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The Impact of Environmental Social Responsibility on Total Factor Productivity: Evidence from Listed Companies in China

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Abstract: In recent years, China's environmental policies have continued to promote sustainable development, and listed companies have increased their environmental investment and strengthened their environmental social responsibility. Although there has been much research on the relationship between environmental performance and total factor productivity of listed companies, the impact of environmental social responsibility on total factor productivity has not yet been fully examined. In this paper, we use panel data regression to investigate the linear and non-linear relationships between environmental social responsibility and total factor productivity. These relationships are tested for robustness, analyzed for between-group differences, and validated by a machine learning model. Firstly, we find that environmental social responsibility can significantly contribute to companies' total factor productivity within a certain range, but it varies across different categories of firms. Secondly, there is an inverted U-shape relationship between environmental social responsibility and total factor productivity, where total factor productivity initially increases with environmental social responsibility but decreases after reaching a certain threshold. Finally, we conclude that environmental social responsibility promotes total factor productivity in the early stages, but when environmental social responsibility reaches a certain threshold, it begins to exert an inhibitory effect on the development of total factor productivity.

Keywords: environmental social responsibility; total factor productivity; inverted U-shape; listed companies; China

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1. Introduction

Environmental protection is crucial for sustainable development [1]. Particularly under suitable policy frameworks, publicly listed companies play an important role in advancing environmental sustainability [2]. By adhering to corporate environmental social responsibility (ESR), these companies reduce environmental harm, establish industry standards, influence societal behavior, and enhance economic outcomes [3]. Meanwhile, Baier, S. L. et al. (2006) [4] highlighted total factor productivity (TFP) as a critical indicator of economic efficiency and growth within publicly listed firms. Further searches of the annual reports of listed companies have identified an increase in the number of company annual reports relating to environmental social responsibility in recent years, especially from 2019 (http://www.jiangsu.gov.cn/art/2024/8/27/art_84323_11334312.html (accessed on 27 August 2024)). Additionally, the Chinese government has also emphasized the importance of ESR in companies' performance (https://www.cet.com.cn/wzsy/ycxw/10100892.shtml (accessed on 2 September 2024)). Therefore, investigating the relationship between ESR and TFP in these companies is important for elucidating the mechanisms through which ESR impacts TFP and providing theoretical support and guidance for future corporate strategies.

Research on the relationship between corporate environmental behavior and TFP has been extensively explored. He et al. (2022) [5] argued that environmental taxes can regulate corporate behavior and promote the development of TFP. Li (2022) [6] found that environmental initiatives by publicly listed companies positively impact TFP. Tunio et al. (2021) [7] supported this view, emphasizing that improvements in corporate environmental performance significantly enhance TFP under linear models. Padilla-Lozano (2022) [8] also corroborated these findings. However, some scholars hold contrary views, suggesting that corporate environmental behavior may inhibit TFP [9,10]. Most existing studies focus on the linear relationship between corporate environmental behavior and TFP, paying less attention to potential non-linear relationships. Additionally, some research is confined to specific sectors, such as Liu et al. (2022) [11] and Zhao et al. (2023) [12] studying heavily polluting industries, while Li et al. (2022) [13] concentrate on the manufacturing sector. Therefore, future research should consider potential non-linear relationships between ESR and TFP. It should also broaden its scope to include a variety of companies, aiming for a comprehensive understanding of how environmental practices impact economic outcomes.

This paper adopts a targeted approach to explore the intricate relationship between corporate ESR and TFP among listed companies. By transcending specific industry constraints, this study enhances the generalizability of its findings, making them applicable across various sectors. The novelty of this research lies in introducing non-linear regression models, which build upon the insights derived from traditional linear models. The robustness of these non-linear conclusions is further validated through advanced techniques, including semi-parametric techniques and random forest regression. The findings provide actionable insights, offering valuable guidance for companies in formulating effective policies that align with both sustainability objectives and productivity enhancement.

2. Literature Review and Hypotheses

2.1. Theoretical Framework

2.1.1. Company Environmental Protection Behaviors Promote TFP

The relationship between company environmental responsibility and TFP is a widely debated academic issue. On the one hand, some scholars hold positive views. Velte (2017) [14] found that ESG metrics contribute to the economic performance of listed companies. Tarmuji et al. (2016) [15] noted that ESG indicators are essential for sustainable development and corporate performance. Giese et al. (2019) [16] suggested that ESG indicators can signal the performance of listed companies. Generally, good ESG indicators imply solid environmental responsibility, which can positively impact company performance. Jiang (2022) [17] supported that corporate environmental responsibility can improve firms' risk-taking ability and positively affect firm value. Chen (2022) [18] also supported this, stating that environmental responsibility enhances firm value. Similarly, Cao (2021) [19] contended that fulfilling environmental responsibility boosts green competitiveness, thereby increasing company value. Hao (2023) [20] noted that corporate environmental responsibility promotes green innovation and high-quality economic development. Li (2019) [21] and Siregar (2021) [22] recognized the value enhancement and significant challenges in implementing corporate environmental responsibility, requiring policy adjustments by the government and companies. Deng (2023) [23] pointed out that improving the environmental ratings of listed companies can contribute to improving TFP. Yu (2024) [24] also agreed that strong ESG can make firms' development more significant. Ge (2022) [9] highlighted that corporate environmental responsibility can promote performance improvement, creating a virtuous cycle of "corporate environmental responsibility—corporate performance improvement". Overall, the good environmental behaviors of listed companies can contribute to company performance.

There are distinctions in the environmental social responsibilities upheld by companies of varying scales. This study delves into the impact of ESR on overall total factor productivity across different company sizes. Halkos et al. (2008) [25] pointed out that the development of total factor productivity in listed companies is affected by the size of the company. Linh et al. (2021) [26] also showed that technology, as well as firm size, have an impact on the total factor productivity of listed companies, and Ding, S. et al. (2016) [27] also supported this idea in their study. Huang et al. (2019) [28] investigated the effects of technological factors on China's TFP, highlighting the benefits of technology spillovers through openness. Fan et al. (2022) [29] examined the impact of environmental regulation on green total factor productivity from the perspective of green technological innovation, aiming to provide insights for more effective policy formulation. This also suggests that the impact of the volume of listed companies and the type of industrial technology on the findings of the panel data regression should be considered in the research process.

From the analysis in Section 2.1.1, we can derive hypotheses H1 and H2.

H1. *ESR is positively associated with TFP.*

H2a. *The promoting effect of ESR on TFP varies among companies of different sizes.*

H2b. *The promoting effect of ESR on TFP varies among companies of different technological levels.*

2.1.2. Company Environmental Protection Behaviors May Inhibit TFP

On the other hand, some studies indicate that environmental responsibility may not significantly enhance economic effects in the short term. Yang (2016) [30] pointed out that social responsibility is negatively related to long-term financial performance in both large and small companies. Shan (2021) [31] and Li (2019) [21] noted that while environmental responsibility can improve economic effects, the time span is unspecified. Wu (2018) [10] cautioned that environmental responsibility might negatively impact firm performance. Although there are a few studies that express negative attitudes towards corporate environmental behaviors on performance, this can also indicate that there is a divergence of research in this area.

