicators	Initial	Extraction				
		Clothing	Home appliance	Pharmaceutical	Construction	Control group
Current ratio $X1$	1	0.842	0.931	0.925	0.639	0.84
Quick ratio $X2$	1	0.907	0.929	0.908	—	0.913
Asset-liability ratio $X3$	1	0.819	0.804	0.763	0.82	0.64
Interest coverage ratio $X4$	1	0.596	0.823	0.775	0.715	0.774
Rate of return on common stockholders' equity (ROE) $X5$	1	0.866	—	0.765	0.847	—
Return on total assets (ROTA) $X6$	1	0.785	0.876	0.817	0.76	—
Accounts receivable turnover ratio $X7$	1	—	0.973	—	—	0.526
Current assets turnover $X8$	1	0.654	0.825	0.644	0.847	0.673
Inventory turnover (ITO) $X9$	1	0.9	0.676	0.757	0.795	0.692
Profit growth rate $X10$	1	—	0.858	0.755	0.809	0.768
Net profit growth rate $X11$	1	0.85	0.847	0.753	0.854	0.76
Net profit margin $X12$	1	—	0.893	0.804	0.767	—
Total assets growth rate $X13$	1	—	0.724	0.765	0.675	0.592
Sales growth rate $X14$	1	0.736	0.952	—	0.753	—
Leadership qualities $X15$	1	0.75	0.773	0.765	—	0.699
Quality of financial information disclosure $X16$	1	—	—	0.733	0.701	0.619
Past performance $X17$	1	—	0.592	—	0.606	0.67
Current ratio $X18$	1	0.832	0.717	0.734	0.736	0.57
Interest coverage ratio $X19$	1	0.843	0.744	0.623	—	0.687
ROE $X20$	1	—	0.802	0.803	0.727	0.693
ROTA $X21$	1	0.846	—	0.892	0.861	0.732
Industry status $X22$	1	0.805	—	0.659	—	0.627
Enterprise size $X23$	1	—	0.78	0.73	0.865	0.804
External guarantees $X24$	1	0.761	0.757	0.713	0.753	0.685
Information sharing degree of supply chain $X25$	1	0.779	0.59	—	0.648	0.706
Product substitutability $X26$	1	—	0.589	0.759	—	0.578
Years of cooperation $X27$	1	0.763	0.724	0.741	0.718	—
GDP growth rate $X28$	1	—	0.604	0.626	0.912	0.668

Table 5: Factor explanation table (clothing industry).

Factor	Name	% of variance	Cumulative %	Indicators contained
$A1$	The current asset factor	19.412	19.412	Quick ratio, current ratio, and current assets turnover
$A2$	Supply chain credit factor	13.375	32.787	Years of cooperation, leadership qualities, and industry status
$A3$	The synthesis factor	10.972	43.759	External guarantees, information sharing degree of supply chain, and ROE
$A4$	Core enterprise profit factor	9.681	53.44	ROTA of core enterprise and interest coverage ratio of core enterprise
$A5$	Solvency factor	7.573	61.013	Current ratio of core enterprise, ITO, and interest coverage ratio
$A6$	Profit factor	7.062	68.075	Net profit growth rate
$A7$	Operating factor	5.918	73.993	ROTA
$A8$	Development factor	5.638	79.631	Sales growth rate and asset-liability ratio

(4) Common Construction Industry Sample Extraction Factors. Table 8 shows that there are ten common component factors extracted from the construction industry samples, which are defined as $D1$–$D10$, and 22 variables, with the cumulative variance explained value accounting for 76.396% of the total variance.

(5) Common Control Group Factors. Table 9 shows that there are eleven common component factors extracted from the control group sample, which are defined as $F1$–$F11$, and 23 variables, with the cumulative variance explained value accounting for 69.193% of the total variance.

3.4. Logistic Regression Model Process. Due to the large number of online supply chain financial index system indicators in this study, to avoid possible multicollinearity between the variable data affecting the experimental results, and to establish the logistic regression model, the common factors extracted from the previous PCA process were used to replace the original index as the independent variable (P) and the enterprise credit risk probability was taken as the dependent variable. Based on the "Z-Score analysis method" by Altman to measure enterprise bankruptcy risk, this study judged whether there was a credit risk in the financing enterprises. The Z-Score calculation formula is

Table 6: Factor explanation table (home appliance industry).

