Operational Research in Engineering Sciences: Theory and Applications
Vol. 7, Issue 1, 2024, pp. 219-237
ISSN: 2620-1607
eISSN: 2620-1747
DOI: https://doi.org/10.31181/oresta/070111

BRIDGING RISKS AND OPPORTUNITIES: OPERATIONAL STRATEGIES FOR SUSTAINABLE GROWTH VIA ESG MANAGEMENT

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Received: 14 November 2023
Accepted: 22 March 2024
First Online: 30 March 2024

Research Paper

Abstract: *As a vital component of our nation's economic landscape, enterprises bear a weighty responsibility in advancing the trajectory of high-calibre sustainable growth. However, presently, listed enterprises often harbour risk factors such as neglecting environmental concerns, failing to fulfil social responsibilities, and possessing imperfect corporate governance mechanisms, all of which imperil the sustainability of enterprises. This paper selects coal enterprises as a case study subject to scrutinize the practical implementation of a system. Initially, the necessity of system construction is scrutinized through literature review and theoretical underpinnings. Subsequently, the paper delves into the Environmental, Social, and Governance (ESG) performance and sustainable development within the coal-heavy industry. ESG, as an evolving framework aligned with climate-conscious initiatives, serves as a robust foundation for actualizing the principles of green development and fostering the comprehensive framework of ecological civilization construction. Finally, employing four evaluation methodologies via Abaqus software, the study concludes that an evaluation system centred on ESG perspectives proves to be more precise and dependable compared to previous models. This comprehensive validation underscores the imperative and viability of erecting a sustainable development evaluation system grounded in ESG principles. Furthermore, fortifying environmental regulations stands poised to enhance the market concentration of high-quality enterprises, propel industrial advancement, and mitigate environmental degradation.*

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Keywords: *ESG, Coal Enterprises, Sustainable Development, Malmquist Model, Threshold Model*

1. Introduction

With the increasing emphasis on ESG factors in the international economic market, research on the sustainable development of enterprises has adopted a new perspective. The Corporate Sustainability Reporting Directive (CSRD), issued on January 20, 2022, mandates that EU companies disclose their organizational management, governance mechanisms, and effectiveness in relation to sustainable development. This directive underscores the necessity of prioritizing sustainable development at the corporate governance level and integrating sustainability issues into corporate governance systems. However, the current triple performance evaluation system often overlooks the critical role of corporate governance in achieving sustainable development.

The sustainable development capacity of companies refers to their ability to continuously enhance productivity, optimize industrial structures, adapt to market environments, and sustain steady growth in future market expansions while achieving economic profitability (Tsang et al., 2023).

The sustainable development capability of enterprises is influenced by several key factors, including internal management, stakeholders, and the social environment (Avramov et al., 2022). Internal factors encompass strategic objectives, management styles, and resource combinations, while the social environment includes industry development, policy frameworks, community demographics, natural resources, and the ecological environment. Relevant stakeholders encompass investors, government entities, supply chain partners, employees, and consumers. The sustainable development of enterprises relies on these factors to create conducive conditions, and, reciprocally, the sustainable growth of enterprises promotes the coordinated development of these factors.

The classification of factors affecting sustainable development capacity includes economic, technological, and human resources (Apergis et al., 2022). Human resources are pivotal as they process and integrate other factors, serving as the implementers and intellectual drivers of technological innovation. Human resources represent the most creative resource factor, and technological innovation is crucial for maintaining competitive advantages and achieving sustainable development. This underscores the essential role of human resources in the sustainable growth of enterprises (Barros et al., 2022).

The coal chemical industry is highly representative within China's industrial system, closely tied to the country's industrialization and various government policies (Shin et al., 2023). Recent government initiatives, including industrial support and environmental protection policies, have significantly impacted the coal chemical industry, providing a framework for analysing the effects of different policies. Utilizing panel data from 26 coal firms between 2016 and 2021, this study establishes an evaluation system for the operational efficiency of coal companies from an ESG perspective. The study incorporates environmental influences and random disturbances in the analysis.

The Malmquist model is employed to assess the operational efficiency of these 26 coal enterprises in both static and dynamic dimensions. Following this, the impact of ESG performance on the operational efficiency of listed coal companies is examined, considering whether this effect is nonlinear under varying financing constraints. The panel threshold method is used to explore the effects of these financing constraints on ESG performance and operational efficiency.

2. Literature Review

In recent years, with the increasing focus on ESG factors, scholars have conducted a series of studies on ESG (Wen et al., 2022). Several researchers have explored the relationship between ESG and corporate efficiency. For instance, an analysis of 2,200 papers on ESG and financial performance revealed that approximately 90% of the studies found a non-negative relationship between ESG and financial performance (Friede et al., 2015). Matos (2020), using data from listed companies in 15 European countries between 2002 and 2011, concluded that good ESG performance is an intangible asset that can drive income growth for companies. Additionally, Halbritter and Dorfleitner (2015) found that a company's strong social and environmental responsibility performance can enhance its economic efficiency.

Cheng et al. (2014) focused on China's listed power generation companies, employing a developed ESG performance evaluation model to quantify data and constructing a panel regression model of ESG and return on capital employed (ROCE). Their findings indicated that superior ESG performance in power companies positively impacts financial performance. Furthermore, Anthony and Howard (1976) conducted an empirical study on 3,276 A-share listed companies and discovered that better ESG responsibility performance leads to increased investor holdings and higher excess returns for the enterprises.