2.1.3. An Exploration of U-Shape

Recent studies have explored the relationship between corporate social responsibility (CSR) and various aspects of corporate performance, revealing complex and multifaceted dynamics. Liu et al. (2021) [32] discovered that CSR impacts sustainable technological innovation performance in an inverted U-shaped manner, effectively enhancing innovation until a critical threshold is reached, beyond which the benefits decline. Al-Shammari et al. (2021) [33] examined the relationship between CEO narcissism and CSR, finding a similar inverted U-shaped relationship, suggesting that moderate CEO narcissism positively influences social responsibility activities, while excessive narcissism has detrimental effects. Pareek et al. (2021) [34] investigated the significance of ownership structure within corporate governance mechanisms, identifying that specific ownership structures significantly influence performance, mainly when moderated by board independence. Li et al. (2021) [35] studied the impact of congruent and incongruent social responsibility on organizational cynicism, highlighting the importance of internal and external perceptions on employee attitudes. Ersoy et al. (2022) [36] focused on the influence of Environmental, Social, and Governance scores on the market value of U.S. commercial banks, emphasizing the importance of robust ESG standards in optimizing market value. Bhatnagar et al. (2023) [37] explored the effects of social responsibility expenditure and business responsibility reporting on firm financial performance, revealing that mandated expenditure enhances firm performance. Pareek et al. (2023) [34] investigated the non-linear impact of executive compensation on performance, finding an inverted U-shaped relationship between executive compensation and ESG scores, indicating that insufficient and excessive compensation can be counterproductive to social responsibility efforts. De la Fuente et al. (2022) [38] highlighted that the ESG performance of publicly listed companies exhibits an inverted U-shaped relationship, further underscoring the nuanced nature of these initiatives' impact on corporate performance. These studies deepen our understanding of the intricate interplay among corporate responsibility, performance, and various organizational factors, underscoring the importance of strategic implementation and balanced approaches to maximize positive outcomes.

From the analyses in Sections 2.1.2 and 2.1.3, we can derive hypothesis H3.

H3. *There is a non-linear inverted U-shaped relationship between ESR and TFP.*

2.1.4. Impact of Greenwashing

The term "greenwashing" originates from China and was derived from the English term "whitewashing". It denotes manipulating public perception regarding the environmentally friendly nature of an organization's products, objectives, and policies. This manipulation is achieved through deceitful green public relations and marketing strategies. The primary aim of such strategies is typically to conceal the environmental shortcomings of the organization or its suppliers and present them as unrelated to these failures. Recently, some publicly traded companies have employed tactics to conceal their environmentally detrimental actions, driven by public opinion and prevailing attitudes, thereby upholding their corporate image. This analysis posits that the perpetuation of "greenwashing" practices by publicly listed firms impacts the operational framework. Lee M. T. et al. (2023) [39] highlighted in their research that the "greenwashing" conduct of listed firms can enhance ESG rating performance, with this performance consequently influencing the financial standing of the company. However, in line with the essence and theoretical underpinnings of "greenwashing", once exposed, such behavior can have adverse repercussions on various facets of company performance. Greenwashing behavior may impact the performance of a company in several ways. First, greenwashing behavior can lead to a loss of consumer trust in the company, which in turn affects its performance. Secondly, greenwashing may expose the company to penalties from the government as well as regulatory authorities, which in turn affects the company's performance. At the same time, investors may withdraw their investment due to the greenwashing behavior of the company, which in turn affects the production behavior and performance of the company. In summary, we hypothesized that greenwashing would inhibit the promotion of TFP by ESR.

From the analysis in Section 2.1.4, we can derive hypothesis H4.

H4. *Greenwashing has a negative impact on the promoting effect of ESR on TFP.*

Thus, most studies have centered on the ESG of listed companies, financial outcomes, and TFP. However, there is a paucity of research focusing on the specific impacts of environmental initiatives and the non-linear relationship between ESR and performance. It is necessary to undertake further exploration of the distinctive influence of ESR on corporate outcomes, particularly TFP.

3. Materials and Methods

3.1. Indicators of Environmental Social Responsibility

In this paper, the environmental social responsibility undertaken by listed companies is expressed as $ESR_{i,t}$. As the index of environmental responsibility undertaken by listed companies is somewhat abstract and difficult to measure, it was referred to in the study by Lin Yan et al. (2021) [40]. A company's environmental social responsibility commitment is often closely related to its environmental protection investment, so it utilizes the scale of environmental protection investment of listed companies to measure their commitment [41]. This method is also supported by Corso (1996) [42], who suggested using the logarithmic form of the data to reflect the scale of the data.

For the environmental investment of listed companies, referring to the research of Zhao et al. (2022) [43] and drawing on the research by Zhang (2019) [44], the company annual reports of listed companies are collected and statistically calculated. The ESR value is calculated according to Equation (1):

$$ESR_{i,t} = ln(1 + Environmental\ Investment_{i,t}) \tag{1}$$

3.2. Measurements of Total Factor Productivity

In this paper, five methods are used for the measurement of total factor productivity: the Ordinary Least Squares (OLS) method, Fixed Effects (FE) method, Levinsohn-Petrin (LP) method, Olley-Pakes (OP) method, and Generalized Method of Moments (GMM) method. In the robustness test section, a random forest (RF) is added to the TFP value calculation. Mundlak (1961) [45] and Hoch (1962) [46] applied the fixed effects model to the field of economics research, but the use of the fixed effects model to estimate TFP underestimates the elasticity of capital output [47]. Blundell and Bond (2000) [48] improved on the basic GMM approach, but the GMM approach uses lagged variables for TFP measurement, which theoretically leads to data information loss. Olley and Pakes (1996) [49] first proposed the OP method to measure TFP, and the LP model is an improvement of the OP method [50]. However, some scholars have compared the LP method with the OP method, and the OP method can better address the sample data inter-determined endogeneity problem caused by sample data bias and the bias problem caused by sample selection bias. The main reason for choosing to use the OP method rather than the LP method to measure TFP is that the LP method may overestimate TFP estimates [51]. The LP method usually assumes a linear relationship, whereas the actual production process may involve non-linear effects and complex constraints that lead to overestimation. The OP method is able to better handle these non-linear relationships and complex constraints, thus providing more accurate TFP estimation, avoiding the overestimation problem that may be caused by the LP method. Therefore, the use of the OP method can more accurately reflect the actual productivity and economic relationships and improve the reliability of the conclusions. Hence, in this paper, referring to Loecker (2007) [52], the OP method is used as the explanatory variable of the primary regression model, and the rest of the measures can be used as the robustness test variables. Measuring TFP can also be done using the data envelopment analysis (DEA) method, but the DEA calculation method applies to balanced panel data, which is more frequently used in regional and industry studies, and if it is unbalanced panel data, a large amount of sample information will be lost, so it is not applicable in this paper. Table 1 describes these methods. It is important to note that the OP estimation method is a semi-parametric estimation method and one of the most used TFP measures in current research in corporate economics [51]. The calculation of TFP using the OP method is shown in Appendix A.

Table 1. Description of TFP measurement methods.

TFP Measurement Method	Description
OLS	Endogeneity is not considered.
FE	Endogeneity and selectivity bias cannot be solved.
OP	Endogeneity and sample selection can be solved without loss of data.
LP	Expanding the absolute value of TFP
GMM	Data will be lost, and suitable instrumental variables need to be found.
DEA	Suitable for balanced panels, mostly used in industry and geographical studies

3.3. Basic Regression Model

The basic regression model of this study, $ESR_{i,t}$, is used to reflect the environmental social responsibility commitment of listed companies, and $TFP_{i,t}$ is used to show the total factor productivity of listed companies. X reflects the full range of control variables used in the regression model. Meanwhile, since the base regression model is set as a fixed effects model, the effects of individual companies and years need to be considered, so here θ_t represents the year effect, and γ_i represents the individual effect. The basic regression model is a panel data regression model. Equation (2) represents the regression model described above as follows:

$$TFP_{i,t} = \beta ESR_{i,t} + \sum_{i,t} \lambda X + \gamma_i + \theta_t + \varepsilon_{i,t} \tag{2}$$

The coefficients preceding the explanatory variables in the fixed effects regression model above reflect the variable's relationship to the total factor productivity of listed companies. In this model, it is sufficient to focus only on the coefficients of the core explanatory variables; the coefficients associated with the control variables are less important.

