Analysis of the Impact of Non-Financial Elements on Financial Risks in Organizations from the Perspective of Various Enterprise Types

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Abstract. This research delves into the impact of non-financial factors on financial risk, assisting enterprises in constructing a robust risk management system to promote sustainable development. It begins by constructing an evaluation index system for corporate financial risk using the entropy-weighted TOPSIS method, which minimizes subjectivity and ensures objective weighting. The study then analyzes the influence of non-financial factors on financial risk using the feature importance output of the XGBoost algorithm. The findings demonstrate that different firm types have distinct effects of non-financial factors on financial risk.Some non-financial indicators such as green invention patent applications, internal control scores, social responsibility and trust index are important across all enterprise types. However, the findings highlight that the impact of non-financial factors on financial risk varies by enterprise type. Based on these conclusions, the paper provides recommendations for corporate risk management to enhance financial health and mitigate potential risks.

Keywords: Financial risk, non-financial factors, machine learning, comprehensive evaluation.

1. Introduction

With the globalization of the economy, markets around the world are becoming increasingly interconnected, presenting both challenges and opportunities for companies worldwide. As companies actively seek to capitalize on various opportunities in the market, they are increasingly recognizing the urgency and importance of preventing financial risks from occurring. Establishing a robust financial risk warning system and effectively managing financial risks are critical for sound internal management. Traditional financial risk assessments rely heavily on financial indicators, which, while useful in reflecting a company's historical performance and current financial state, often suffer from time lags and limitations. These indicators may not fully capture a company's future development prospects or potential risks. In contrast, non-financial indicators provide a unique advantage in revealing core competencies, assessing future trends, and predicting emerging risks. Therefore, when constructing a financial risk warning system, it is crucial to integrate both financial and non-financial indicators for a more comprehensive assessment.

In financial risk assessment, researchers initially constructed numerous evaluation systems based on financial indicators. For instance, Cao Juping (2024) utilized 16 financial metrics, such as capital turnover, operating profit margin, and debt-to-asset ratio from 2022 to build a financial risk evaluation framework [1]. Yang Ling (2024) focused on Jiangxi Copper to establish 17 financial indicators, including the current ratio, quick ratio, and cash ratio, for assessing financial risk [2]. Tang Ruixue et al. (2024) conducted a comprehensive assessment of financial risk from the perspectives of financing, investment, operations, and profit distribution. As corporate data management systems continue to upgrade, some non-financial metrics have also been collected and stored, indicating that non-financial indicators significantly impact financial risk [3]. For example, Zhang Dan (2022) argued that non-financial indicators greatly influence financial risk assessments and suggested that relevant personnel should prioritize developing and refining non-financial indicator systems [4]. Tong Siqi (2022) noted that non-financial metrics can reveal credit risks and potential data misconduct early, providing a more comprehensive and timely perspective for risk assessment [5]. Miao Cancan (2022) established a financial risk early warning indicator system using both financial and non-financial indicators, comparing results to show that models incorporating non-financial indicators outperform those relying solely on financial indicators, thus improving the accuracy of corporate financial risk early warnings [6]. Based on this, some scholars have begun to develop methods that combine non-financial and financial factors for a comprehensive assessment of financial risks. For example, Li Cai (2022) used BP neural networks to predict the financial risks of feed companies, achieving a high overall accuracy rate with accurate early warning results [7]; Qiu Yang (2023) explored the application of factor analysis and binary logistic regression in assessing financial risks of listed manufacturing companies, achieving an overall prediction accuracy of 89.3% [8]; and Gao Qian (2024) utilized both financial and non-financial indicators based on a logistic regression model to investigate corporate financial risks, resulting in prediction accuracy of 93.5% [9]. Assessing the impact of non-financial factors on financial risk proves difficult due to their complexity. This complicates the selection of non-financial elements when creating a comprehensive evaluation system. Prior studies primarily focused on integrating non-financial data into analytical models and analyzing how financial indicators affect financial risks. While some studies included non-financial indicators, their effects remain inadequately quantified. The influence of non-financial indicators on financial risk varies depending on the type of organization, and this study examines the significance of different kinds of non-financial indicators on the impact of financial risk.