Scholars have delved into the link between social responsibility and enterprise sustainability. Li et al. (2021) suggest that embedding social responsibility in corporate culture spurs innovation, boosts profits, and advances social development. Clément et al. (2023) find that CSR achievement and technological innovation synergize, offering competitive advantages and fostering sustainable development. Fang et al. (2023) conducted an empirical study on heavily polluting firms in Shanghai and Shenzhen. They discovered a notable positive association between the quality of social responsibility information disclosure and the sustainable development capability of these enterprises. Seo et al. (2024) highlighted that ESG reports, which incorporate both qualitative and quantitative indicators, can effectively measure and assess the strength of their implementation. Consequently, constructing a sustainable development performance evaluation system based on the ESG concept addresses the deficiency of quantitative indicators and provides a new perspective for evaluating sustainable development performance.

3. The Basic Situation of ESG Performance and Sustainable Development Ability of Enterprises in Heavy Polluting Industries

ESG, an abbreviation for Environmental, Social, and Governance, represents a concept that extends beyond green investment, encompassing the non-financial development of enterprises and serving as a comprehensive index for evaluating their operations (Shaikh, 2022). Currently, there is no unified authoritative definition of ESG in China, leading each organization and institution to define it from their own perspectives. The specific meanings of each component in ESG vary (Bhandari et al., 2022). This paper refers to the "Research Report on ESG Evaluation System of Chinese Listed Companies" for its definition of ESG. Here, "Environmental" (E) denotes the investment and effectiveness of enterprises in ecological aspects, emphasizing the protection of the environment and the reduction of negative impacts. "Social" (S) implies that enterprises should fulfil social responsibilities and contribute to society by actively adapting to and maintaining the economic and social environment, and being accountable to the community, the public, local government, employees, investors, and other stakeholders. "Governance" (G) pertains to corporate governance, where enterprises must focus on efficient internal governance, including the establishment of a robust management structure, a conducive internal management environment, and effective operational processes. Current research on ESG primarily concentrates on three areas: ESG scoring, ESG information disclosure, and ESG investment (Lee et al., 2022).

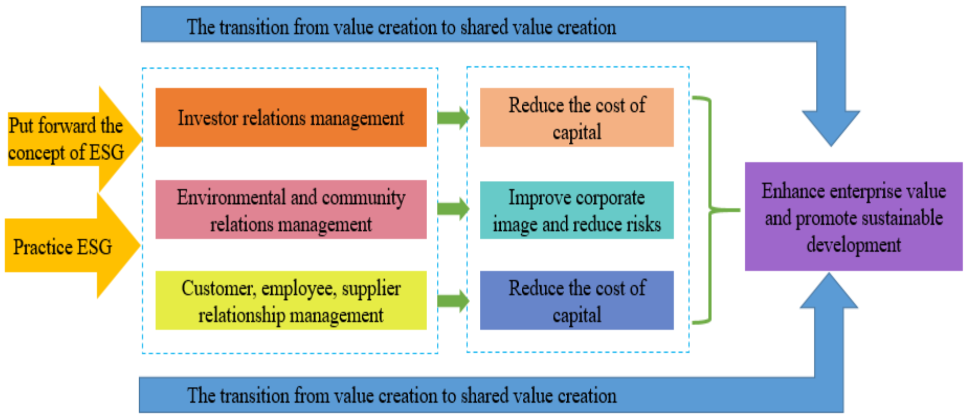


Figure 1. Stakeholders Promote Sustainable Anti-War Mechanism.

Sustainable development from the perspective of ESG entails the pursuit of high-quality and enduring growth by integrating environmental stewardship, social responsibility, and effective corporate governance (Khan, 2022), as depicted in Figure 1. To achieve this, enterprises must align with the principles of sustainable development and fully incorporate ESG concepts into their management practices. This approach ensures not only the preservation of economic stability and consistent profitability (Shanaev & Ghimire, 2022) but also enhances the enterprise's environmental performance, actively fulfils social responsibilities, and optimizes corporate governance structures (Cornell, 2021). For enterprises to attain sustainable development, attention must be given to both financial and non-financial performance. Sustainable development capacity can be enhanced only when economic performance is balanced with environmental and social governance considerations (Luo, 2022).

Bloomberg employs 44 ESG analysts covering 11,500 companies Li et al. (2023), providing clients with environmental, social, and governance metrics. It offers objective ESG data through sources like corporate accountability reports, annual reports, ESG news reports, and corporate governance reports. This study uses Bloomberg's ESG ratings to assess the ESG performance of companies in China's heavy pollution industries. Table 1 shows the ESG performance ratings of Chinese companies in heavy polluting industries from 2010 to 2019.

Table 1: ESG Performance of Enterprises in Heavy Polluting Industries from 2010 to 2019 (Source: Bloomberg Database)

Year	Mean Value	Mid-Value	Maximum Value	Minimum Value
2010	15.68	14.88	33.06	7.85
2011	15.96	14.88	33.47	7.85
2012	18.09	19.42	40.50	7.85
2013	19.55	19.83	40.91	8.68
2014	20.10	20.25	42.98	8.68
2015	20.50	20.25	45.45	8.68
2016	21.23	20.66	50.00	9.50
2017	22.18	21.28	54.55	11.57
2018	23.31	21.90	55.79	11.98
2019	24.09	23.14	55.79	11.98

Table 1 shows that the highest and lowest ESG performance ratings of companies in heavily polluting industries are 55.79 and 7.85, respectively, indicating a significant disparity in ESG performance. This suggests a wide variation in ESG responsibility awareness among managers. Comparing the median and average scores reveals that the median ESG performance rating from 2012 to 2019 is consistently lower than the average, indicating generally poor ESG performance in these industries. Although the annual average ESG performance has improved year by year, it remains at a low level overall, highlighting substantial room for improvement.

