A study on the differential impact of non-financial factors on ESG performance under different corporate natures

Nan Zou[1, #], Di Zeng[2, #, *]

[1]Department of Psychology, Sun Yat-sen University, Guangzhou, China, 510006

[2]School of Mathematics, Nanjing Audit University, Nanjing, China, 211815

*Corresponding author: ZKDbdqh666@163.com

#These authors contributed equally.

Abstract. Investigating how non-financial elements shape ESG performance across various company types is crucial for advancing corporate governance and ensuring sustainable business practices. This research examines Chinese listed companies between 2014 and 2022 to understand these dynamics. It starts by analyzing the variance in ESG scores between state-owned and privately-owned firms using kernel density estimation. The study then employs K-means clustering to categorize companies into high, medium, and low ESG performers and tracks their progress over time. The LightGBM algorithm and Shapley value are utilized to assess how diverse non-financial factors uniquely affect ESG outcomes for state-owned and private enterprises.Findings indicate that state-owned firms tend to have more consistent ESG scores, whereas their private counterparts display greater variability. Key factors influencing ESG scores in state-owned companies include capital intensity, market concentration, and equity distribution, while in private firms, the financial inclusion index, digitalization efforts, and R&D spending are more influential. Additionally, the study highlights that formal and informal environmental policies differentially affect ESG performance in state-owned and private companies. The paper concludes with suggestions to improve ESG standards and support sustainable growth in businesses.

Keywords: ESG performance, firm nature, non-financial factors, machine learning.

1. Introduction

Amidst the trends of globalization and the pursuit of sustainability, the criteria of Environmental, Social, and Governance (ESG) have emerged as pivotal gauges for assessing a company's enduring value and its capacity for sustainable operations. The scrutiny from investors, regulatory bodies, and society at large has compelled businesses to balance financial success with a commitment to environmental stewardship, social welfare, and robust corporate governance. In the context of China's "dual carbon" goals—achieving a peak in carbon emissions and ultimately carbon neutrality—ESG has become a cornerstone in the strategic development of corporations. Despite this, scholarly work has predominantly centered on financial factors' influence on ESG, neglecting the diverse impacts of non-financial elements, particularly across various types of enterprises. This study aims to address this void by dissecting how non-financial factors influence ESG performance across different corporate forms, thereby offering tailored ESG management strategies.

The nexus between ESG performance and corporate valuation has garnered significant interest from researchers and industry practitioners alike. A comprehensive review by Friede et al. (2015) indicated that a majority of studies affirm a positive correlation between ESG and financial performance[1]. Godfrey (2005) suggested that corporate social responsibility bolsters intangible assets, such as brand reputation, thereby enhancing shareholder value[2]. Ashwin et al. (2016) discovered that firms with robust ESG disclosures tend to have lower stock volatility and higher financial returns[3]. In China, Li Ting (2021) noted that corporations' social responsibilities to various stakeholders positively influence their value[4]. Li Shenlan (2023) found that corporate performance across environmental, social, and governance dimensions significantly correlates with overall financial performance metrics[5]. Contrarily, Di (2020) observed that ESG ratings for European banks had a negative impact on their value enhancement[6]. Giese et al. (2019) explained that ESG performance influences firm value through both systemic and unique risks[7]. Yuan Yehu (2021) determined that both ESG scores and media attention positively affect firm value, with media attention acting as a mediator[8]. Duan Ao Han (2024) highlighted that the cost of financing serves as a mediator between ESG performance and corporate value, with a more pronounced effect on non-state-owned enterprises[9]. While financial factors have been shown to bolster ESG practices, as indicated by Li Chao's (2023) study using the PVAR method[11], the essence of ESG underscores the significance of non-financial metrics in corporate growth. This study seeks to provide more directed ESG management strategies by comparing the ESG performance of state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs) and by deeply examining the varied impacts of non-financial factors on ESG performance across different corporate forms.

To encapsulate, this paper sets out to investigate the effects of non-financial factors on ESG performance across various corporate entities. It utilizes kernel density estimation to compare ESG performance disparities between SOEs and non-SOEs. The K-means clustering technique is then applied to grade companies into high, medium, and low ESG performers, tracking their performance trajectories and analyzing the catalysts for change. The lightGBM algorithm and Shapley value method are engaged to assess how non-financial factors sway ESG performance. This paper's contributions are threefold: it identifies significant ESG performance disparities among different corporate properties, it uncovers the heterogeneity of non-financial factors' influence on ESG performance across corporate types, and it offers insights to refine ESG management practices.

2. Research Theory and Methods

2.1. Research Theory

In analyzing the ESG performance of state-owned enterprises versus non-state-owned enterprises, this study will investigate how these companies seek to balance the demands of different stakeholders. State-owned enterprises typically place greater emphasis on meeting governmental and public expectations, while non-state-owned enterprises may focus more on shareholder and market demands. By comparing the ESG performances of these two categories, we can unveil their strategies and effectiveness in addressing the needs of various stakeholders. Moreover, differences may exist in their information disclosure practices, which affect how investors and other stakeholders assess these enterprises. Given that state-owned enterprises are often closely tied to national policies and strategies, they tend to adhere to governmental regulations and standards in environmental, social, and governance matters, potentially resulting in overall higher ESG performance. They also benefit from stable funding sources and broader social influence, granting them more resources and capabilities in fulfilling social responsibilities and implementing environmental protection. In contrast, non-state-owned enterprises might excel in specific ESG dimensions, as they enhance their brand image and market competitiveness through differentiated social responsibility practices. For instance, non-state-owned enterprises may adopt more advanced environmental protection technologies and management measures to attract environmentally conscious consumers[10]. Based on this, we propose the following hypothesis:

Hypothesis 1: There is a significant difference in ESG performance between state-owned and non-state-owned firms.