3.4. Inverted U-Shape Analysis Model

The inverted U-shaped relationship is a commonly observed non-linear pattern in empirical studies. Swaab (2014) [53] employed quadratic terms of the core explanatory variables in regressions to investigate inverted U-shaped in psychology research. To test the existence of the inverted U-shaped relationship, the researcher included the squared terms of the explanatory variables in the regression model and identified the inverted U-shaped relationship based on the significance of the coefficients of the quadratic terms and their heteroscedasticity with the coefficients of the primary terms. While this is a conventional method, it has notable limitations. Lind and Mehlum (2010) [54] criticized this approach and introduced the U-test (The results of the U-test indicate whether the second-order derivative is negative, and the extreme point lies in the data interval) to enhance the reliability of trend analysis conclusions. Simonsohn and Nelson (2014) [55] suggested an improved approach to determine the presence of an inverted U-shaped relationship, using the quadratic term in conjunction with breakpoint regression. Additionally, Scott Kostyshak (2017) [56] highlighted the potential of non-parametric regression to test for trends in the data and investigate the presence of a U-shaped or inverted U-shaped relationship between the variables.

In summary, recent literature suggests that incorporating the quadratic terms of the main explanatory variables in the regression model alone may lead to biased conclusions. Moreover, although non-parametric methods are conceptually compelling, they do not yield specific coefficients for the model fit. Meanwhile, utilizing breakpoint regression can significantly change the trajectory of the data around the breakpoints, presenting challenges in accurately assessing the trend except at these specific points. Consequently, this paper utilizes a combination of adding the quadratic term of ESR and U-test in the panel data regression model to analyze the U-shaped mechanism.

This study utilizes a combination of methods, integrating quadratic terms into the regression model along with the U-test. This approach aims to produce more reliable and resilient conclusions regarding the non-linear connection between the ESR of listed companies and TFP. The regression model incorporating quadratic terms is presented in Equation (3) with the following expression:

$$TFP_{i,t} = \alpha_1 ESR_{i,t} + \alpha_2 ESR_{i,t}^2 + \sum_{i,t} \lambda X + \gamma_i + \theta_t + \varepsilon_{i,t} \tag{3}$$

According to the above model setting, the focus is on the regression coefficients of the primary and secondary terms in the model; if the coefficients of the primary term are significantly positive, and the coefficients of the secondary term are significantly negative, it means that there is an inverted U-shaped relationship between listed companies' commitment to environmental responsibility and total factor productivity. Further, we are also able to calculate the threshold at which ESR leads to a decrease in TFP. The calculation of the threshold is based on the regression coefficients of the primary and secondary terms, and the threshold represents the inflection point of the inverted U-shaped relationship. Specifically, the inflection point can be obtained by dividing the coefficient of the primary term by twice the coefficient of the quadratic term and taking the opposite number. We use $ESR_{threshold}$ to indicate the threshold of ESR. The calculation of $ESR_{threshold}$ is shown in Equation (4):

$$ESR_{threshold} = -\frac{\alpha_1}{2\alpha_2} \quad (4)$$

To make the U-shaped analysis more credible, a semi-parametric generalized additive model (GAM) is introduced (Rigby,1996) [57], inspired by Scott Kostyshak (2017) [56], and further enhanced by incorporating the random forest algorithm from the field of machine learning. A brief description of both approaches follows.

A GAM is a flexible statistical model for analyzing the relationship between one or more explanatory variables (inputs) and response variables (outputs). Unlike traditional linear models, GAMs allow the use of smoothing functions to capture more complex relationships than just straight lines. Specifically, suppose you have a dataset with n samples, each including one or more explanatory variables X and a response variable Y. The GAM model is expressed in the following form:

$$Y = \beta_0 + f_1(X_1) + f_2(X_2) + \ldots + f_n(X_n) + \varepsilon \quad (5)$$

where Y is the response variable to be predicted or explained; β_0 is a constant term, similar to the intercept in linear regression; f is the smoothing function applied to each explanatory variable, which captures the non-linear relationship between the explanatory variable and the response variable; ε is the error term, which represents the portion of Y that is unexplained by the model. On this basis, the dependent variable Y can be predicted based on the regression equation, with the predicted values smoothed, and the smoothed curves are examined to see if there are points where the second-order derivative is less than 0. If such points exist, there is an inverted U-shaped relationship. Then, we add ESR, TFP, and control variables in Equation (6):

$$TFP = \beta_0 + f_1(ESR) + \sum_{i=2}^{n} f_n(Controlvariables_n) + \varepsilon \quad (6)$$

The random forest method is like the GAM idea; only the fitting function is different. In this part, we describe a random forest. The random forest model includes two parts. Firstly, the random forest contains several decision trees. So, the first step is to calculate the decision tree. Secondly, the prediction of the random forest is the average of the predictions of all the decision trees. The first step is shown in Equation (7):

$$h(x;\Theta) = \sum_{j=1}^{J} c_j \cdot I(x \in R_j) \quad (7)$$

In Equation (8), Θ represents the parameters of the decision tree; R_j is the feature space region corresponding to the j-th leaf node of the tree; c_j is the predicted value of the j-th leaf node; I is the indicator function, which takes the value of 1 when x falls into the region R_j and 0 otherwise. The second step is shown in Equation (8). If the random forest consists of B decision trees,

$$f(x) = \frac{1}{B} \sum_{b=1}^{B} h(x;\Theta_b) \quad (8)$$

In the same way, we add ESR, TFP, and control variables in Equation (9):

$$TFP = \frac{1}{B} \sum_{b=1}^{B} h(ESR, Controlvariables; \Theta_b) \quad (9)$$

The process described above is how we train the machine learning models. We used 20% of the data to train the GAM and random forest models and set the parameters. Then, the trained models were validated using the remaining 80% of the data for prediction.

Performance metrics (MSE) were calculated to assess the predictive effectiveness of the models, and fit curves of the actual values to the predicted values were plotted to visualize the results. Further, we measured the fitted curves. If the second-order derivatives of the fitted curves are negative within a certain range, there is an inverted U-shaped relationship between the variables. The process of prediction is shown below. Equations (10) and (11) are prediction equations.

$$\widehat{TFP} = \beta_0 + f_1(ESR) + \sum_{i=2}^{n} f_n(Controlvariables_n) \tag{10}$$

$$\widehat{TFP} = \frac{1}{B}\sum_{b=1}^{B} h(ESR, Controlvariables; \Theta_b) \tag{11}$$

In summary, we used 20% of the data, which included ESR, TFP, and control variables, to process the equations shown above to get parameters, then used the remaining 80% of the data, which included only ESR and control variables, to predict TFP. On this basis, we can get MSE in this data fitting. The flow chart is shown in Figure 1 to further illustrate the above process.

