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Research on Credit Evaluation Indicator System of High-Tech SMEs: From the Social Capital Perspective

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Abstract: High-tech small- and medium-sized enterprises (SMEs) play an important role in the high-quality economic development in a country. Nevertheless, due to the difficulties banks or other financial institutions have in accurately assessing their credit levels, financing difficulties have become the biggest bottleneck restricting the progress of high-tech SMEs, and therefore, this paper aims to construct a credit evaluation indicator system of high-tech SMEs. Based on prior studies and the characteristics of high-tech SMEs, this paper constructs an indicator system from financial and nonfinancial dimensions, including 22 measurement indicators reflecting the operation status, development potential, quality, and competitiveness of an enterprise. Principal component analysis (PCA) and a Delphi-analytic hierarchy process (AHP) method are employed for the evaluation. This indicator system innovates from the social capital perspective, and by setting more novel nonfinancial indicators, the system achieves a more comprehensive evaluation of credit level. This paper also performs an empirical application using the data from 125 enterprises in the Beijing–Tianjin–Hebei region of China, and further performs an empirical study on the external environment's impact on the credit level. The empirical results all show consistency with existing studies, verifying the workability and validity of the indicator system we constructed.

Keywords: high-tech SMEs; credit evaluation; indicator system; social capital

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1. Introduction

High-tech enterprises are those which utilize engineering and science more than the average industry norm, with characteristics of high innovation and significant development potential [1]. They are the main sources of creation, innovation, and transformation of technology, playing an essential role in promoting high-quality growth of the economy [2–4]. Among enterprises, small- and medium-sized enterprises (SMEs) are significantly different from large-sized ones. The criteria defining SMEs are usually based on certain items which reflect the enterprise scale, such as the number of employees, sales value, etc. But the definition is not universal, varying from country to country, and from one institution to another [5]. Except for the scale difference, SMEs additionally have some features, such as strengths of reactivity and flexibility, and the weaknesses of resource limitation and fund shortage [6].

High-tech SMEs are the most active groups in the innovation market [7]; however, they often suffer from obtaining financial support from credit institutions, and even go bankrupt due to a break in the capital chain, which has always been a major constraint on their growth and development [8]. This may be because there is information asymmetry between high-tech SMEs and the credit market, such as incomplete financial system records and information opacity [9,10]. Whether credit institutions pass loan applications for enterprises heavily depends on their credit level [11]. In other words, if financial institutions can better predict the credit levels of high-tech SMEs, the efficiency of the loan can be improved greatly [12].

The purpose of this paper is to construct a credit evaluation indicator system to accurately and comprehensively assess the credit level of high-tech SMEs. With regard to the credit evaluation systems of high-tech SMEs, early research focused on financial indicators such as operating capacity, solvency, profitability, and growth capacity [13,14]. With the deepening of research, scholars began to add some nonfinancial indicators to the evaluation system such as innovation ability and public supervision [15,16]. Although the existing research on the construction of the indicator system has been relatively comprehensive, the vital impact of social capital on enterprise credit has been ignored. The term "social capital" is the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit [17]. Previous studies have shown that high social capital represents a high level of external trust for individuals and social units [18,19]. Considering the importance of social capital in the evaluation of credit levels, we construct an indicator system of high-tech SMEs from the perspective of social capital.

According to the previous indicator setting and characteristics of high-tech SMEs, the indicator system, with an emphasis on nonfinancial indicators, consists of four first-level indicators, eight second-level indicators, and twenty-two third-level indicators. This paper utilizes the data from 125 enterprises in the Beijing–Tianjin–Hebei region of China to calculate the credit levels of three provincial administrative regions, verifying the workability and effectiveness of the indicator system. Subsequently, this paper conducts an empirical study on the impact of the external environment on the regional credit level, results of which show consistency with existing research, further demonstrating the robustness of the indicator system. This indicator system plays an important role in helping financial institutions identify the credit and qualification of enterprises, and thus make their lending decisions, contributing to broadening financing channels for SMEs [15]. At the same time, benefiting from the credit level evaluation results, high-tech SMEs are more willing to regulate their behavior in a targeted way, which will further alleviate the capital constraints they face [13].

The remainder of this paper is organized as follows. Section 2 summarizes the previous literature relevant to this study. Section 3 shows the construction and empirical application of the credit level evaluation indicator system. Section 4 further conducts an empirical study on the impact of the external environment on the credit level to verify the validity of the evaluation results. Section 5 concludes and points out the contributions of this paper.

2. Literature Review

2.1. Credit Evaluation Indicator Systems of High-Tech SMEs

Credit evaluation is popular in existing studies of SMEs, and various methods such as model evaluation [20,21] and indicator system evaluation have been adopted in relevant literatures to study such issues. We are concerned with the latter, which has become one hotspot in this field [22], but there is still a lot of room for research. Table 1 summarizes some of the credit evaluation indicator systems for high-tech SMEs using this method.

Table 1. Summary of partial credit evaluation indicator system of high-tech SMEs.

References	Key Evaluation Attributes of Indicator System
Bao, S.; Yin, Y. (2009) [23]	Debt paying ability, Profitability, Operating ability, Cash flow analysis, Innovation ability, Development ability, Basic enterprise quality, Enterprise development prospects, Historical credit record
Huo, H. (2012) [24]	Profitability, Solvency, Operation ability, Development ability, Enterprise scientific and technological value, Enterprise basic quality, Innovation ability, Development potential
Chen, D. (2017) [13]	Basic quality, Profitability, Operation ability, Cash flow status, Solvency, Innovation ability, Growth ability
Tong, Q.; et al. (2017) [15]	Asset credit, Financial credit, Innovation and development ability, Public credit supervision, Bidding supervision
Chen, Y. (2018) [14]	Solvency, Profitability, Operating capability, Growth capability, Technology innovation capability, Enterprise quality, Enterprise credit record, Enterprise development prospects
Du, J. (2022) [16]	Enterprise quality, Operators quality, Industry prospects, Financial situation, Innovation ability

Financial characteristics usually reflect the financial performance and repayment ability of SMEs [25]. As shown in Table 1, all of the scholars pay attention to financial characteristics and set financial indicators in the evaluation system they developed [15,16]. Among all financial attributes, solvency, profitability, operating capability, and growth capability are the most common, which can be measured by some specific indicators [13,14,23,24]. As for solvency, it is usual to use the current ratio, asset liability ratio and other relevant indicators for measurement [24]. With regard to profitability, scholars usually use ROE (Return on Equity) to measure [13]. As to the operating capability attribute, the turnover index can well reflect the actual performance [14], such as the accounts receivable turnover, inventory turnover, etc. Growth capability, unlike other attributes, reflects the long-term survival of enterprises, which is usually measured by certain growth rate indicators, such as the net profit growth rate [14].

Although financial indicators can be used as objective quantitative information to measure the credit level of SMEs, previous studies have also stated that the majority of SMEs are not listed on the financial market, and their financial statements may be incomplete or unaudited [26], resulting in the widespread of financial information distortion of high-tech SMEs [24]. This is a global problem and it has been suggested that existing market arrangements and regulatory oversight should be strengthened to ensure the truthful disclosure of financial quality [27]. Therefore, some studies have begun to shift their focus to nonfinancial indicators in the credit evaluation of SMEs [28], such as management style [29], production efficiency, business plans, public supervision [30–32], etc. With the deepening of research in this field, more nonfinancial indicators have been proposed and used to evaluate the credit level of high-tech SMEs. For example, distributor and customer networks and supply chain information provide the material of relevant external subjects of enterprises, the corporate resume and awards won by enterprises reflect the public perception of the corporate image, and the innovation ability and development prospects highlight the soft power of enterprises to a certain extent [30,33,34]. However, SMEs usually lack sophisticated information disclosure mechanisms [35,36], and therefore there is also a significant challenge in obtaining nonfinancial information and verifying its authenticity.

2.2. Influencing Factors of Enterprise Credit

According to existing research, the influencing factors of enterprise credit can be broadly divided into two aspects: internal factors and external factors. In terms of internal factors, Altman (1968) [37] found that the solvency, profitability, liquidity, asset scale, and asset utilization efficiency of enterprises may have greater influence on enterprise credit levels. Zhang et al. (2013) [38] performed a comprehensive analysis, the result of which also showed that the financial situation and innovation capacity have a significant effect on the credit risk of high-tech enterprises. In addition, some studies focus on one specific factor, among which Bao et al. (2020) [39] found that other comprehensive income (OCI) volatility influences the credit rating, and Cao et al. (2022) [40] substantiated the impact of innovation strategies on enterprise credit.

Previous studies have shown that external environmental factors, such as the social environment, economic environment, political environment, cultural environment and so on, may have influence on the credit levels of enterprises. For example, Liu and Zeng (2014) [41] found that government supervision and the punishment of dishonesty enable enterprises to choose different credit strategies. Chi and Li (2017) examined the effects of economic policy uncertainty on banks' credit risks [42]. Li et al. (2020) indicated that culture plays a vital role in fostering honesty and thus promoting credit levels [43]. Zhao and Chen (2022) [44] concluded that government departments, financial institutions, and other stockholders all have different degrees of influence on enterprise credit risk.

2.3. Comment on Literature

In sum, although the current research on the credit evaluation of high-tech SMEs has gradually deepened, and a considerable number of evaluation systems have been formed, the selection of specific indicators still needs to be improved. For example, some indicators measuring the social capital can be added. Furthermore, most existing studies have focused on verifying the effects of certain single factors, and studies related to comprehensive credit evaluation need to be supplemented urgently. Considering that most of the internal influencing factors in existing studies have a high degree of coincidence with the selection of credit evaluation system indicators, this paper chooses external variables as influencing factors to carry out the empirical test.

3. Research on Credit Evaluation Indicator System of High-Tech SMEs

3.1. Construction of Indicator System

Based on previous research and the characteristics of high-tech SMEs, an evaluation indicator system was constructed in accordance with the basic design principles, meaning that it must be scientific, objective, complete, and workable [45]. The indicator system is generally divided into financial and nonfinancial dimensions. For high-tech SMEs, financial indicators are the intuitive and direct mapping of the performance over the past period, while nonfinancial indicators reflect the status of other aspects [24].