Differences in environmental, social and governance (ESG) performance between state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs) mainly stem from their different governance structures, strategic objectives, stakeholder relationships and external constraints. NSOEs excel in environmental protection and social responsibility due to their national ownership background, which makes them more inclined to respond to government policies and social objectives, such as promoting social stability and environmental responsibility. They usually receive government policy support and financial advantages and are able to undertake more social responsibility and environmental governance projects. In contrast, NSOEs focus more on market-oriented and innovative strategies, and pursue the enhancement of corporate value and brand reputation[11]. They may be more flexible in corporate governance, attracting investors by improving transparency and information disclosure, and seeking a balance between financial performance and ESG performance[12]. As a result, SOEs may be better in terms of ESG balance, while non-SOEs may perform better in terms of governance and market competitiveness. Based on this, we propose the following hypotheses:

Hypothesis 2: The impact of non-financial factors on ESG performance varies significantly depending on the nature of the enterprise.

2.2. Research methodology

2.2.1 Kernel Density Estimation

Kernel Density Estimation (KDE) is a non-parametric technique used to estimate the probability density function. It smooths data points to construct a continuous probability density function. This approach assists in analyzing the distribution characteristics of data. KDE does not rely on specific distribution assumptions, making it suitable for exploring unknown distributions in data. Given a set of independently and identically distributed sample data, the expression for kernel density estimation is:

$$\hat{f}_h(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - X_i) \tag{1}$$

The estimated density function at point x is denoted as $\hat{f}_h(x)$; n represents the sample size; $K(\ )$ refers to the kernel function, which determines the smoothness of the estimate; h is the bandwidth parameter, controlling the width of the kernel function. $K_h(x - X_i) = \frac{1}{h}K\left(\frac{x - X_i}{h}\right)$ is the kernel function with bandwidth h. The kernel function $K(x)$ is a symmetric function that integrates to 1, with common examples including the Gaussian, uniform, and triangular kernels. These kernel functions smooth the contribution of each sample point's density around its vicinity to approximate the true density distribution.

2.2.2 K-Means clustering analysis

K-Means clustering serves as a widely utilized unsupervised learning algorithm designed to partition data into K distinct clusters. This method maximizes the similarity among data points within each cluster while minimizing similarity across different clusters. The algorithm's objective lies in minimizing the sum of squared distances between each data point and its corresponding cluster centroid. The operational framework of the K-Means clustering algorithm can be distilled into several key steps:

(1) Initialize centroids

Select a value for K, which represents the number of clusters. Randomly initialize K centroids, which serve as the cluster centers. These centroids may be randomly chosen from K points within the dataset or generated randomly.

(2) Assign data points to the nearest cluster

For each data point, compute its Euclidean distance to all centroids using the formula as follows:

$$d(x_i, c_j) = \sqrt{\sum_{m=1}^{d}\left(x_{im} - c_{jm}\right)^2} \tag{2}$$

In this context, data x_i point represents an individual observation, while a centroid c_j denotes the mean of cluster j. The dimension d pertains to the attributes of the data point. Assign data points to the cluster corresponding to the nearest centroid.

(3) Update the centroid.

For each cluster, calculate the average of all data points within that cluster and designate it as the new centroid:

$$c_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i \tag{3}$$

In this context, c_j represents all data points within cluster j, while c_j symbolizes the new centroid of cluster j.

(4) Iterative Repetition

Repeat steps 2 and 3 until the centroids stabilize or the specified number of iterations is reached. The K-Means clustering algorithm is a simple and efficient method that is relatively easy to implement. It exhibits low computational complexity for large datasets, allowing for quick convergence. Furthermore, the results of clustering are straightforward to interpret, as centroids can be viewed as representatives of the clusters.

2.2.3 K-Means clustering analysis

LightGBM operates on the principles of Gradient Boosting Decision Trees (GBDT). Its primary objective is to optimize the loss function through the combination of multiple weak learners, typically decision trees. GBDT represents an ensemble learning method that focuses on iteratively training several decision trees, where each tree aims to correct the prediction errors of its predecessor. Given a specific training dataset (X, y), the goal is to learn a function F(x) that minimizes a designated loss function L(y, F(x)).

$$F(x) = \sum_{m=1}^{M} \gamma_m h_m(x) \tag{4}$$

The variable $h_m(x)$ represents the m weak learner, which is a decision tree, γ_m has a corresponding weight, and M denotes the total number of trees. The choice of the loss function typically involves squared loss and cross-entropy loss. Gradient Boosting Decision Trees (GBDT) employ gradient descent principles to progressively construct new trees that fit the residuals of the current model. By minimizing the negative gradient of the loss function, they find the optimal increment. LightGBM optimizes GBDT in several key ways: First, it uses a leaf-wise splitting strategy, unlike traditional tree models that grow level-wise, selecting leaf nodes where the loss function decreases the most for splitting. Second, it conducts feature value discretization based on histograms, converting continuous feature values into discrete bins and leveraging histogram data structures to enhance processing speed and memory efficiency. Specifically, for feature x, it divides it into K discrete intervals $\{B_k\}_{k=1}^{K}$, approximating the feature values within each interval by their mean, thereby reducing computational load.

$$\hat{L}\left(y, F(x)\right) = \sum_{k=1}^{K} \frac{1}{n_k} \sum_{i:x_i \in B_k} L\left(y_i, F\left(B_k\right)\right) \tag{5}$$

In this context, n_i represents the number of samples that fall within the interval B_k. Additionally, LightGBM incorporates a regularization term to prevent model overfitting. The mathematical foundations of SHAP derive from Shapley values, a fair distribution method that originates from cooperative game theory. This method is particularly useful for assessing the contribution of each participant (feature) to the overall payoff (model prediction). Shapley values delineate the marginal contribution of each participant to the total payoff in cooperative games. For machine learning models, Shapley values assess each feature's contribution to the model prediction. Given a feature set and a model output denoted as f,the Shapley value for feature i is calculated as follows:

$$\phi_i = \sum_{S \subseteq N,\ \{i\}} \frac{|S|!\left(|N|-|S|-1\right)!}{|N|!}\left[f\left(S \cup \{i\}\right) - f\left(S\right)\right] \quad (6)$$

In this context, S represents a subset excluding feature i. $f\left(S \cup \{i\}\right)$ indicates the predicted value of the model when feature i is included, while f(s) represents the predicted value when feature i is not included. The Shapley value determines feature i's marginal contribution by evaluating all possible combinations. By integrating LightGBM with SHAP, we can achieve interpretability in LightGBM model predictions. The specific steps include: Model Training: Training the model using LightGBM. SHAP Value Calculation: Utilizing TreeSHAP to quickly assess each feature's contribution to the prediction for every data point. Model Interpretation: Employing visualization tools to illustrate feature importance and interactions between features. For instance, suppose we have a LightGBM model predicting a company's ESG score; we can employ SHAP values to clarify the model's output.