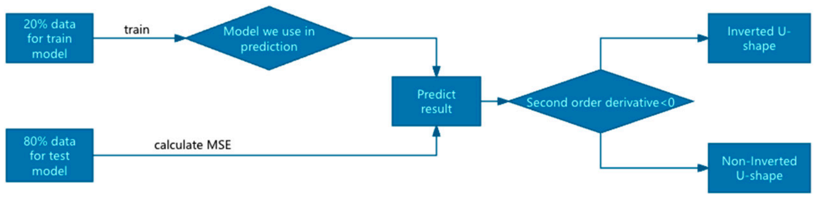

Figure 1. Process for machine learning analysis.

In summary, this paper uses three methods to test the inverted U-shaped relationship between TFP and ESR and the total factor productivity of listed companies. This makes the results of the inverted U-shaped relationship test more robust and expands the idea of the U-test beyond the linear model.

3.5. Data Description

The data used in this paper cover the period of listed companies from 2011 to 2022 (excluding ST and PT companies). The core explanatory variable of this study is the total factor productivity of listed companies, which is measured and calculated using the OP method. The value of listed companies' ESR is determined by taking the logarithm of the investment in environmental protection.

To ensure a comprehensive analysis of the relationship between ESR and TFP, we include control variables such as company size, total asset turnover (ATO), return on assets (ROA), percentage of fixed assets (Fixed), return on equity (ROE), book-to-market ratio (BM), and management cost ratio (Mfee). Company size and percentage of fixed assets account for differences in resources and asset composition, while ATO, ROA, and ROE control for operational efficiency and profitability. The BM reflects growth expectations, and the management cost ratio captures the impact of administrative expenses. These variables help isolate the impact of environmental investments on TFP by accounting for various firm-specific factors that could influence productivity.

The above data are mainly sourced from the WIND database and the companies' annual reports. However, some of the data are vacant or incomplete due to non-disclosure by the company or other reasons. Therefore, data cleaning is needed in the empirical study. First, we merge the data into a panel dataset. Then, preliminary descriptive statistics are performed on the data to understand the overall distribution of the data. In this process, possible missing values and outliers are identified and culled accordingly. Finally, we check the data again to ensure the accuracy of the data. Meanwhile, due to the possible bias introduced by COVID-19 in 2019, the data are further explored in the robustness test section.

4. Results

4.1. Descriptive Statistics and Correlation Analysis

Table 2 shows the descriptive statistics of explanatory, dependent, and control variables mentioned in Section 3.5.

Table 2. Summary statistics.

Variables	Observation	Meaning of Indicators	Mean	Std	Min	Max
TFP	25,962	Total factor productivity	6.706	0.868	2.560	11.160
ESR	25,962	Environmental social responsibility	0.408	0.462	0.000	5.204
Assets	25,962	Natural logarithm of total corporate assets which can reflect company size	22.290	1.261	19.570	26.452
ROA	25,962	Return on assets	0.042	0.063	−0.382	0.255
Fixed	25,962	Percentage of fixed assets	0.221	0.152	0.002	0.725
BM	25,962	Book-to-market ratio	1.050	1.174	0.052	10.089
Mfee	25,962	Management cost ratio	0.084	0.065	0.007	0.641
ROE	25,962	Return on equity	0.066	0.125	−0.962	0.415
ATO	25,962	Total asset turnover	0.657	0.426	0.055	2.891

Table 2 displays the maximum, minimum, mean, and standard deviation of the data employed in the empirical investigation. The descriptive statistics highlight the key explanatory variables, specifically, the dedication to environmental stewardship among publicly traded entities and total factor productivity. Regarding the TFP of listed companies, the maximum value is 11.16, the minimum value is 2.56, and the mean value is 6.706. In general, listed companies demonstrate a noteworthy level of TFP; however, the data's standard deviation is 0.868, indicating some degree of variability within the dataset. Regarding the ESR, the minimum value is 0, the maximum value is 5.204, and the mean value is 0.408. This implies a comparatively low overall level of ESR among listed companies, with a standard deviation of 0.462, suggesting modest variability in the data. Moreover, it is evident that listed companies exhibit significant size diversity. Table 2 illustrates the remaining control variables utilized in the model, excluding the time variable and the individual variable, which are replaced by the stockid of the listed companies.

Table 3 presents the correlation between the variables explored in this study. The findings indicate a significant positive correlation between the TFP of listed companies and the value of their ESR. Through the correlation analysis in Table 3, there is a positive correlation between environmental social responsibility commitment and the total factor productivity of listed companies. This relationship lays a strong foundation for the feasibility of the subsequent study. Except for the fixed assets variable and the management expense ratio variable, all the other variables show a positive correlation with TFP, consistent with the conclusion reached by Zhao et al. (2020) [58].

Table 3. Cross-correlations matrix.

	TFP	ESR	Size	ROA	Fixed	BM	Mfee	ROE	ATO
TFP	1.000								
ESR	0.567 ***	1.000							
Assets	0.729 ***	0.790 ***	1.000						
ROA	0.113 ***	0.017 ***	−0.001	1.000					
Fixed	−0.143 ***	0.045 ***	0.071 ***	−0.094 ***	1.000				
BM	0.479 ***	0.480 ***	0.624 ***	−0.228 ***	0.068 ***	1.000			
Mfee	−0.597 ***	−0.111 ***	−0.344 ***	−0.179 ***	−0.067 ***	−0.255 ***	1.000		
ROE	0.207 ***	0.099 ***	0.107 ***	0.903 ***	−0.082 ***	−0.119 ***	−0.221 ***	1.000	
ATO	0.557 ***	0.166 ***	0.083 ***	0.173 ***	−0.010	0.019 ***	−0.434 ***	0.206 ***	1.000

*** denotes significant at a 1% level of significance.

4.2. Basic Fixed Effects Model Regression

Table 4 reports the outcomes of the Equation (2. The control variables were categorized into three groups for the investigation: variables related to size, performance indicators pertaining to TFP, and other relevant variables. Incorporating diverse control variables into the regression model yielded five distinct result sets, which are presented in the table's conclusions. Columns (1)–(4) of the regression outcomes present the results of panel data regressions conducted under different conditions: without control variables; with control only over the body of listed companies; managing solely the performance of listed companies; excluding total factor productivity and managing the remaining variables separately from the previous ones. On the contrary, Column (5) showcases the outcomes of the regression encompassing all control variables.

Table 4. Basic fixed effects model regression.

Variables	(1) TFP	(2) TFP	(3) TFP	(4) TFP	(5) TFP
ESR	0.789 ***	0.162 ***	0.677 ***	0.919 ***	0.233 ***
	(0.041)	(0.038)	(0.035)	(0.036)	(0.030)
Size control variables		YES			YES
Remaining performance controls			YES		YES
Remaining control variables				YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES
Observations	25,962	25,962	25,962	25,962	25,962
R^2	0.355	0.452	0.609	0.622	0.793

Figures in parentheses below the coefficients indicate the cluster-robust standard errors of the regression coefficients. *** indicates that the coefficient is significant at 0.1% level of significance. The same applies to subsequent tables.

In Table 4, the results of regressions (1)–(5) reveal a significant link between the ESR initiatives of publicly listed companies and TFP, supported by a 0.1% significance level. Moreover, it is evident that the R-squared values enhance the model's goodness of fit. The consistent adjustment of control variable combinations serves as a robustness test, affirming the reliability and stability of the empirical regression findings. The findings in this section of the study illustrate that the ESR of listed companies has a facilitating effect on TFP, similar to that of Tunio R. A. (2021) [7]. H1 can be accepted.

4.3. Inverted U-Shaped Curve Analysis

After regressing the underlying econometric model, we conducted non-linear analyses. The main research aim of this paper is to investigate the presence of an inverted U-shaped relationship between the ESR levels of listed companies and TFP. Following the model setup, the quadratic term of the ESR variable is incorporated into the primary regression model for further analysis.