Factor	Name	% of variance	Cumulative %	Indicators contained
$B1$	Solvency factor	14.413	14.413	Current ratio, quick ratio, and asset-liability ratio
$B2$	Capital efficiency factor	11.21	25.622	Current assets turnover, ROTA, and ITO
$B3$	Operating factor	9.974	35.597	Sales growth rate and accounts receivable turnover ratio
$B4$	Credit factor	8.372	43.969	Leadership qualities, years of cooperation, and past performance
$B5$	Profit factor	7.215	51.184	Profit growth rate and net profit growth rate
$B6$	Supply chain development factor	6.499	57.683	Current ratio of core enterprise, information sharing degree of supply chain, and product substitutability
$B7$	Supply chain environment and credit factor	6.15	63.833	External guarantees, GDP growth rate, and enterprise size
$B8$	The core enterprise profit factor	5.61	69.443	Interest coverage ratio of core enterprise and ROE of core enterprise
$B9$	Development factor	4.646	74.089	Interest coverage ratio and total assets growth rate
$B10$	Revenue quality factor	4.169	78.258	Net profit margin

Table 7: Factor explanation table (pharmaceutical industry).

Factor	Name	% of variance	Cumulative %	Indicators contained
$C1$	Solvency factor	14.525	14.525	Current ratio, quick ratio, and asset-liability ratio
$C2$	Capital efficiency factor	9.796	24.321	ROTA, ITO, and current assets turnover
$C3$	Core enterprise solvency factor	7.867	32.187	Current ratio of core enterprise, enterprise size, and interest coverage ratio of core enterprise
$C4$	Profit factor	7.307	39.494	Profit growth rate and net profit growth rate
$C5$	Revenue quality factor	6.652	46.146	Interest coverage ratio and net profit margin
$C6$	Core enterprise operating factor	6.388	52.534	ROTA of core enterprise and ROE of core enterprise
$C7$	The synthesis factor	5.373	57.907	ROE and external guarantees
$C8$	Development factor	4.936	62.843	Product substitutability, industry status, and GDP growth rate
$C9$	Supply chain credit factor	4.516	67.359	Leadership qualities and years of cooperation
$C10$	Credit factor	4.322	71.682	Quality of financial information disclosure
$C11$	Capital factor	4.193	75.875	Total assets growth rate

Table 8: Factor explanation table (construction industry).

Factor	Name	% of variance	Cumulative %	Indicators contained
$D1$	Supply chain credit factor	17.439	17.439	Enterprise size, external guarantees, information sharing degree of supply chain, current ratio of core enterprise, and quality of financial information disclosure
$D2$	Development factor	12.135	29.574	Sales growth rate, total assets growth rate, and ROE
$D3$	Solvency factor	8.834	38.408	Asset-liability ratio and current ratio
$D4$	Profit factor	6.641	45.049	Profit growth rate and net profit growth rate
$D5$	Capital efficiency factor	6.305	51.354	Current assets turnover and ROTA
$D6$	Revenue quality factor	5.646	57	Interest coverage ratio and net profit margin
$D7$	Supply chain relationship factor	5.247	62.247	ROE of core enterprise, years of cooperation, and past performance
$D8$	Core enterprise operating factor	4.958	67.205	ROTA of core enterprise
$D9$	Macroeconomic factor	4.634	71.839	GDP growth rate
$D10$	Management factor	4.557	76.396	ITO

Table 9: Factor explanation table (control group).

Factor	Name	% of variance	Cumulative %	Indicators contained
$F1$	Current assets factor	10.918	10.918	Quick ratio, current assets turnover, and current ratio
$F2$	Core enterprise credit factor	8.598	19.516	Enterprise size, current ratio of core enterprise, and external guarantees
$F3$	Profit factor	7.587	27.102	Profit growth rate and net profit growth rate
$F4$	Core enterprise operating factor	7.06	34.163	ROTA of core enterprise
$F5$	Supply chain credit factor	6.777	40.94	Information sharing degree of supply chain and industry status
$F6$	Operating factor	5.147	46.087	Leadership qualities and accounts receivable turnover ratio
$F7$	Core enterprise profit factor	5.015	51.103	ROE of core enterprise and interest coverage ratio of core enterprise
$F8$	Security factor	4.872	55.974	Asset-liability ratio and past performance
$F9$	Credit factor	4.483	60.457	Interest coverage ratio and quality of financial information disclosure
$F10$	Development factor	4.372	64.829	GDP growth rate and total assets growth rate
$F11$	Product factor	4.364	69.193	ITO and product substitutability