3. Real data analysis

3.1. Data pre-processing

3.1.1 Data sources

(1) Explained variable: CSI ESG rating. Currently, the mainstream ESG rating systems in China include the CSI ESG rating, the Business Gateway Green ESG rating, and the Wind ESG rating, etc. Among them, the CSI ESG rating covers all A-shares and bond issuers with wide coverage and long backtesting time. Among them, the CSI ESG ratings cover all A-shares and bond-issuing entities, with wide coverage and long backtesting time. Therefore, the subsequent ESG data in this paper are taken from the CSI index platform, and the CSI ESG ratings of listed companies from 2014 to 2022 are selected. In the special case that the ESG ratings of listed companies labeled as "ST" in financial crisis may be affected by the company's financial situation, this paper will remove the listed companies in financial crisis according to the rating adjustment mechanism of the CSI, so as to reduce its impact on the accuracy and reliability of ESG rating data.

(2) Non-financial indicators: Main non-financial indicators: regional environmental regulation intensity. In this paper, we first refer to the practice of Chen Shiyi et al. (2018)[24], based on the frequency of words related to ‘environmental protection’ in the government work reports of each province, to construct the strength of the implementation of environmental regulation of prefecture-level municipal governments. In general, the higher the proportion of heavy industry in the city, the greater the impact of the government's environmental governance, so the more comprehensive and specific the elaboration of environmental protection work in the government work report, the more likely that the environmental regulations will be implemented in the implementation process, and the more obvious the effectiveness of environmental protection. In this paper, 15 environmental terms that can reflect the government's attention to environmental protection in a more comprehensive way are selected from the three aspects of ‘environmental protection goal’, ‘environmental protection target’ and ‘environmental protection measures’, as shown in Table 1. Based on this vocabulary collection, text statistics and analyses of the work reports of 30 provincial governments were carried out using python.

Table 1 Government environmental protection dimensions and environmental protection vocabulary selection

Environmental protection dimensions	Selected Vocabulary
Environmental objectives	environmental protection、environmental protection
Environmental Protection Objectives	Pollution、Energy Consumption、Emission、Ecology、Air、Green、Chemical Oxygen Demand、Sulphur Dioxide、Carbon Dioxide、 PM10、PM2.5
Environmental Measures	Emission Reduction、Low Carbon

As for other non-financial indicators, the other non-indicators we have selected mainly include six aspects totalling 13. The source of the data is the Wind database, which is categorised as shown in Table 2 below. As shown in Table 2 above, the selection of non-financial indicators needs to fully consider their impact on ESG performance. The specific meanings of the above indicators are as follows[13-23]:

Table 2 Indicator symbols

Category	Indicator	Symbol
Key non-financial indicators	Environmental regulation	X_1
Explained Variables	CSI ESG ratings	ESG
Finance and Investment	Financing constraints	Z_1
	Enterprise Value Multiples	Z_3
	Capital Intensity	Z_6
	Company Size	Z_2
Corporate Governance and Structure	Board size	Z_4
	Direct controlling shareholders' shareholding	Z_5
	Concentration of shareholding	Z_{13}
Markets and Competition	Herfindahl Index	Z_7
Technology and Innovation	Degree of digital transformation	Z_8
	Amount of R&D investment	Z_{12}
Economy & Society	Financial Inclusion Composite Index	Z_9
	Total Factor Productivity	Z_{10}
Human Resources & Diversity	Percentage of women at the supervisory level	Z_{11}

The above indicators are selected to ensure that the study can comprehensively assess the impact of non-financial factors on ESG performance across different firm properties. Other factors that may affect ESG performance are also controlled to improve the reliability of the study. In turn, the specific impact of different corporate nature on ESG performance can be identified and explained more accurately.

3.1.2 Data preprocessing

Data pre-processing is a key step in order to ensure the accuracy and reliability of the results of subsequent analyses. This stage mainly carries out the processing of missing values, outliers and normalisation of data. Among them, the normalisation processing formula is shown in below:

$$X^{'} = \frac{x - \min(x)}{\max(x) - \min(x)}. \tag{7}$$

Provide the above normalisation process, which can maintain the integrity and consistency of the data on the basis of. Further eliminate the impact of different indicator outlines and value ranges. Improve the stability of the data at the same time, more convenient for subsequent difference analysis and visualisation.

3.2. Differential analysis of ESG performance under different corporate natures

3.2.1 Descriptive statistical analysis

In this paper, the preprocessed data are divided into state-owned enterprises and non-state-owned enterprises according to the nature of enterprises. The results of descriptive statistical analysis of the main indicators are shown in Tables 3 and 4 below.