Firstly, we employed three non-linear fitting approaches to fit available data, namely random forest fit, Generalized Additive Model (GAM) semi-parametric method fit, and quadratic fit. The fitted images are shown in Figures A1–A3. Figures A1–A3 are included in Appendix B.

Figure A1 illustrates the fitting of the data by the random forest method, and the image shows that there is still a downward curved inverted U-shaped tendency despite the fluctuation of the fitted curve. Figure A2 presents the fitting results using the GAM semi-parametric model, where the inverted U-shape is more obvious, and Figure A2 displays the basic quadratic fitting, where the fitted curve is significantly inverted U-shaped. In Figure A3, on the left side of the inverted U-shaped relationship, an increase in ESR levels may lead to an increase in productivity. This may be because investment in ESR in the early stages of a company's life improves resource utilization efficiency and thus increases total factor productivity [59]. In the middle stage of the inverted U-shaped relationship, an increase in ESR may reach a critical point, i.e., the optimal point. At this stage, the company may have maximized productivity gains, and further input increases may result in diminishing marginal benefits. On the right-hand side of the inverted U-shaped relationship, continued increases in the level of ESR may lead to a decline in productivity. This may be due to companies over-investing in ESR programs, leading to a diversion of resources and a reduction in profitability, or there may be social programs that are unrelated to production activities and affect the company's core business. Overall, within a certain range, active ESR can significantly contribute to total factor productivity, but when listed companies focus too much on ESR initiatives, it can instead have a dampening effect on total factor productivity.

To verify the robustness of the conclusions from the above non-linear fit, it was assessed using an empirical research approach by performing a panel data regression based on Equation (3) and conducting a U-test. Based on Table 5, the findings from (1)–(2) suggest that as listed companies intensify their commitment to ESR, there is a discernible pattern of decreasing marginal impact on total factor productivity. Initially, a rise in ESR initiatives yields substantial enhancements in total factor productivity by ushering in novel management methodologies, technological advancements, and optimized resource allocation strategies. However, as the magnitude of responsibility escalates, organizations encounter additional expenses such as environmental inputs and social program outlays, which can adversely affect productivity and result in diminishing marginal returns. To validate the presence of a concave-shaped relationship, a U-test was conducted. The U-test results reveal a t-value of 5.85, with a p-value of 0, indicating statistical significance at a 0.1% confidence level. This signifies the affirmation of the U-test and the rejection of the initial hypothesis, confirming the existence of an inverted U correlation between listed companies' ESR efforts and TFP. From Table 5, it is noted that when ESR increases to about 2.17, the improvement in ESR will inhibit company TFP.

Table 5. Inverted U-shaped curve analysis: panel data regression.

Variables	**(1) TFP**	**(2) TFP**
ESR	1.438 ***	0.549 ***
	(0.075)	(0.053)
ESR^2	−0.316 ***	−0.127 ***
	(0.031)	(0.017)
Control variables	NO	YES
Time fixed effects	YES	YES
Individual fixed effects	YES	YES
Observations	25,962	25,962
R^2	0.570	0.940
U-test	t = 5.85 ***, p = 0 ***, ESR = 2.17 when curve get max	

Figures in parentheses below the coefficients indicate the cluster-robust standard errors of the regression coefficients. *** indicates that the coefficient is significant at 0.1% level of significance. t- and p-values of the U-test mean the test result is significant at the 0.1% level of significance.

After testing the U-shaped trend using panel data regression, the analysis continued with the semi-parametric generalized additivity model (GAM) and the random forest machine learning model. Table 6 presents the regression goodness of fit (MSE) and test conclusions for both approaches.

Table 6. Inverted U-shaped curve analysis: GAM and random forest.

	Goodness of Fit of the Model	**Inverted U-Shape Test**
GAM	0.459	Pass
Random forest	0.659	Pass

The result in Table 6 illustrates that the curves fitted using the GAM method have the same inverted U-shape as the random forest method.

In summary, the inverted U-shaped relationship between ESR and total factor productivity TFP of listed companies holds true, whether through panel data regression or semi-parametric GAM with random forest method. It also indicates that the effect of listed companies' ESR on TFP is promoted and suppressed as ESR keeps increasing. Thus, H3 can be accepted.

4.4. Robustness Analysis

These tests allow researchers to discern variations in the regression coefficients of key variables by including or excluding regressions and by replacing specific variables. Incorporating diverse control variables in the preceding model is a form of robustness testing. In this section, the robustness of the main regression model was tested using several methods. First, we replaced the explanatory variables to check for consistency. Second, we employed instrumental variable regression with added interaction fixed effects. Robustness tests for regressions containing quadratic terms are similar to those for the main regression. In this section, the control variables in the empirical tables include all of those mentioned in Section 3.5.

Table 7 presents the outcomes of the robustness test on the fundamental regression model. Table 7 illustrates the replacement of explanatory variable measurements for analysis.

Table 7. Robustness analysis: basic regression.

Variables	**(1) TFP-OLS**	**(2) TFP-LP**	**(3) TFP-GMM**	**(4) TFP-FE**	**(5) TFP-RF**
ESR	0.468 ***	0.437 ***	0.224 ***	0.493 ***	0.502 ***
	(0.028)	(0.029)	(0.034)	(0.028)	(0.028)
Control variables	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES
Observations	25,962	25,962	25,962	25,962	25,962
R^2	0.929	0.884	0.688	0.690	0.933

Figures in parentheses below the coefficients indicate the cluster-robust standard errors of the regression coefficients. *** indicates that the coefficient is significant at 0.1% level of significance.

The empirical analysis employs a variety of econometric techniques including OLS, fixed effects, and GMM, in order to robustly estimate the impact of ESR on TFP, while also addressing potential endogeneity issues that may arise from omitted variable bias or measurement errors. Like previous model explorations, this model is fixed in both the time and individual firm dimensions, with controlled variables. The findings from the robustness test indicate that total factor productivity is measured using various metrics. Moreover, it suggests that the listed companies' environmental social responsibility enhances the company's total factor productivity. The robustness test demonstrates that listed companies' ESR initiatives can effectively boost their TFP, with a significant enhancement effect observed at the 0.1% significance level.

To make the robustness test more robust, a new TFP indicator, TFP-RF, was developed by implementing the random forest model using the values of TFP-OLS, TFP-GMM, and TFP-LP. We conducted a robustness test, which yielded consistent conclusions.

After conducting robustness tests with the explanatory variables replaced, the endogeneity issue must be discussed because of its importance in the empirical model. Based on experience, the core explanatory variable ESR's first-lag and second-lag terms can be selected as an instrumental variable, using L.ESR and L2.ESR to denote this instrumental variable. Table 8 shows the instrumental variable 2SLS regression results.

Table 8. Robustness analysis: basic regression.

Variables	(1) Step 1 ESR	(2) Step 2 TFP	(3) Step 1 ESR	(4) Step 2 TFP
L.ESR	0.564 ***			
	(0.013)			
L2.ESR			0.312 ***	
			(0.018)	
ESR		0.271 ***		0.227 ***
		(0.042)		(0.061)
Control variables	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES
Kleibergen–Paap rk LM	147.422 ***		69.924 ***	
Kleibergen–Paap rk Wald F	1876.489		315.344	
	[16.38]		[16.38]	
Observations	19,126	19,126	16,078	16,078

Figures in parentheses below the coefficients indicate the cluster-robust standard errors of the regression coefficients. *** indicates that the coefficient is significant at 0.1% level of significance. *** in Kleibergen–Paap rk LM means that instrumental variables test pass.