3.1 Preliminary Discussion on the Relationship between ESG Performance and Sustainable Development Ability of Enterprises in Heavily Polluting Industries

Drawing upon the correlation between ESG average overall performance and sustainable development capacity (Broadstock et al., 2021), this study further examines pertinent data concerning ESG performance ratings and sustainable development capacity within heavily polluting industries among A-share listed companies over the past three years. Dot plots and trend charts depicting the ESG performance and sustainable development capacity of various enterprises in each year are constructed to ascertain the alignment of their respective trends. Figure 2 displays the dot plot and trend chart illustrating the ESG performance of A-share listed companies for the years 2017 to 2019, respectively.

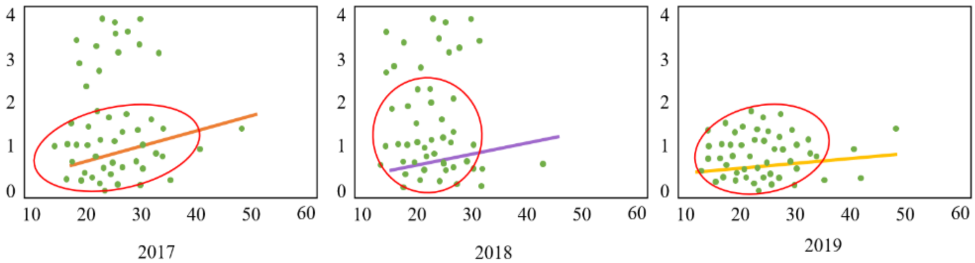


Figure 2. Dot Plot and Trend Chart of ESG Performance and Sustainability

Figure 2 reveals a notable correlation between the sustainable development potential of companies within heavily polluted industries among A-share listed corporations and their corresponding ESG performance levels in the same year. Specifically, higher ESG ratings are associated with elevated levels of sustainable development potential among enterprises. This preliminary observation suggests a strong correlation between robust ESG performance and the potential for sustainable improvement among companies operating within China's heavily polluted industries.

3.2 Evaluation Method

3.2.1 Malmquist Index Model

The Malmquist index method serves as a tool for gauging the dynamic shifts in productivity (TFPst) from period s to period t, with the results dissected into technical progress, technical efficiency, pure technical efficiency, and scale efficiency (Shu & Tan, 2023). This index not only depicts the total change across all Decision Making Units (DMUs) annually but also captures the individual change within each DMU for each year. Here, (Xs,Ys) denotes the input-output quantities in period s, while (Xt, Yt) represents those in period t. D0s(Xs,Ys) signifies the distance function of the input-output vector based on the technology in period s, whereas D0t(Xt,Yt) denotes the distance function relative to the technology of period t. Furthermore, M0s(Xs,Ys,Xt,Yt) and M0t(Xs,Ys,Xt,Yt) symbolize the Malmquist productivity index of the output angle in periods s and t, respectively.

To address potential discrepancies in evaluation results stemming from arbitrary period selections, where M0s(Xs,Ys,Xt,Yt)≠M0t(Xs,Ys,Xt,Yt), the geometric mean of Malmquist productivity indices from two different periods is employed as the

$$
\begin{aligned}
TFP_{st} &= M_0(X_s,Y_s,X_t,Y_t) = [M_0^s(X_s,Y_s,X_t,Y_t) * M_0^t(X_s,Y_s,X_t,Y_t)]^{\frac{1}{2}} \\
&= \left[\frac{D_0^s(X_t,Y_t)}{D_0^s(X_s,Y_s)} * \frac{D_0^t(X_t,Y_t)}{D_0^t(X_s,Y_s)}\right]^{\frac{1}{2}} = \frac{D_0^t(X_t,Y_t)}{D_0^s(X_s,Y_s)} * \left[\frac{D_0^s(X_t,Y_t)}{D_0^t(X_t,Y_t)} * \frac{D_0^s(X_s,Y_s)}{D_0^t(X_s,Y_s)}\right]^{\frac{1}{2}} \\
Ech &= \frac{D_0^t(X_t,Y_t)}{D_0^s(X_s,Y_s)} \\
Tch &= \left[\frac{D_0^s(X_t,Y_t)}{D_0^t(X_t,Y_t)} * \frac{D_0^s(X_s,Y_s)}{D_0^t(X_s,Y_s)}\right]^{\frac{1}{2}}
\end{aligned}
\qquad (1)
$$

Malmquist productivity index. In equation (6), Ech represents technical efficiency, while Tch denotes technological progress (1).