Table 3 Results of descriptive statistical analysis of the main indicators of state-owned enterprises

Indicators	mean	std	min	max	median	sv
X_1	4.54E-03	1.10E-03	2.27E-03	7.60E-03	4.39E-03	0.2431
ESG	2.96E+01	9.97E+00	1.35E+01	5.50E+01	2.72E+01	0.336296
Z_1	-3.84E+00	2.14E-01	-4.35E+00	-3.39E+00	-3.83E+00	-0.055767
Z_2	2.28E+01	1.18E+00	2.07E+01	2.55E+01	2.26E+01	0.052011
Z_3	7.14E+01	3.19E+02	9.11E+00	3.32E+03	3.18E+01	4.469104
Z_4	9.22E+00	1.09E+00	7.00E+00	1.20E+01	9.00E+00	0.118211
Z_5	3.50E+01	1.14E+01	1.41E+01	6.22E+01	3.50E+01	0.325549
Z_6	3.83E+00	6.08E+00	5.83E-01	3.47E+01	1.86E+00	1.588272
Z_7	1.93E-01	1.78E-01	4.12E-02	1.00E+00	1.37E-01	0.92317
Z_8	2.16E+00	1.90E+00	0.00E+00	5.82E+00	1.61E+00	0.875755
Z_9	3.24E+02	7.83E+01	1.66E+02	4.53E+02	3.27E+02	0.241795
Z_{10}	6.99E+00	9.18E-01	5.23E+00	9.18E+00	6.97E+00	0.131362
Z_{11}	2.08E-01	1.13E-01	4.76E-02	4.67E-01	1.76E-01	0.543453
Z_{12}	7.13E+08	1.54E+09	2.36E+07	9.81E+09	1.91E+08	2.158673
Z_{13}	3.28E+01	1.33E+01	8.20E+00	6.22E+01	3.24E+01	0.404099

Note: The data in the table are expressed in scientific notation, where'E'stands for 'multiplied by a power of 10'. For example, 4.54E-03 represents 4.54 x 10^-3, or 0.00454.'

From the above table, it is easy to see that in terms of ESG performance, non-SOEs show greater volatility with higher standard deviation and coefficient of variation, implying that they are not as stable as SOEs in terms of ESG performance; while in terms of environmental regulation, non-SOEs show greater relative volatility, reflecting the instability of non-SOEs in terms of informal environmental regulation.

Table 4 Results of descriptive statistical analyses of key indicators for non-state enterprises

Indicators	mean	std	min	max	median	sv
X_1	4.55E-03	1.58E-03	0	7.89E-03	4.46E-03	0.348248
ESG	2.97E+01	1.20E+01	8.7565	7.01E+01	2.63E+01	0.403164
Z_1	-3.80E+00	2.21E-01	-4.554226	-2.97E+00	-3.80E+00	-0.05822
Z_2	2.21E+01	8.73E-01	19.978045	2.66E+01	2.20E+01	0.039586
Z_3	4.37E+01	1.84E+02	1.450299	4.69E+03	2.40E+01	4.214885
Z_4	8.17E+00	1.31E+00	4	1.10E+01	9.00E+00	0.159829
Z_5	3.27E+01	1.43E+01	1.04	8.50E+01	2.98E+01	0.437336
Z_6	2.29E+00	1.17E+00	0.439289	1.04E+01	2.04E+00	0.510962
Z_7	1.77E-01	1.42E-01	0.041188	1.00E+00	1.37E-01	0.799774
Z_8	1.56E+00	1.42E+00	0	6.31E+00	1.39E+00	0.910989
Z_9	3.24E+02	7.81E+01	160.76	4.61E+02	3.27E+02	0.240853
Z_{10}	6.61E+00	6.98E-01	4.992043	9.67E+00	6.55E+00	0.105613
Z_{11}	2.13E-01	1.25E-01	0	6.15E-01	1.90E-01	0.587408
Z_{12}	1.41E+08	2.56E+08	143994.45	4.37E+09	8.54E+07	1.811479
Z_{13}	2.94E+01	1.41E+01	4.1456	8.50E+01	2.66E+01	0.480317

In terms of the financial inclusion composite index, the volatility of SOEs and non-SOEs is similar. However, in terms of firm size, enterprise value, capital intensity, Herfindahl index, total factor productivity and amount of R&D investment, SOEs show greater volatility; in terms of financing constraints, size of the board of directors, proportion of shares held by direct controlling shareholders, degree of digital transformation, percentage of women in supervisory layers, and degree of concentration of shareholding, non-SOEs show greater volatility, suggesting that non-SOEs are in a governance structure that is They are more diversified in terms of governance structure and more active in technological innovation and business model transformation.

3.2.2 Density variability test

The Kernel Density Estimate (KDE) curves in Figure 1 offer a visual representation of the distribution of ESG performance for both state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs) across the years from 2014 to 2022. Initially, in 2014, the ESG performance distributions for SOEs and NSOEs were closely aligned, with NSOEs exhibiting a slightly broader spread and higher volatility.