Based on the instrumental variable test outcomes displayed in Table 8, the lagged ESRs of one and two periods, along with the annual industry averages of ESRs, are deemed reliable instrumental variables. During the initial phase of the two-stage least squares regression analysis, these instrumental variables satisfactorily passed both the weak instrumental variable test and the over-identification test. Furthermore, the positive influence of the ESR of listed corporations on TFP remains statistically significant at the 0.1% confidence level during subsequent regression stages. This outcome reinforces the credibility of the results from the preceding section.

This study conducts a thorough investigation into the robustness of the U-shaped analysis. The stability of the trend analysis equation is confirmed through a robust examination that involves substituting explanatory variables. TFPs calculated by OLS, GMM, LP, FE, and RF methods are used as the main explanatory variable for the inverted U-shaped robustness test. The results are presented in Table 9, which includes the individual fixed effect.

Table 9. Robustness analysis: robustness test of the inverted U-shaped curve equation.

Variables	(1) TFP-OLS	(2) TFP-GMM	(3) TFP-LP	(4) TFP-FE	(5) TFP-RF
ESR	1.014 ***	0.984 ***	0.595 ***	1.058 ***	1.065 ***
	(0.048)	(0.048)	(0.057)	(0.049)	(0.049)
ESR^2	−0.218 ***	−0.218 ***	−0.147 ***	−0.227 ***	−0.228 ***
	(0.019)	(0.018)	(0.018)	(0.020)	(0.020)
Control variables	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES
Observations	25,962	25,962	25,962	25,962	25,962
R^2	0.934	0.891	0.694	0.940	0.938

Figures in parentheses below the coefficients indicate the cluster-robust standard errors of the regression coefficients. *** indicates that the coefficient is significant at 0.1% level of significance.

For further robustness testing, the robustness test was conducted using the instrumental variable method, and in this paper, 2SLS regressions were conducted using the one-period lagged and two-period lagged terms of ESR and its squared term as instrumental variables. The specific findings are shown in Table 10. We use instrumental variable regression to analyze the robustness.

Table 10. Robustness analysis: robustness test of the inverted U-shaped curve equation.

Variables	(1) Step 1 ESR	(2) Step 1 ESR^2	(3) Step 2 TFP	(4) Step 1 ESR	(5) Step 1 ESR^2	(6) Step 2 TFP
L.ESR	0.455 ***	−0.266 *				
	(0.029)	(0.126)				
$L.ESR^2$	0.0484 ***	0.778 ***				
	(0.013)	(0.072)				
L2.ESR				0.265 ***	−0.111	
				(0.033)	(0.170)	
$L2.ESR^2$				0.0222	0.457 ***	
				(0.018)	(0.109)	
ESR			1.194 ***			1.139 ***
			(0.073)			(0.111)
ESR^2			−0.234 ***			−0.198 ***
			(0.026)			(0.035)
Control variables	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES
Kleibergen–Paap rk LM		423.413 ***			228.476 ***	
Kleibergen–Paap rk Wald F		767.543			199.574	
		[7.03]			[7.03]	
Observations	19,126	19,126	19,126	16,078	16,078	16,078

Figures in parentheses below the coefficients indicate the cluster-robust standard errors of the regression coefficients. * indicates that the coefficient is significant at the 5% level of significance; similarly, *** indicates that the coefficient is significant at 0.1% level of significance. *** in Kleibergen–Paap rk LM means that instrumental variables test pass.

The robustness tests presented in Tables 9 and 10 demonstrate the existence of a non-linear correlation between the ESR of publicly traded companies in terms of environmental responsibility and TFP. This observation confirms the findings from the earlier non-linear regression model, showing strong robustness and reliability.

In this paper, the non-linear relationship between ESR and TFP is of great importance. Therefore, more robustness analyses are needed to verify the robustness of the relationship. Table 11 presents the results of further robustness tests. Columns (1)–(2) present the results of the regression with the addition of time–individual interaction fixed effects. Columns (3)–(4) show the results of the regression with replacement regressions, where two different regression methods, OLS and Poisson regression, are used in this section. Columns (5)–(6) modify the time intervals of the regression to analyze robustness through different sample windows.

The regression findings in Table 11 reveal that the primary and secondary terms of the core explanatory variable, ESR, are significantly positive and negative, respectively. This pattern holds even after adding interaction fixed effects and changing the regression method to time-split regressions by sample window. These adjustments further validate the conclusions drawn from previous empirical studies. The time-split regression also demonstrates the robustness of the results across different time frames, addressing any potential bias in the selected timeframe for the company data.

Table 11. Robustness analysis: robustness test of the inverted U-shaped curve equation.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	TFP					
	Adding Interaction Effects		Replacement Regression Model		Time Intervals	
			OLS	Poisson	2012–2019	2020–2022
ESR	1.433 ***	0.550 ***	0.147 ***	0.0964 ***	0.580 ***	1.002 ***
	(0.075)	(0.053)	(0.023)	(0.008)	(0.067)	(0.094)
ESR^2	−0.314 ***	−0.128 ***	−0.0138 *	−0.0244 ***	−0.137 ***	−0.211 ***
	(0.030)	(0.017)	(0.006)	(0.003)	(0.022)	(0.027)
Control variables	NO	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	NO	YES	YES	YES
Individual fixed effects	YES	YES	NO	YES	YES	YES
interaction fixed effects	YES	YES	NO	NO	NO	NO
Observations	25,962	25,962	25,962	25,962	15,194	10,768
R^2	0.374	0.796	0.853	0.030	0.739	0.777

Figures in parentheses below the coefficients indicate the cluster-robust standard errors of the regression coefficients. * indicates that the coefficient is significant at the 5% level of significance; similarly, *** indicates that the coefficient is significant at 0.1% level of significance.

4.5. Analysis of Company Size and Industry Type

This paper uses two different methods of analyzing heterogeneity to ensure the reliability of this heterogeneity study: group regression and regression with cross-multiplier terms. Incorporating a cross-multiplier term involving the firm size dummy variable and the ESR index facilitates the execution of the Chow test.

Based on the empirical findings presented in Table 12, ESR practices positively influence the TFP of publicly listed companies, regardless of their size. However, the extent to which ESR practices affect companies' TFP varies according to their size. Upon further examination of the cross-multiplier term of ESR with the dummy variable for company size, it is apparent that the coefficient of this cross-multiplier term holds a significant value at the 0.1% significance level. This result indicates that the Chow test is successful and provides evidence that ESR indeed exerts a varying impact on TFP for companies of different sizes. The effect in small companies is stronger by 97 percent.

Table 12. Analysis of company size.

Variables	(1) TFP	(2) TFP	(3) TFP
	Small Company	Large Company	Chow Test
ESR	2.618 **	0.270 ***	1.352 ***
	(0.273)	(0.028)	(0.159)
Large×ESR			−1.119 ***
			(0.151)
Large			0.089 ***
			(0.021)
Control variables	YES	YES	YES
Time fixed effects	YES	YES	YES
Individual fixed effects	YES	YES	YES
Observations	3638	22,324	25,962
R^2	0.756	0.779	0.795
Between-group coefficient difference test	Chi = 3.38 *		

Figures in parentheses below the coefficients indicate the cluster-robust standard errors of the regression coefficients. ** and *** indicate that the coefficient is significant at the 1% and 0.1% levels of significance. * in the between-group coefficient difference test Chi statistic means the coefficient difference is significant.

