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Analyzing the effect of ESG ratings on spatial heterogeneity of firms' total factor productivity based on improved K-means algorithm

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ABSTRACT

Answering the spatial relationship between ESG ratings and total factor productivity of enterprises can provide a reference for the high-quality development of macroeconomy and the sustainable and healthy development of enterprises. In this paper, the improved K-means algorithm-PCA-K-means is used to measure the principal component data corresponding to the economic development level of 26 central cities, based on which and cluster analysis is conducted to classify the regions and city types of East, Central and West China. Furthermore, benchmark regression and spatial heterogeneity analyses were conducted using a fixed-effects model. The study shows that ESG ratings have a significant positive relationship on firm-wide factors. Observing the PCA-K-means clustering results, it can be found that there is no significant positive effect between the economic development speed and the ESG ratings of enterprises, which indicates that there is a difference in the impact of ESG ratings on the total factor productivity of enterprises in different regions. Therefore, the spatial heterogeneity analysis shows that the correlation coefficients of ESG rating performance in the central and western regions are 0.0163 and 0.0275, respectively, and ESG rating performance has a greater impact on enterprises in the central and western regions compared with the eastern region. The effect of ESG rating on total factor productivity of enterprises in resource-dependent cities and old industrial bases is not significant.

Keywords: principal components, K-means, fixed effects model, benchmark regression, spatial heterogeneity

1. Introduction

Once proposed, the new quality productivity has triggered great attention from the theoretical and practical circles. New quality productivity is driven by the deepening application of technology, characterized by new industries, new business forms and new modes, and constructing a new type of

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social relations and social system system productivity [1-2]. From a micro point of view, the development of new quality productivity, the ultimate goal is to optimize the enterprise investment structure and thus enhance the total factor productivity of enterprises. Therefore, the proposal of new quality productivity provides a new research perspective for the study of enterprise total factor productivity [3-5].

ESG (Environment, Social Responsibility and Corporate Governance) investment strategy and value predictability have attracted much attention.ESG is different from the traditional evaluation model that only focuses on financial indicators in the past, and it is an investment concept and evaluation paradigm that focuses on the comprehensive performance of enterprises' environment, social responsibility and corporate governance [6-8]. In terms of policy orientation, the government has gradually increased its efforts to promote the development of ESG [9].

Enterprises are an important guarantee for the country's economic and technological strength, and moreover, the foundation of the founding of a country and the basis of a strong country. In recent years, Chinese enterprises have been leading the world in some segments, forming an industrial structure with complete content, clear map and leading technology, which has greatly promoted the modernization of the national industrial economic system [10-11]. However, behind the rapid development of enterprises there still exists the structural contradiction of excessive empowerment of resources, refined but not sharp, large but not strong, which restricts the healthy development of industry in a certain scale and field [12-13]. As an important support for the development of the real economy, enterprises are of great significance in promoting the process of realizing high-quality development in China. Therefore, in the context of the diversification and complexity of the world economic pattern, focusing on improving the productivity of enterprises, firmly promoting the pace of modernization of Chinese enterprises, realizing the leap in the quality of factors and the change of production efficiency, and comprehensively promoting the strategic transformation and upgrading of industries are of great practical significance in accelerating the green construction and high-quality development of Chinese enterprises [14-16].

The ESG concept emphasizes long-term sustainable development, which brings the possibility of improving the production efficiency of enterprises when the path of traditional enterprises relying excessively on high energy consumption and high inputs to achieve returns is blocked. However, does ESG performance affect corporate production operations? Does the effect on productivity manifest itself as a facilitator or inhibitor? What mechanism of action exists for the operation of this process? Is there some difference in this impact under different conditions? These questions urgently need to be sorted out and studied [17-20]. Therefore, in the context of basing on the new development stage, implementing the new development concept, accelerating the construction of the new development pattern and high-quality development, exploring the relationship between corporate ESG performance and productivity is conducive to providing empirical evidence for implementing the ESG concept and realizing the double-effective leap in the efficiency and quality of manufacturing enterprises [21-23].

Literature [24] describes the correlation between ESG ratings and enterprise total factor productivity, and discusses in detail the impact and mechanism of each ESG indicator on enterprise total factor productivity. Literature [25] combined the fixed effects model and the staggered difference-in-differences method to reveal that digital transformation promotes the ESG performance of enterprises to a certain extent, which in turn promotes the total factor productivity of enterprises. Literature [26] analyzed the data of Chinese listed companies and found that ESG performance is positively correlated with total factor productivity (TFP), and ESG performance influences TFP through financial constraints and innovation input channels. Literature [27], in a study to assess the impact of ESG performance on GTFP, found that ESG performance has a significant effect on green technology efficiency improvement, but is not obvious in promoting green technology progress. Literature [28] used a two-way fixed effects model, mediation analysis and moderation model to analyze how ESG performance affects the total factor productivity of downstream firms, and pointed out that the monopoly of firms' rights negatively moderates ESG performance and downstream firms' TFP, and that ESG performance improves the dilemma of financing constraints. Literature [29] analyzes and explores the ESG-related data of listed firms in China, and based on the heterogeneity analysis, it is learned that the ESG performance of firms with high attention and good reputation has a more significant impact on total factor productivity. Literature [30] points out that the implementation of ESG performance standards by Chinese firms positively contributes to the improvement of employee efficiency and the reduction of financing costs, which in turn positively affects the improvement of firms' total factor productivity. All of the above studies have affirmed the positive impact of corporate ESG performance on corporate total factor productivity, but there is a gap in the studies based on spatial heterogeneity.