$$Z = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.42X_4 + 0.998X_5, \quad (1)$$

where $X1$ = working capital/total assets, $X2$ = accumulated retained earnings/total assets, $X3$ = EBIT/total assets, $X4$ = book value of owner's equity/total liabilities, and $X5$ = sales income/total assets. Based on this analysis method, when the Z-Score of the enterprise is less than 1.2, it is in danger of going bankrupt. Therefore, a Z-Score of more than 1.2 was taken as the evaluation standard for the dependent variable P. For enterprises with default risk, the value of P was 1, and for the enterprises without default risk, the value of P was 0. Based on the above criteria, the sample datasets were classified, as shown in Table 10.

3.4.1. Comprehensive Test. Table 11 shows that the logistic regression model significance values for each group were all 0, which indicated that the logistic regression equation results were all significant, that is, the model factors selected had a significant impact on the financial credit risk for the SMEs' online supply chain and the model measures adopted in this study had practical significance.

3.4.2. Hosmer Lemeshow Test. The Hosmer Lemeshow test tests the goodness of fit of the model. The results in Table 12 show that the significance values for each group were more than the significance level $\alpha = 0.05$, indicating that there were no significant differences between the actual distribution and the predicted distribution; that is, the goodness of fit of the model was good.

3.4.3. Logistic Regression Results. The sample data were input into SPSS 22 software for the binary logistic regression analysis, with the "forward conditional" regression method set. The method adopted a step-by-step method to select the variables, with the condition for the variables entering the regression model being whether the probability value of the likelihood parameter estimation ratio statistic was less than a 90% significance level. The model calculation results in

Table 10: Sample data classification.

Groups	Risky ($Z < 1.2$).	No risk ($Z \geq 1.2$).	Total
Clothing industry	10	31	41
Home appliance industry	16	67	83
Pharmaceutical industry	15	101	116
Construction industry	14	114	128
Control group	30	181	211

Table 11: Omnibus tests for the model coefficients.

Group	Step	Chi-square	d*f*	Sig.
Clothing industry	3	21.942	3	0.000
Home appliance industry	3	43.194	3	0.000
Pharmaceutical industry	4	51.652	4	0.000
Construction industry	5	70.358	5	0.000
Control group	4	77.206	4	0.000

Table 12: Hosmer Lemeshow test.

Group	Step	Chi-square	d*f*	Sig.
Clothing industry	3	7.196	8	0.516
Home appliance industry	3	2.347	8	0.968
Pharmaceutical industry	4	5.027	8	0.755
Construction industry	5	.895	8	0.999
Control group	4	9.612	8	0.293

Table 13 established the regression prediction model for the occurrence probability of online supply chain financial credit risk in the sample group and the control group for the clothing, home appliances, pharmaceutical industries, and construction industries, as follows:

(a) The probability prediction model for financial credit risk occurrence in the clothing industry online supply chain is

$$P_1 = \frac{1}{1 + e^{-(-3.268A1+1.639A6-1.553)}}. \quad (2)$$

Table 13: Variables in the equation.