Analyses of size differences show that the cross-multiplier terms of the company size dummy variable and the ESR index play an important role in the regressions, suggesting that there is a difference between large and small firms in terms of the impact of ESR initiatives on TFP. We set an assets variable greater than 21 as 1, reflecting large companies, while otherwise 0. Table 12 of the empirical study shows that ESR contributes significantly more to TFP in small firms than in large companies. This difference can be attributed to the scale of operation of large companies, which allows them to exploit economies of scale and optimize productivity. This operational advantage enables large firms to manage their ESR costs more effectively. In contrast, small firms tend to focus on niche markets because they lack the resources and scale of operation of large companies. While large-scale firms continue to pursue environmental policies, small-scale firms should pay more attention to ESR, as ESR can have a stronger effect on small-scale firms' TFP promotion.

After exploring the effect of different sizes on the mechanism, we move on to explore the effect of the company's industry type on the mechanism. The research classifies listed companies into high-tech and non-high-tech types. Similar to the previous approach, group regressions are used to introduce regressions with cross-multiplier terms, and the significance of the coefficients of the cross-multiplier terms is explored. According to the empirical results in Table 13, although the coefficient on the cross-multiplier term of ESR with company industry type is not significant, the between-group coefficient difference test of the subgroup regression significantly rejects the original hypothesis and is significant at the 0.1% significance level. The effect in high-tech companies is stronger by 57 percent. This suggests that the strength of the effect of ESR on TFP differs between high-tech and non-high-tech companies. The effect of ESR on TFP is stronger in high-tech companies than in non-high-tech companies.

Table 13. Analysis of company industry type.

Variables	(1) TFP	(2) TFP	(3) TFP
	High-Tech	Non-High-Tech	Chow Test
ESR	0.322 ***	0.205 ***	0.227 ***
	(0.041)	(0.039)	(0.033)
High-tech×ESR			0.0244
			(0.034)
High-tech			0.0309
			(0.027)
Control variables	YES	YES	YES
Time fixed effects	YES	YES	YES
Individual fixed effects	YES	YES	YES
Observations	11,202	14,760	25,962
R^2	0.792	0.788	0.793
Between-group coefficient difference test		Chi = 12.09 ***	

Figures in parentheses below the coefficients indicate the cluster-robust standard errors of the regression coefficients. *** indicates that the coefficient is significant at 0.1% level of significance. *** in the between-group coefficient difference test Chi statistic means the coefficient difference is significant.

Companies in high-tech industries are usually engaged in the development of technology-intensive products or services and thus have a high degree of technological sophistication and innovation. In contrast, non-high-tech industrial firms usually focus on traditional production or service areas and thus have relatively low technological sophistication and innovation capacity. The gap between high-tech industrial firms and non-high-tech industrial firms stems from the differences in their industry environments, technology levels, and market demands. These differences also affect their business models, organizational frameworks, and management practices, which in turn affect their competitiveness and performance outcomes. The results of the industrial form heterogeneity analysis show that there is a significant difference in the regression coefficients between high-tech and non-high-tech industrial firms. It is worth noting that the positive impact of ESR on TFP is more pronounced for high-tech industrial firms. High-tech enterprises' emphasis on ESR stems from the need for market competition, their unique industry characteristics, and the need for technological innovation. By actively undertaking ESR, these firms can expand their competitive advantage, increase TFP, and achieve sustainable development goals. In contrast, non-high-tech industrial entities prioritize short-term performance over sustainable development, resulting in much less effective environmental responsibility initiatives in the sector. This highlights the tendency of listed companies to increase total factor productivity by pursuing high technology and technological transformation. Table 13 provides the results of the industry effects analysis. Based on Tables 12 and 13, H2a and H2b can be accepted.

Listed companies' ESRs play a significant role in fostering small-size companies and those focused on high-tech sectors. Moreover, this finding can provide direction for the company's future policy formulation.

Since this paper includes the quadratic term of the ESR to explore a U-shaped relationship, it is reasonable to use a regression equation with a quadratic term when examining heterogeneity. Following the grouping of the equation incorporating the quadratic term for heterogeneity analysis and Chow test, detailed findings are presented in Table 14.

Table 14. Analysis of company size and industry types for inverted U-shape.

Variables	**(1) TFP**	**(2) TFP**	**(3) TFP**	**(4) TFP**	**(5) TFP**	**(6) TFP**
	Small Company	**Large Company**	**Chow Test**	**High-Tech**	**Non-High-Tech**	**Chow Test**
ESR	3.481 ***	0.595 ***	0.536 ***	0.586 ***	0.532 ***	0.552 ***
	(0.474)	(0.055)	(0.053)	(0.090)	(0.068)	(0.054)
ESR^2	−1.596 ***	−0.129 ***	2.121 **	−0.127 ***	−0.120 ***	−0.125 ***
	(0.569)	(0.018)	(0.395)	(0.035)	(0.020)	(0.017)
Large× ESR^2			−2.246 ***			
			(0.395)			
Large			0.003			
			(0.012)			
High-tech× ESR^2						−0.01
						(0.014)
High-tech						0.038
						(0.023)
Control variables	YES	YES	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES	YES	YES
Observations	3638	22,324	25,962	11,202	14,760	25,962
R^2	0.759	0.783	0.797	0.794	0.790	0.796
Between-group coefficient difference test		Chi = 6.69 **			Chi = 0.10	

Figures in parentheses below the coefficients indicate the cluster-robust standard errors of the regression coefficients. ** and *** indicate that the coefficient is significant at the 1% and 0.1% levels of significance. ** in the between-group coefficient difference test Chi statistic means the coefficient difference is significant.

Based on the empirical data presented in Table 14, it is noted that for small-scale enterprises, the U-shaped curve delineated by the ESR index of publicly traded companies and the total factor productivity exhibits a more pronounced gradient in comparison to larger enterprises, characterized by distinct peaks. Nevertheless, the disparity in the curvature of the U-shaped graph is less discernible among companies with varying industrial sectors, particularly between those in high-technology and non-high-technology sectors.

For small-sized companies, the U-shaped curve formed by the ESR index of listed companies and total factor productivity is steeper than that of large-sized companies, and it has more obvious "spikes". However, the difference in the U-shaped curve is not obvious for companies with different industrial sector distributions, especially for high-tech and non-high-tech companies. At the same time, due to flexibility and resource constraints, the productivity of small-scale firms exhibits a clear "spike" when ESR inputs reach their optimal point. This implies there is a threshold point at which the positive benefits of ESR are maximized but beyond which the negative effects rapidly emerge. In contrast, for large firms, because of the availability of resources and strong management capabilities, the productivity change around the optimal point of ESR inputs is more moderate, with no clear "spike" but rather a wider plateau.

For companies in the high-tech industry that allocate significant resources to technological innovation and research and development, ESR programs can expedite productivity enhancements through technological advancements and innovations. However, excessive investments may result in resource fragmentation and heightened management intricacies, which would diminish productivity. Conversely, while less pioneering, non-high-tech companies can derive substantial benefits from ESR initiatives in bolstering brand reputation and fostering customer loyalty. Nevertheless, imprudent investments may lead to managerial challenges and resource misallocation. Variances in resource distribution and management practices between high-tech and non-high-tech enterprises predominantly revolve around technology and innovation investments, yet both categories demonstrate comparable competencies in resource administration and organizational adaptations in ESR project implementations.