This paper proposes using machine learning models to filter non-financial indicators based on the nature of enterprises, and then explores the similarities and differences in how these indicators influence financial risk across different types of businesses. Empirical results reveal the following: The influence of non-financial indicators on financial risk is different in different firm nature.Further analysis shows that across both enterprise types, indicators such as green patent applications, internal control scores, social responsibility and trust index consistently play a significant role in financial risk prediction. This underscores the universal importance of these factors in cross-enterprise risk assessment. The study makes two key contributions: first, it quantifies the impact of non-financial indicators on financial risk using the XGBoost model; second, it ranks the importance of these indicators across different enterprise types, highlighting their heterogeneity.

2. Research Principles and Methods

2.1. The construction of the enterprise financial risk assessment system

2.1.1 Construction of Evaluation Index System

Financial evaluation indicators should depict the financial health and operational performance of each enterprise [10]. Each selected evaluation indicator reflects a certain characteristic size of the evaluation object from different aspects. When multiple evaluation indicators form an index system, the principle of constructing an evaluation index system lies in systematic, scientific, comparable, measurable, and independent. Based on this principle, in order to construct financial risk assessment indicators reflecting various enterprises. This article adopts 23 financial evaluation indicators, it selection of these 23 indicators furnishes a robust framework for evaluating an enterprise's financial health, enabling the identification of potential financial risks. Through the examination of the trends and interdependencies among these indicators, one can pinpoint areas of financial management and operational processes that may pose risks to the company, as shown in the Table 1 below:

Table 1. Financial Indicators System

Indicator	unit	symbol	Indicator	unit	symbol
Registered capital	yuan	x_1	Total operating revenue	yuan	x_{13}
Main business income	yuan	x_2	Operating revenue	yuan	x_{14}
Asset liability ratio	%	x_3	Total operating cost	yuan	x_{15}
Asset return rate	%	x_4	Operating cost	yuan	x_{16}
Return on equity	%	x_5	Sales expenses	yuan	x_{17}
Capital expenditure	yuan	x_6	Management fee	yuan	x_{18}
The total annual salary of directors, supervisors, and executives	yuan	x_7	Financial expenses	yuan	x_{19}
Monetary funds	yuan	x_8	Investment Income	yuan	x_{20}
Total current assets	yuan	x_9	Operating profit	yuan	x_{21}
Total assets	yuan	x_{10}	Total profit amount	yuan	x_{22}
Total current liabilities	yuan	x_{11}	Net profit	yuan	x_{23}
Total liabilities	yuan	x_{12}			

All of these indicators are obtained by analyzing the three main financial statements of enterprises - balance sheet, income statement, and cash flow statement. With these 23 evaluation indicators, a multi-index evaluation system is established to use the final output results as an important manifestation of financial risk assessment for various enterprises [11].

2.1.2 Entropy weight-TOPSIS Method

The entropy weight-TOPSIS method is an objective weighting method that can maximize the avoidance of subjective weighting on the characteristics of the supply. The principle based on the entropy weight method refers to the variability of the indicators, that is, the higher the variability, the higher the corresponding weight. Normalize and standardize the feature indicator data to ensure the non-negativity of the data, resulting in:

$$a_{ij} = \frac{x_{ij}-x_{min}}{x_{max}-x_{min}} \tag{1}$$

where a_{ij} is the normalized data, x_{max} and x_{min} are the maximum and minimum values of each indicator respectively. The value of the i evaluation object regarding the j indicator object is denoted as a_{ij}, forming the data matrix $A = \left(a_{ij}\right)_{9380\times23}$. Utilizing the normalized matrix $A = \left(a_{ij}\right)_{9380\times23}$ to calculate $p_{ij}(i = 1,2,\ldots,9380, j = 1,2,\ldots,23)$, that is, the weight of the i evaluation object concerning the j indicator value:

$$p_{ij} = \frac{a_{ij}}{\sum_{i=1}^{9380} a_{ij}} (i = 1,2,\ldots,9380; j = 1,2,\ldots,23) \tag{2}$$

