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The Impact of Financial Risk Management System under Big Data on the Performance of Small and Medium-sized Enterprises

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Abstract

In the past five years, financial risk events have occurred frequently, and the traditional financial risk management system has been unable to resolve the risks in the current network economy era in a timely manner. Big data technology is a research hotspot in recent years. This paper selects the data of my country's small and medium-sized board listed companies on June 31, 2022, and constructs a financial risk management system that combines financial indicators and non-financial indicators from the perspectives of financial risk early warning mechanism, big data theory and decision tree analysis. The empirical results show that big data technology promotes the construction of financial risk management system, and the improvement of financial risk management system is significantly positively related to the performance of small and medium-sized enterprises.

Keywords

Financial Risk; SMEs; Corporate Performance; Big Data.

1. Introduction

According to the statistics of the Ministry of Industry and Information Technology, by the end of 2021, more than 99% of the 48.42 million enterprises in the country are small and medium-sized enterprises. However, due to the problems of small scale, backward financial management, and low investment capacity, SMEs have low financial risk early warning ability, which is not conducive to the healthy long-term development of SMEs.

In recent years, big data technology has developed vigorously. According to the "2021-2022 China Big Data Industry Development Report", my country's big data industry market will maintain sustained and rapid growth in the next three years, and the scale is expected to exceed 1.15 trillion yuan by the end of 2023.

Therefore, making full use of big data technology and building an effective financial risk management system for small and medium-sized enterprises will help small and medium-sized enterprises to improve their financial risk defense capabilities and improve corporate performance to a certain extent.

2. Literature Review

2.1. Financial Risk Early Warning Mechanism

Zhang Simeng believes that the analysis of financial risk prediction should include risk types, risk levels, risk reasons and possible consequences. At the same time, the evaluation and feedback of the effect should be carried out to optimize the quality of future early warning. Xue Fei believes that financial risk early warning and safety management should start from two aspects: system construction and personnel management, which is more conducive to normal financial turnover and rational allocation of funds.

Pan Wen Tsao et al. used quantum revolving gates to optimize four algorithms, QFOA, QABC, QPSO, and QACO, and constructed a corporate financial early warning model, quantified various data, and tested the model's predictive ability. Li Xiaoyan took six principles of comprehensiveness, importance, scientificity, objective quantification, comparability, and operability as the selection principles of risk early warning indicators, and applied the Internet of Things technology combined with the nearest neighbor propagation algorithm to financial management early warning.

2.2. Big Data Technology

Song Biao et al. verified that compared with only using financial indicators, using big data indicators at the same time performed better in terms of false alarm rate and missed alarm rate, and believed that relying on big data technology to strengthen information search can improve the effectiveness of financial early warning. Melnikova EV believes that big data can conduct in-depth analysis of massive heterogeneous data, so as to obtain the importance and relevance of various issues, thereby significantly improving the ability of scientometrics research efficiency. Wright Len Tiu believes that big data and its analysis and application can be used as an indicator of an organization's innovative ability to respond to market opportunities, and can ultimately outline more information at the end of the value chain for business innovation to meet the best balance between customer needs and cost control.

2.3. Factors Affecting the Performance of SMEs

Under the scientific and reasonable guiding ideology, small and medium-sized enterprises will surely rise and develop steadily, but there are still many problems in small and medium-sized enterprises, and performance evaluation is affected by various factors. Costache Catalina et al. used the association rules method and quantitative statistical method of data mining to explore the facilitators and obstacles of the sustainable development of small and medium-sized enterprises. Sun Weidong et al. explored the positive effect of labor productivity of small, medium and micro enterprises from the perspective of exogenous production factors, so that the internal capabilities of enterprises can be supplemented under favorable external conditions. Under the scientific and reasonable guiding ideology, the development of "specialized, refined and innovative" small and medium-sized enterprises is bound to advance steadily. Li Lifei believes that small and medium-sized enterprises should be supported by leading enterprises and take digital transformation as the direction in order to achieve high-quality development in the new development pattern. Dong Zhiyong and others believe that in the future, my country should focus on promoting the high-quality development of SMEs from four aspects: institutional mechanisms, basic investment, business environment and digital empowerment. Lu Minfeng and others believe that digital technology should be used as the starting point to build a management system and mechanism for small and medium-sized enterprises with digital technology as the core, so as to enhance the overall core competitiveness of high-quality small and medium-sized enterprises.