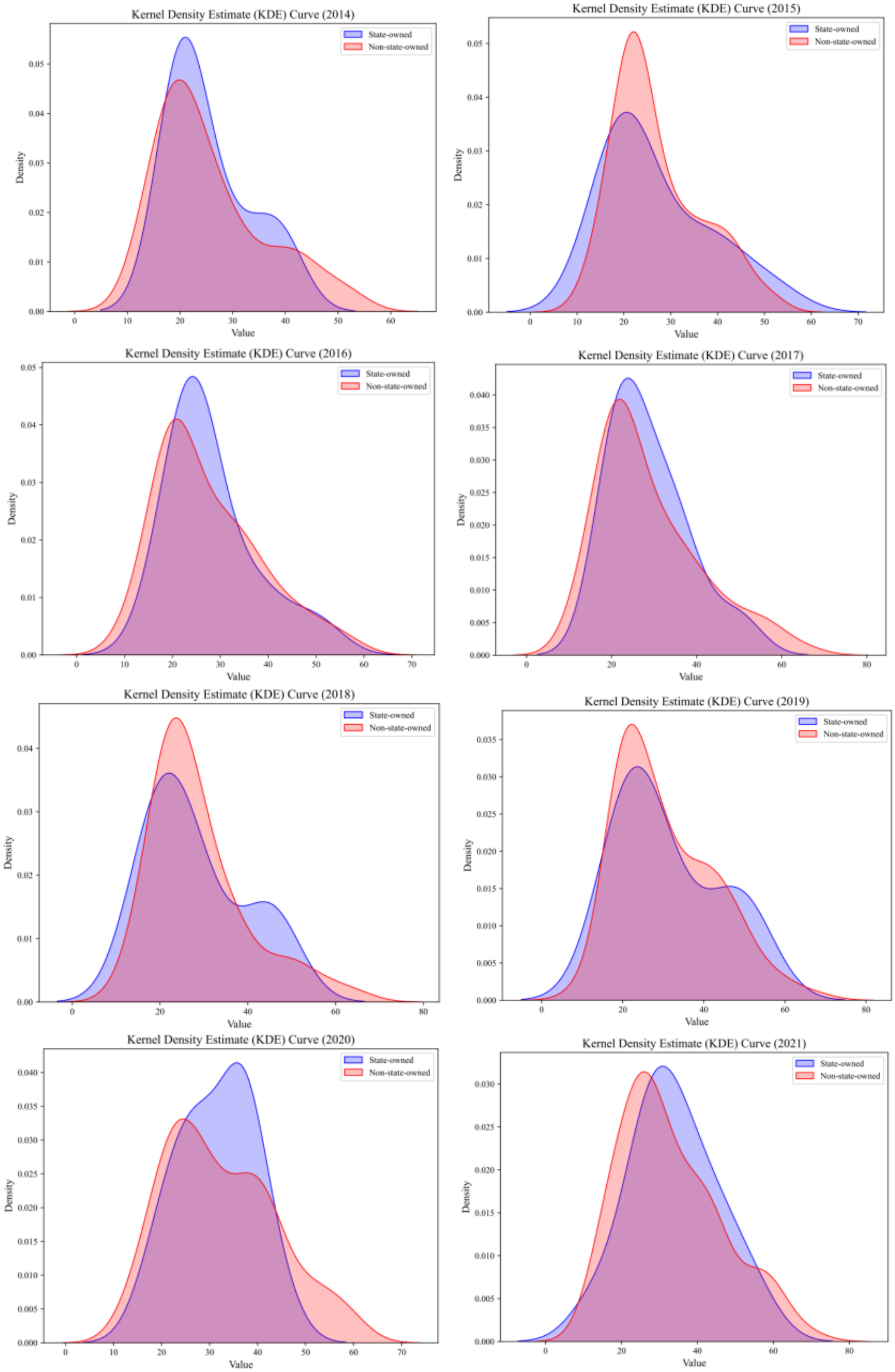
As we move into 2015, the ESG performance distribution for SOEs becomes more focused, while NSOEs display a more extensive distribution, indicating a greater degree of variability among non-state-owned firms. This pattern continues into 2016, with NSOEs maintaining a wider distribution and higher volatility in their ESG performance.

The divergence in ESG performance distribution between SOEs and NSOEs becomes more pronounced in 2017, with SOEs showing a more concentrated distribution and NSOEs a wider one. This trend persists in 2018 and 2019, with SOEs maintaining a concentrated distribution and NSOEs remaining more dispersed.

By 2020, both SOEs and NSOEs show a concentrated ESG performance distribution, yet SOEs demonstrate an even more focused pattern. In 2021, while both types of enterprises have a spread out distribution, SOEs still show a more concentrated ESG performance.

Finally, in 2022, the ESG performance distribution for both SOEs and NSOEs is concentrated, with the gap between them narrowing significantly. This suggests a convergence in ESG performance distribution over time.

In essence, the ESG performance of SOEs tends to be more stable and focused, contrasting with the more varied and volatile performance of NSOEs. Over the years, the distribution gap between SOEs and NSOEs in terms of ESG performance has been gradually diminishing.



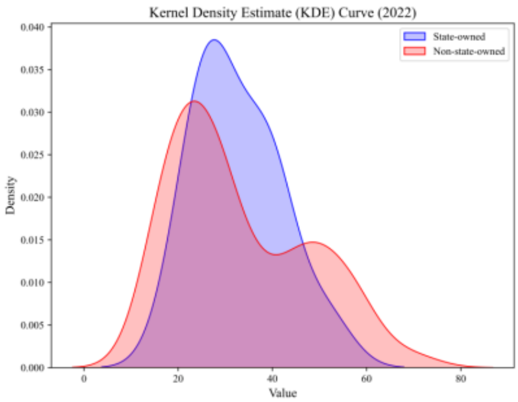


Fig.1 Density distribution of SOEs and non-SOEs, 2014-2022

In summary, it is easy to see that the ESG performance of state-owned enterprises is usually more stable and concentrated, while the ESG performance of non-state-owned enterprises is more dispersed and volatile; and the difference in the distribution of ESG performance between state-owned enterprises and non-state-owned enterprises shows a gradual trend of narrowing as time goes by.

3.2.3 K-Means cluster analysis

On the basis of data preprocessing and descriptive statistical analysis, we use K-Means clustering method to classify the ESG performance of enterprises of different natures into three grades: high, medium and low, to study in-depth the trend of ESG performance of different enterprise natures over time, and to further analyse the driving factors behind the dynamic changes in ESG performance.