		B	SE	Wald	df	Significance	Exp (B)
Clothing industry							
Step 3[a]	$A1$	−3.268	1.328	6.051	1	0.014	0.038
	$A6$	1.639	0.728	5.076	1	0.024	5.152
	$A8$	1.152	0.863	1.783	1	0.182	3.165
	Constant	−1.553	0.574	7.314	1	0.007	0.212
Home appliance industry							
Step 3[a]	$B1$	−4.648	1.312	12.542	1	0.000	0.010
	$B5$	−1.241	0.419	8.753	1	0.003	0.289
	$B9$	−1.571	0.471	11.116	1	0.001	0.208
	Constant	−3.978	0.998	15.878	1	0.000	0.019
Pharmaceutical industry							
Step 4[a]	$C1$	−4.547	1.278	12.658	1	0.000	0.011
	$C2$	−2.545	0.951	7.163	1	0.007	0.079
	$C4$	−0.643	0.337	3.640	1	0.056	0.526
	$C5$	−2.529	0.998	6.425	1	0.011	0.080
	Constant	−5.433	1.311	17.165	1	0.000	0.004
Construction industry							
Step 5[a]	$D2$	−5.380	1.877	8.212	1	0.004	0.005
	$D3$	−7.806	2.797	7.790	1	0.005	0.000
	$D5$	−2.053	0.770	7.103	1	0.008	0.128
	$D6$	−2.905	1.178	6.079	1	0.014	0.055
	$D9$	1.297	0.666	3.790	1	0.052	3.659
	Constant	−8.331	2.530	10.842	1	0.001	0.000
Control group							
Step 4[a]	$F1$	−1.759	0.454	15.046	1	0.000	0.172
	$F3$	−0.730	0.165	19.496	1	0.000	0.482
	$F8$	−1.071	0.182	34.663	1	0.000	0.343
	$F11$	−0.632	0.307	4.232	1	0.040	0.531
	Constant	−2.259	0.213	112.870	1	0.000	0.104

(b) The probability prediction model for financial credit risk occurrence in the home appliance industry online supply chain is

$$P_2 = \frac{1}{1 + e^{-(-4.648B1 - 1.241B5 - 1.571B9 - 3.978)}}. \quad (3)$$

(c) The probability prediction model for financial credit risk occurrence in the pharmaceutical industry online supply chain is

$$P_3 = \frac{1}{1 + e^{-(-4.547C1 - 2.545C2 - 0.643C4 - 2.529C5 - 5.433)}}. \quad (4)$$

(d) The probability prediction model for financial credit risk occurrence in the construction industry online supply chain is

$$P_4 = \frac{1}{1 + e^{-(-5.38D2 - 7.806D3 - 2.053D5 - 2.905D6 + 1.297D9 - 8.331)}}. \quad (5)$$

(e) The probability prediction model for financial credit risk occurrence in the control group online supply chain is

$$P_5 = \frac{1}{1 + e^{-(-1.759F1 - 0.73F3 - 1.071F8 - 0.632F11 - 2.259)}}. \quad (6)$$

Here, $P_i\,(i = 1, 2, \cdots, 6)$ is the default probability of the financing enterprises in different industries, and $Ai\,(i = 1, 6)$, $Bi\,(i = 1, 5, 9)$, $Ci\,(i = 1, 2, 4, 5)$, $Di\,(i = 2, 3, 5, 6, 9)$, and $Fi\,(i = 1, 3, 8, 11)$, respectively, represented the corresponding common factors extracted from the PCA. Except for $C4$ and $D9$, the significance values for the other variables were less than 0.05, which indicated that these variables had a significant impact on the occurrence probability of enterprise credit risk at a 90% significance level. Except for $A6$ and $D9$, which had negative effects on the credit risk of online supply chain finance, all other factors were found to have positive effects.

3.4.4. Model Prediction Results. Logistic models can not only output the regression equation parameters to calculate the event probabilities but also simulate and predict the input model data samples. There were two prediction results. One result was that the model judged a company without default risk to have a default risk, and the other result was that the companies with

Table 14: Classification table.

Group	Observed		Predicted P 0	Predicted P 1	Percentage correct
Clothing industry	P	0	28	2	93.5
		1	4	7	60.0
	Overall percentage				85.4
Home appliance industry	P	0	64	3	95.5
		1	6	10	62.5
	Overall percentage				89.2
Pharmaceutical industry	P	0	98	3	97.0
		1	5	10	66.7
	Overall percentage				93.1
Construction industry	P	0	112	2	98.2
		1	2	12	85.7
	Overall percentage				96.9
Control group	P	0	307	6	98.1
		1	36	19	34.5
	Overall percentage				88.6

default risk that were originally set as risk groups were judged to have no default risk. Table 14 shows that the comprehensive prediction accuracy of each model was more than 85%, that is, the model prediction accuracy was high.