3. Theoretical Analysis and Hypothesis

Under the big data environment, the construction of financial risk management system has a certain impact on the performance of small and medium-sized enterprises. The research on "financial crisis early warning theory" and "big data theory" provides theoretical support for verifying the correlation.

First of all, the "financial crisis early warning theory" means that the financial situation of an enterprise faces a failure early warning, which is the processing of a large amount of original information and data. By analyzing the company's financial statements, investment and financing plans and other audit materials, and using factor analysis, comparative analysis, ratio

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analysis and other methods, it is possible to analyze and predict the company's future operations and investment activities, and find potential financing risks, investment risks, and capital recovery risks. and income distribution risk. Therefore, the establishment of a reasonable financial risk management mechanism is conducive to the timely correction of the business direction, the planning of capital allocation and the optimization of development decisions. Secondly, the core element of "big data theory" is the data mining algorithm . A large amount of data has been deposited since the establishment of an enterprise. Based on different scientific algorithms, it is possible to deeply mine effective internal information, to quickly process large-scale, unbounded and disordered data sets according to needs, and to study historical laws and future trends.

Based on the above theoretical analysis, this paper puts forward relevant assumptions:

H_1: Big data technology promotes the construction of financial risk management system.

H_2: The improvement of financial risk management system is significantly positively correlated with the performance of SMEs.

4. Research Design

4.1. Sample Selection and Data Sources

This article selects the data of my country's small and medium-sized board listed companies as of June 31, 2022 as a sample. In order to ensure the reliability of the research conclusions, this paper screened the samples as follows: (1) Eliminate null values and logical error items; (2) Adjust the data format to unify the format; (3) Eliminate abnormal data and garbled characters; (4) Eliminate String symbol; (5) Exclude small and medium-sized enterprises with less than 5 years of company existence and less than 3 years of relevant financial data before 2022, and finally screen out 200 companies and 2,000 pieces of data. Among them, the variable data comes from the Wind database, the Sina Finance Shanghai and Shenzhen stock market (individual stock) database and the 2022 semi-annual financial reports of some listed companies.

4.2. Variable Description

(1) Explained variable

Using the Z-Score financial early warning model and actual indicators to generate multivariate financial formulas, calculate the financial risk level, and measure the financial health of listed companies. Using the first-level indicators and non-financial indicators such as profitability, operating ability, growth ability and cash flow of listed companies, the key performance indicators of small and medium-sized enterprises are obtained through comprehensive evaluation. Therefore, this paper selects the financial risk degree (Z-Score) and the return on total assets (RRTA) as the explained variables.

(2) Explanatory variables

For specific small and medium-sized enterprises, the screening of financial data can directly reflect the objective situation of the enterprise, and the quantification of non-financial indicators is directly related to the comprehensiveness and scientificity of performance evaluation. This paper obtains the financial data and non-financial data of small and medium-sized enterprises through big data, and combines the analytic hierarchy process to establish mixed indicators to improve the applicability of the enterprise financial risk early warning model. This paper takes stockholders' equity turnover (ET), return on equity (ROE), net profit growth (Net growth), information coverage (Coverage) and customer satisfaction (CS) as explanatory variables.

(3) Moderator

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Industry nature (BN): If the enterprise is a manufacturing enterprise, the value is 1, otherwise the value is 0;

Asset size (AUM): expressed as the logarithm of the total assets of the enterprise .

(4) control variable

This paper takes the operating capacity and cash flow of listed companies as control variables, mainly including: total asset turnover (TAT) and cash flow ratio (CFR). See Table 1 for a description of the variables.