Next, calculate the entropy value of the j indicator:

$$e_j = -\frac{1}{ln\,n}\sum_{i=1}^{9380} p_{ij}\, ln\, p_{ij}\ (j = 1,2,\ldots,23) \tag{3}$$

Calculate the coefficient of variation of the j indicator:

$$g_j = 1 - e_j (j = 1,2,\ldots,23) \tag{4}$$

where for the j indicator, a larger e_j indicates a smaller degree of variation in the indicator value. Calculate the weight of the j indicator:

$$\omega_j = \frac{g_j}{\sum_{j=1}^{23} g_j} (j = 1,2,\ldots,23) \tag{5}$$

The Topsis method [12], based on data, is a method for ranking samples. The basic idea is to construct an idealized target based on sample data, mainly using the "ideal solution" and "negative ideal solution" of decision problems for ranking and selection, also known as the Approximation Ideal Solution Ranking Method, abbreviated as the Ideal Solution Method. The normalized decision matrix is obtained using the vector normalization method. For a multi-attribute decision-making problem, let the decision matrix $A = (a_{ij})_{9380\times23}$, the normalized decision matrix $A = (a_{ij})_{9380\times23}$, where

$$b_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{9380} a_{ij}^2}} (i = 1,2,\ldots,9380; j = 1,2,\ldots,23) \tag{6}$$

Construct a weighted normalized matrix $C = (c_{ij})_{9380\times23}$, and let the attribute weight vector $\omega = [\omega_1, \omega_2, \ldots, \omega_{23}]^T$, then:

$$c_{ij} = \omega_j \cdot b_{ij} \ (i = 1,2,\ldots,9380; j = 1,2,\ldots,23) \tag{7}$$

Next, determine the positive ideal solution C^* and negative ideal solutionC^0. Let the j attribute value of the positive ideal solution C^*, and the j attribute value of the negative ideal solution c_j^0, then the positive ideal solution is:

$$c_j^* = \begin{cases} \max\limits_i c_{ij}, x_j \\ \min\limits_i c_{ij}, x_j \end{cases} j = 1,2,\ldots,23 \tag{8}$$

$$c_j^0 = \begin{cases} \max\limits_i c_{ij}, x_j \\ \min\limits_i c_{ij}, x_j \end{cases} j = 1,2,\ldots,23 \tag{9}$$

Then, calculate the distance of each alternative solution to the positive ideal solution and negative ideal solution. The distance from the alternative solution d_i to the positive ideal solution is:

$$s_i^* = \sqrt{\sum_{j=1}^{23} \left(c_{ij} - c_j^*\right)^2}, i = 1,2,\ldots,9380 \tag{10}$$

The distance from the alternative solution d_i to the negative ideal solution is:

$$s_i^0 = \sqrt{\sum_{j=1}^{23} \left(c_{ij} - c_j^0\right)^2}, i = 1,2,\ldots,9380 \tag{11}$$

Calculate the ranking index value of each solution (i.e., comprehensive evaluation index), which is:

$$f_i^* = \frac{s_i^0}{(s_i^0 + s_i^*)}, i = 1,2,\ldots,9380 \tag{12}$$

Finally, arrange the advantages and disadvantages of the schemes in descending order according to f_j^*.

2.1.3 Differential Analysis

Differential analysis [13] is a statistical method used to test whether there are significant differences among the mean values of multiple samples. The core of differential analysis lies in comparing the variability between different groups and within groups to evaluate whether intergroup differences may be due to random errors or the experimental treatments themselves. Initially, the mean financial risk refers to the average value of a financial indicator over a certain period. Analyzing the mean financial risk in financial and risk management can help investors and managers understand a company's financial performance and potential risk conditions.

$$\bar{x}_{ij} = \frac{1}{n}\sum_{i=1}^{n} x_{ij}\,, j = 1,2,\dots,23 \tag{13}$$

Here, n represents the number of enterprises. When it is a state-owned enterprise, $n = 882$; when analyzing non-state-owned enterprises, $n = 994$.