In this paper, a PCA-K-means algorithm for evaluating and categorizing the economic development level of cities is proposed by combining the characteristics of principal component analysis and K-means clustering algorithm. The data of A-share listed manufacturing companies from 2007-2024 are selected for the study, and the relationship between ESG rating performance and total factor productivity is regressed and analyzed by using LP measurement method and fixed effect model. Through the PCA-K-means algorithm, the 26 central cities are clustered into 4 categories based on the composite score of the principal components of the economic development level, and the regions and city types in the East, Central and West are divided, and the spatial heterogeneity test is thus conducted to explore the spatial heterogeneity of the impact of ESG ratings on the total factor productivity of enterprises.

2. ESG rating systems and total factor productivity

ESG is a code of conduct for enterprises to undertake environmental (E), social (S) and corporate governance responsibilities (G) in the process of development, and is also a criterion for investors to evaluate the sustainable development and green operation of enterprises. Compared with traditional non-financial indicators, ESG pays more attention to the impacts of enterprises' own business activities on the environment, society and internal governance. In this paper, we believe that under the ESG framework, environmental responsibility (E) is the responsibility of enterprises for what they do in the environment, including environmental governance, energy consumption, low carbon emissions, renewable energy use, etc., to protect the environment from the perspective of both governance and improvement. Social responsibility (S) is closely related to the concepts of “sharing” and “sustainable development”, and is a dynamic conceptual system, which should require enterprises to assume responsibility for stakeholders, forming a harmonious symbiosis between the economy and society, and thus promoting the sustainable development of society. Corporate governance (G) is the pursuit of different goals due to the separation of ownership and operation rights of the principal and the agent, which requires the development of a series of institutional arrangements through the governance structure to coordinate and balance the parties.

Total Factor Productivity (TFP), the residual after eliminating factor inputs is the total factor productivity in a broad sense. The output when various factor inputs are kept at a given level is the total factor productivity. By attributing various factors such as labor, capital and raw materials to total factors and calculating their output efficiency based on the total inputs of the overall factors per unit of time, most of the current methods of measuring total factor productivity are based on the perspective of the overall factors.

3. Related technical studies

3.1. Improved K-means algorithm-PCA-K-means

The principal component analysis method realizes dimensionality reduction by calculating the covariance matrix and the correlation coefficient matrix by orthogonal transformation, and finally obtains mutually independent principal components. Using A_i to denote the eigenvector of the eigenvalue pair in the covariance matrix S of X, the principal component Y_i can be expressed by the original index X as:

$$Y_i = a_{i1}X_1 + a_{i2}X_2 + a_{i3}X_3 + \ldots + a_{ip}X_p = A_i^T X \tag{1}$$

K-means is a distance-based unsupervised clustering algorithm, which can effectively distinguish different indicator class clusters by dividing the sample into K class clusters by a given value of K. The steps of K-means algorithm are as follows:

1) Select K objects from the data as initial clustering centers.

2) For each sample point, calculate the distance from the center and divide each sample point into the nearest class cluster.

3) Calculate the sum of the distances between each clustering center and the points in the cluster as the cost.

4) Calculate the minimum cost function until the minimum cost or the maximum number of iterations is reached then stop the algorithm.

In this paper, the combination of principal component analysis, K-mean clustering algorithm, classification, the specific steps of the algorithm is as follows:

1) Set the data under the normal phase as a matrix:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix} \tag{2}$$

Standardize the matrix to get matrix X^*.

2) Use principal component analysis to process the standardized matrix X^*. First calculate the correlation number matrix R of X^*, then find the eigenvalues and eigenvectors, calculate the contribution rate and cumulative contribution rate, and select the appropriate principal components.

3) Clustering cities with K-means algorithm. Compare the results of clustering the city data with K-means algorithm after principal component analysis and clustering the city directly with K-means algorithm.

3.2. Fixed effects model

In linear regression on panel data, a fixed-effects model is usually used when the cross-sectional units are all the units of the aggregate, i.e., there is no need to use the sample to infer the aggregate. A fixed effects model, in simple terms, means that all parameters to be estimated in the model are constants except for the random disturbance term.