Table 1. Variable Description

variable type	variable name	symbol	illustrate
Explained variable	financial risk	Z − score	$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 0.99X5$
	return on total assets	RRTA	Total Profit/Average Total Assets
	cost profit margin	RPCE	Total Profit/Total Costs
Explanatory variables	Shareholders' Equity Turnover	ET	Sales Revenue/Average Shareholders' Equity
	Roe	ROE	Net Profit/Average Shareholders' Equity
	Net profit growth rate	NG	Net profit for the current year / Net profit for the previous year -1
	information coverage	Covera	Part of the card data has been mastered / card data
	customer satisfaction	CS	Customer satisfaction with goods/services
	Creativity	CA	level of enterprise creativity
Moderator	Industry nature	β_i	If the enterprise is a manufacturing enterprise, the value is 1, otherwise the value is 0
	Asset size	γ_i	Expressed by logarithm of the total assets of the enterprise
control variable	total asset turnover	TAT	Total Sales Revenue/Average Total Assets
	cash flow ratio	CFR	Net cash flow from operating activities/current liabilities at the end of the period

5. Empirical Results and Analysis

This paper uses panel data to construct a financial risk management model and a key performance evaluation model for SMEs.

5.1. Model Establishment

Based on H_1this, this paper establishes a revised Z − scorefinancial early warning model.

Z − scoreThe basic discriminant function of the model is:

$$Z = 1.2ET + 1.4ROE + 3.3NG + 0.6Coverage + 0.99CS + \varepsilon_i$$

Adjusted according to corrections, where:

ET =Sales revenue/average shareholders' equity reflects the efficiency of the company's use of the owner's assets and the company's operating capabilities. ROE = Net profit/average shareholders' equity reflects the efficiency of listed companies in utilizing capital invested by shareholders, and reflects the level of capital use and management. NG = This year's net

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profit/last year's net profit -1, directly reflects the company's performance growth, and comprehensively measures the company's operating effectiveness and operating capacity. Coverage =Part of the listed data has been mastered/listed data, which is the degree of mastery of the competitor's sales data. CSIt is the customer 's satisfaction with the goods/services. As a non-financial indicator, it reflects the company's operation and after-sales capabilities. β_i represents the dummy variable that adjusts the nature of the industry, γ_i represents the asset size of the listed company, and ε_i is the residual item.

ZThe smaller the value, the higher the financial risk of the company and the more likely a financial crisis; Zthe larger the value, the opposite. At that time $Z < 1.8$, the company was in bankruptcy; $1.8 < Z < 2.675$ at that time, it was difficult to directly judge the financial situation; $Z > 2.675$at that time, the company's financial situation was healthy. Depending on the nature of the company's industry and the size of its assets, the standard will also change accordingly, so adjustment variables are added to correct it.

The traditional financial risk early warning judgment relies on people's subjective analysis of financial statements. The method is incomplete and inefficient. The establishment of the new model proves that big data technology can promote the construction of financial risk management system.

Based on H_2 this, this paper establishes a performance evaluation model for SMEs that integrates financial risk indicators.

$$\begin{gathered}\mathrm{RRTA} = -1.914\mathrm{ET} + 0.672\mathrm{ROE} + 0.0005\mathrm{NG} + \\ 0.166\ln\mathrm{Coverage} - 4.968\ln\mathrm{CS} + 6.1119 + \beta_i - \gamma_i + \varepsilon_i\end{gathered}$$

5.2. Descriptive Statistics

The descriptive statistics of the main variables are shown in Table 2.