Furthermore, the standard deviation of financial risk is an important statistical measure that reflects the volatility or uncertainty of financial data. A larger standard deviation indicates higher data dispersion, meaning greater fluctuations in financial performance.

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_{ij} - \bar{x}_{ij}\right)^2} \tag{14}$$

Finally, the coefficient of variation in financial analysis is a useful statistical measure that can help us better understand and evaluate the relative volatility of financial data. By standardizing the ratio of the standard deviation to the mean, the coefficient of variation provides a dimensionless measure, which is particularly useful for comparing financial indicators of different scales or units.

$$CV = \frac{s}{\bar{x}_{ij}} \times 100\% \tag{15}$$

2.2. Importance analysis of non-financial indicators based on XGBoost

2.2.1 Selection of non-financial indicators

Non-financial performance indicators [14] should depict the quality and efficiency of operations of each enterprise, as well as their impact on society, the environment, and employees. Non-financial performance indicators can help companies better understand the overall performance of their business and promote sustainable development. Based on the principles of selecting financial indicators, non-financial risk assessment indicators for each enterprise are constructed. This paper uses 19 non-financial performance indicators as shown in the Table 2 below:

Table 2. Non-financial Indicators

Indicator	symbol	Indicator	symbol
Trust index	y_1	Supplier, Customer, and Consumer Rights and Responsibilities	y_{11}
Enterprise strategy stimulates progress	y_2	Environmental responsibility	y_{12}
Total number of green patent applications	y_3	Social Responsibility	y_{13}
Total number of green invention patent applications	y_4	Internal Control Index Score	y_{14}
The total number of applications for green utility model patents	y_5	Internal supervision	y_{15}
Continuous green innovation level of enterprises	y_6	Internal Control Information Disclosure Index	y_{16}
Herfindahl index	y_7	The logarithmic equivalent of comprehensive air pollution	y_{17}
Lerner index	y_8	The logarithm of total pollution equivalent	y_{18}
Shareholders' Responsibilities	y_9	Current lifecycle	y_{19}
Employee Responsibilities	y_{10}		

All these indicators are data collected through various channels, including but not limited to self-prepared social responsibility reports by companies, evaluation reports by third-party organizations, and data from government and regulatory agencies. With these 19 evaluation indicators, a multi-index evaluation system is established to output results as an important representation of non-financial risk assessment for each enterprise [15].

2.2.2 XGBoost Model

The XGBoost algorithm [16] is an ensemble learning method based on gradient boosting. Its core idea is to iterate using weak learners (such as decision trees) to continuously optimize the predictive performance of the ensemble model. XGBoost expands the loss function with a second-order Taylor expansion and introduces first and second derivatives. The flow of the XGBoost algorithm is as follows:

(1)Calculate the first and second derivatives of the loss function with respect to the samples. The first derivative is:

$$g_i = \frac{\partial L(y_i,\hat{y}_i)}{\partial \hat{y}_i} \tag{16}$$

where $L(y_i, \hat{y}_i)$ is the loss function; y_i is the true value of the i sample; $\hat{y}_i$ is the predicted value of the i sample by the model. The second derivative is:

$$g_i' = \frac{\partial^2 L(y_i,\hat{y}_i)}{\partial \hat{y}_i^2} \tag{17}$$

(2)Initialize the model:

$$f_0(x_i) = arg_\gamma min \sum_{i=1}^{n} L(y_i, \gamma) \tag{18}$$

where f_0 is the initial model (also known as the base classifier); x_i is the parameter of the i sample; γ is the constant that minimizes the loss function; n is the number of samples.