3.2.2 Threshold Model

Panel threshold estimation is employed to investigate the threshold effect, acknowledging the nonlinear relationship among variables. In threshold regression, variations in threshold variables above and below a critical value yield differential impacts on the explained variable. The pivotal aspect is the threshold cost of the threshold variable (Raghunandan & Rajgopal, 2022). A fundamental characteristic of the threshold model is its piecewise function, which segments sample observations based on the threshold value. Specifically, when the threshold variable q ≤ γ, the influence coefficient is β, whereas when q > γ, the influence coefficient is B2. The model can be expressed as follows:

The panel threshold model can be incorporated into a comprehensive formula,

$$\begin{cases} y_{it} = \mu_{it} + \beta_1' x_{it} + \theta X_{it} + \varepsilon_{it}, q_{it} \leq \gamma \\ y_{it} = \mu_{it} + \beta_2' x_{it} + \theta X_{it} + \varepsilon_{it}, q_{it} > \gamma \end{cases} \quad (2)$$

which captures the nuanced interactions among variables and thresholds within a panel dataset.

$$y_{it} = \mu_{it} + \beta_1' x_{it} I(q_{it} \leq \gamma) + \beta_2' x_{it} I(q_{it} > \gamma) + \theta X_{it} + \varepsilon_{it} \quad (3)$$

In equation (3), qi represents the threshold variable, y signifies the explained variable, x denotes the explanatory variable, specifically the threshold-dependent variable, and X stands for the control variable. The parameter r denotes the unknown threshold, while αi represents the individual intercept term, and εi is the random disturbance term. Additionally, I (·) represents the indicator function, where I equals 1 when the conditions within parentheses are satisfied; otherwise, I equals 0.

3.2.3 Standardized Data by Extreme Value Method

Based on the indicator selection outcomes outlined above, a mixture of financial and non-financial indicators, as well as positive and negative indicators, are identified (Baker et al., 2022). Given the divergent nature of these indicators, direct data

$$ij' = \begin{cases} \frac{Xij - Xmin}{Xmax - Xmin}, & X \ is \ positive \\ \frac{Xmax - Xij}{Xmax - Xmin}, & X \ is \ negative \end{cases} \quad (4)$$

comparison becomes challenging, necessitating data standardization to enhance comparability. The min-max standardization approach is employed to scale the selected data within the range of (0, 1). The standardization process unfolds as follows:

Following standardization, it's possible for the data to assume a value of 0. To mitigate the occurrence of meaningless data, the standardized data undergoes translation, with an adjustment amount of 0.0001 applied to minimize errors, expressed as X'' = X' + 0.0001.

The mutation series method, as an evaluation approach, entails hierarchical decomposition of data while considering their relative importance. This method employs normalization and comprehensive analysis to assess the target object. The primary steps encompass: firstly, identifying the applicable mutation model type for the index; secondly, determining the normalization formula based on the number of indicators; and finally, utilizing the normalization formula to compute results and conduct comprehensive analysis.

Depending on the specific hierarchical structure of the index, different mutation series models are deemed appropriate (Billio et al., 2021), as delineated in Table 2. The folding mutation model is applicable when an indicator comprises one sub-indicator, while the cusp mutation model is employed when an indicator consists of two sub-indicators, and so forth. The normalization formula for up to four sub-indicators is provided. Upon computing the evaluation outcomes of indicators utilizing the aforementioned normalization formula, distinct values are selected based on the independence or complementarity of indicators. The minimum value among independent indicators is designated as the outcome, while the average value of complementary indicators is utilized. Subsequent analysis and assessment of enterprise performance ensue.

Table 2: Commonly Utilized Mutation System Models and Normalization Formulas

Mutant system type	Abrupt system model	Normalization formula
Folding mutation model	$f(x) = x^3 + ax$	$x_a = a^{1/2}$
Cusp mutation model	$f(x) = x^4 + ax^2 + bx$	$x_a = a^{1/2}, x_b = b^{1/3}$
Dovetail mutation model	$f(x) = \frac{1}{5}x^5 + \frac{1}{3}ax^3 + \frac{1}{2}bx^2 + cx$	$x_a = a^{1/2}, x_s = b^{1/3}, x_e = c^{1/4}$
Butterfly mutation model	$f(x) = \frac{1}{6}x^6 + \frac{1}{4}ax^4 + \frac{1}{3}bx^3 + \frac{1}{2}cx^2 + dx$	$x_a = a^{1/2}, x_s = b^{1/3}, x_e = c^{1/4}$ $x_l = d^{1/5}$

The three tiers of selected indicators interact synergistically to establish the evaluation criteria for the two tiers of indicators. Likewise, the two tiers of indicators combine to establish the evaluation criteria for the first tier of indicators. Consequently, the average value of the mutation series data derived from the three tiers of indicators and the two tiers of indicators is adopted as the evaluation outcome. Environmental performance, social accountability overall performance, and company governance overall performance are independent of each other and collectively constitute the comprehensive performance assessment framework for enterprises.

4. Empirical Study of ESG Performance on the Operational Efficiency Measurement of Listed Coal Companies

4.1 Dynamic Evaluation of Operational Efficiency Based on the Malmquist Index Model

The Malmquist model is applied to analyse the operational efficiency of listed coal companies dynamically. To ensure objectivity and accuracy, input index values and original output values are selected after eliminating environmental factors and random errors for calculation. The Malmquist index evaluates the total factor productivity of 26 listed coal companies from 2016 to 2021, enabling longitudinal comparison and understanding of industry-wide development and changes. Results are presented in Table 3.