3.1.1. Financial Indicators

A total of 10 third-level financial indicators (x_1–x_{10} in Table 2) were selected under the four second-level indicators of operating capacity, solvency, profitability, and growth capacity. Operating capacity refers to the asset operation efficiency of an enterprise [14]. Solvency refers to the ability to repay debt [23]. Profitability refers to the capacity to make a profit [14], and growth capacity refers to the ability to extend the existing business [13]. The first describes the operation status of an enterprise, while the last three manifest the enterprise development potential.

The design of the financial indicators in this paper drew on well-established practices from the existing literature [13–15], while innovation and development took place mainly in nonfinancial indicators. Therefore, nonfinancial indicators are presented in detail below.

Table 2. Credit evaluation indicator system of high-tech SMEs.

Dimensions	First-Level Indicators	Second-Level Indicators	Third-Level Indicators	Data Description
Financial indicators	Enterprise operation status	Operating capacity	Accounts receivable turnover rate (x_1)	Net income from credit sales/average balance of accounts receivable
			Inventory turnover rate (x_2)	Operating cost/average inventory balance
			Turnover rate of current assets (x_3)	Net main business income/average total current assets
	Enterprise development potential	Solvency	Current ratio (x_4)	Current assets/current liabilities
			Quick ratio (x_5)	Quick assets/current liabilities
			Asset liability ratio (x_6)	Total liabilities/total assets
		Profitability	Return on equity (x_7)	Net profit/net assets
		Growth ability	Growth rate of operating revenue (x_8)	Increase in operating Revenue/revenue of the previous period
			Net profit growth rate (x_9)	Net profit growth/net profit of the previous period
			Capital accumulation rate (x_{10})	Increase in owner's equity/amount at the beginning of the year
Nonfinancial indicators	Enterprise quality	Enterprise credit activity record	Tax credit rating (x_{11})	Rated by the tax assessment score
			Number of lawsuits (x_{12})	Number of judicial cases related to the enterprise
		External evaluation	Risk information (x_{13})	Self-risk + associated risk + prompt risk information
			Public opinion information (x_{14})	Positive information/negative information
	Enterprise competitive-ness	Innovation ability	Total content of scientific and technological innovation (x_{15})	Converted from several intellectual property right indicators
			R&D investment (x_{16})	Investment amount in research and development
			Patent implementation rate (x_{17})	Number of patents authorized/total number of patents
		Social capital	Working years of senior manager (x_{18})	Average number of working years of the legal person and the chairman
			Educational level of senior manager (x_{19})	Associate degree or below = 1, bachelor degree = 2, master degree = 3, doctor degree = 4
			Number of affiliated enterprises of senior manager (x_{20})	Number of enterprises that is directly or indirectly controlled by the senior manager
			Number of foreign investment enterprises (x_{21})	Number of enterprises abroad that is invested by the focal enterprise
			Number of suppliers and customers (x_{22})	Number of suppliers + number of customers

3.1.2. Nonfinancial Indicators

We constructed two first-level indicators, four second-level indicators, and twelve third-level indicators (x_{11}–x_{22} in Table 2) for nonfinancial indicators. One of the first-level indicators is enterprise quality, which contains two second-level indicators of enterprise credit activity records and external evaluation. Another is enterprise competitiveness, which also sets two second-level indicators of innovation ability and social capital. The descriptions of these indicators are as follows:

Enterprise credit activity records: "Tax credit rating (x_{11})" was included to measure the credit level from the perspective of taxation, reflecting the fundamental credit activity of an enterprise [46]. "Number of lawsuits (x_{12})" judges whether SMEs operate in compliance [45].

External evaluation: "Risk information (x_{13})" describes the enterprise risk objectively assessed by external organizations [47], and we summed the self-risk, related risk, and prompt risk provided by a public information inquiry platform to measure this indicator. "Public opinion information (x_{14})" dynamically responds to external public opinion evaluation of an enterprise [48]. In this paper, the ratio of positive information to negative information was used as the proxy variable of this indicator.

Innovation capability: Based on the "R&D investment (x_{16})" [14] which is commonly used in existing studies to measure the innovation capability, this paper added "total content of scientific and technological innovation (x_{15})" and "patent implementation rate (x_{17})" to measure the achievement level of innovation. "Total content of scientific and technological innovation (x_{15})" contains comprehensive information on multiple types of scientific and technological innovation achievements [49]. "Patent implementation rate (x_{17})" reflects the ability of enterprises to commercialize their innovation achievements, which are calculated by the number of authorized patents, not just the number of applied patents [50].

Social capital: Existing literature has shown that social capital exerts an important influence on high-tech SMEs by providing them with resources [7,17]. From manager and organizational perspectives, five third-level indicators reflecting the social connections and resources were embedded in this indicator. "Working years of senior manager (x_{18})," "educational level of senior manager (x_{19})" and "number of affiliated companies of senior manager (x_{20})," evaluate the intangible value of social resources possessed by employees at the manager level [5]. From the perspective of organizations, "number of foreign investment enterprises (x_{21})" and "number of suppliers and customers (x_{22})" reflect the business transactions and social interaction between enterprises and relevant external entities [51].

With reference to the above indicator settings, this research established a credit evaluation indicator system, as shown in Table 2, which consists of four first-level indicators, eight second-level indicators, and twenty-two third-level indicators in financial and nonfinancial domains.

3.2. Empirical Application of Indicator System

In this section, we conducted an empirical application using enterprise data from 2014–2018 in the Beijing–Tianjin–Hebei region to verify the operability and validity of the indicator system.

3.2.1. Sample Selection

This study chose the Beijing–Tianjin–Hebei region of China as the sample research area. This region, which includes two municipalities of Beijing and Tianjin and 11 cities in Hebei province, is a typical urban cluster for economic development in China. According to the strategy of the coordinated development of the Beijing–Tianjin–Hebei region, the urban cluster put emphasis on innovation-driven development [52]. Furthermore, existing studies, such as *China's Regional Science and Technology Innovation Evaluation Report*, show that the Beijing–Tianjin–Hebei region has generally outperformed other areas in terms of science and technology innovation, with Beijing and Tianjin in particular taking the lead in China [53,54]. Considering that it is typical and representative, the Beijing–Tianjin–Hebei region is an ideal sample region for our empirical study.

For the Beijing–Tianjin–Hebei region, China initiated the strategy of the coordinated development of this region in early 2014 [55]. From then until now, significant progress has been made in the development of science and technology innovation. Chinese President Xi concluded and divided two phases of the work, taking the end of 2018 as the time node [56]. As he said, in the five years before 2018, the work had achieved the expected results of seeking ideas, laying foundations and making a breakthrough; starting from 2019, the coordinated development of the Beijing–Tianjin–Hebei region has entered a new phase of advancing challenging work. The first stage of 2014–2018 is mature and complete given that the work in this period has been accomplished; in contrast, the work in the second stage from 2019 to the present is still under way, and existing research has also shown that the credit level of high-tech SMEs in this region presented a reverse trend in 2018 [57]. Therefore, it is a better choice to use the data which is relatively stable in 2014–2018 as the sample to perform the verification of the indicator system.

As for sample enterprises, following the principle of typicality, the SMEs in the growth enterprise market (GEM) from the Shenzhen Stock Exchange (SZSE) were chosen to conduct the empirical study, because they had outstanding performances among high-tech SMEs, and their financial data were easily acquired. We screened out the SMEs according to *Statistical Classification of Large, Small and Micro Enterprises* [58] in China, which differentiate SMEs from large enterprises by the number of employees and operation revenue scale in different industries. For example, SMEs in software and information technology services industry refer to enterprises with business revenues of up to 100,000,000 CNY and no more than 300 employees. Based on this criterion, 125 enterprises (as shown in Table A1 in Appendix A) were finally selected as the study sample in this paper.

3.2.2. Data Collection and Processing

This study collected data from multiple sources. All the financial data were from the RESSET database (https://db.resset.com/common/main.jsp, accessed on 8 September 2022), while the nonfinancial data were mainly obtained from the enterprises' official websites and annual reports, as well as from credit information reference platforms such as Qichacha (https://www.qcc.com/, accessed on 8 September 2022).

In this paper, the data were processed as follows. Firstly, the median values of corresponding indicators were used to fill in the missing data. Secondly, the PCA method is very sensitive to the numerical variance, and if the dimensionality difference of each indicator is significantly large, it may lead to bias in the extraction of principal components [59,60]. Therefore, this study used the range standardization method for data normalization, as shown in formula (1). Thirdly, for the negative indicators, the final value is 1 minus the normalized original value.

$$X_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x_i is the original value of the indicator, X_i is the standard value, and x_{max} and x_{min} represent the maximum and minimum values, respectively.

3.2.3. Evaluation Process

The comprehensive evaluation methods can be roughly divided into two categories: objective and subjective methods [59]. Objective methods include the principal component analysis (PCA) method, whose evaluation process depends on the values themselves, and does not involve the subjective judgment of experts [61,62]. In contrast, subjective methods, such as the Delphi-analytic hierarchy process (AHP) method, are not influenced by specific values of the sample, but depend entirely on the subjective experience of the experts [63]. Nevertheless, both methods have their own limitations. Considering the characteristics of the credit evaluation indicator we selected, this study used a combination of these two methods.

Currently, there is a general consensus on the specific indicator settings for the financial dimension and the PCA method has been applied maturely to this type of study [24]; we therefore followed this objective method for the financial dimension. As for the nonfinancial dimension, considering that most of the indicators in this section were introduced innovatively and the data were collected from multiple channels, the Delphi technology is more applicable to the process of determining the weights of nonfinancial indicators, which require expert advice in this study.