Table 5 Results of three levels of ESG performance of state-owned enterprises and non-state-owned enterprises during 2014-2022

Nature of enterprise	State-owned enterprise			Non-state-owned enterprise		
Year	low	medium	high	low	medium	high
2014	20.72	30.77	39.07	17.95	27.63	43.68
2015	20.06	37.63	51.15	20.63	30.58	42.78
2016	23.66	37.56	50.03	19.71	33.48	49
2017	22.62	34.31	49.69	20.07	33.59	52.05
2018	19.06	27.15	45.08	20.92	31.9	52.37
2019	21.43	32.31	49.61	21.35	35.73	51.16
2020	21.28	28.25	38.09	23.43	39.03	53.82
2021	13.46	29.62	46.45	23	39.14	57.76
2022	26.15	39.27	51.41	19.33	29.8	51.67

As can be seen from Table 5 and Figure 2 above, the high-level ESG performance of both state-owned enterprises and non-state-owned enterprises shows an upward trend during 2014-2022, which is related to the promotion of national policies, the public's expectation of sustainable development, and the enterprises' own emphasis on social responsibility. However, the growth of high-level ESG performance of non-state-owned enterprises is relatively small, reflecting the diversity and complexity of ESG management of non-state-owned enterprises. The middle-rated ESG performance of non-SOEs shows a greater volatility trend compared to SOEs, indicating more uncertainty in ESG management of non-SOEs. The low-grade ESG performance of state-owned enterprises shows an overall downward trend during 2014-2022, indicating that the number of enterprises with low-grade ESG performance decreases and the overall level of state-owned enterprises in ESG improves. The decline in the low-ranking ESG performance of non-state-owned enterprises is relatively small, reflecting the unevenness of their ESG management and the lack of investment or mismanagement of some enterprises in ESG.

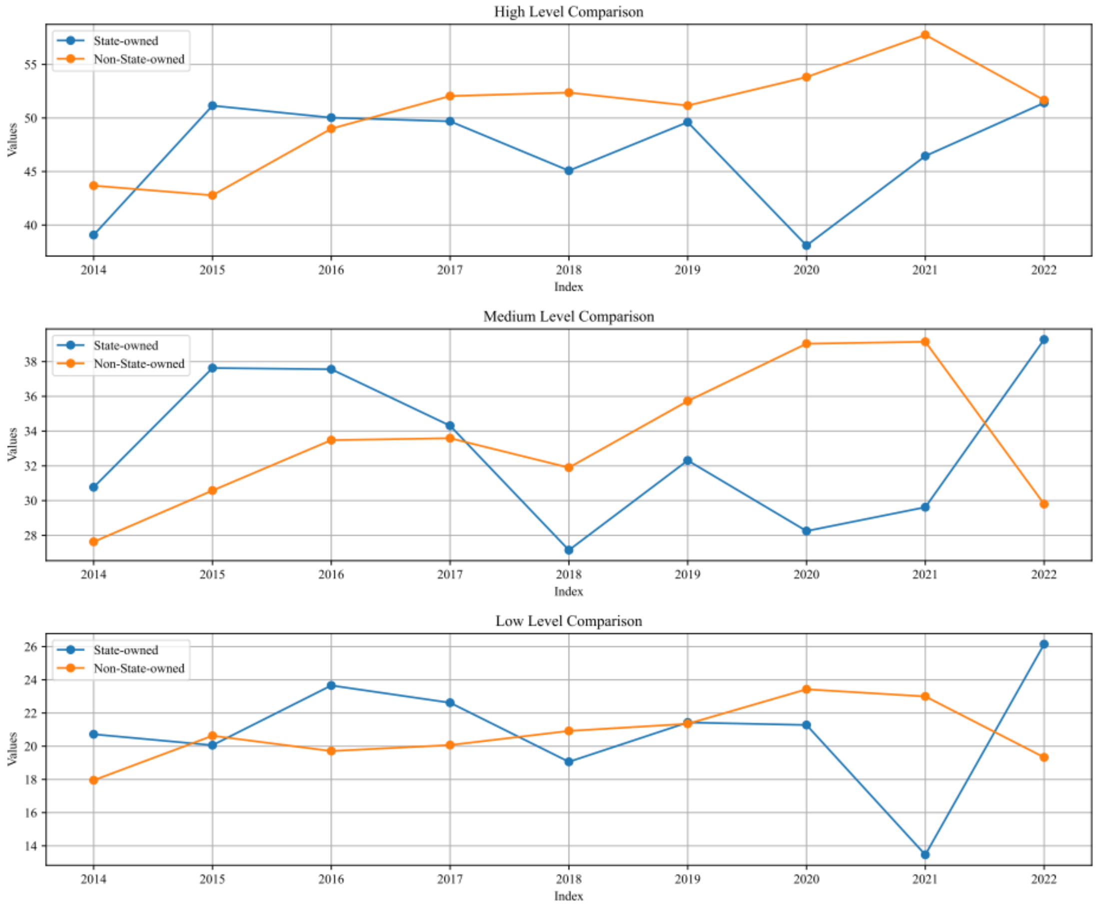


Fig. 2 Trend of ESG changes of different enterprise natures under high and low grades

The above analysis shows that the overall ESG performance of state-owned enterprises is better, and the ESG performance of state-owned enterprises in the middle, high and low grades all show a certain upward trend. The ESG performance of non-state-owned enterprises shows greater fluctuations in different grades.

3.3. Differential analysis of the impact of non-financial factors on ESG performance

3.3.1 LightGBM vs. SHAP analysis

After analysing the dynamic trend of ESG performance by K-Means clustering, we further use the LightGBM+SHAP method to explore the extent to which non-financial factors influence ESG performance across different firm natures (SOEs vs. non-SOEs). This step is a deepening of the previous two parts of the analysis, and by quantifying the contribution of each feature to the model output, we are able to identify more precisely the key non-financial factors that affect ESG performance. The results of the SHAP values for specific SOEs and non-SOEs are shown in Figures 3 and 4 below.

As can be seen from Figure 3, the ESG performance of state-owned enterprises is greatly influenced by capital intensity, market concentration and equity concentration. Among them, in terms of capital intensity (Z6), the capital intensity of SOEs has a significant positive impact on ESG performance. This indicates that capital-intensive SOEs invest more resources in ESG, which improves their ESG performance. In terms of Herfindahl index (Z7), Herfindahl index is a measure of market concentration, and its effect on ESG performance of SOEs is also more significant. This implies that SOEs with higher market concentration have more significant ESG performance. In addition, in terms of the degree of equity concentration (Z13), the degree of equity concentration also has a greater impact on the ESG performance of SOEs, which is closely related to the firm's decision-making efficiency and resource allocation capacity.