4. Analysis of the Risk Evaluation Results

4.1. A Significant Positive Correlation Was Found between the Enterprise Asset Structures and Credit Risk. This study mainly adopted the asset-liability ratio to describe the enterprise asset structures. Except for the clothing industry, the FCA results revealed that the asset-liability ratio had a negative correlation with the enterprise credit risk scores in the other industries, with the influence coefficients for the significant factors $B1$, $C1$, $D3$, and $F8$ that included the asset-liability ratio in the logistic regression model all being found to be negative. This result indicated that the higher the asset-liability ratio, the higher the online supply chain financial credit risk occurrence probability. Although the impact direction of the indicator was different in the different industries, on the whole, because the indicator reflects the enterprise dependence on debt financing and is closely related to the actual enterprise growth rate and sustainable growth rate, most scholars have tended to believe that there is an inverted U-shaped relationship between the asset-liability ratio and enterprise performance; that is, when the asset-liability ratio is low, the two are positively correlated, but beyond a certain range, the liabilities inhibit the enterprise performance improvements and increase the default probabilities. The difference in the influence direction in the different industries also indicated that the analysis of specific problems needs to be combined with the actual industry situation, such as the development mode and the industry characteristics.

4.2. There Was a Significant Negative Correlation Found between Solvency, Profitability, Enterprise Capital Efficiency, and Credit Risk. The enterprises' solvency indexes included the current ratio and quick ratio to describe the short-term solvency and the interest coverage ratio to describe the long-term solvency. The current ratio can be used to measure the ability of the current assets to be realized before the maturity of the short-term debt for debt repayment. The influencing coefficients $A1$, $B1$, $C1$, $D3$, and $F1$ in the logistic regression model were, respectively, −3.268, −4.648, −4.547, −7.806, and −1.759, which were the factors with the largest influencing coefficients. Second, the quick ratio can directly reflect the enterprise's short-term solvency and is a more intuitive and credible supplement to the current ratio. However, the value of this index varied greatly in different industries. For example, in the construction industry, the quick assets accounted for a small proportion, and the risk indication effect of the index was relatively weak. Finally, the interest coverage ratio reflects the enterprise's profitability and the profit level guarantee degree for debt repayment. The empirical results found that the higher the interest coverage ratio, the higher the SME default risk in the home appliance industry, and the lower the SME default risk in the other industries. Combined with the specific data, the reason for this unreasonable conclusion may have been because of the negative interest coverage ratio. Because of the ratio of the profit before interest and tax to interest expenses, the negative interest coverage ratio value may have been the result of a negative profit before tax from poor enterprise income, or a negative interest expense because the enterprise deposit interest income was greater than the loan interest expense. If it was the latter reason, this means that the enterprise has sufficient capital, good operating conditions, and low credit risk and indicates that when evaluating enterprise credit risk based on the interest coverage ratio, it is necessary to judge the value, positive or negative, and also comprehensively consider the enterprise profit before interest and tax, interest expenses, and other indicators.

The enterprise's profitability index mainly included the net profit growth rate, the profit growth rate, and the total assets growth rate. The enterprise's profit growth rate was the

most intuitive index to measure the enterprise's operating efficiency, with the included factors $B5$, $C4$, and $F3$ being −1.241, −0.643, and −0.73, indicating that this had a certain reference significance for the risk assessment of SME default. The total assets growth rate, which reflected the enterprise asset scale growth and was the main index for the analysis of the enterprise capital accumulation and development abilities, was found to have a positive influence on credit risk reduction in the home appliance and construction enterprises.

The assets turnover indicator index was used to assess the enterprise's capital efficiency. The capital efficiency, and especially the use and turnover of liquid assets, indicates whether enterprises have sufficient liquid assets for debt servicing, and also reflects the returns on enterprise asset investment to a certain extent; therefore, it is helpful when predicting enterprise credit risk.

4.3. For SMEs in the Pharmaceutical and Construction Industries, a Significant Negative Correlation Was Found between Revenue Quality and Credit Risk. For these two industries, revenue quality was mainly determined by the net profit margin, which was included in the profit factor $C5$ and the income quality factor $D6$, the influence coefficients for which were −2.529 and −2.905. Therefore, the higher the net profit margin, the lower the enterprise default risk. Gao also confirmed that the net profit margin had a significant positive impact on the sustainable enterprise growth rate when using the Van Horn sustainable economic growth model to analyze the financial situation in the listed Chinese pharmaceutical manufacturing enterprises.