Table 3: Overall Total Factor Productivity and its Decomposition of Listed Coal Companies

Year	Technical Efficiency Change Index	Technological Progress Change Index	Pure Technical Efficiency Change Index	Scale Efficiency Change Index	Total Factor Productivity Change Index
2016-2017	1.011	1.145	1	1.011	1.157
2017-2018	1.09	1.065	0.994	1.097	1.161
2018-2019	1.031	0.99	0.996	1.035	1.02
2019-2020	0.968	0.984	1.013	0.955	0.952
2020-2021	1.195	1.02	0.975	1.225	1.219
Mean value	1.056	1.039	0.996	1.061	1.097

Between 2016 and 2017, the operating efficiency of 26 listed coal companies recorded a value of 1.157, marking a 15.7% increase primarily attributed to enhancements in the technological progress change index and scale efficiency change index. This suggests that these companies have largely achieved a harmonized integration of enterprise resource allocation and production factors, thereby unlocking the potential of advanced technology. Each company's internal resource allocation has begun to take shape, fostering a cluster effect that propels technical efficiency into an effective state. Furthermore, the positive growth in the technological progress efficiency change index indicates the emergence of a development paradigm guided by scientific and technological innovation, capable of effectively leveraging research achievements and expanding industrial scale.

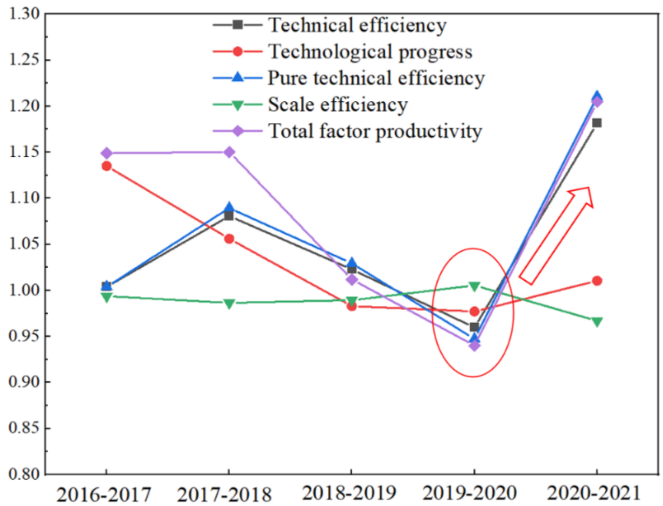
From 2017 to 2018, the operating efficiency of listed coal companies witnessed marginal change, registering a mere 0.35% increase compared to the previous year's total factor productivity change index. This slight uptick was predominantly influenced by a 7% decline in the technological progress change index and a reduction in both technical efficiency and pure technical efficiency. Despite a notable 8.5% increase in scale efficiency from the preceding year, the overall operating efficiency remained relatively stable due to offsetting factors.

Between 2018 and 2019, despite a reduction in the growth rate of total factor productivity among 26 listed coal companies, it continued to trend upward. With the exception of the scale efficiency change index, both the pure technical efficiency change index and the technological progress change index were below 1, suggesting that all enterprises managed to leverage their prior developmental experiences during this period. A significant aggregation of resources and prudent allocation of factors within the company facilitated sophisticated production processes. However, inadequate application of science and technology in practical settings led to overlooked technological progress efficiency across various input resources, resulting in incomplete transformation of technological advantages and a modest increase in the total factor productivity change index.

From 2019 to 2020, despite a 1.3 percentage point increase in the pure technical efficiency change index, overall technical efficiency, scale efficiency, and technological progress change index all exhibited a downward trajectory. Consequently, the overall operating efficiency value decreased by 6.67% compared to the preceding year, indicating a degree of imbalance in resource allocation within coal enterprises, diminished capacity for technology-driven advancements, and compromised business efficiency.

Between 2020 and 2021, the operating efficiency value of listed coal companies reached 1.219, the highest value observed within the study period, primarily attributable to a remarkable 28.27% surge in scale efficiency compared to the previous year. Thus, despite a partial reduction in the pure technical efficiency variable index, the exceptional scale efficiency contributed to overall technical efficiency enhancement. Leveraging long-term investments in scientific research and technological transformation, enterprises effectively applied technological progress to daily production practices and management, thereby bolstering operational efficiency.

Figure 3: Total Factor Productivity Changes of Listed Coal Companies from 2016 to



2021.

In synopsis, post the elimination of environmental factors and random errors, the aggregate measure of the total factor productivity across 26 listed coal enterprises from 2016 to 2021 stood at 1.097, reflecting a 9.7% augmentation. On average, the change index of firm technical efficiency increased by 5.6%, wherein the variation in pure technical efficiency registered at 0.996, marking a slight decrease of 0.4%. The change index of scale efficiency experienced a notable upsurge of 6.1 percentage points, reaching 1.061, while the technological progress change index averaged at 1.039, representing a 3.9% expansion. It is evident that the enhancement of total factor productivity among listed coal companies predominantly hinges on improvements in scale efficiency and technological progress. The change index of pure technical efficiency remains largely proximate to 1, indicating that alterations in the technical efficiency change index of coal enterprises are primarily dictated by variations in the scale efficiency index. As depicted in the figure above, the change indices of firm total factor productivity, technical efficiency, technological progress, and scale efficiency exhibit significant fluctuations, whereas the oscillations in pure technical efficiency are relatively subdued. The variability in the firm technical efficiency change index closely aligns with that of the scale efficiency change index.

The Malmquist index model is deployed to evaluate the total factor productivity of 26 listed coal entities from 2016 to 2021, facilitating cross-sectional comparison of these enterprises. The steadiness of coal industry development is gauged by contrasting the change indices of total factor productivity across individual coal firms. The outcomes are delineated in Table 5.