- Financial indicators

Firstly, we checked whether the sample was suitable for PCA. The Kaiser–Meyer–Olkin (KMO) value of 0.614 was greater than 0.5, and the *p*-value of the Bartlett sphericity test was close to 0, meaning that it passed the significance test. Secondly, we conducted PCA on the sample data. According to the PCA results, there were four actors with eigenvalues greater than 1 and the cumulative variance contribution of 71.14%, which means that the four principal components (PCs) contained 71.14% of the information from the original indicators. Therefore, the PCA results were deemed satisfactory.

As shown in Table 3, "Current ratio (X_4)" and "Quick ratio (X_5)" had higher loadings on PC_1, "Accounts receivable turnover rate (X_1)" and "Inventory turnover rate (X_2)" had higher loadings on PC_2, "Growth rate of operating revenue (X_8)" and "Capital accumulation rate (X_{10})" loaded higher on PC_3, and "Asset liability ratio (X_6)" and "Return on equity (X_7)" loaded higher on PC_4. Except for PC_4, the rest of the extracted principal components explained most of the information about the solvency, operating capacity, and growth ability of the company, respectively, which also indicated that the classification of the third-level indicators in the previous section was credible and robust.

Table 3. Factor score coefficient matrix.

Financial Indicators	**Elements**			
	PC_1	**PC_2**	**PC_3**	**PC_4**
Accounts receivable turnover rate (X_1)	−0.005	0.527	−0.070	0.055
Inventory turnover rate (X_2)	0.009	0.535	−0.014	−0.014
Turnover rate of current assets (X_3)	0.025	0.125	0.392	−0.286
Current ratio (X_4)	0.492	0.002	0.046	−0.120
Quick ratio (X_5)	0.495	0.013	0.049	−0.128
Asset liability ratio (X_6)	−0.052	−0.007	0.118	−0.503
Return on equity (X_7)	−0.166	0.022	0.062	0.604
Growth rate of operating revenue (X_8)	0.064	−0.060	0.506	−0.028
Net profit growth rate (X_9)	−0.033	−0.003	0.158	0.146
Capital accumulation rate (X_{10})	0.018	−0.072	0.398	0.002

According to the factor score coefficient in Table 3, the expression of four principal components Z_1– Z_4 could be obtained:

$$\text{Principal component } Z_1 = -\,0.005X_1 + 0.009X_2 + 0.025X_3 + \ldots\ \ldots + 0.018X_{10} \quad (2)$$

$$\text{Principal component } Z_2 = 0.527X_1 + 0.535X_2 + 0.125X_3 + \ldots\ \ldots - 0.072X_{10} \quad (3)$$

$$\text{Principal component } Z_3 = -\,0.070X_1 - 0.014X_2 + 0.392X_3 + \ldots\ \ldots + 0.398X_{10} \quad (4)$$

$$\text{Principal component } Z_4 = -\,0.055X_1 - 0.014X_2 - 0.286X_3 + \ldots\ \ldots + 0.002X_{10} \quad (5)$$

Taking the factor variance contribution rate as the weight, the financial indicator score was obtained:

$$\text{Financial score} = 21.584\%Z_1 + 17.141\%Z_2 + 17.064\%Z_3 + 15.352\%Z_4 \quad (6)$$

- Nonfinancial indicators

We applied the integrated Delphi–AHP method to evaluate nonfinancial indicators. Firstly, the Delphi technique was used to identify major indicators, which usually need several rounds of consultation with an expert group [64]. Secondly, the AHP method can solve the complex decision-making problems of unstructured multi-elements and multi-level correlations, which are employed to determine the weight or relative importance of the indicators [64].

We performed the evaluation following the steps of this method. Firstly, we constructed the evaluation model with a hierarchical structure, based on which we designed the scoring questionnaire and invited the expert group to score it, and obtained a total of 21 valid questionnaires. Secondly, based on the results of the questionnaires, Yaahp (a software which can perform AHP) was applied to conduct the consistency test in this study. The results showed a satisfactory consistency index Cr of 0.068 < 0.1. Combining the weights of each indicator finally determined by Yaahp, we can see that the expression (7) for the nonfinancial indicators is as follows:

$$\begin{aligned}\text{Nonfinancial score} = {} & 0.0245\, X_{11} + 0.0980\, X_{12} + 0.0179\, X_{13} + 0.0026\, X_{14} + 0.4535\, X_{15} + 0.0557\, X_{16} + 0.2051\, X_{17} + \\ & 0.0230\, X_{18} + 0.0071\, X_{19} + 0.0272\, X_{20} + 0.0232\, X_{21} + 0.0624\, X_{22}\end{aligned} \tag{7}$$

3.2.4. Evaluation Results

Based on the credit evaluation process above, the financial and nonfinancial scores can be calculated separately, and the final credit score can be obtained by summing the two components. The scoring results are shown in Figure 1.

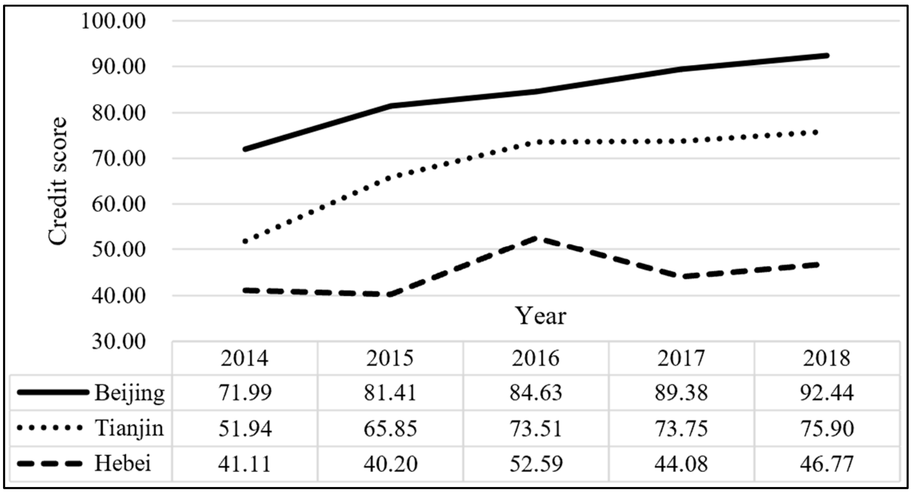

Figure 1. Credit scores of high-tech SMEs in Beijing–Tianjin–Hebei region.

Figure 1 shows that the credit scores of high-tech SMEs in Beijing and Tianjin are significantly better than those in Hebei, which is consistent with the existing research. For example, He et al. (2022) evaluated the credit risk of high-tech SMEs in the Beijing–Tianjin–Hebei region through the data envelopment analysis method and drew the conclusion that the credit risks of enterprises in Hebei were higher than those in Beijing and Tianjin [57]. In other words, the high-tech SMEs in Beijing and Tianjin had better performance in credit evaluation than Hebei. However, it may not be a satisfactory conclusion for the government, which emphasizes the coordinated development of the whole region in the long term. Therefore, the Hebei government should pay more attention to improving the credit situation of high-tech SMEs, narrowing the gap with the other two municipalities and achieving balanced development.

In addition to the cross-sectional variance analysis of the three provincial-level administrative regions, this paper additionally analyzed the development trend from 2014–2018 vertically as a whole. Except for a brief decline in Hebei in 2017, the credit level of the Beijing–Tianjin–Hebei region showed a continuous upward trend in these years. Furthermore, this finding also shows consistency with the existing studies [57]. The decline in Hebei province in 2017 is comprehensible according with the reality. Hebei formulated a *Development plan for high-tech SMEs* [65] in 2016, which stimulated the high-tech SMEs and resulted in a great promotion in the credit level in 2016, followed by a fall back to the normal level in 2017. In conclusion, the findings of this paper imply that the credit levels of the high-tech SMEs in the Beijing–Tianjin–Hebei region are improving gradually, and there is hope that the financing difficulties constraining the development of SMEs will be alleviated.

4. Empirical Study on External Environment's Impact on Credit Levels

To further examine the validity of the indicator system, we conducted an empirical analysis of the impact of the external environment on credit levels based on the scores calculated in Section 3.

4.1. Hypotheses Development

Considering the regional environmental factors in previous studies and the characteristics of high-tech SMEs, the study selected five external environmental influencing factors: namely economic, financial, infrastructural, cultural, as well as the scientific and technological innovation environment. We then proposed the hypothesis respectively as follows.

Previous studies have shown that the regional economy has a positive effect on the credit levels of enterprises in the region [66]. In the case of stagnant economic growth, firms face business difficulties and some of them may act dishonestly as a consequence in order to gain short-term benefits, which would lower their credit levels [67]. Therefore, we hypothesized the following:

Hypothesis 1 (H1). *Regional economic level positively affects the credit levels of regional enterprises.*

The development of enterprises is inseparable from financial support. In general, the higher the financial level in a region, the larger the scale of financing, which helps high-tech SMEs to obtain funding support for their production and business activities [68], and further improves the credit level [44]. Based on these arguments, we formulated the following hypothesis:

Hypothesis 2 (H2). *The regional financial level positively affects the credit levels of regional enterprises.*

Regional infrastructure influences credit levels by affecting the information balance [69] of enterprises. For instance, platform information-sharing can reduce information asymmetry and lower transaction costs [70]. In addition, network traces play an increasingly positive role in enhancing enterprise credit awareness [71]. The following hypothesis was proposed:

Hypothesis 3 (H3). *The regional infrastructural level positively affects the credit levels of regional enterprises.*

Prior studies have indicated that regional culture affects the quality of life of residents [72], including managers and employees of enterprises. Further, the integrity and corporate social responsibility of entrepreneurs can also affect the credit level of a firm [73]. Accordingly, we formulated the following hypothesis:

Hypothesis 4 (H4). *The regional cultural level positively affects the credit level of regional enterprises.*

Scientific and technological innovation is important to enhance competitiveness of high-tech SMEs. Previous studies have shown that enterprises with higher innovation capacity mostly have higher credit levels [74], and technological innovation in SMEs has a positive impact on enterprise credit [75,76]. Thus, we hypothesized the following:

Hypothesis 5 (H5). *Regional scientific and technological innovation level positively affects the credit levels of regional enterprises.*

Based on the hypotheses above, this study further selected specific variables to measure the five external environmental influencing factors, as shown in Table 4.