If the model is built from only the cross-sectional units as a starting point, the basic form is as in (3):

$$Y_{it} = \mu + \alpha_i + X_{it}\beta_{it} + \mu_{it} \tag{3}$$

$$i = 1,2,\ldots,T; t = 1,2,\ldots,T \tag{4}$$

μ indicates the mean value of the cross-section unit over all time, i.e., the total mean. α_i denotes the difference between the intercepts of different cross-sectional units and the total mean μ:

$$\alpha_{it} = \mu + \alpha_i \tag{5}$$

If the model is built from the starting point of time only, the basic form is as in (6):

$$Y_{it} = \mu + \lambda_t + X_{it}\beta_{it} + \mu_{it} \tag{6}$$

$$i = 1,2,\ldots,T; t = 1,2,\ldots,T \tag{7}$$

μ denotes the mean value over all time of the intercept unit, i.e., the total mean. λ_i denotes the difference between different time intercepts and the total mean μ:

$$\alpha_{it} = \mu + \lambda_t \tag{8}$$

In a fixed effects model, either the parameter vector β_{it}, or α_i, λ_i, is a fixed constant once it is estimated.

3.3. LP measurement methodology

The LP method also distinguishes the residual ε_{it} in the OLS method into two parts, an observable ω_{it} related to the capital and labor input factors, and a residual v_{it} that is not related to the capital and labor input factors and is expected to be zero. The expression of the LP method for ω_{it} that affects a firm's labor and capital input decisions is:

$$\omega_{it} = \omega(m_{it}, k_{it}) \tag{9}$$

m_{it} for intermediate goods inputs. Thus the LP method is modeled as:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega(m_{it,} k_{it}) + v_{it} \tag{10}$$

The advantage of the LP method over the OLS method is that by separating the part of the OLS method that ε_{it} is related to capital and labor inputs into $\omega(m_{it} k_{it})$, it is possible to control for the part of ε_{it} that affects capital and labor inputs and control for endogeneity. The advantage of the LP method over fixed effects is that $\omega(m_{it}, k_{it})$ can be related to individual firms as well as change over time, which is more in line with the reality of business operations than the fixed-effects assumption that the productivity of firms is only related to individual firm heterogeneity and is not related to changes over time.The LP method and the OP method, both of which can solve the problems faced by the OLS method. However, for enterprises in the manufacturing industry, if the investment activities of enterprises are not continuous, the investing enterprises will have years with zero investment data in the statistics, which may have an impact on the measurement of the OP method. Therefore, the choice of LP and OP depends mainly on the quality and continuity of the data of investment variables and intermediate input variables.

4. Impact of ESG ratings on spatial heterogeneity of firms' total factor productivity

4.1. Empirical findings and analysis

In this paper, the data of A-share listed manufacturing companies from 2007 to 2024 are selected as the research sample. Listed companies with abnormal financial status (e.g. ST, PT mark) are excluded. The samples of companies with missing key indicators or zero key indicators are excluded. After the screening of the data was completed, an unbalanced panel dataset was obtained with a total of 21,000 sample observations. In order to mitigate the effect of outliers, continuous variables were subjected to 1% and 99% two-sided shrinkage. The paper utilizes Stata software for data processing and regression analysis.

The explanatory variable of this paper is total factor productivity (TFP). The core explanatory variable in this paper is enterprise ESG rating. At present, several organizations at home and abroad have carried out the development and rating of ESG ratings. Relevant control variables are set in terms of enterprise financial indicators and internal governance level: enterprise size (Size), gearing ratio (Lev), return on equity (ROE), growth capacity (Growth), shareholding ratio of the top five shareholders (Top5), Tobin's Q value (TobinQ), the number of directors (Board), and age of the enterprise (ListAge), Nature of Ownership (SOE). Some of these firms changed the nature of ownership during the sample period and were not automatically excluded from the fixed effects regressions.

4.1.1. Benchmark regression analysis. For the reliability of the empirical results, the choice of whether to use a random effects or fixed effects model is determined by the Hausman test. In this paper, the P-value is found to be significant at 1% statistical level by Hausman test, so the fixed effect model is chosen for regression. The regression results of total factor productivity of enterprises measured by LP method are shown in Table 1. Columns (1) and (2) are the results of regressing total factor productivity on ESG ratings only without adding control variables, with model R^2 of 0.261 and 0.514, respectively.

Column (1) is the result of the regression without controlling for individual fixed effects and year fixed effects, and the correlation coefficient of the core explanatory variable ESG ratings (ESG) is significant at the 1% level. Column (2) is the regression result controlling for individual fixed effects and year fixed effects, and the coefficient on ESG ratings (ESG) is significant at the 10 percent level, with both columns yielding significantly positive results.