Table 2. Descriptive Statistics for Primary Variables

Variable	MAX	MIN	$\bar{X}$	p	Me	σ^2	*Kurtosis*	*skewness*	CV
RRTA	79,334	-6,175	8,125	19,325	2,321	373,456	10,647	3.241	2,378
EY	2,087	0.226	0.875	0.549	0.63	0.301	-0.519	0.79	0.627
ROE	82.81	-35.71	9,616	22,634	5.1	512.32	6,466	1,892	2,354
NG	51475.98	-8258.71	2186.95	11748.44	15.81	138025738.91	18.89	4.27	5.37
Coverage	5	1	2.7	1.218	2.5	1.484	-0.545	0.45	0.451
CS	4	1	2.4	0.821	2.5	0.674	-0.447	-0.279	0.342
TAT	1.9	0.079	0.487	0.396	0.352	0.157	8.606	2.68	0.813
CFR	1612.924	-43.459	87.015	360.421	7.211	129903.172	19.675	4.421	4.142

Based on RRTA, the coefficient of variation (CV) is 2.378, which is greater than 0.15, and there may be outliers in the current data. In this paper, outliers and indicators with more prominent performance are screened out, deleted or processed to make the coefficient of variation normal, and follow-up analysis is continued.

As can be seen from Table 2, the average RRTA of SMEs is 8.125%, while the maximum and minimum values are 79.334% and -6.175%, respectively, which is a huge difference, indicating that the total asset utilization rate of different SMEs is different. larger. The average value of shareholders' equity turnover (ET) is 0.875 times, and the variance is 0.301. The overall turnover efficiency is relatively high and stable, reflecting the strong overall operating capacity. The average value of the net profit growth rate (NG) is 2186.95%, indicating that the overall growth ability of small and medium-sized enterprises is strong and the profit conversion efficiency is high. However, due to the large variance, it shows that the growth levels of different

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enterprises vary greatly. According to the expert score of 1-5, the customer satisfaction (CS) of the sample enterprises is only 2.4 points, which is lower than the average level, indicating that the quality management capabilities of the sample enterprises are still insufficient, and process control and after-sales feedback should be strengthened.

5.3. Decision Tree Regression Analysis

(1) Analysis process:

Arrange the data of the training set, establish a regression model of decision number based on this, and obtain the decision tree structure.

The decision tree is built and feature importance is calculated.

Apply the constructed decision tree regression model to training and testing data to obtain model evaluation results.

The model is evaluated by the prediction accuracy of the test data.

(2) Model parameters

Table 3. Model parameters

parameter name	parameter value
training time	0.007s
data segmentation	0.7
data shuffling	no
Cross-validation	no
Node Split Evaluation Criteria	friedman_mse
Feature points selection criteria	best
Maximum feature scale to consider when dividing	None
Minimum number of samples for internal node splitting	2
Minimum number of samples for leaf nodes	1
Minimum weight of samples in leaf nodes	0
maximum depth of tree	10
maximum number of leaf nodes	50
node partition impurity threshold	0

(3) Model Evaluation Results

Table 4. Model Evaluation Results

	MSE	RMSE	MAE	MAPE	R^2
Training set	0.243	0.493	0.373	70.284	0.999
test set	78.581	8.865	5.417	51.801	0.704

The above table shows the prediction evaluation indicators of the cross-validation set, training set and test set, and the prediction effect of the decision tree is measured by quantitative indicators. Among them, the hyperparameters can be continuously adjusted through the evaluation indicators of the cross-validation set to obtain a reliable and stable model.

● MSE (Mean Squared Error): Visually displays the difference between the estimator and the estimator. The smaller the MSE value, the higher the model accuracy.

● RMSE (root mean square error): is the square root of MSE, the smaller the value, the higher the model accuracy.

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● MAE (Mean Absolute Error): The absolute error is taken as the mathematical average, which can better represent the error level of the overall estimated value. The smaller the MAE value, the more reasonable and effective the model is.

● MAPE (Mean Absolute Percentage Error) converts the mean absolute error into a percentage. Similarly, the smaller the MAPE value, the more reasonable and effective the model is.

● R^2: Comparing the predicted value with only the mean, the closer the result is to 1, the more accurate the model is.