To gain a more direct insight into the actual progress of operating efficiency within each listed coal company, the total factor productivity change index (TFP) serves as the evaluative criterion. Relative to the aggregate mean, listed coal enterprises are categorized into four groups: robust development (TFP > 1.2), developmental (1.1 ≤ TFP < 1.2), stable (1 ≤ TFP < 1.1), and declining (TFP < 1), as delineated in Table 4.

Table 4: Classification of Development Types for 26 Listed Coal Companies from 2016 to 2021

Development Type	Index Basis	Quantity	Company Name
Strong Developmental	TFP≥1.2	1	Huaibei Mining
Developmental	1.1≤TFP<1.2	9	Meijin Energy, power Investment Energy, Orchid technology, Panjiang shares, Anyuan Coal industry, Huaihe Energy, Shanxi Coking, Jinkong Coal industry, Lu ‘an Huaneng
Robust	1≤TFP <1.1	15	Jingyuan Coal Power, Jizhong Energy, Shanxi Coking Coal, Yongtai Energy, Yankuang Energy, Huayang Shares, Dayou Energy, Shanghai Energy, Shanmei International, Cloud Coal Energy, Hengyuan Coal Power, Kailuan Shares, China Shenhua, Pingmei Shares, China Coal Energy
Fading	TFP≤1	1	Yunwei Stock

Table 5: Total Factor Productivity and Decomposition of 26 Listed Coal Companies

Company Name	Technical Efficiency Change Index	Technological Progress Change Index	Pure Technical Efficiency Change Index	Scale Efficiency Change Index	Total Factor Productivity Change Index
Jingyuan Coal Power	1.042	1.033	1.005	1.038	1.076
Meijin Energy	1.06	1.04	0.994	1.067	1.103
Jizhong Energy	1.033	1.045	0.988	1.045	1.08
Shanxi Coking Coal	1.018	1.044	0.979	1.04	1.063
Power Transmission Energy	1.119	1.031	1	1.113	1.148
Orchid Technology Innovation	1.012	1.042	0.97	1.042	1.054
Yongtai Energy	1	1.006	1	1	1.006
Yankuang Energy	1.028	1.039	0.991	1.037	1.068
Panjiang Stock	1.087	1.041	0.996	1.091	1.132
Anyuan Coal Industry	1.093	1.047	0.999	1.025	1.073
Great Energy	1.042	1.03	1.017	1.025	1.073
Shanghai Energy	1.037	1.034	0.991	1.047	1.072
Shanmei International	1	1.048	1	1	1.048
Huaihe Energy	1.072	1.052	1.011	1.06	1.127
Yunwei Stock	0.944	1.03	1	0.944	0.972
Shanxi Coal	1.074	1.048	1.004	1.07	1.126
Cloud Coal Energy	1.045	1.044	1	1.045	1.091
Hengyuan Coal Power	1.017	1.035	1	1.017	1.053
Huaibei Mining	1.542	1.042	0.973	1.584	1.606
Kailuan Stock	1.02	1.041	0.986	1.035	1.062
Jinkeng Coal Industry	1.073	1.027	1	1.073	1.101
China Shenhua	1	1.052	1	1	1.052
Pingmei Coal	1.022	1.035	0.979	1.044	1.058
Lu ‘an Ring Energy	1.061	1.041	1.002	1.06	1.105
China Coal Energy	1.011	1.067	1.001	1.01	1.079
Mean value	1.056	1.039	0.996	1.061	1.097

(1) Singularly, Huaibei Mining stands as the lone listed coal enterprise exhibiting robust development. Huaibei Mining's remarkable total factor productivity, soaring to 1.606, marks a notable 60.6% surge over the past six years. This notable lead in total factor productivity predominantly stems from a substantial increase of 58.4% in scale efficiency change index during the specified period. This signifies the enterprise's adeptness in judiciously allocating internal resources and production factors, thereby fostering economies of industrial scale. However, there exists a slight deficiency in the pure technical efficiency change index. Addressing this aspect through technological advancements and enhancing efficiency in technology transformation could further bolster enterprise operational efficiency.

(2) Notably, a total of nine companies exhibit developmental tendencies. Among them, Meijin Energy, Panjiang Stock, and Anyuan Coal primarily witness improvements in total factor productivity driven by technological progress and scale efficiency changes. However, there remains a need for improvement in the pure technical efficiency change index. Expanding technological advantages through enhanced innovation capabilities could facilitate a transition towards robust development.

(3) A diverse array of fifteen companies emerges as robust entities. Particularly noteworthy is that, apart from a slightly elevated technological growth change index, the indices of the remaining three companies hover around 1. Thus, these entities could enhance their technological prowess, intensify efforts in scientific research and development, and propel industrial structural upgrades. Expanding the scale effect of operations and other capabilities would further augment operational efficiency. For China Energy, Shanxi Coking Coal, Yongtai Energy, Huayang Shares, Shanghai Energy, Kailuan Shares, and Pingmei shares, technological innovation stands as the primary constraint on operational efficiency. To address this, emphasis should be placed on enhancing technical efficiency, increasing technological investments, and fostering comprehensive technological progress within these enterprises.

(4) Singularly, Yunwei Stock emerges as the sole declining entity among listed coal groups. The decline in its total factor productivity primarily stems from a reduction in scale efficiency. Notably, Yunwei Stock's scale efficiency change index plunges to the lowest level of 0.944 from 2016 to 2021, representing only 59.6% of Huaibei Mining's highly developed scale efficiency. Besides, effectiveness in technological development and pure technical efficiency at the frontier, other indices fall below 1. To enhance enterprise operational efficiency, Yunwei Stock must not only ramp up efforts in technological research and development but also strategize on expanding industrial scale and fostering a cluster effect to augment overall operational efficiency.