Columns (3) and (4) incorporate firm-level control variables that may affect firms' total factor productivity in the regression, and the model R^2 is 0.748 and 0.759, respectively, which is significantly higher than columns (1) and (2). Column (3) controls for individual fixed effects, and the regression coefficient of the core explanatory variables with total factor productivity is 0.124. Column (4) further controls for individual and year fixed effects, and the regression coefficient of the core explanatory variables with total factor productivity is 0.247, and the coefficients of the core explanatory variables of the two columns are significantly positive, indicating that the publication of firms' ESG ratings can increase firms' total factor productivity . From the regression coefficients of the control variables in column (4) and their significance, it can be seen that the size of the enterprise (Size) is positively correlated with the total factor productivity of the enterprise at the 1% significance level. This is due to the scale effect brought about by the increase in the size of the enterprise, which in turn increases the total factor productivity of the enterprise.

From the perspective of corporate gearing ratio (Lev), the higher the corporate gearing ratio, the higher the level of corporate total factor productivity. The return on equity (ROE) and growth are significantly positively correlated with total factor productivity, indicating that the better the utilization of assets, the stronger the profitability, and the higher the productivity level of the enterprise. The coefficient of the proportion of shares held by the top five shareholders (Top5) is -0.126, which is significantly negatively correlated with total factor productivity, indicating that the higher the concentration of shareholdings, resulting in the aggravation of the principal-agent problem of the controlling shareholders and the management, and weakening the investment in technological innovation, thus inhibiting the total factor productivity of the enterprise. From the perspective of Tobin's Q (TobinQ), as one of the indicators to measure the performance and development ability of enterprises, Tobin's Q will significantly increase the level of total factor productivity of enterprises. There is a positive relationship between the number of directors (Board) and enterprise total factor productivity, indicating that an increase in the size of the board of directors is conducive to increasing the total factor productivity of the enterprise. In terms of the number of years of listing (ListAge), the longer the number of years a firm has been listed, the principal-agent problem between shareholders and executives may prevent the firm from making optimal decisions, and thus productivity decreases compared to previous years.

Table 1. Benchmark regression

Variable	(1)	(2)	(3)	(4)
	tfp_lp	tfp_lp	tfp_lp	tfp_lp
ESG	0.772***	0.377*	0.124***	0.247*
	(35.1224)	(1.7526)	(8.34187)	(1.724)
Size			0.552***	0.567***
			(42.184)	(39.9975)
Lev			0.145***	0.203***
			(3.1242)	(4.0873)
ROE			0.723***	0.651***
			(18.6127)	(18.2642)
Growth			0.174***	0.182***
			(17.0639)	(16.9364)
SOE			0.00820	0.0255
			(0.3579)	(1.0284)
Top5			-0.133**	-0.126*
			(-2.0251)	(-1.8465)
TobinQ			0.0117***	0.0354***
			(3.1742)	(9.2784)
Board			0.0366	0.0415
			(1.1242)	(1.2846)
ListAge			0.114***	-0.0132
			(7.6354)	(-0.6557)
_cons	8.224***	8.008***	-3.729***	-3.527***
	(350.457)	(306.645)	(-13.2679)	(-12.1674)
Individuals	No	Yes	Yes	Yes
Year	No	Yes	No	Yes
N	21000	21000	21000	21000
R^2	0.261	0.514	0.748	0.759

4.1.2. Further analysis. After analyzing that entering the ESG rating has a significant positive effect on firm total factor, this paper further analyzes the relationship between ESG rating performance and firm total factor productivity, and the results are shown in Table 2. Columns (1) and (2) are the results without adding control variables, where column (1) is the result of not controlling for individual fixed effects and year fixed effects, and column (2) is the result of controlling for individual and year fixed effects, and the results are all positive at the 1% significance level, and the model achieves a better goodness-of-fit after adding firm-level control variables in columns (3) and (4), and the model achieves a better goodness-of-fit after adding control variables in column (4) and controlling for individual and year fixed effects, the correlation coefficient of the core explanatory variable ESG rating performance (esg) is 0.0149, which is positive at the 1% significance level, suggesting that firms strengthening ESG concepts, focusing on environmental, social, and corporate aspects of performance, and improving ESG ratings, will contribute to the improvement of total factor productivity.

Table 2. Further analysis

Variable	(1)	(2)	(3)	(4)
	tfp_lp	tfp_lp	tfp_lp	tfp_lp
ESG	0.0648***	0.0374***	0.0163***	0.0149***
	(8.2136)	(6.2575)	(3.5267)	(3.5946)
Size			0.532***	0.522***

			(35.7811)	(32.5528)
Lev			0.192*** (3.9514)	0.257*** (5.1274)
ROE			0.684*** (16.8142)	0.657*** (16.2247)
Growth			0.185*** (17.0425)	0.186*** (17.254)
SOE			0.0168 (0.5557)	0.0196 (0.7014)
TOP5			-0.146** (-2.0475)	-0.241*** (-3.4287)
TobinQ			0.00214 (0.6325)	0.0328*** (8.5416)
Board			0.0587* (1.7045)	0.0664 (1.9842)
ListAge			0.124*** (8.6242)	-0.0214 (-1.0412)
_cons	8.562*** (182.4687)	8.278*** (202.5327)	-3.074*** (-10.0214)	-2.774*** (-8.3152)
Individuals	No	Yes	Yes	Yes
Year	No	Yes	No	Yes
N	17800	17800	17800	17800
R^2	0.009	0.400	0.675	0.694