Table 4. Specific variables of external environmental influencing factors.

Influencing Factors	Specific Variables	References
Economic environment (D_1)	Per capita GDP (d_1)	[77–79]
	Total imports and exports (d_2)	
	Total retail sales of social consumer goods (d_3)	
	Average monetary wage (d_4)	
Financial environment (D_2)	Balance of loans of financial institutions (d_5)	[80,81]
	General budget expenditure of local finance (d_6)	
	Scale of social financing (d_7)	
Infrastructural environment (D_3)	Urban road area at the end of the year (d_8)	[82,83]
	Turnover of goods (d_9)	
	Internet penetration rate (d_{10})	
Cultural environment (D_4)	Average number of students in colleges per 100,000 residents (d_{11})	[73,84]
Scientific and technological innovation environment (D_5)	Number of patents licensing (d_{12})	[85,86]
	Turnover of technology market (d_{13})	
	Internal expenditure of R&D funds (d_{14})	
	Main business income of high-tech enterprises (d_{15})	

4.2. Empirical Test

4.2.1. Data Collection

Clearly, the explained variable is the credit scores of regional SMEs, which have already been calculated in the empirical application of the evaluation indicator system in Section 3.2.4.

As for explanatory variables, we obtained the data of 15 variables (d_1–d_{15}) of five external environmental factors from the Easy Professional Superior (EPS) platform (http://www.epsnet.com.cn/, accessed on 25 October 2022), which is a professional data service platform in China. A series of professional databases, such as the China Regional Economy Database, China City Data, China High-tech Industry Database, and China Finance Database, are included in this platform, which are the main data sources used in our research.

4.2.2. Data Analysis and Results

We would like to use a multiple regression model to test the effect of five external environmental factors on credit levels. One of the assumptions in multiple regression is that explanatory variables should not be highly correlated with each other [87], and the Pearson correlation coefficient is usually used to measure the strength of the association between two variables. As shown in the correlation matrix in Table A2 (see Appendix B), some variables were highly correlated with each other; for example, the correlation coefficient of d2 and d4 was as high as 0.9, which may lead to a severe multicollinearity problem, resulting in the distortion of model estimates [88]. Therefore, it is necessary to select a more appropriate regression method to eliminate the effects of multicollinearity.

To overcome the interference of multicollinearity, this paper used the principal component regression (PCR) method for empirical testing. Using principal component analysis (PCA) to extract several uncorrelated principal components (PCs) and making them replace the original variables of the linear regression model [89] can effectively avoid regression bias caused by multicollinearity. The PCR procedure is divided into two stages. The first stage uses the PCA method to extract principal components, and the second stage establishes a linear regression model and estimates the regression coefficients [90]. The detailed analysis process is as follows.

- PCA

The result of the KMO (Kaiser–Meyer–Olkin) test showed the KMO value of 0.857, indicating that the explanatory variables were suitable for PCA. Two principal components with eigenvalues greater than 1 were extracted, the cumulative variance contribution of which was 91.22% (see Table A3 in Appendix C), indicating that it reflected most of the information of the original variables. The results of the PCA were satisfactory.

According to the factor score coefficients (see Table A4 in Appendix C) of the two principal components, F_1 and F_2, we obtained the expression (8–9) of them:

$$\begin{aligned} F_1 = \sqrt{9.023} \times (&0.122d_1 + 0.101d_2 - 0.116d_3 + 0.083d_4 + 0.007d_5 - 0.048d_6 + 0.015d_7 - 0.124d_8 \\ &-0.127d_9 + 0.066d_{10} + 0.114d_{11} + 0.049d_{12} + 0.058d_{13} + 0.082d_{14} + 0.118d_{15}) \end{aligned} \tag{8}$$

$$\begin{aligned} F_2 = \sqrt{4.661} \times (&-0.070d_1 + 0.017d_2 + 0.220d_3 + 0.053d_4 + 0.187d_5 + 0.227d_6 + 0.161d_7 + 0.069d_8 \\ &+0.080d_9 - 0.150d_{10} - 0.025d_{11} + 0.128d_{12} + 0.112d_{13} + 0.065d_{14} - 0.050d_{15}) \end{aligned} \tag{9}$$

According to the loading coefficients of F_1 and F_2, we concluded that:

F_1 mainly included the information on variables d_1, d_2, d_8, d_9, d_{11}, etc., reflecting the economic, infrastructural, and cultural environmental factors.

F_2 mainly included the information on variables d_5, d_6, d_7, d_{12}, d_{13}, etc., reflecting the financial, as well as scientific and technological innovation environmental factors.

- Regression model

We established a principal component regression model with the regional credit level as the dependent variable and two principal components as independent variables.

$$Y = \alpha_0 + \alpha_1 F_1 + \alpha_2 F_2 + \varepsilon \tag{10}$$

In model (10), Y represents the credit score of regional high-tech SMEs; F_1 and F_2 represent the two principal components; α_0 represents the intercept term; α_1 and α_2 represent the coefficient of each principal component; and ε represents the residual term.

Before the analysis of regression model (10), tests of the classical linear regression model (CLRM) assumptions such as normality, heteroscedasticity, and autocorrelation were conducted on the data, as shown in Appendix D. After these tests, a bivariate regression model was conducted and the regression results were given as follows:

As shown in Table 5, R-squared was 0.889, indicating that the extracted principal components had strong interpretability on the credit level. Moreover, the p-value of both F_1 and F_2 were less than 0.01, reflecting that the relationship between the two principal components and the dependent variable was significant, as well as suggesting that five external environmental factors had significant impacts on the credit levels of regional high-tech SMEs.

Table 5. Regression results.

Variables	Model (10)
F_1	16.426 *** (1.750)
F_2	4.861 *** (1.750)
Constant	65.569 *** (1.691)
Observations	15
R-squared	0.889

Asterisk sign *** means the p-value is less than 0.01, and standard error is in parentheses.

As a whole, the empirical results are congruent with existing research on the influence of the external economic environment [42,67], financial environment [44,68], infrastructural environment [69,70], cultural environment [43,73], and scientific and technological innovation environment [75,76] on the regional credit level. Therefore, we can conclude that the evaluation indicator system we constructed is valid and the evaluation results are reliable.

5. Discussion

5.1. Summary

This study constructed a credit evaluation indicator system for high-tech SMEs from the social capital perspective, which consists of four first-level indicators, eight second-level indicators, and twenty-two third-level indicators.

Using the data of high-tech SMEs in the Beijing–Tianjin–Hebei region to apply the indicator system empirically, this paper verified that the evaluation results are consistent with existing research on the ranking of the credit level of high-tech SMEs in this region, which indicated that the indicator system we constructed is workable and valid. Furthermore, the result of the empirical analysis of the impact of the external environment on the credit level was also supported by existing studies, further proving the robustness of the indicator system.

5.2. Theoretical Contribution

This paper contributes to deepening the relevant literature in the field of credit evaluation of high-tech SMEs. Firstly, compared with previous indicator systems, this paper put forward a new perspective of credit evaluation, namely social capital perspective, which takes another important step forward in the construction of indicator systems for high-tech SMEs [17]. The introduction of the new perspective enriches the existing credit evaluation research and makes it possible to accurately assess the credit level of SMEs that lack historical financial data [91].

Secondly, this paper innovates the data acquisition method for credit level-related studies. Previous studies mostly obtained data from a single channel, such as Wind database or other official data agencies [57], which made the evaluation results less comprehensive and difficult to update dynamically. This paper provides a multi-channel data acquisition method that makes full use of internet big data (e.g., public opinion information), which greatly improves the completeness and real-time updating ability of the data.

Thirdly, this paper enriches and extends the existing research related to the credit evaluation of high-tech SMEs by establishing an indicator system. Previously, most international studies in this field have been conducted through mathematical modeling [20], and the indicator system evaluation method has been widely used because of its superior interpretability. However, there is still ample room for in-depth exploration and research. This paper provides a new and unique perspective to further understand the credit level of high-tech SMEs by developing a feasible and effective multilevel indicator system.

5.3. Practical Implications

This study performs an empirical application with the sample of high-tech SMEs in the Beijing–Tianjin–Hebei region of China, and its results further provide some practical implications to the high-tech SMEs, financial institutions, and government departments.

First, this paper provides directions for high-tech SMEs to improve their credit level. The establishment of the indicator system makes it no longer difficult for high-tech SMEs to carry out self-examination of their own credit level. The self-assessment helps high-tech enterprises to identify their own deficiencies and improve their credit level in the right direction, thus reducing financing barriers and alleviating the financing difficulties commonly faced by SMEs.

Second, the indicator system constructed in this paper helps financial institutions to assess the credit level of high-tech SMEs. It helps banks and other departments to accurately identify the credit and qualification of enterprises, provides ex-ante prevention of non-performing loans, plays a crucial role in enhancing the efficiency of investment decisions, and helps to promote the healthy and orderly development of the financial industry.

Third, the evaluation results show that the credit scores of high-tech SMEs in the research region are still of varying levels, especially in Hebei Province, which is detrimental to the coordinated development of this region. Therefore, policy- and decision-makers should pay attention to the credit level improvement of high-tech SMEs and create a good external business environment (e.g., an economic, scientific and technological innovation environment) to promote the upward development of high-tech SMEs.