(3) Iteratively build the tree model:

For the t iteration, calculate the predicted value $\hat{y}_i^{(t-1)} = f_{t-1}(x_i)$ of the current model $f_{i-1}(x_i)$. Next, calculate the sample residuals $r_i^{(t)} = y_i - \hat{y}_i^{(t-1)}$. Third, use the residuals $r_i^{(t)}$obtained in the previous step as the new true values of the samples and fit a new regression tree model:

$$h_t(x) = \sum_{j=1}^{m_t} \omega_j I(x \in R) \tag{19}$$

where R is the sample capacity; ω_j represents the score of the j leaf node at the t iteration; I is the indicator function for the leaf node corresponding to sample x, i.e. $x \in R$ if true and 0 otherwise; m_t represents the number of leaf nodes. Fourth, for each leaf node, calculate its score $\omega_j (j = 1,2, \ldots, m_t)$, where the calculation formula for ω_j is:

$$\omega_j = -\frac{G_j}{H_j+\lambda} \tag{20}$$

where G_j is the sum of gradients of all samples on the j leaf node; H_j is the sum of second derivatives of all samples on the j leaf node; λ is the regularization parameter used to control the weight of the leaf node to prevent overfitting. Fifth, update the model:

$$f_t(x) = f_{t-1}(x) + \eta h_t(x) \tag{21}$$

where η is the learning rate.

(4)Output the final model:

$$f(x) = \sum_{t=1}^{T} \eta h_t(x) \tag{22}$$

where T is the maximum number of iterations. This paper has a total of 23 non-financial risk assessment indicators, covering 1876 companies, each with data for the years 2015-2019, resulting in 9380 samples. The data is divided into training and test sets at a ratio of 7:3. When the learning rate is 0.1, the regularization term L_2, subsample rate, tree feature sampling rate, and node feature sampling rate are all set to 1, while the regularization term L_1, minimum weight of samples in leaf nodes are set to 0, and the maximum tree depth is 10.

3. Empirical analysis

3.1. Data Sources and Preprocessing

This study utilized financial statements and non-financial data of publicly listed companies from 2015 to 2019, sourced from MarkNet and Sina Finance. The dataset includes 23 financial metrics such as debt-to-asset ratio, return on assets, sustained innovation level, market competition intensity, and market pricing power, along with 19 non-financial indicators. During the data filtering process, we excluded companies with incomplete financial reports and samples with substantial missing data from 2015 to 2019, culminating in a final sample size of 9,380. For the few missing values present in this dataset, we applied mean imputation to ensure completeness and the absence of outliers.

To facilitate research and enhance analytical accuracy and efficiency, we transformed negative indicators into positive ones. Given the distinct meanings of each indicator, significant discrepancies in dimensions emerged. To optimize the model evaluation, we conducted normalization on all indicators to balance their informational contributions within the model, ensuring analytical objectivity and fairness.

3.2. Financial Risk Assessment and Differentiation Analysis Results

This study employed the Entropy Weight TOPSIS method to analyze multiple enterprises, selecting 23 financial indicators from each company covering the years 2015 to 2019. This approach produced a comprehensive evaluation index of financial risk for each enterprise annually. We calculated the entropy weights for each evaluation indicator, deriving values for information entropy, utility of information, and weight coefficients.

Table 3. Weight of Financial Risk Comprehensive Capability Evaluation System

Indicator Name	Information entropy value	Information utility value	weight coefficient
Net profit	0.9998	0.0002	0.08%
Operating profit	0.9996	0.0004	0.14%
Total assets	0.9485	0.0515	18.23%
Monetary funds	0.9451	0.0549	19.43%
selling expenses	0.9999	0.0001	0.04%
Management expenses	0.9999	0.0001	0.03%
business income	0.9604	0.0396	14.02%
Total profit	0.9997	0.0003	0.12%
Financial expenses	0.9999	0.0001	0.02%
income from investment	0.9975	0.0025	0.87%
Total liabilities	0.9999	0.0001	0.04%
Return on equity	1	0	0.00%
Total current assets	0.9471	0.0529	18.73%
Asset return rate	0.9999	0.0001	0.04%
Operating costs	0.9999	0.0001	0.02%
Registered capital	0.9999	0.0001	0.03%
Total operating revenue	0.9604	0.0396	14.01%
Total operating cost	0.9999	0.0001	0.02%
Total current liabilities	0.9999	0.0001	0.04%
Main business income	0.9604	0.0396	14.01%
Asset liability ratio	1	0	0.01%
Total annual salary of directors, supervisors, and executives	0.9999	0.0001	0.05%
Capital expenditure	1	0	0.01%