4.2. Analysis of spatial heterogeneity

4.2.1. Cluster evaluation analysis. High-quality economic development is a complex social problem, which is promoted by the integrated efforts of five major concepts, which interact with each other. The main purpose of this study is to rank and classify the economic high-quality development of 26 central cities so as to provide some reference for analyzing the spatial heterogeneity of ESG ratings and enterprise total factor productivity.

This study uses the principal component clustering model, so the object of clustering is not the original data but the principal component data after processing by principal component analysis, i.e., the original data of each city is brought into the above formula, and the results are obtained as shown in Table 3. The steps of using SPSS to perform data standardization are as follows: analysis - description statistics - description, select the 10 variables in this paper into the "variables" dialog box, and check "save the normalized values as variables", which is the standard data converted from the original data in this study.

Table 3. Descriptive statistics

	N	Min	Max	Mean	SD
ESG	20	0.835	3.751	2.322	0.728
Size	20	2.354	47.966	17.842	12.635
Lev	20	3.045	25.048	14.022	5.926
ROE	20	82.836	99.98	93.814	4.251
Growth	20	66.214	93.245	74.896	7.879
SOE	20	91.428	99.433	94.175	2.172
TOP5	20	0.482	138.082	13.422	30.172

TobinQ	20	6.623	127.042	40.711	32.876
Board	20	0.058	5.897	0.745	1.162
ListAge	20	0.059	91.247	20.745	25.336

Performing principal component analysis automatically normalizes the raw data, so you can run the software by directly inputting the raw data. The specific steps are:

1) Enter the data and select Analyze - Dimensionality Reduction - Factor Analysis.

2) Select the 10 indicators into the variable box.

3) Check the initial solution, KMO and Bartlett's test of sphericity, correlation matrix, unrotated factor solution, gravel plot, based on the eigenvalue greater than 1, maximum variance method, rotated solution, display factor score coefficient matrix, and other settings, click OK to execute the program. Thus this set of experimental data can be analyzed for principal component analysis. Then observe the total variance explained as shown in Table 4.

In the table, five principal components with eigenvalues greater than 1 were extracted and the cumulative contribution reached 84.543% > 80%, pointing out that the cumulative explained variance extracted in the field of social sciences reaches more than 60% indicating that the common factors are reliable, so this set of data can be subjected to principal component analysis. As can be seen from the table, the first principal component has an eigenvalue of 6.072 and a variance contribution of 37.124%, which makes it the most important principal component. The eigenvalues of the second, third, fourth and fifth principal components are all greater than 1 but decreasing in importance in that order. The five principal components contain most of the information about the economic development of the 26 cities, so the reduced five principal components can be used instead of the original 10 indicators to analyze the quality of economic development.

Table 4. Observe the total variance interpretation table

Constituent	Initial eigenvalue			Extracting the load of the load		
	Total	Percentage of variance	Cumulative %	Total	Percentage of variance	Cumulative %
1	6.072	37.124	37.124	6.072	37.124	37.124
2	2.684	16.845	53.969	2.684	16.845	53.969
3	2.031	12.428	66.397	2.031	12.428	66.397
4	1.365	9.519	75.916	1.365	9.519	75.916
5	1.223	8.627	84.543	1.223	8.627	84.543
6	0.714	5.428				
7	0.611	4.587				
8	0.346	2.135				
9	0.289	1.562				
10	0.252	1.745				

In this study, the principal component clustering model was used, so the clustering was not for the original data but for the principal component data after the principal component analysis process, and the results were obtained as shown in Table 5.

Table 5. The cities correspond to main components

	1	2	3	4	5
Shanghai	1211.267	1177.92	76.921	-109.212	585.677
Nanjing	801.84	775.897	54.574	-42.584	379.038
Wuxi	720.087	705.156	49.459	-40.463	343.582
Changzhou	611.494	608.697	38.88	-24.206	285.755
Suzhou	841.816	832.87	65.579	-63.511	416.312
Nantong	671.499	676.633	45.321	-36.831	322.547
Yancheng	563.599	584.428	33.687	-28.121	273.878
Yangzhou	592.136	597.554	36.183	-29.062	280.716
Zhengjiang	694.61	688.109	40.819	-35.874	334.166
Taizhou	514.76	527.97	31.335	-19.819	246.614
Hangzhou	970.837	966.17	98.386	-67.929	442.267
Lingbo	925.431	942.79	86.62	-81.837	425.997
Jiaxing	752.651	784.862	89.801	-60.488	331.458
Huzhou	670.687	697.236	77.983	-38.835	276.653
Shaoxing	769.047	778.271	52.479	-56.624	375.705
Jinghua	606.392	631.025	40.235	-37.921	307.5
Zhoushan	840.9	851.073	50.478	-68.56	422.475
Tongzhou	587.217	613.221	34.95	-32.184	294.737
Hefei	542.595	550.43	44.972	-15.945	264.711
Wuhu	529.808	539.829	37.802	-20.009	258.948
Maanshan	456.616	471.372	42.234	-9.147	229.939
Tongling	532.058	574.62	78.377	-92.048	319.257
Anqing	380.626	421.516	29.026	-5.848	194.003
Xuancheng	445.199	496.525	56.157	-31.51	254.154
Chizhou	414.041	472.113	48.335	-16.766	233.475
Chuzhou	422.657	462.632	52.794	-28.985	230.641