5.4. Limitations and Future Research

This paper has the following limitations. First, the research sample used in this paper only includes 125 high-tech SMEs in the Beijing–Tianjin–Hebei region from 2014 to 2018, and subsequent studies can be conducted by expanding the sample scope in multiple dimensions, such as selecting more regions to join the sample, not just the better-performing Beijing–Tianjin–Hebei city cluster, or other important time periods can also be selected to examine the similarities and differences between their findings and those of this study. Second, as for the weight determination method of the indicator system, neither the objective nor the subjective methods are perfect. Future research could apply a combination of the methods which effectively avoid the drawbacks of these two traditional methods [92] and use more accurate techniques to evaluate the quality, such as bootstrap [93]. Third, the data analysis methods in this paper are all classical statistic methods, such as principal component analysis. Currently, big data algorithms can help to improve the efficiency and accuracy of credit assessments [94], and thus, future research could make full use of big data technology and AI algorithms in order to conduct research related to corporate credit.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The following 125 high-tech SMEs in the Beijing-Tianjin-Hebei region were selected in this study.

Table A1. Key information of 125 sample enterprises.

Number	Company Name	Location	Stock Code
1	Beijing Zhongkehaixun Digital S&T Co., Ltd.	Beijing	300810
2	Beijing Compass Technology Development Co., Ltd.	Beijing	300803
3	Beijing Zuojiang Technology Co., Ltd.	Beijing	300799
4	NCS TESTING TECHNOLOGY Co., Ltd.	Beijing	300797
5	Citic Press Corporation	Beijing	300788
6	Beijing Zhidemai Technology Co., Ltd.	Beijing	300785
7	Lakala Payment Co., Ltd.	Beijing	300773
8	CSPC Innovation Pharmaceutical Co., Ltd.	Hebei	300765
9	Pharmaron Beijing Co., Ltd.	Beijing	300759
10	BYBON Group Company Limited	Beijing	300736
11	Beijing Andawell Science& Technology Co., Ltd.	Beijing	300719
12	Dark Horse Technology Group Co., Ltd.	Beijing	300688
13	JONES TECH PLC	Beijing	300684
14	Yusys Technologies Co., Ltd.	Beijing	300674
15	Beijing Beetech Inc.	Beijing	300667
16	Client Service International, Inc.	Beijing	300663
17	Beijing Career International Co., Ltd.	Beijing	300662
18	SG MICRO CORP	Beijing	300661
19	Shunya International Martech (Beijing) Co., Ltd.	Beijing	300612
20	Si-Tech Information Technology Co., Ltd.	Beijing	300608
21	Rianlon Corporation	Tianjin	300596
22	Suplet Power Co., Ltd.	Beijing	300593
23	BeiJing Certificate Authority Co., Ltd.	Beijing	300579
24	BEIJING WANJI TECHNOLOGY Co., Ltd.	Beijing	300552
25	Brilliance Technology Co., Ltd.	Beijing	300542
26	Beijing Advanced Digital Technology Co., Ltd.	Beijing	300541
27	Beijing Global Safety Technology Co., Ltd.	Beijing	300523
28	Beijing E-techstar Co., Ltd.	Beijing	300513
29	Thunder Software Technology Co., Ltd.	Beijing	300496
30	Shijiazhuang Tonhe Electronics Technologies Co., Ltd.	Hebei	300491
31	Beijing Science Sun Pharmaceutical Co., Ltd.	Beijing	300485
32	Beijing Hezong Science&Technology Co., Ltd.	Beijing	300477
33	Global Infotech Co., Ltd.	Beijing	300465
34	NAVTECH INC.	Beijing	300456
35	Beijing Ctrowell Technology Corporation Limited	Beijing	300455

Table A1. *Cont.*

Number	Company Name	Location	Stock Code
36	Beijing Hanbang Technology Corp.	Beijing	300449
37	Baoding Lucky Innovative Materials Co., Ltd.	Hebei	300446
38	Beijing ConST Instruments Technology Inc.	Beijing	300445
39	Beijing SOJO Electric Co., Ltd.	Beijing	300444
40	Baofeng Group Co., Ltd.	Beijing	300431
41	Beijing Chieftain Control Engineering Technology Co., Ltd.	Beijing	300430
42	Hebei Sitong New Metal Material Co., Ltd.	Hebei	300428
43	BEIJING INTERACT TECHNOLOGY Co., Ltd.	Beijing	300419
44	Beijing Kunlun Tech Co., Ltd.	Beijing	300418
45	Tianjin Keyvia Electric Co., Ltd.	Tianjin	300407
46	Beijing Strong Biotechnologies, Inc	Beijing	300406
47	Beijing Tianli Mobile Service Integration, INC.	Beijing	300399
48	Beijing Tensyn Digital Marketing Technology Joint Stock Company	Beijing	300392
49	Feitian Technologies Co., Ltd.	Beijing	300386
50	Beijing Sanlian Hope Shin-Gosen Technical Service Co., Ltd.	Beijing	300384
51	Beijing Sinnet Technology Co., Ltd.	Beijing	300383
52	BEIJING TONGTECH Co., Ltd.	Beijing	300379
53	TIANJIN PENGLING GROUP Co., Ltd.	Tianjin	300375
54	Beijing Hengtong Innovation Luxwood Technology Co., Ltd.	Beijing	300374
55	Huizhong Instrumentation Co., Ltd.	Hebei	300371
56	Beijing Etrol Technologies Co., Ltd.	Beijing	300370
57	Nsfocus Information Technology Co., Ltd.	Beijing	300369
58	Hebei Huijin Electromechanical Co., Ltd.	Hebei	300368
59	NetPosa Technologies, Ltd.	Beijing	300367
60	BEIJING FOREVER TECHNOLOGY Co., Ltd.	Beijing	300365
61	COL Digital Publishing Group Co., Ltd.	Beijing	300364
62	Kyland Technology Co., Ltd.	Beijing	300353
63	Beijing VRV Software Corporation Limited.	Beijing	300352
64	Taikong Intelligent Construction Co., Ltd.	Beijing	300344
65	TIANJIN MOTIMO MEMBRANE TECHNOLOGY Co., Ltd.	Tianjin	300334
66	Top Resource Conservation & Environment Corp.	Beijing	300332
67	Beijing Watertek Information Technology Co., Ltd.	Beijing	300324
68	Beijing Bohui Innovation Biotechnology Co., Ltd.	Beijing	300318
69	OURPALM Co., Ltd.	Beijing	300315
70	Boomsense Technology Co., Ltd.	Beijing	300312
71	GI Technologies Group Co., Ltd.	Beijing	300309
72	TOYOU FEIJI ELECTRONICS Co., Ltd.	Beijing	300302
73	Leyard Optoelectronic Co., Ltd.	Beijing	300296
74	Beijing HualuBaina Film&Tv Co., Ltd.	Beijing	300291
75	BEIJING LEADMAN BIOCHEMISTRY Co., Ltd.	Beijing	300289
76	Beijing Philisense Technology Co., Ltd.	Beijing	300287

Table A1. *Cont.*

Number	Company Name	Location	Stock Code
77	Sansheng Intellectual Education Technology Co., Ltd.	Beijing	300282
78	BEIJING THUNISOFT CORPORATION LIMITED	Beijing	300271
79	Hebei Changshan Biochemical Pharmaceutical Co., Ltd.	Hebei	300255
80	Beijing Enlight Media Co., Ltd.	Beijing	300251
81	Beijing Trust&Far Technology Co., Ltd.	Beijing	300231
82	TRS Information Technology Co., Ltd.	Beijing	300229
83	Ingenic Semiconductor Co., Ltd.	Beijing	300223
84	Beijing Jiaxun Feihong Electrical Co., Ltd.	Beijing	300213
85	BEIJING E-HUALU INFORMATION TECHNOLOGY Co., Ltd.	Beijing	300212
86	Staidson (Beijing) Biopharmaceuticals Co., Ltd.	Beijing	300204
87	Beijing Comens New Materials Co., Ltd.	Beijing	300200
88	MASTERWORK GROUP Co., Ltd.	Tianjin	300195
89	SINO GEOPHYSICAL Co., Ltd.	Beijing	300191
90	Beijing Jetsen Technology Co., Ltd.	Beijing	300182
91	Business-intelligence of Oriental Nations Corporation Ltd.	Beijing	300166
92	LandOcean Energy Services Co., Ltd.	Beijing	300157
93	Shenwu Environmental Technology Co., Ltd.	Beijing	300156
94	Xiongan Kerong Environment Technology Co., Ltd.	Hebei	300152
95	Beijing Century Real Technology Co., Ltd.	Beijing	300150
96	Beijing XIAOCHENG Technology Stock Co., Ltd.	Beijing	300139
97	CHENGUANG BIOTECH GROUP Co., Ltd.	Hebei	300138
98	Hebei Sailhero Environmental Protection High-tech Co., ltd.	Hebei	300137
99	Tianjin Jingwei Huikai Optoelectronic Co., Ltd.	Tianjin	300120
100	Tianjin Ringpu Bio-Technology Co., Ltd.	Tianjin	300119
101	Beijing JIAYU Door, Window and Curtain Wall Joint-Stock Co., Ltd.	Beijing	300117
102	Hebei Jianxin Chemical Co., Ltd.	Hebei	300107
103	LESHI INTERNET INFORMATION & TECHNOLOGY CORP., BEIJING	Beijing	300104
104	HENGXIN SHAMBALA CULTURE Co., Ltd.	Beijing	300081
105	Sumavision Technologies Co., Ltd.	Beijing	300079
106	Beijing eGOVA Co., Ltd.	Beijing	300075
107	Beijing Easpring Material Technology Co., Ltd.	Beijing	300073
108	Beijing Sanju Environmental Protection & New Materials Co., Ltd.	Beijing	300072
109	Spearhead Integrated Marketing Communication Group	Beijing	300071
110	BEIJING ORIGINWATER TECHNOLOGY Co., Ltd.	Beijing	300070
111	Beijing Highlander Digital Technology Co., Ltd.	Beijing	300065

Table A1. *Cont.*

Number	Company Name	Location	Stock Code
112	BlueFocus Intelligent Communications Group Co., Ltd.	Beijing	300058
113	Beijing Water Business Doctor Co., Ltd.	Beijing	300055
114	Hiconics Eco-energy Technology Co., Ltd.	Beijing	300048
115	Hwa Create Co., Ltd.	Beijing	300045
116	Beijing Shuzhi Technology Co., Ltd.	Beijing	300038
117	Beijing SuperMap Software Co., Ltd.	Beijing	300036
118	Gaona Aero Material Co., Ltd.	Beijing	300034
119	Tianjin Chase Sun Pharmaceutical Co., Ltd.	Tianjin	300026
120	Beijing Beilu Pharmaceutical Co., Ltd.	Beijing	300016
121	Beijing Dinghan Technology Group Co., Ltd.	Beijing	300011
122	BEIJING LANXUM TECHNOLOGY Co., Ltd.	Beijing	300010
123	Toread Holdings Group Co., Ltd.	Beijing	300005
124	Lepu Medical Technology (Beijing) Co., Ltd.	Beijing	300003
125	Beijing Ultrapower Software Co., Ltd.	Beijing	300002

Appendix B

Result of the correlation coefficient test of original variables is as follows:

Table A2. Correlation matrix of variables.