From Table 3, which presents the entropy values and weights of the financial risk comprehensive capability evaluation system, it is clear that the most significant indicator for financial risk assessment is cash funds, with a weight of 19.43%. In contrast, the net asset return rate holds the smallest weight at 0.00%. Both capital expenditure and debt-to-asset ratio are also low contributors, each with a weight of 0.01%. This indicates that cash funds are deemed a critical indicator in financial risk evaluation, whereas the net asset return rate, capital expenditure, and debt-to-asset ratio have minimal impact on the assessment of financial risk.

The comprehensive evaluation index derived from the entropy weight TOPSIS method indicates that a larger index correlates with lower risk. Additionally, the analysis computes the average and coefficient of variation for each year, represented in Figure 1 and Figure 2, which illustrate the distribution of the average evaluation index and its coefficient of variation, respectively. The coefficient of variation demonstrates the fluctuations in financial risk assessment across different years. Notably, from 2015 to 2019, there is a discernible upward trend in the mean financial risk assessment, suggesting a gradual reduction in financial risk during this period. Concurrently, the coefficient of variation also increases, indicating a rising degree of volatility in financial risk.

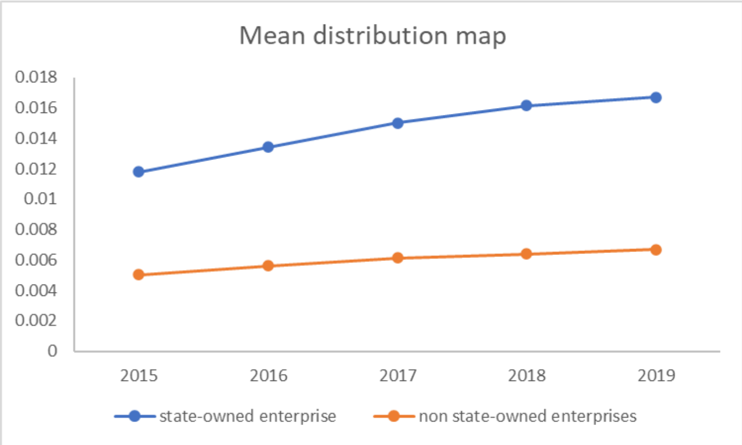

Figure 1. Distribution of Average Comprehensive Evaluation Index

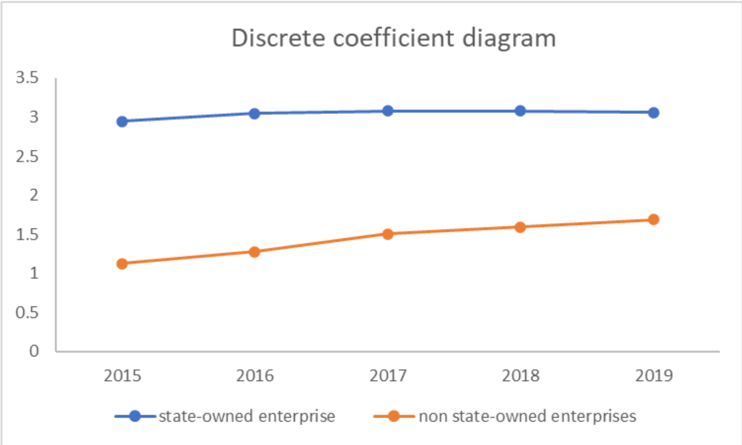

Figure 2. Distribution of Discrete Coefficient of Comprehensive Evaluation Index

3.3. Results of the Impact of Non-Financial Indicators Based on XGBoost on Financial Risk

This paper categorizes all enterprises into state-owned and non-state-owned sectors. It utilizes collected data on all non-financial indicators of each company to compute a comprehensive financial risk evaluation index using the entropy-weighted TOPSIS method. The study introduces the XGBoost machine learning algorithm to train and test data from all non-financial indicator variables in both state-owned and non-state-owned enterprises. It calculates the mean and variance of metrics such as MSE (Mean Squared Error), RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error) over multiple training iterations. The results, detailed in Table 4, reveal relatively low means and errors, indicating the effective predictive capability of the XGBoost algorithm.