4.2 Empirical Study on the Impact of Business Efficiency through Threshold Effect Identification

Upon reviewing prior research, it is evident that the influence of financing constraints (FC) on enterprise operations manifests varied effects. Given this observation, exploring whether the influence of ESG factors on the operational efficiency of listed coal companies varies under different degrees of financing constraints becomes imperative (Zumente & Lāce, 2021). Hence, commencing from the nexus between financing constraints and enterprise operational efficiency, this study employs financing constraints as the threshold variable to investigate the impact of ESG on the operational efficiency of coal enterprises across varying financing constraints, utilizing the FC index to gauge the extent of enterprise financing constraints.

Through scrutinizing the influence of ESG performance on the operational efficiency of listed coal companies, a panel threshold regression model is subsequently employed to delve into potential heterogeneity in the impact of ESG performance on enterprise operational efficiency across diverse financing constraints. Consequently, Hansen panel threshold estimation is applied to analyse the threshold effect.

$$y_{it} = \mu_{it} + \beta_1' x_{it} I(q_{it} \leq \gamma) + \beta_2' x_{it} I(q_{it} > \gamma) + \theta X_{it} + \varepsilon_{it} \quad (5)$$

In the model, qi represents the financing constraint, yi signifies the operating efficiency of listed coal companies, xi denotes the ESG performance, while X comprises the control variables encompassing market power, capital intensity, per capita profit, and the number of production personnel. Furthermore, 4t stands for the individual intercept term, € represents the random disturbance term, and I (·) denotes the indicative function, wherein I equals 1 when the conditions within the brackets are met, otherwise, I equals 0.

The threshold estimation findings are depicted in Table 6. The outcomes indicate that the financing constraints among the 26 listed coal enterprises can be bifurcated into higher and lower segments at the threshold value of 0.5311. Under varying degrees of financing constraints, the ESG performance of these enterprises significantly influences their operational efficiency. These findings hold significance at a confidence level of 5%.

Table 6: Threshold Regression Test Based on Financing Constraints

Model	Threshold	Lower	Upper
Th-1	0.5311	0.3553	0.7080

In this investigation, the data pertaining to listed coal enterprises undergo examination utilizing single and double thresholds successively. The outcomes of the examination are illustrated in Table 7 below. As per the findings derived from the threshold impact assessment, when the financing constraint is considered as the threshold variable, the single threshold effect is statistically significant at the confidence level of 5%, whereas the double threshold does not pass the test. This observation reinforces the presence of a nonlinear relationship between the impacts of ESG performance on the operational efficiency of coal enterprises. Hence, a single threshold model is constructed for estimation purposes.

Table 7: Threshold Significance Test Based on Financing Constraints

Threshold	RESS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	0.3185	0.0021	26.04	0.0033	14.2724	18.2283	21.4464
Double	0.2864	0.0019	16.79	0.1667	24.8020	38.1706	52.3966

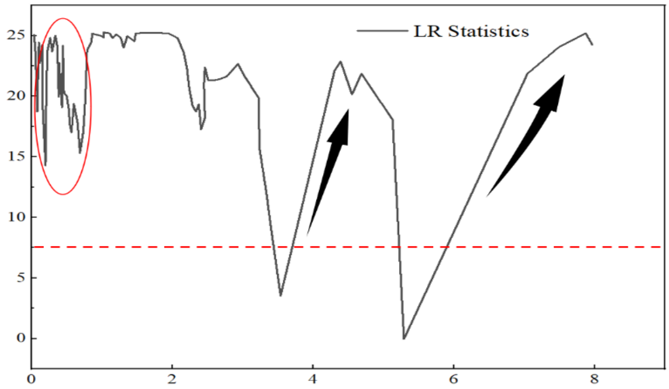


Figure 4: Threshold Regression Estimation Results

The findings regarding the threshold effect are depicted in Figure 4. This model incorporates a single threshold variable, namely financing constraint. The estimated value of the single threshold is 0.5311, signifying statistical significance at the 5% confidence level. Thus, the investigation categorizes the influence of ESG performance on the operational efficiency of listed coal enterprises into two intervals based on distinct financing constraints, namely FC≤0.5311 and FC>0.5311.

Table 8: Threshold Regression Estimation Results Based on Financing Constraints

E	Coef.	Std.Err	*t*	[95% Conf. Interval]	
MP	0.0571	0.0107	5.36	0.0360	0.0782
CI	-0.0445	0.0156	-2.86	-0.0754	-0.0137
PCP	0.0022	0.0005	4.13	0.0011	0.0032
PP	8.66e-06	1.17e-06	7.38	6.34e-06	0.0001
-cat#c.esg					
0	0.0026	0.0014	1.91	-0.0001	0.0055
1	-0.0009	0.0021	-0.45	-0.0051	0.0032
Constant term	0.2826	0.0475	5.94	0.1885	0.3767
Sigma_u	0.1561				
Sigma_e	0.0537				
rho	0.9840				

*Note: F test that all u-i=0:F (25,124)=39.93

In Table 8, the panel threshold model exhibits overall significance. In comparison with the threshold regression model, the control variables in the threshold regression model demonstrate consistent directionality and statistical significance of the estimated coefficients. According to the regression outcomes, the coefficient for market power stands at 0.0571, suggesting a positive correlation between alterations in market power and enterprise operational efficiency. As market power increases, so does the operational level of the enterprise, resulting in enhanced operational efficiency. Conversely, the estimated coefficient for capital intensity is -0.0445, indicating that elevations in the capital intensity of coal enterprises correspond to reductions in their operational level, underscoring the necessity to maintain capital intensity within a reasonable range. The coefficient for profit per capita is 0.0022, indicating a favourable impact of profit per capita on enterprise operational efficiency.