Observing the PCA-K-means clustering results, the specific clustering results are shown in Figure 1. In terms of the provinces, Shanghai alone belongs to the first category. Suzhou in Jiangsu is located in the second category, Nanjing, Wuxi, Nantong, Zhenjiang and Changzhou belong to the third category, while the remaining Yancheng, Yangzhou and Taizhou belong to the fourth category. Zhejiang's Hangzhou, Ningbo and Zhoushan are in the second category, Jiaxing, Huzhou, Shaoxing and Jinhua are in the third category, while the remaining Taizhou is in the fourth category. The eight cities in Anhui Province, Hefei, Wuhu, Maanshan, Tongling, Anqing, Xuancheng, Chizhou, and Chuzhou, all belong to the fourth category. Comparison of the city principal components of the integrated score rankings can be found in the rankings of the first is the first category in the cluster analysis, ranked 2-5 is the second category in the cluster analysis, ranked 6-14 is the third category in the cluster analysis, ranked 15-26 is the fourth category in the cluster analysis, the two sides of the results obtained are completely consistent.

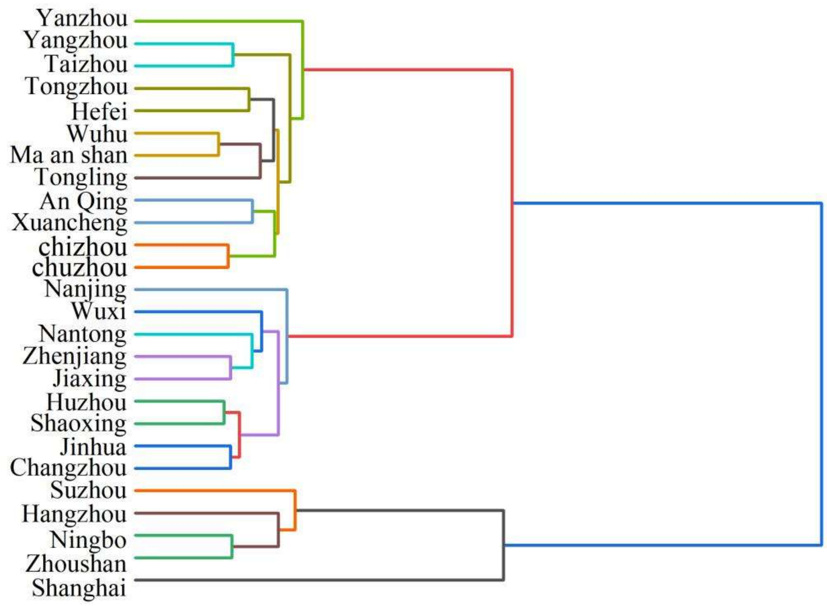

Fig. 1. Cluster result

In addition, the GDP growth rate of 26 cities is summarized as shown in Figure 2, from which it can be found that Anhui is in the leading position and Shanghai is in the lagging position in the average GDP growth rate of 26 cities, which shows that the economic development speed is not positively related to the ESG ratings of enterprises.