Table 4. Mean and standard deviation of evaluation indicators

evaluating indicator	state-owned enterprise		non-state-owned enterprises	
	mean value	standard deviation	mean value	standard deviation
MSE	0.000676	0.000303	0.000022	0.000012
RMSE	0.024254	0.009897	0.004395	0.001807
MAE	0.004793	0.001788	0.001232	0.000425
MAPE	35.54251	9.924875	16.98455	4.721688

Moreover, the XGBoost algorithm provides insights into the feature importance of all non-financial indicators. Figure 3 and 4 illustrate the feature importance ranking for state-owned and non-state-owned enterprises, respectively. These graphs demonstrate the contribution of explanatory variables to predicting financial risk.

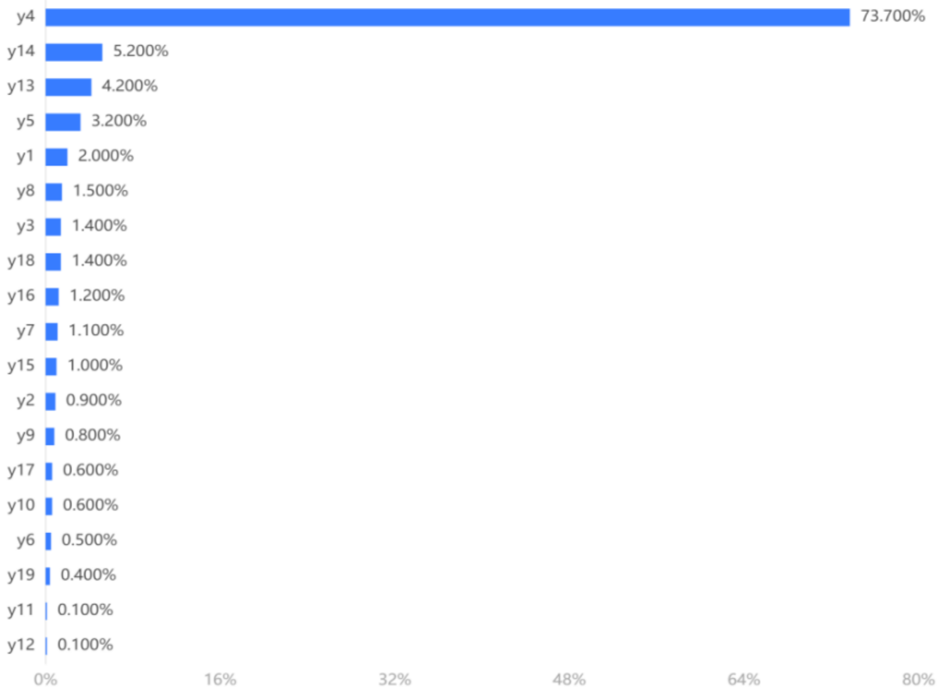

Figure 3. Ranking of Importance of Characteristics of State-owned Enterprises

In the results derived from the algorithm, the rankings of various indicators in the XGBoost algorithm correspond to each indicator's significance for financial forecasting. As illustrated in Figure 3, the importance ranking of features for state-owned enterprises shows that the total number of green invention patents holds the highest significance at 73.700%. This underscores the substantial contribution of the total number of green invention patent applications to predicting financial risk. Following this, the internal control index score and social responsibility indicators are also noteworthy. Conversely, as presented in Figure 4, the importance rankings for private enterprises indicate that social responsibility, internal control information disclosure index, and the total number of green patents hold considerable significance. A comparative analysis reveals that for different types of enterprises, the total number of green invention patents, internal control index scores, social responsibility and trust index all exhibit high significance levels.