Furthermore, the number of production personnel exhibits a significant positive correlation at the 1% confidence level, implying that augmentations in internal production personnel effectively enhance operational efficiency within coal enterprises.

Concerning the coefficient estimation of ESG performance on the operational efficiency of coal enterprises, within the framework of the single threshold model, the impact of ESG performance on operational efficiency can be delineated into two primary stages:

Stage 1: Low financing constraint period ($FC \leq 0.5311$): During this phase, enterprises exhibiting commendable ESG performance tend to embrace social responsibilities in their business operations positively. Additionally, leveraging their strengths in corporate governance, they enhance operational efficiency, thus facilitating enterprise development. When financing constraints are minimal, the estimated impact of ESG performance on coal enterprises' operational efficiency is positive. This suggests that enterprises with strong ESG performance enjoy enhanced reputations, attracting skilled professionals and subsequently bolstering operational efficiency.

Stage 2: High financing constraint period ($FC > 0.5311$): As financing constraints continue to escalate, the benefits derived from ESG performance on operational efficiency gradually plateau. During this stage, heightened capital pressures compel increased investment in ESG performance, posing challenges in translating ESG performance into economic gains. Consequently, this impedes the enhancement of enterprise management standards. Nevertheless, despite the constraints encountered in this phase, ESG performance still plays a pivotal role in enhancing operational efficiency in coal enterprises, albeit to a lesser extent compared to the preceding stage.

5. Conclusion

Environmental factors wield considerable influence on the measurement of operational efficiency within listed coal companies. Upon mitigating the impact of environmental factors and random errors, the comprehensive efficiency of most coal enterprises experiences a decline. This is evidenced by the average operational efficiency of coal enterprises dropping from 0.792 to 0.568, underscoring the substantial impact of external environmental factors and random interference on operational efficiency measurement. Moreover, scale efficiency and pure technical efficiency emerge as pivotal constraints on the operational efficiency of listed coal enterprises. From a static perspective, the initially overestimated scale efficiency of coal enterprises in the first stage, buoyed by favourable environmental conditions and serendipity, experiences a notable decline upon the elimination of environmental factors and random errors. Subsequently, all enterprises revert to a phase of either increasing or unchanged economies of scale. Scale efficiency emerges as the primary impediment to enhancing operational efficiency within coal enterprises. ESG performance exerts a positive influence on the operational efficiency of coal enterprises. Leveraging Bloomberg's ESG performance index, this study employs regression analysis via a random Tobit model, revealing a significant positive impact of ESG performance on the operational efficiency of listed coal companies at a 5%

confidence level. This is primarily attributable to the adoption of ESG principles, disclosure of relevant ESG information by enterprises, and consequent enhancement of stakeholder perception in business activities. The cultivation of a positive social image through robust ESG performance enhances enterprise reputation, enabling coal companies to attain elevated economic benefits and social esteem. This study devises an operational efficiency evaluation index system for listed coal companies, delineating operational efficiency analysis and research from both static and dynamic perspectives within the framework of "input-output-environment." Building upon the measurement outcomes of three models, the study deliberates on the ramifications of ESG performance on the operational efficiency of coal enterprises.

6. Study Limitations

(1) The utility of simplistic financial data indices is constrained, offering an incomplete portrayal of coal enterprise operational efficiency. Presently, varying disclosure standards across enterprises regarding unanticipated output stemming from operational activities impede uniform analysis.

(2) The absence of explicit legal standards governing ESG performance disclosure in China has resulted in non-participation of certain coal enterprises in early-stage ESG performance scoring initiatives. Consequently, the study's focus on the years 2016 to 2021 may present limitations owing to data selection constraints.

7. Prospects

Firstly, both theoretical analysis and empirical evidence, domestically and internationally, underscore the profound impact of government policies on the coal chemical industry. Strengthening environmental regulations, for instance, fosters market consolidation among high-quality enterprises, drives industrial upgrading, and mitigates environmental degradation. As nations worldwide prioritize clean energy, China's strategic imperative of achieving carbon neutrality sets demanding benchmarks for the coal chemical sector to transition towards industry excellence. Secondly, employing a tripartite game model involving government entities, pollution control firms, and polluters, this study reveals that transient environmental protection policies wield limited influence on market efficiency and emission reduction. Only robust and persistent environmental regulations spur enterprises to enhance pollution control measures. Empirical analysis substantiates this theoretical conjecture, indicating a marked shift in regional environmental regulation behaviour pre- and post-central environmental inspection team assessments. Formerly ad-hoc environmental protection policies have evolved into regular, stringent regulations, notably enhancing enterprise productivity and fostering a brighter outlook for environmentally responsible coal chemical enterprises. Lastly, government support policies, predominantly through demonstration projects, incentivize enterprises to bolster patent creation, thereby augmenting productivity and propelling industrial transformation and upgrading. However, this effect manifests with a discernible lag, typically spanning approximately three stages. Policymakers and enterprises alike must uphold faith and patience in the positive outcomes of industrial policies.

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