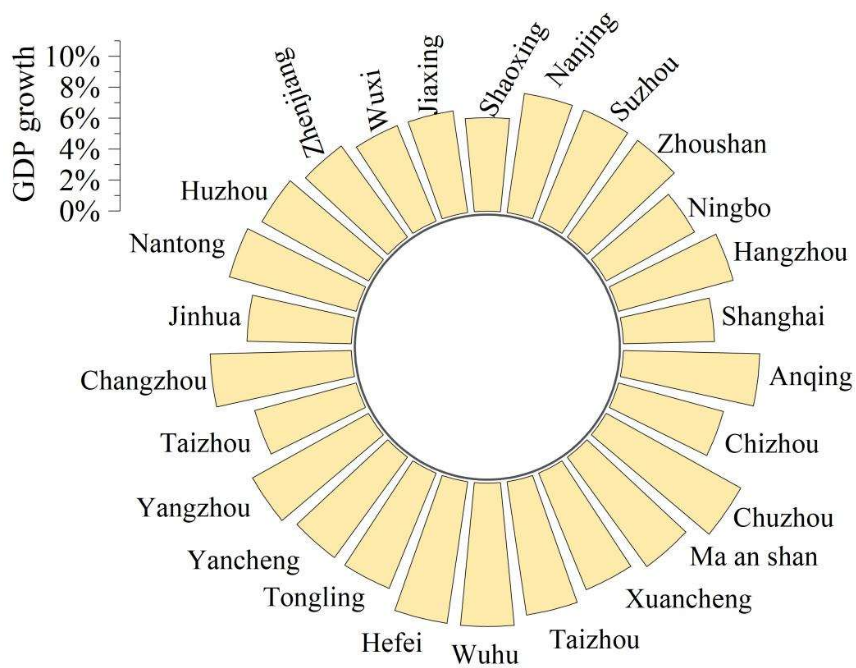

Fig. 2. GDP growth

4.2.2. Heterogeneous results across firm regions. The regional division of East, Central and West is shown in Figure 3. Due to the existence of disparities in factor resources and economic development levels in different provinces, the possible differences in the impact of ESG rating performance on corporate total factor productivity were analyzed for heterogeneity. Among them, the eastern region contains Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan, the central region contains Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan, and the western region contains Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Ningxia, Qinghai, Xinjiang, and Chongqing.

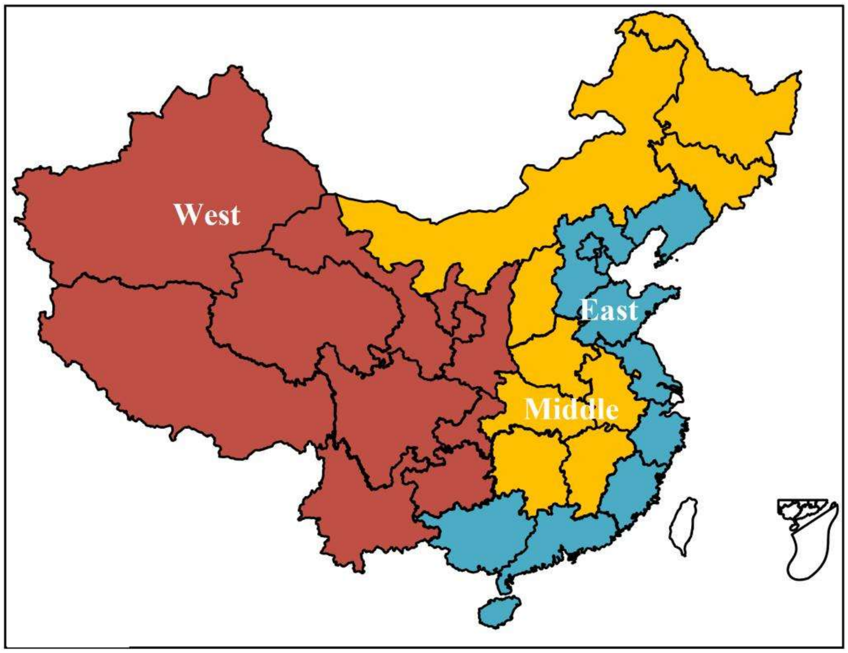

Fig. 3. The division of the central and western regions

The central and western regions are relatively backward in terms of economic development, knowledge and technology compared to the eastern region, and the related study divides the enterprises into east, center and west for regression. The results are shown in Table 6, column (1), column (2) and column (3) results indicate that the ESG rating performance of enterprises in the East, Central and West regions can significantly and positively promote the total factor productivity of enterprises. In addition the results also show that the correlation coefficients of the core explanatory variables of ESG rating performance for firms in the central and western regions are 0.0163 and 0.0275, respectively, which are larger than the correlation coefficients of 0.0132 in the eastern region, suggesting that ESG rating performance has a greater impact on firms in the central and western regions.

Table 6. Heterogeneity in different enterprise regions

	(1)	(2)	(3)
Variable	East	Middle	West
ESG	0.0132** (2.4572)	0.0163* (1.8354)	0.0275** (2.1647)
_cons	-2.914*** (-6.8475)	-2.833*** (-4.6278)	-1.549 (-1.6354)
Control variable	Yes	Yes	Yes
Individuals	Yes	Yes	Yes
Year	Yes	Yes	Yes
N	12250	3250	5500
R^2	0.711	0.711	0.647

A total of 20 indicators were clustered and analyzed using Python for a total of 2082 counties in the country in 2024, and the classification scatter plot is shown in Fig. 4, which ultimately yielded four categories, namely resource-dependent cities, non-resource-dependent cities, old industrial bases, and non-old industrial bases.