	Y	d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8	d_9	d_{10}	d_{11}	d_{12}	d_{13}	d_{14}	d_{15}
Y	1	0.511 **	−0.358	0.409 **	0.750 **	0.344 **	0.297	0.145 *	−0.442 **	−0.289 **	0.021	0.500 **	0.442 **	0.830 **	0.717 **	0.238 **
d_1	0.511 **	1	0.350 **	−0.650 **	0.262 **	0.368	−0.015	0.317	−0.507 **	−0.959 **	0.263	0.712 **	0.242 **	0.252 **	0.181 **	0.612 **
d_2	−0.358	0.350 **	1	−0.342	0.900 **	0.675 **	0.276	0.681 **	−0.119 **	−0.406 **	0.071	0.879 **	0.549 **	0.302 **	0.862 **	0.495 **
d_3	0.409 **	−0.650 **	−0.342	1	−0.191	0.438	0.153 **	0.354	0.641 **	0.690 **	−0.504	−0.485	0.123	0.057	−0.145	−0.545 *
d_4	0.750 **	0.262 **	0.900 **	−0.191	1	0.375 **	0.453	0.539 *	−0.782 **	−0.804 **	−0.033	0.479 **	0.117 **	0.500 **	0.930 **	0.609 **
d_5	0.344 **	0.368	0.675 **	0.438	0.375 **	1	0.274 **	0.874 **	−0.366	−0.341	−0.334	0.553 *	0.937 **	0.104 **	0.305 **	0.431
d_6	0.297	−0.015	0.276	0.0153 **	0.453	0.274 **	1	0.734 **	0.069	0.093	−0.399	0.133	0.109 **	0.436 *	0.479	0.088
d_7	0.145 *	0.317	0.681 **	0.354	0.539 *	0.874 **	0.734 **	1	−0.426	−0.349	−0.201	0.560 *	0.239 **	0.857 **	0.764 **	0.491
d_8	−0.442 **	−0.507 **	−0.119 **	0.0641 **	−0.782 **	−0.366	0.069	−0.426	1	0.967 **	−0.253	−0.256 **	−0.622 *	−0.406 **	-0.081	−0.724 **
d_9	−0.289 **	−0.959 **	−0.406 **	0.0690 **	−0.804 **	−0.341	0.093	−0.349	0.967 **	1	−0.254 **	−0.955 **	−0.114 *	−0.006	−0.083	−0.920 **
d_{10}	0.021	0.263	0.071	−0.504	−0.033	−0.334	−0.399	−0.201	−0.253	−0.254 **	1	0.207	−0.177	−0.142	0.002	0.364
d_{11}	0.500 **	0.712 **	0.879 **	−0.485	0.479 **	0.553 *	0.133	0.560 *	−0.256 **	−0.955 **	0.207	1	0.165 **	0.714 **	0.309 **	0.931 **
d_{12}	0.442 **	0.242 **	0.549 **	0.123	0.117 **	0.937 **	0.109 **	0.239 **	−0.622 *	−0.114 *	−0.177	0.165 **	1	0.972 **	0.635 **	0.056
d_{13}	0.830 **	0.252 **	0.302 **	0.057	0.500 **	0.104 **	0.436 *	0.857 **	−0.406 **	−0.006	−0.142	0.714 **	0.972 **	1	0.958 **	0.334 **
d_{14}	0.717 **	0.181 **	0.862 **	−0.145	0.930 **	0.305 **	0.479	0.764 **	−0.081	−0.083	0.002	0.309 **	0.635 **	0.958 **	1	0.434 **
d_{15}	0.238 **	0.612 **	0.495 **	−0.545 *	0.609 **	0.431	0.088	0.491	−0.724 **	−0.0920 **	0.364	0.931 **	0.056	0.334**	0.434 **	1

* Correlation is significantly at 0.1 level (both sides). ** Correlation is significantly at 0.05 level (both sides).

Appendix C

Results of PCA are as follows:

Table A3. Total variance explained.

PCs	Initial Eigenvalues			Sum of the Squares of Extracted Loads			Sum of the Squares of Rotated Loads		
	Total	Var%	Sum%	Total	Var%	Sum%	Total	Var%	Sum%
F_1	9.837	65.577	65.577	9.837	65.577	65.577	9.023	60.150	60.150
F_2	3.847	25.646	91.223	3.847	25.646	91.223	4.661	31.073	91.223
F_3	0.727	4.850	96.073						
F_4	0.319	2.126	98.199						
F_5	0.099	0.661	98.859						
F_6	0.066	0.440	99.299						
F_7	0.040	0.266	99.565						
F_8	0.032	0.213	99.778						
F_9	0.019	0.125	99.903						
F_{10}	0.010	0.066	99.969						
F_{11}	0.002	0.016	99.985						
F_{12}	0.001	0.009	99.994						
F_{13}	0.001	0.005	99.999						
F_{14}	0.000	0.001	100.000						
F_{15}	0.000	0.000	100.000						

Table A4. Factor score coefficient matrix.

Variables	Elements	
	PC_1	PC_2
GDP per capita (d_1)	0.122	−0.070
Total import and export volume (d_2)	0.101	0.017
Total retail sales of social consumer goods (d_3)	−0.116	0.220
Average monetary wage (d_4)	0.083	0.053
Balance of loans of financial institutions (d_5)	0.007	0.187
General budget expenditure of local finance (d_6)	−0.048	0.227
Scale of social financing (d_7)	0.015	0.161
Urban road area at the end of the year(d_8)	−0.124	0.069
Turnover of goods (d_9)	−0.127	0.080
Internet penetration rate (d_{10})	0.066	−0.150
Average number of students in colleges of per 100,000 residents (d_{11})	0.114	−0.025
Number of patents licensing (d_{12})	0.049	0.128
Turnover of technology market (d_{13})	0.058	0.112
Internal expenditure of R&D funds (d_{14})	0.082	0.065
Main business income of high-tech enterprises (d_{15})	0.118	−0.050

Appendix D

Normality test. We conducted Shapiro-Wilk test on the disturbances. Theoretically in the test, null hypothesis is that the disturbances are normally distributed. Therefore, if *p*-value is above 0.05, it shows that the test result is insignificant, then we couldn't reject the null hypothesis, and normal distribution is accepted. Oppositely, if *p*-value is less than 0.05, then null hypothesis is rejected and we can conclude it is not normal. The S-W test result showed that *p*-value was 0.512, indicating that the data are normally distributed.

Heteroskedasticity test. We carried out White's test in this paper. White's test for null hypothesis is homoskedasticity, against alternative hypothesis is unrestricted heteroskedasticity. The results showed that *p*-value was 0.225, so that the null hypothesis was accepted, revealing that there was no evidence of heteroskedasticity.

Autocorrelation test. The assumption of uncorrelated error terms was checked using Wooldridge test on the panel data in this paper. The null hypothesis is no first-order autocorrelation. The result of *p*-value was equal to 0.657, therefore we couldn't reject the null hypothesis, indicating that autocorrelation didn't significantly affect the model.

Multicollinearity test. After extracting two PCs from original variables, the multicollinearity problem was eliminated, and we further conducted the VIF test to confirm it. As we expected, the VIF of two PCs were all 1.00, showing that there was no multicollinearity in the model.