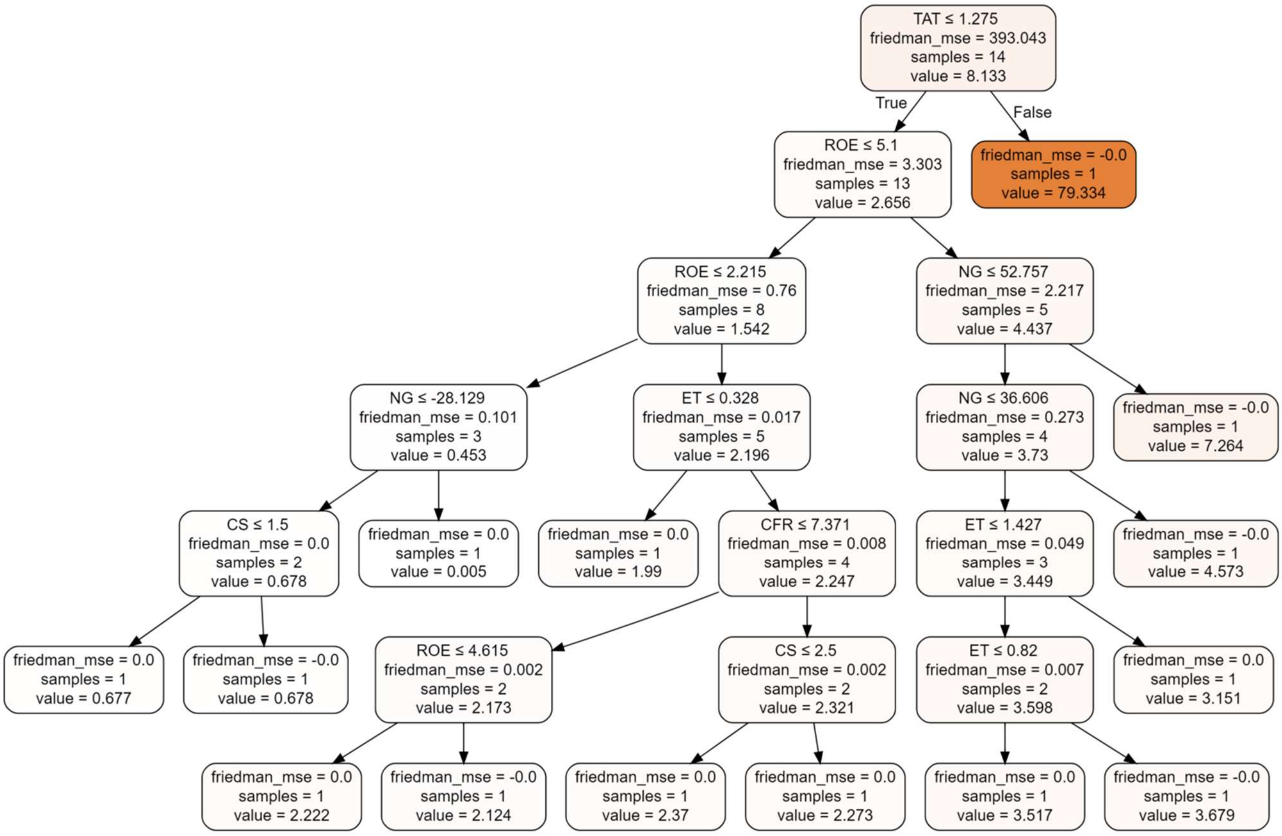

Figure 1. Decision tree structure

(4) Test data to predict evaluation results

Table 5. predict evaluation results

Predicted result Y	RRTA	ET	ROE	NG	Coverage	CS	TAT	CFR
3.5169	4.346	0.5405	6.43	17.974	2	2	0.3593	-12.4884
3.1514	2.0243	1.689	7.18	17.715	3	3	0.5017	16.2209
7.2637	43.7584	1.2708	52.58	376.825	5	3	1.0617	101.1607
0.677	-6.1749	0.399	-35.71	-8258.711	1	1	0.0793	6.0454
3.1514	1.8259	1.5001	6.22	-13.674	2	2	0.5809	7.2574
2.2215	2.8658	0.4024	3.69	62.232	2	3	0.2787	-43.4589

5.4. Robustness Test

(1) Replacement metrics

In this paper, the robustness test is carried out by replacing the measurement indicators, and the original explanatory variable in model 2 is replaced by the return on total assets (RRTA)

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with the profit rate on costs and expenses (RPCE), other conditions remain unchanged, and substituted into the original model for regression analysis.