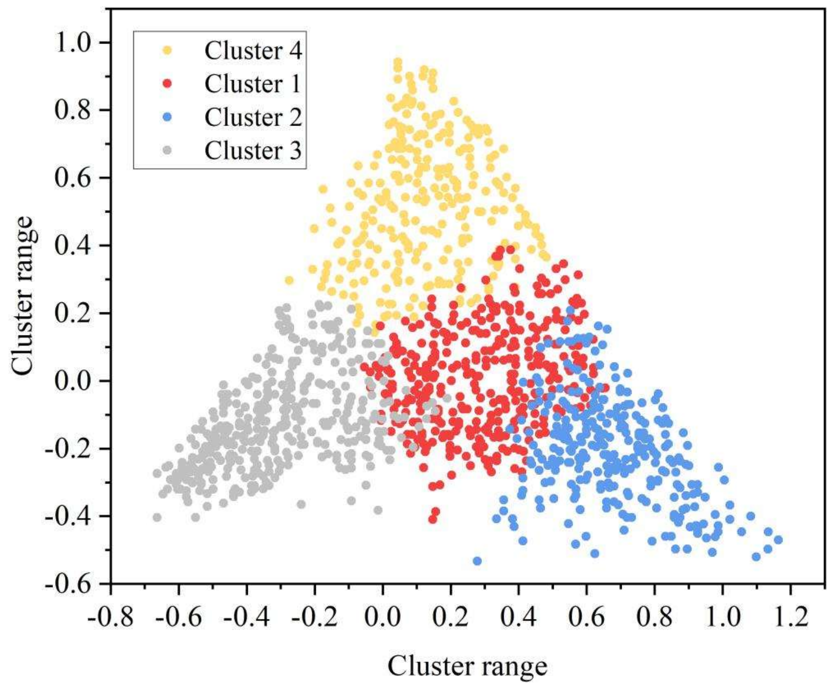

Fig. 4. Classification scatter diagram

This study is based on the National List of Resource-Dependent Cities (2013) and the National Old Industrial Base Adjustment and Transformation Plan (2013-2022) issued by the State Council, and this paper divides the sample into enterprises belonging to resource-dependent cities and non-resource-dependent cities, as well as enterprises belonging to old industrial bases and those not belonging to old industrial bases, and consequently conducts a heterogeneity test. The specific results are shown in Table 7.

ESG rating performance significantly promotes the total factor productivity development of enterprises in non-resource-dependent cities and non-old industrial bases. Because ESG itself is a market-oriented tool, it can only play a full role in areas with a high degree of marketization, while the transformation of resource-dependent cities and old industrial bases is not thorough enough, and the local business environment and development methods are not market-oriented enough, which makes the effect of ESG rating performance not significant.

Table 7. Heterogeneity test

	(1)	(2)	(3)	(4)
	Resource -dependent cities	Non-resource -dependent city	Old industrial base	Non-old industrial base
ESG	0.016 (1.32)	0.012** (2.26)	0.008 (0.72)	0.013** (2.28)
ROE	0.322*** (8.63)	0.322*** (13.78)	0.242*** (5.87)	0.335*** (14.37)
ListAge	0.012 (0.63)	-0.006 (-0.64)	0.015 (1.06)	-0.006 (-0.69)
Size	0.058*** (9.58)	0.064*** (28.89)	0.058*** (17.69)	0.063*** (28.54)
Tobinq	-0.007* (-1.82)	-0.003* (-1.75)	-0.004 (-0.78)	-0.005** (-2.37)
Lev	0.064*** (3.25)	0.095*** (7.48)	0.048 (1.54)	0.088*** (7.94)
Top5	0.022 (1.28)	0.012** (2.24)	0.020** (2.23)	0.009* (1.75)
Board	0.132 (1.18)	0.054 (1.35)	0.463*** (3.14)	0.048 (0.98)
SOE	0.002 (0.08)	-0.007* (-2.34)	-0.002 (-0.24)	-0.005 (-1.48)
Constant	1.967*** (19.95)	2.008*** (94.96)	1.985*** (27.85)	2.004*** (82.74)
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Observed value	986	6625	1078	6579
R-squared	0.814	0.807	0.647	0.812

5. Conclusion

This paper focuses on exploring the impact of spatial heterogeneity of ESG ratings on firms' total factor productivity using the improved K-means algorithm-PCA-K-means with a fixed-effects model to explore the relationship between ESG ratings performance and total factor productivity level ESG ratings on firms' total factor productivity. The results of the study show that:

1) ESG ratings are positively correlated with firms' total factor productivity at 1% and 10% significance levels.

2) Dividing the 26 cities into different categories, there is no positive relationship between regions with fast economic development and ESG ratings of enterprises. It indicates that the impact of ESG ratings on the total factor productivity of enterprises may also differ between different provinces and regions due to the existence of disparities in factor resources and economic development levels.

3) The analysis of spatial heterogeneity shows that the effect of ESG ratings on enterprises in the central and western regions is more significant. The effect of ESG ratings on enterprises in resource-dependent cities and old industrial bases is not effective.

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