References

1. Neville, C.; Lucey, B.M. Financing Irish High-Tech SMEs: The Analysis of Capital Structure. *Int. Rev. Financ. Anal.* **2022**, *83*, 102219. [CrossRef]
2. Nunes, P.M.; Serrasqueiro, Z.; Leitão, J. Is There a Linear Relationship between R&D Intensity and Growth? Empirical Evidence of Non-High-Tech vs. High-Tech SMEs. *Res. Policy* **2012**, *41*, 36–53. [CrossRef]
3. Siegel, D.S.; Westhead, P.; Wright, M. Science Parks and the Performance of New Technology-Based Firms: A Review of Recent U.K. Evidence and an Agenda for Future Research. *Small Bus. Econ.* **2003**, *20*, 177–184. [CrossRef]
4. Balkin, D.B.; Markman, G.D.; Gomez-Mejia, L.R. Is Ceo Pay in High-Technology Firms Related to Innovation? *Acad. Manag. J.* **2000**, *43*, 1118–1129. [CrossRef]
5. Ogubazghi, S.K.; Muturi, W. The Effect of Age and Educational Level of Owner/Managers on SMMEs' Access to Bank Loan in Eritrea: Evidence from Asmara City. *Am. J. Ind. Bus. Manag.* **2014**, *4*, 632–643. [CrossRef]
6. Terziovski, M. Innovation Practice and Its Performance Implications in Small and Medium Enterprises (SMEs) in the Manufacturing Sector: A Resource-Based View. *Strateg. Manag. J.* **2010**, *31*, 892–902. [CrossRef]
7. Partanen, J.; Möller, K.; Westerlund, M.; Rajala, R.; Rajala, A. Social Capital in the Growth of Science-and-Technology-Based SMEs. *Ind. Mark. Manag.* **2008**, *37*, 513–522. [CrossRef]
8. Moro, A.; Fink, M. Loan Managers' Trust and Credit Access for SMEs. *J. Bank. Financ.* **2013**, *37*, 927–936. [CrossRef]
9. Chen, Y.; Huang, R.J.; Tsai, J.; Tzeng, L.Y. Soft Information and Small Business Lending. *J. Financ. Serv. Res.* **2015**, *47*, 115–133. [CrossRef]
10. D'Aurizio, L.; Oliviero, T.; Romano, L. Family Firms, Soft Information and Bank Lending in a Financial Crisis. *J. Corp. Financ.* **2015**, *33*, 279–292. [CrossRef]
11. Tsolas, I.E. Firm Credit Risk Evaluation: A Series Two-Stage DEA Modeling Framework. *Ann. Oper. Res.* **2015**, *233*, 483–500. [CrossRef]
12. Calabrese, R.; Marra, G.; Osmetti, S.A. Bankruptcy Prediction of Small and Medium Enterprises Using a Flexible Binary Generalized Extreme Value Model. *J. Oper. Res. Soc.* **2016**, *67*, 604–615. [CrossRef]
13. Chen, D. Initial Analysis on Index Selection of Science and Technology SME Financing Credit Evaluation. *Sci. Technol. Manag. Res.* **2017**, *37*, 64–68. [CrossRef]
14. Chen, Y. Construction and Application of the Technology-Based SMEs Credit Risk Assessment Index System. In *2018 International Conference on Economy, Management and Entrepreneurship (ICOEME 2018)*; Atlantis Press: Boao, China, 2018.
15. Tong, Q.; Zhang, D.; Yu, J. Construction of credit evaluation indicator system for technology-based SMEs. *Econ. Res. Guide* **2017**, *13*, 19–20.
16. Du, J. Research on the Construction of Credit Rating System for Technological SMEs Based on Big Data—Take Zhangjiang Enterprise Credit System as an Example. *Econ. Res. Guide* **2022**, *18*, 13–15.
17. Nahapiet, J.; Ghoshal, S. Social Capital, Intellectual Capital, and the Organizational Advantage. *Acad. Manag. Rev.* **1998**, *23*, 242–266. [CrossRef]
18. Guiso, L.; Sapienza, P.; Zingales, L. The Role of Social Capital in Financial Development. *Am. Econ. Rev.* **2004**, *94*, 526–556. [CrossRef]
19. Paal, B.; Wiseman, T. Group Insurance and Lending with Endogenous Social Collateral. *J. Dev. Econ.* **2011**, *94*, 30–40. [CrossRef]
20. Gao, G.; Wang, H.; Gao, P. Establishing a Credit Risk Evaluation System for SMEs Using the Soft Voting Fusion Model. *Risks* **2021**, *9*, 202. [CrossRef]
21. Xie, R.; Liu, R.; Liu, X.-B.; Zhu, J.-M. Evaluation of SMEs' Credit Decision Based on Support Vector Machine-Logistics Regression. *J. Math.* **2021**, *2021*, e5541436. [CrossRef]
22. Wang, W. A SME Credit Evaluation System Based on Blockchain. In Proceedings of the 2020 International Conference on E-Commerce and Internet Technology (ECIT), Zhangjiajie, China, 24–26 April 2020; pp. 248–251.
23. Bao, S.; Yin, Y. Credit evaluation and empirical analysis of small and medium-sized technology-based enterprises. *Sci. Technol. Prog. Policy* **2009**, *26*, 143–148.
24. Huo, H. Credit risk index system and evaluation method of high-tech small and medium-sized enterprises. *J. Beijing Univ. Technol. Soc. Sci. Ed.* **2012**, *14*, 60–65. [CrossRef]
25. Voulgaris, F.; Zopounidis, D.C. On the Evaluation of Greek Industrial SME's Performance via Multicriteria Analysis of Financial Ratios. *Small Bus. Econ.* **2000**, *15*, 127–136. [CrossRef]
26. Ma, Y.; Ansell, J.; Andreeva, G. Exploring Management Capability in SMEs Using Transactional Data. *J. Oper. Res. Soc.* **2016**, *67*, 1–8. [CrossRef]
27. Piskorski, T.; Seru, A.; Witkin, J. Asset Quality Misrepresentation by Financial Intermediaries: Evidence from the RMBS Market: Asset Quality Misrepresentation by Financial Intermediaries. *J. Financ.* **2015**, *70*, 2635–2678. [CrossRef]
28. Grunert, J.; Norden, L. Bargaining Power and Information in SME Lending. *Small Bus. Econ.* **2012**, *39*, 401–417. [CrossRef]

29. Lugovskaya, L. Predicting Default of Russian SMEs on the Basis of Financial and Non-Financial Variables. *J. Financ. Serv. Mark.* **2010**, *14*, 301–313. [CrossRef]
30. Angilella, S.; Mazzù, S. The Financing of Innovative SMEs: A Multicriteria Credit Rating Model. *Eur. J. Oper. Res.* **2015**, *244*, 540–554. [CrossRef]
31. Psillaki, M.; Tsolas, I.E.; Margaritis, D. Evaluation of Credit Risk Based on Firm Performance. *Eur. J. Oper. Res.* **2010**, *201*, 873–881. [CrossRef]
32. Tsai, M.F.; Wang, C.J. On the Risk Prediction and Analysis of Soft Information in Finance Reports. *Eur. J. Oper. Res.* **2017**, *257*, 243–250. [CrossRef]
33. Tobback, E.; Bellotti, T.; Moeyersoms, J.; Stankova, M.; Martens, D. Bankruptcy Prediction for SMEs Using Relational Data. *Decis. Support Syst.* **2017**, *102*, 69–81. [CrossRef]
34. Zhu, Y.; Xie, C.; Wang, G.-J.; Yan, X.-G. Comparison of Individual, Ensemble and Integrated Ensemble Machine Learning Methods to Predict China's SME Credit Risk in Supply Chain Finance. *Neural Comput. Appl.* **2017**, *28*, 41–50. [CrossRef]
35. Chen, X.; Wang, X.; Wu, D.D. Credit Risk Measurement and Early Warning of SMEs: An Empirical Study of Listed SMEs in China. *Decis. Support Syst.* **2010**, *49*, 301–310. [CrossRef]
36. Dietrich, A. Explaining Loan Rate Differentials between Small and Large Companies: Evidence from Switzerland. *Small Bus. Econ.* **2012**, *38*, 481–494. [CrossRef]
37. Altman, E.I. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *J. Financ.* **1968**, *23*, 589–609. [CrossRef]
38. Zhang, M.; He, Y.; Zhou, Z. Study on the Influence Factors of High-Tech Enterprise Credit Risk: Empirical Evidence from China's Listed Companies. *Procedia Comput. Sci.* **2013**, *17*, 901–910. [CrossRef]
39. Bao, M.X.; Billett, M.T.; Smith, D.B.; Unlu, E. Does Other Comprehensive Income Volatility Influence Credit Risk and the Cost of Debt? *Contemp. Account. Res.* **2020**, *37*, 457–484. [CrossRef]
40. Cao, Z.; Chen, S.X.; Lee, E. Does Business Strategy Influence Interfirm Financing? Evidence from Trade Credit. *J. Bus. Res.* **2022**, *141*, 495–511. [CrossRef]
41. Liu, J.; Zeng, J.F. Multi-Stage Game of Government Supervision and Green Manufacture. *Syst. Eng.* **2014**, *32*, 12–17.
42. Chi, Q.; Li, W. Economic Policy Uncertainty, Credit Risks and Banks' Lending Decisions: Evidence from Chinese Commercial Banks. *China J. Account. Res.* **2017**, *10*, 33–50. [CrossRef]
43. Li, W.; Xu, X.; Long, Z. Confucian Culture and Trade Credit: Evidence from Chinese Listed Companies. *Res. Int. Bus. Financ.* **2020**, *53*, 101232. [CrossRef]
44. Zhao, X.; Chen, H. Research on Influencing Factors and Transmission Mechanisms of Green Credit Risk. *Environ. Sci. Pollut. Res.* **2022**, *29*, 89168–89183. [CrossRef] [PubMed]
45. Yang, Y.; Chu, X.; Pang, R.; Liu, F.; Yang, P. Identifying and Predicting the Credit Risk of Small and Medium-Sized Enterprises in Sustainable Supply Chain Finance: Evidence from China. *Sustainability* **2021**, *13*, 5714. [CrossRef]
46. Yu, X.; Fang, J. Tax Credit Rating and Corporate Innovation Decisions. *China J. Account. Res.* **2022**, *15*, 73–93. [CrossRef]
47. Huang, X.; Liu, X.; Ren, Y. Enterprise Credit Risk Evaluation Based on Neural Network Algorithm. *Cogn. Syst. Res.* **2018**, *52*, 317–324. [CrossRef]
48. Li, G. Research on the Mechanism of Internet Public Opinion Risk Evolution and Management for Chinese State-Owned Enterprise. In Proceedings of the 2013 5th International Conference on Intelligent Human-Machine Systems and Cybernetics, Hangzhou, China, 26–27 August 2013; pp. 368–373.
49. Kleinknecht, A.; Van Montfort, K.; Brouwer, E. The Non-Trivial Choice between Innovation Indicators. *Econ. Innov. New Technol.* **2002**, *11*, 109–121. [CrossRef]
50. Pavitt, K. Patent Statistics as Indicators of Innovative Activities: Possibilities and Problems. *Scientometrics* **2005**, *7*, 77–99. [CrossRef]
51. Zahra, S.A. Harvesting Family Firms' Organizational Social Capital: A Relational Perspective. *J. Manag. Stud.* **2010**, *47*, 345–366. [CrossRef]
52. The Coordinated Development of the Beijing-Tianjin-Hebei Region is Fundamentally Driven by Innovation. Available online: http://www.gov.cn/zhengce/2015-09/16/content_2932641.htm (accessed on 4 September 2022).
53. China's Regional Innovation Capacity Monitoring Report 2016-2017 and China's Regional Science and Technology Innovation Evaluation Report 2016–2017 Were Officially Released. Available online: https://www.most.gov.cn/kjbgz/201709/t20170901_134714.html (accessed on 4 September 2022).
54. China's Regional Science and Technology Innovation Evaluation Report 2018 Was Released. Available online: http://www.ce.cn/culture/gd/201810/30/t20181030_30657850.shtml (accessed on 4 September 2022).
55. Coordinated Development of the Beijing-Tianjin-Hebei Region. Available online: https://www.ndrc.gov.cn/gjzl/jjjxtfz/201911/t20191127_1213171.html (accessed on 4 September 2022).
56. Jinping Xi Visited and Presided over a Forum on the Coordinated Development of the Beijing-Tianjin-Hebei Region. Available online: http://www.cppcc.gov.cn/zxww/2019/01/21/ARTI1548029666876103.shtml (accessed on 4 September 2022).
57. He, P.; Shen, Y.; Li, G. Research on Credit Risk of Science and Technology SMEs in Beijing-Tianjin-Hebei Region. *Rev. Econ. Res.* **2022**, 119–133. [CrossRef]