Table 6. Replacement metrics

variable	RPCE
ET	0.0586 ** (-2.0902)
ROE	0.0000 ** (7.7631)
NG	0.0001 ** (-5.9983)
Coverage	0.0209 ** (-2.6582)
CS	0.9298 ** (-0.0899)
TAT	0.6541 ** (0.4595)
CFR	0.0000 ** (6.4084)
DW	1.8940
R^2	0.9941
F	287.5800
P	0.000000

According to the above table, financial indicators such as cost and profit rate are significantly positively correlated with the performance level of SMEs. Therefore, optimizing the financial risk management system is conducive to greatly improving the performance of SMEs, which proves that the model is robust, and null hypothesis 2 is established.

(2) Add missing variables

By reviewing previous literature, it is found that two non-financial indicators of industry nature (β_i) and innovation ability (CA) have a significant impact on the performance of SMEs, adding these two missing variables to carry out regression analysis on the return on total assets (RRTA).

Table 7. Add missing variables

Variable	Std. Error	RRTA
ET	9.7395	0.0547** (-2.1748)
ROE	0.4768	0.0000** (7.6589)
NG	0.0013	0.0001** (-6.2021)
Coverage	3.2173	0.0786** (-1.9587)
CS	3.9489	0.6445** (-0.4757)
TAT	39.2462	0.8757** (0.1605)
CFR	0.0468	0.0001** (6.6239)
CA	2.3409	0.7275** (-0.3584)
β_i	5.6352	0.2936 ** (1.1086)
R^2	--	0.9951 **
F	--	227.5442
P	--	0.0000 **

Seen from the above table that the industry nature (β_i) has a certain correlation with the performance of SMEs, and the innovation capability (CA) has a significant positive correlation with the performance of SMEs. There is a slight difference in significance, the article argues that the results have not changed, and the model is robust.

6. Conclusions and Recommendations

6.1. Optimize the Model Setting and Consider Multiple Factors

Z-Score model has certain limitations and shortcomings, and does not consider all factors, and does not separately analyze the situation of companies with debt restructuring and high recovery rates. At the same time, the influence of scenery cycle effect factors and market changes on the model is not considered. The weights of the model are not completely fixed, and some factors are greatly influenced by experts. On this basis, the model should increase the theoretical basis of the economy, enrich financial and non-financial variables, expand the forecast range to the financial risk of the entire investment portfolio, update accounting information in a timely manner, and improve market sensitivity.

6.2. Attach Importance to Technology Construction and Make Full Use of Big Data Centers

This paper verifies that big data technology can promote the construction of financial risk management system. Small and medium-sized enterprises have developed rapidly in recent years. At the same time, massive data brings difficulties to the retrieval of target information. The use of big data technology and the construction of data centers can quickly identify valid data and reduce labor costs and repetitive work input. The retrieval of a large amount of information enables enterprises to quickly screen out suitable financial indicators and non-financial indicators, establish mixed indicators, and promote the construction of a financial risk management system.

6.3. Establish a Diversified Financial Risk Management System

This paper verifies that the improvement of the financial risk management system is significantly positively correlated with the performance of SMEs. Due to small scale, backward financial management, and low investment capacity, SMEs have low financial risk early warning capabilities, which is not conducive to healthy long-term development. The construction of the financial risk management system is conducive to the timely discovery of index loopholes by enterprises, timely prevention and resolution of risks, and promotion of the performance level of small and medium-sized enterprises.

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