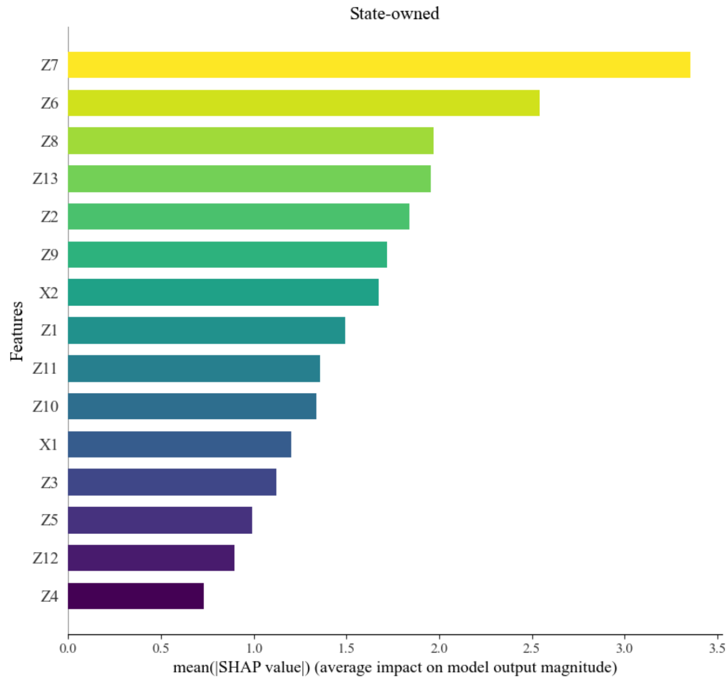


Fig. 3 The result of SHAP value of state-owned enterprises

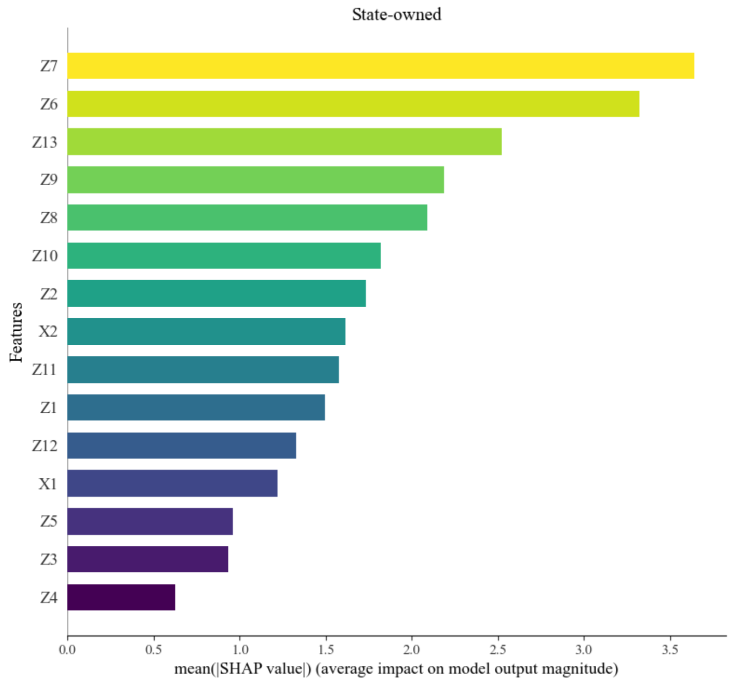


Fig. 4 Graph of SHAP value results for non-state-owned enterprises

As can be seen from Figure 4, the ESG performance of non-state-owned enterprises, on the other hand, is strongly influenced by the financial inclusion composite index, the degree of digital transformation and the amount of R&D investment. Among them, in terms of financial inclusion composite index (Z9), the financial inclusion composite index of non-state-owned enterprises has a significant positive impact on ESG performance. This suggests that the performance of non-state-owned enterprises in financial inclusion contributes to their ESG performance. In terms of the degree of digital transformation (Z8), the degree of digital transformation also has a greater impact on the ESG performance of non-SOEs. It indicates that digital transformation can improve the operational efficiency and environmental friendliness of enterprises. In terms of the amount of R&D investment (Z12), the impact of the amount of R&D investment on the ESG performance of non-state-owned enterprises is also more significant. The investment in R&D by non-state-owned enterprises also contributes to their ESG performance, especially in terms of innovation and environmentally friendly technologies.

The above analysis shows that ESG factors vary across firms, with the ESG performance of SOEs being more affected by capital intensity, market concentration, and equity concentration, while the ESG performance of non-SOEs is more affected by the financial inclusion index, the degree of digital transformation, and the amount of R&D investment. Among them, non-financial factors have a significant impact on ESG performance, and non-financial factors play an important role in the ESG performance of both SOEs and non-SOEs. In addition, the nature of the enterprise further affects its ESG performance by influencing its resource allocation, decision-making efficiency and market positioning.

4. Conclusions

This study delves into the differential impact of non-financial factors on firms ESG performance under different firms nature. In terms of the distributional characteristics of ESG performance, descriptive statistical analyses and KDE curves reveal that state-owned firms usually exhibit more stable and concentrated ESG performance, while non-state-owned firms show greater volatility. In terms of the dynamics of ESG performance, K-Means cluster analysis reveals that different grades of ESG performance show different trends over time. State-owned enterprises (SOEs) show an upward trend in high-grade ESG performance, while low-grade performance declines, indicating that SOEs are more mature and effective in ESG management. In addition, in terms of the impact of non-financial factors, LightGBM+SHAP analyses reveal the impact of the role of non-financial factors on ESG performance. For SOEs, capital intensity, market concentration and degree of equity concentration are the key influencing factors, while for non-SOEs, the impact of financial inclusion composite index, degree of digital transformation and amount of R&D investment are more significant. Finally, we make the following recommendations in response to the findings:

(1) Strengthen ESG information disclosure and transparency. For state-owned enterprises (SOEs), it is recommended to strengthen the disclosure requirements of ESG information to ensure the accuracy and timeliness of the information. For non-state-owned enterprises, voluntary ESG reporting should be encouraged, and guidance and training should be provided to help enterprises understand the importance of ESG reporting and provide technical support for report preparation.