58. Statistical Classification of Large, Small and Micro Enterprises. Available online: https://view.officeapps.live.com/op/view.aspx?src=http%3A%2F%2Fwww.stats.gov.cn%2Ftjgz%2Ftzgb%2F201801%2FP020180103343283760282.docx&wdOrigin=BROWSELINK (accessed on 7 September 2022).
59. Fan, J.; Zhong, D.; Zhang, Y.; Yu, S.; Chu, J.; Yu, M.; Zhao, H.; Huang, Y. A Hybrid Approach Based on Rough-AHP for Evaluation in-Flight Service Quality. *Multimed. Tools Appl.* **2022**, *81*, 30797–30819. [CrossRef]
60. Liu, R.X.; Kuang, J.; Gong, Q.; Hou, X.L. Principal Component Regression Analysis with Spss. *Comput. Methods Programs Biomed.* **2003**, *71*, 141–147. [CrossRef] [PubMed]
61. Miškić, S.; Stević, Ž.; Marinković, D. Evaluating the Efficiency of a Transport Company Applying an Objective-Subjective Model. *Int. J. Manag. Sci. Eng. Manag.* **2022**, 1–15. [CrossRef]
62. Diakoulaki, D.; Mavrotas, G.; Papayannakis, L. Determining Objective Weights in Multiple Criteria Problems: The Critic Method. *Oper. Res.* **1995**, *22*, 763–770. [CrossRef]
63. Zoraghi, N.; Amiri, M.; Talebi, G.; Zowghi, M. A Fuzzy MCDM Model with Objective and Subjective Weights for Evaluating Service Quality in Hotel Industries. *J. Ind. Eng. Int.* **2013**, *9*, 38. [CrossRef]
64. Zhang, Z. Construction of Mathematical Modeling for Teaching Evaluation Index System Based on the Delphi AHP Method. *Sci. Program.* **2022**, *2022*, e7744067. [CrossRef]
65. Development Plan for High-Tech SMEs in Hebei Province (2016–2020). Available online: https://kjt.hebei.gov.cn/www/xxgk2020/228104/228107/229136/index.html (accessed on 3 December 2022).
66. Maksimovic, V.; Demirgüç-Kunt, A. *Firms as Financial Intermediaries: Evidence from Trade Credit Data*; Available SSRN 632764; World Bank Group: Washington, DC, USA, 2001.
67. Tan, Y.Z.; Wang, C.; Guo-Feng, L.I. Economic Performance and Influencing Factors of the Credit Environment—Empirical Study Based on CEI and Chinese Provincial and Prefecture-Level City Data. *Econ. Surv.* **2014**, *31*, 144–149. [CrossRef]
68. Aivazian, V.A.; Santor, E. Financial Constraints and Investment: Assessing the Impact of a World Bank Credit Program on Small and Medium Enterprises in Sri Lanka. *Can. J. Econ. Can. Déconomique* **2008**, *41*, 475–500. [CrossRef]
69. Zhao, B.; Lyu, X.; Qi, N. Construction and Optimization of Transboundary Business Financial Credit Network in the Era of 5G Communication. *Wirel. Commun. Mob. Comput.* **2022**, *2022*, 1–14. [CrossRef]
70. Moro, A.; Fink, M.; Maresch, D. Reduction in Information Asymmetry and Credit Access for Small and Medium-Sized Enterprises. *J. Financ. Res.* **2015**, *38*, 121–143. [CrossRef]
71. Kusi, B.A.; Agbloyor, E.K.; Ansah-Adu, K.; Gyeke-Dako, A. Bank Credit Risk and Credit Information Sharing in Africa: Does Credit Information Sharing Institutions and Context Matter? *Res. Int. Bus. Finance* **2017**, *42*, 1123–1136. [CrossRef]
72. Aman, J.; Abbas, J.; Shi, G.; Ain, N.U.; Gu, L. Community Wellbeing Under China-Pakistan Economic Corridor: Role of Social, Economic, Cultural, and Educational Factors in Improving Residents' Quality of Life. *Front. Psychol.* **2022**, *12*, 6718. [CrossRef] [PubMed]
73. Belás, J.; Sopková, G. Significant Determinants of the Competitive Environment for SMEs in the Context of Financial and Credit Risks. *J. Int. Stud.* **2016**, *9*, 139–149. [CrossRef]
74. Griffin, P.A.; Hong, H.A.; Woo, R.J. Corporate Innovative Efficiency: Evidence of Effects on Credit Ratings. *J. Corp. Financ.* **2018**, *6*, 352–373. [CrossRef]
75. Zhu, C.; Zhang, R.; Zhang, X.; Zhu, C. SMEs' Technological Innovation and Entrepreneur Credit: Based on a Social Capital Perspective. *Sci. Technol. Prog. Policy* **2010**, *10*, 65–69.
76. Piga, C.A.; Atzeni, G. R&d Investment, Credit Rationing and Sample Selection. *Bull. Econ. Res.* **2007**, *59*, 149–178. [CrossRef]
77. Zhou, X.; Tang, X.; Zhang, R. Impact of Green Finance on Economic Development and Environmental Quality: A Study Based on Provincial Panel Data from China. *Environ. Sci. Pollut. Res.* **2020**, *27*, 19915–19932. [CrossRef]
78. Awokuse, T.O. Trade Openness and Economic Growth: Is Growth Export-Led or Import-Led? *Appl. Econ.* **2008**, *40*, 161–173. [CrossRef]
79. Fisher, W.H.; Hof, F.X. Conspicuous Consumption, Economic Growth, and Taxation: A Generalization. *J. Econ.* **1997**, *66*, 35–42. [CrossRef]
80. Guariglia, A.; Poncet, S. Could Financial Distortions Be No Impediment to Economic Growth after All? Evidence from China. *J. Comp. Econ.* **2008**, *36*, 633–657. [CrossRef]
81. Chen, H. Development of Financial Intermediation and Economic Growth: The Chinese Experience. *China Econ. Rev.* **2006**, *17*, 347–362. [CrossRef]
82. Donaldson, D. Railroads of the Raj: Estimating the Impact of Transportation Infrastructure. *Am. Econ. Rev.* **2018**, *108*, 899–934. [CrossRef]
83. Kleinrock, L. An Internet Vision: The Invisible Global Infrastructure. *Ad. Hoc. Netw.* **2003**, *1*, 3–11. [CrossRef]
84. Belas, J.; Smrcka, L.; Gavurova, B.; Dvorsky, J. The Impact of Social and Economic Factors in the Credit Risk Management of SME. *Technol. Econ. Dev. Econ.* **2018**, *24*, 1215–1230. [CrossRef]
85. Abraham, B.P.; Moitra, S.D. Innovation Assessment through Patent Analysis. *Technovation* **2001**, *21*, 245–252. [CrossRef]
86. Guellec, D.; Van Pottelsberghe de la Potterie, B. From R&D to Productivity Growth: Do the Institutional Settings and the Source of Funds of R&D Matter? *Oxf. Bull. Econ. Stat.* **2010**, *66*, 353–378. [CrossRef]
87. Senaviratna, N.; Cooray, T. Diagnosing Multicollinearity of Logistic Regression Model. *Asian J. Probab. Stat.* **2019**, *5*, 1–9. [CrossRef]

88. Mansfield, E.R.; Helms, B.P. Detecting Multicollinearity. *Am. Stat.* **1982**, *36*, 158–160. [CrossRef]
89. Tran, H.; Kim, J.; Kim, D.; Choi, M.; Choi, M. Impact of Air Pollution on Cause-Specific Mortality in Korea: Results from Bayesian Model Averaging and Principle Component Regression Approaches. *Sci. Total Environ.* **2018**, *636*, 1020–1031. [CrossRef]
90. Sedghi, S.; Sadeghian, A.; Huang, B. Mixture Semisupervised Probabilistic Principal Component Regression Model with Missing Inputs. *Comput. Chem. Eng.* **2017**, *103*, 176–187. [CrossRef]
91. Jørgensen, F.; Ulhøi, J.P. Enhancing Innovation Capacity in SMEs through Early Network Relationships. *Creat. Innov. Manag.* **2010**, *19*, 397–404. [CrossRef]
92. Shi, Y.; Ge, X.; Yuan, X.; Wang, Q.; Kellett, J.; Li, F.; Ba, K. An Integrated Indicator System and Evaluation Model for Regional Sustainable Development. *Sustainability* **2019**, *11*, 2183. [CrossRef]
93. Fisher, A.; Caffo, B.; Schwartz, B.; Zipunnikov, V. Fast, Exact Bootstrap Principal Component Analysis for p > 1 Million. *J. Am. Stat. Assoc.* **2016**, *111*, 846–860. [CrossRef] [PubMed]
94. Wang, D.; Hua, Y.; Zhu, J. Research on personal credit dynamic evaluation index system based on big data technology—From the social capital perspective. *Int. Bus.* **2020**, 115–127. [CrossRef]