4.4. For the SMEs in the Construction Industry, a Significant Negative Correlation Was Found between Enterprise Development Capability and Credit Risk but the Macroeconomic Environment Was Found to Have an Opposite Effect. Development factor $D2$ included the sales growth rate and ROE, with the influence coefficient in the model being −5.38, which was found to only have less impact than the solvency factor. Wang used an entropy weight TOPSIS method to evaluate the business performances of various construction enterprises, finding that the sales growth rate and ROE, respectively, ranked fifth and seventh, which further confirmed the results of this study.

The macroeconomic environment index was assessed from the GDP growth rate. The logistic regression model found that this had a negative impact on the supply chain financial credit risk in the construction industry's SMEs, which was somewhat unexpected. As is well known, because the real-estate industry is a national economy pillar industry, the real-estate prosperity level represents the development level of a region to a certain extent, with regional economic development boosting local real-estate prosperity. However, behind this prosperity, "real-estate bubbles" can occur. The 2008 financial crisis that originated in the United States and then swept the world was caused by the collapse of the US real-estate market. Therefore, these logistic regression results were reasonable and acted as a reminder that it is not recommended to be blindly optimistic about an industry's prospects based only on GDP growth rates and other macroindicators as attention needs to be paid to the significant risks hidden behind the apparent prosperity.

4.5. The Impact of External Guarantees and the Supply Chain Information Sharing Degree on SME Credit Risk Needs to Be Further Determined. The PCA indicated that factors $A3$, $D1$, $F2$, and $F5$, which included two indicators, had higher explanatory values for the total variance; however, the logistic regression indicated that these factors were not significant. The data processing found that the average scores for the two indicators in the top 10% of the home appliance and construction industry SMEs were 0 and 5.85 and the average scores for the last 10% were 4.85 and 0.92, which indicated that the larger the external guarantees and the higher the supply chain information sharing, the better the enterprise credit levels, and the smaller the default probability. Many studies have proven that the external guarantee behavior of core enterprises can increase their default risk, which can then have adverse effects on audit opinions and commercial credit financing. Therefore, improving internal control quality could reduce the external guarantee scale. Supply chain information sharing can increase construction supply chain agility, improve overall supply chain operating efficiency, and further enhance the total value and competitive advantage of the whole supply chain. Zhu also emphasized the positive role of improving the supply chain information sharing degree and risk identification and prevention when discussing relevant suggestions for commercial banks on preventing online supply chain financial credit risks. As the abovementioned indicators were all determinative indicators, there is a strong subjectivity in this study, especially as the experimental results for the indicators that should have performed significantly were not ideal. Therefore, future research studies need to improve the indicator measurement methods to obtain more accurate and convincing results.

5. Conclusions and Recommendations

This study aims to construct a method for assessing the credit risk of SMEs under online supply chain finance. This study constructed an online supply chain financial credit risk evaluation index system with 28 indicators from four aspects: financing enterprise qualification, core enterprise qualification, supply chain operations, and the macroeconomic environment. PCA and logistic regression models were then used to analyze the credit risks in 368 enterprises from the clothing, home appliance, pharmaceutical industries, and construction industries. The supply chain SME credit risks were evaluated and predicted, with the model prediction accuracy being found to be good. The following conclusions were made based on the results:

(1) The online supply chain financial credit risk influencing factors had some similarities. As the risk evaluation core index, the current ratio was found to be applicable to the SMEs in all industries, except for

the construction industry; the quick ratio and net profit growth rate were suitable for SME credit risk assessments in the other three industries; the current assets turnover, interest coverage ratio, and asset-liability ratio were applicable to the credit risk assessments of SMEs in three industries except the clothing industry, and the profit growth rate impacted the credit risk evaluation in the home appliance and pharmaceutical industry SMEs; the total assets growth rate had an impact on the home appliance and construction industry; and credit SME risk evaluation, ROTA, and the net profit margin had an impact on the SME credit risk evaluations in the pharmaceutical and construction industries.

(2) There were significant differences found in the SME credit risk evaluation indicators in different industries. When evaluating SME credit risks, it is necessary to pay greater attention to the ITO in the pharmaceutical industry enterprise and pay greater attention to the sales growth rate, ROE, and GDP growth rate in the construction industry.

(3) The online supply chain finance credit risk predictions are more accurate when evaluations are focused on specific industries. The comparison of the model regression results between the experimental groups and the control groups found that the control group's fitting accuracy was significantly lower than that of the subindustry samples. This indicated that when evaluating online supply chain finance credit risks, to ensure credible results, corresponding evaluation indexes must be selected based on industry characteristics and development status.