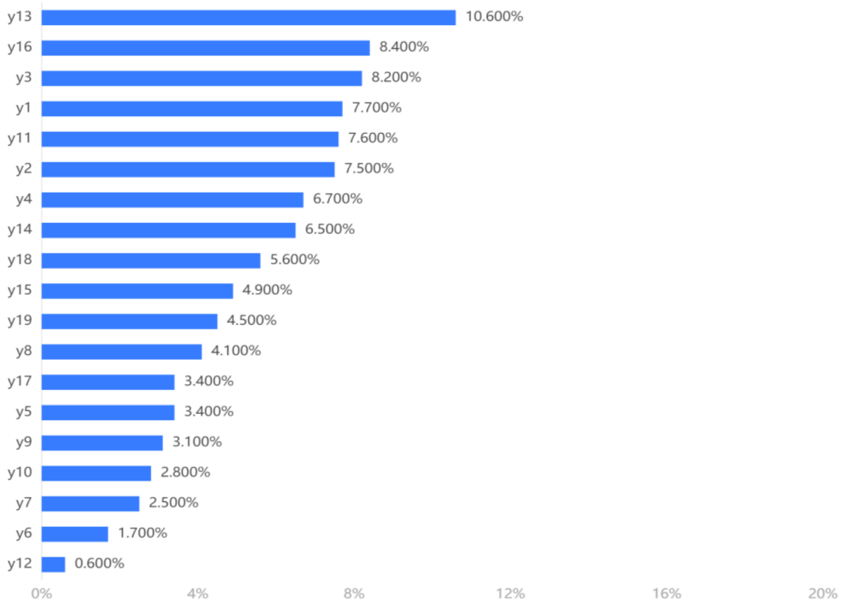

Figure 4. Ranking of Importance of Characteristics of Non-State-owned Enterprises

4. Conclusion

The analysis of financial risk levels reveals consistent patterns for both state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs). SOEs exhibit a rising trend in mean financial risk assessments annually, indicating a growing risk over time. Although NSOEs also show an upward trend, the increase is comparatively smaller. Both categories demonstrate increasing standard deviations and coefficients of variation, signifying heightened volatility in financial risk across different years. This trend highlights a gradual rise in financial risk uncertainty, necessitating the implementation of effective risk management strategies.

To address escalating financial risks, enterprises must enhance their internal controls to ensure the accuracy and legality of transactions, thereby mitigating risks arising from mismanagement. Optimizing debt structures by increasing the proportion of long-term liabilities can alleviate short-term repayment pressures. Strengthening risk management capabilities through the establishment of specialized teams is essential for identifying, assessing, and controlling risks.

For SOEs, the number of green invention patent applications serves as a significant non-financial indicator influencing financial risks, followed by internal control index scores and social responsibility. In contrast, for NSOEs, the overall volume of green patent applications is the primary non-financial indicator, emphasizing the importance of technological innovation and intellectual property protection. Social responsibility and the disclosure of internal control information also play a considerable role for NSOEs, indicating the significance of maintaining a positive social image and robust corporate governance.

Notably, SOEs generally focus more on green invention and utility model patents, whereas NSOEs prioritize the overall number of green patent applications. Both types of enterprises underscore the importance of social responsibility, highlighting its role in financial risk management. SOEs typically achieve higher scores on internal control indices, suggesting stricter management practices, while NSOEs exhibit higher trust indices and strategic aggressiveness, indicating greater market flexibility.

In conclusion, both SOEs and NSOEs must consider both traditional financial indicators and non-financial factors in managing financial risks. Enhancing capabilities in areas such as green patents, social responsibility, and internal management can mitigate financial risks and promote sustainable development. Enterprises should intensify efforts in technological innovation and strengthen commitments to social responsibility. Furthermore, learning from each other’s strengths—such as SOEs' internal control transparency and NSOEs' strategic flexibility—can further refine risk management practices.

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