(2) Establish differentiated ESG incentive policies. For state-owned enterprises, it is recommended to set up a mechanism linking ESG performance to the performance appraisal of corporate leaders to incentivise corporate management to pay more attention to ESG performance. For non-state-owned enterprises, the government can encourage enterprises to make more efforts in environmental protection, social responsibility and internal governance through tax incentives and financial subsidies.

(3) Provide specialised ESG funding support. The government can set up corresponding ESG special funds to provide enterprises with financial support for ESG projects, especially for non-state-owned enterprises that have potential in ESG performance but insufficient funds.

(4) Establish an ESG assessment and rating system. Establish a set of scientific and fair ESG assessment and rating system to regularly assess and rate the ESG performance of enterprises, and use the rating results as an important basis for enterprises to obtain government support and market recognition.

References

[1] Friede, G., Busch, T., & Bassen, A. (2015). ESG and Financial Performance: Aggregated Evidence from More than 2000 Empirical Studies. Journal of Sustainable Finance & Investment, 5(4), 210-233.

[2] Godfrey, P. C. (2005). The Relationship between Corporate Philanthropy and Shareholder Wealth: A Risk Management Perspective. Academy of Management Review, 30(3), 777-798.
[3] Ashwin Kumar, N. C., Smith, C., Badis, L., Wang, N., Ambrosy, P., & Tavares, R. (2016). ESG Factors and Risk-Adjusted Performance: A New Quantitative Model. Journal of Sustainable Finance & Investment, 6(3), 292-300.
[4] Li T, Li Y. (2021). Stakeholder-based empirical analysis of corporate social responsibility and corporate value. China economic and trade guide (in Chinese), 2021(6), 94-96.
[5] Li, Shenlan. (2023). Correlation between ESG performance and comprehensive financial performance: A case study of information technology service listed companies. Operations Research and Fuzzy, 13(5), 5741-5753.
[6] Di Tommaso, C., & Thornton, J. (2020). Do ESG Scores Affect Bank Risk Taking and Value? Evidence from European Banks. Corporate Social Responsibility and Environmental Management, 27(4), 2286-2298.
[7] Giese, G., Lee, L., Melas, D., Nagy, Z., & Nishikawa, L. (2019). Foundations of ESG Investing: How ESG Affects Equity Valuation, Risk, and Performance. The Journal of Portfolio Management, 45(5), 69-83.
[8] Yuan Yehu,Xiong Xiaohan. (2021). A study on the relationship between ESG performance and corporate performance of listed companies - based on the moderating role of media attention. Jiangxi Social Science, 41(10), 68-77.
[9] Duan Aohan. (2024). Research on the impact of ESG performance of listed companies on enterprise value. E-Commerce Review, 13(3), 7747-7758.
[10] Li, Shenlan. (2023). A study on the correlation between ESG performance and comprehensive financial performance - A case study of information technology service listed companies. Operations Research and Fuzzy Science,13(5), 5741-5753.
[11] Li Chao. An empirical study on the economic effects of ESG practices in Chinese listed companies[D]. University of Science and Technology of China, 2023.
[12] Lu Jiarui.Research on the impact of ESG disclosure transparency on corporate finance cost[D]. Jilin University,2023.
[13] Jinglin Liao, Hu Yan, Xiang Houjun. Does the development of digital inclusive finance alleviate corporate financing constraints? The moderating effect based on corporate social responsibility[J]. Journal of Yunnan University of Finance and Economics, 2020, 36(9): 73-87.
[14] Zhang Lin, Zhao Haitao. Does corporate environmental, social and corporate governance (ESG) performance affect corporate value? An empirical study based on A-share listed companies[J]. Wuhan Finance, 2019(10): 36-43.
[15] Xuan Zhao, Nai-Bin Dong. Digital finance, corporate digital transformation and ESG performance: empirical evidence based on A-share listed companies in Shanghai and Shenzhen from 2011-2021[J]. Journal of Southwest University (Social Science Edition), 2023, 49(5): 130-140.
[16] Yang Baojun. Journalism ethics [D/OL]. Beijing: Renmin University of China Press 2010 [2012-11-01].
[17] Guo Hengtai, Shi Fu'an. Digital Inclusive Finance, Financing Constraints and Corporate Social Responsibility[J]. Journal of Shanghai Lixin College of Accounting and Finance, 2023, 35(2): 3-15.
[18] Wang Rong. The impact of corporate ESG performance on R&D investment - the mediating effect of financing constraints[J]. Baidu Academic, 2024.
[19] Zhang Si-Yun. A study on the impact of digital transformation on corporate ESG performance[J]. hanspub.org, 2024, e-commerce review.
[20] Haijun Wang, Songzheng Wang, Chen Zhang, et al. Does Digital Transformation Improve Corporate ESG Responsibility Performance? --An empirical study based on MSCI index[J]. Foreign Economy and Management, 2023(6): 19-35.

[21] Wang Zhenjie, Wang Hui. Low-carbon city pilot policy and high-quality development of enterprises - A test based on the two-dimensional perspective of economic efficiency and social benefit[J]. Economic Management, 2022, 44(6): 43-62.
[22] Yu Xiao, Liu Yi, Chai Yueting, et al. Qualification audit and filing model of the main body of Internet drug trusted trading environment[J]. Journal of Tsinghua University (Natural Science Edition), 2012, 52(11): 1518.
[23] Yang Yan et al. The Impact of Corporate Social Responsibility Performance on Firm-Specific Risks. An analysis based on stakeholder perspective[J]. Research on Financial Issues, 2015.
[24] Chen Shiyi,Chen Dengke. Haze Pollution, Government Governance and High Quality Economic Development[J]. Economic Research, 2018.(2): 20-34.