Based on the empirical results from this study, the following suggestions are given for the online supply chain finance credit risk management: (1) For banks, third-party online supply chain finance platforms can be used for cooperation and docking to sort, collect, and store supply chain transaction, financial, and credit information for suitable credit risk assessment models. Credit risk precontrol systems need to be actively established and virtuous feedback cycles must be developed by recording, summarizing actual risk events, constantly updating and improving credit risk evaluation systems, and improving credit risk identification abilities. (2) SMEs seeking financing need to pay greater attention to enhancing their own operating and development abilities, improving their capital efficiency and revenue quality, improving solvency, accelerating enterprise information construction, realizing data exchange, improving interaction efficiency, improving enterprise risk control abilities, and optimizing their enterprise operating modes. (3) In addition to focusing on their operations and management, core enterprises need to make full use of their core supply chain leading positions and advantages, strengthen supplier management, speed up the construction of supply chain information sharing platforms, enhance the stability of supply chain relationships, promote a good competitive atmosphere in the industry, and improve overall supply chain profitability and efficiency, all of which could reduce the supplier's credit risk probabilities that could cause losses to the bank and itself.

With the continuous combination of supply chain finance and technological means, how to discuss the risk factors existing in supply chain finance and the impact of financial technology on supply chain finance from the perspective of the new financial technology background has become one of the key issues to be studied urgently. At the same time, it is also a research perspective that scholars rarely pay attention to and this is also the focus of future discussions.

Data Availability

The data are available from the following website: https://www.qianzhan.com/xdata/.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] D. M. Lambert and M. C. Cooper, "Issues in supply chain management," *Industrial Marketing Management*, vol. 29, no. 1, pp. 65–83, 2000.

[2] S. G. Chen, F. J. Lin, and C. H. Liang, "Intelligent maximum power factor searching control using recurrent Chebyshev fuzzy neural network current angle controller for SynRM drive system," *IEEE Transactions on Power Electronics*, vol. 36, no. 3, pp. 3496–3511, 2021.

[3] I. D. Blackman, C. P. Holland, and T. Westcott, "Motorola's global financial supply chain strategy," *Supply Chain Management: International Journal*, vol. 18, no. 2, pp. 132–147, 2013.

[4] M. B. Gordy, "A comparative anatomy of credit risk models," *Journal of Banking & Finance*, vol. 24, no. 1-2, pp. 119–149, 2000.

[5] P. Basu and S. K. Nair, "Supply Chain Finance enabled early pay: unlocking trapped value in B2B logistics," *International Journal of Logistics Systems and Management*, vol. 12, no. 3, pp. 334–353, 2012.

[6] S. C. Rice and D. P. Weber, "How effective is internal control reporting under SOX determinants of the disclosure of existing material weaknesses," *Journal of Accounting Research*, vol. 50, no. 3, pp. 811–843, 2012.

[7] Y. Zhu, C. Xie, B. Sun, G. J. Wang, and X. G. Yan, "Predicting China's SME credit risk in supply chain financing by logistic regression, artificial neural network and hybrid models," *Sustainability*, vol. 8, no. 5, p. 433, 2016.

[8] J. Chen, S. Hu, and X. Xie, "Risk evaluation model building of logistics financial business for the bank and empirical research," *Bio/Technology: An Indian Journal*, vol. 10, no. 9, pp. 3724–3731, 2014.

[9] R. Silvestro and P. Lustrato, "Integrating financial and physical supply chains: the role of banks in enabling supply chain integration," *International Journal of Operations & Production Management*, vol. 34, no. 3, pp. 298–324, 2014.

[10] W. M. Mou, W. K. Wong, and M. Mcaleer, "Financial credit risk evaluation based on core enterprise supply chains," *Sustainability*, vol. 10, no. 10, pp. 3699–3717, 2018.

[11] N. Nehrebecka, "COVID-19: stress-testing non-financial companies: a macroprudential perspective. The experience of Poland," *Eurasian Econ Rev*, vol. 11, no. 2, pp. 283–319, 2021.

[12] N. Nehrebecka, "Distribution of credit-risk concentration in particular sectors of the economy, and economic capital before and during the COVID-19 pandemic," *Economic Change and Restructuring*, vol. 834, p. 1264, 2022.