4.6. The Impact of Greenwashing

In this paper, we quantified the "greenwashing" behavior of listed companies and constructed dummy variables based on the "greenwashing" index to analyze the differences between companies with high and low levels of "greenwashing". We also constructed a dummy variable using the "greenwashing" index to examine the variation in mechanisms between these two groups. The analysis is based on data from the years 2018 to 2022.

The "greenwashing" index refers to Hu X et al. (2023) [60]. The "greenwashing" behavior index is constructed using the available company indicators, all of which are obtained from the WIND database. The specific index construction is shown in Equation (12).

$$GWS_{it} = \left(\frac{ESG_{dis,it} - \overline{ESG_{dis}}}{\sigma_{dis}}\right) - \left(\frac{ESG_{per,it} - \overline{ESG_{per}}}{\sigma_{per}}\right) \quad (12)$$

The calculation of this indicator represents the difference between the normalized relative position disclosure score to peers in the distribution of a company's ESG and the normalized ESG performance score of a company against its peers. The first term of Equation (12 is a standardized indicator of a company's position relative to its peers in the distribution of ESG disclosure scores. The second term is a standardized indicator representing the company's position relative to its peers in the modified ESG performance score distribution. A frequency distribution histogram was used to reflect the GWS data obtained, as shown in Figure 2.

According to Figure 2, the GWS appears close to the left-skewed distribution of the normal distribution because the calculation of the GWS is a process of standardizing the ESG data. In this study, a "greenwashing" index greater than 1 was categorized as serious "greenwashing" behavior; when the GWS value is between -1 and 1, it is weak greenwashing; and when the GWS value is less than -1, it is no greenwashing. The results of the specific group regressions and between-group coefficient difference tests are shown in Table 15.

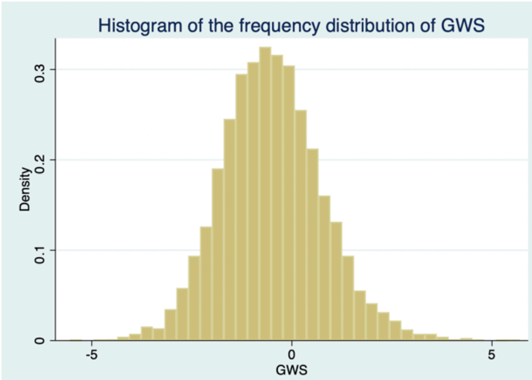

Figure 2. Histogram of the frequency distribution of GWS.

Table 15. "Greenwashing" impact analysis.

Variables	(1)	(2)	(3)	(4)
	TFP	**TFP**	**TFP**	**TFP**
	Full Sample	**Heavy "Greenwashing"**	**Weak "Greenwashing"**	**No "Greenwashing"**
ESR	0.246 ***	0.065	0.265 **	0.315 ***
	(0.033)	(0.065)	(0.100)	(0.093)
Control variables	YES	YES	YES	YES
Time fixed effects	YES	YES	YES	YES
Individual fixed effects	YES	YES	YES	YES
Observations	7211	836	5027	1348
R^2	0.801	0.710	0.811	0.776

Figures in parentheses below the coefficients indicate the cluster-robust standard errors of the regression coefficients. ** and *** indicate that the coefficient is significant at the 1% and 0.1% levels of significance.

Based on the findings in Table 15, the sample explored in this part of the study had more companies that were not "greenwashed" or had a low level of "greenwashing" than companies with a high level of "greenwashing". This also suggests that in the five years from 2018 to 2022, although there are companies that "greenwash" themselves, the percentage of companies that "greenwash" to a high degree is still relatively small. This indicates that listed companies are still a minority when it comes to "moral hazard" in the context of environmental regulation.

In this part of the study, it is still necessary to focus on the regression results. Columns (1)–(4) of the above table represent the full-sample panel data regression, the panel data regression of severely "greenwashed" companies, and the panel data regression of companies that are less "greenwashed" or cover up their environmental work. The regression coefficient of the environmental social responsibility of listed companies on total factor productivity is 0.065 for companies with severe "greenwashing", 0.265 for companies with weak "greenwashing", and 0.315 for no "greenwashing" companies. The coefficients of core explanatory variables in (3) and (4) are significant at a 99% and 99.9% confidence level of cluster standard error, which confirms that the selected samples are still in line with the conclusions obtained from the previous main regression model. The effect in no greenwashing companies and weak greenwashing companies is stronger than in heavy greenwashing companies.

However, according to the empirical findings, it can be noted that the regression coefficients of different subgroups vary significantly. Therefore, it can be concluded that the promotion of total factor productivity by listed companies' ESR is stronger for companies that do not "greenwash" or do not disclose their environmental behaviors, while the promotion of this mechanism is weaker and insignificant in companies with higher levels of "greenwashing". H4 can be accepted.

5. Discussion

According to the conclusions of previous empirical studies, ESR can promote TFP within a certain range, and the non-linear relationship between ESR and TFP exists, which is robust and presents an inverted U-shape. These conclusions remain valid after further verification by the semi-parametric GAM model and the random forest algorithm.

Previous research is mainly about the linear relationship between company behavior and performance, and there are few studies utilizing machine learning techniques [2,5,14]. Compared with previous studies, this study does not merely explore the linear relationship between corporate environmental behavior and total factor productivity. We do not simply study the promotion or inhibition effect but introduce non-linear relationships into the study and further verify them using machine learning methods. In addition, the threshold can be calculated through non-linear models, which provide practical guidance for the implementation of company environmental behavior and policy formulation. The conclusions obtained are more in line with real-world economic phenomena, namely that excessive attention to environmental issues can lead to a decline in production capacity.

In summary, the research perspective, research methods, and practical significance of this article have been expanded compared with previous studies.

6. Conclusions

This research shows a significant positive correlation between the ESR level of listed companies and their TFP. However, this relationship is non-linear, presenting an inverted U-shaped curve. Initially, as ESR increases, TFP rises. Beyond a certain threshold, further increases in ESR lead to a decline in TFP. This effect is more pronounced in smaller companies, which show a greater improvement effect compared to larger companies. Additionally, companies in high-tech industries benefit more from ESR initiatives, while practices like "greenwashing" undermine these positive effects. The findings have far-reaching ramifications for corporate governance practices. However, this study has several limitations. The sample is from China and may not be broad enough to fully represent different industries and regions, and the methods used to measure ESR and TFP could introduce bias. Although the inverted U-shaped relationship between ESR and TFP is identified, factors such as external market conditions and government policies were not explored in depth. Future research could address these gaps by expanding the dataset, using dynamic models, and conducting industry-specific analyses. Additionally, it should examine the role of government policies in shaping the relationship between ESR and TFP, investigate the mechanisms behind greenwashing, and develop improved methods for assessing its impact on firm performance. Exploring how technological advancements affect the outcomes of ESR initiatives could also provide new insights.

To promote ESR and TFP, the government can play a key role by implementing various fiscal incentives such as tax breaks, financial rewards, and preferential loan rates. Introducing a company social responsibility award to honor companies excelling in environmental protection and social responsibility can boost industry enthusiasm and support sustainable development. The government can also develop differentiated policy measures for companies of different sizes and industries. For small companies, providing specialized training, consulting services, and financial support is crucial. For high-tech industry companies, offering more R&D funding, technical support, and tax reductions can drive the development and application of green technologies and products, facilitating industrial upgrading and achieving coordinated economic, social, and environmental development. For relevant government departments, establishing a comprehensive and scientific environmental impact assessment system is essential. This system can regularly and impartially evaluate the ESR of listed companies and impose appropriate penalties on those failing to meet standards, ensuring companies fulfill their social responsibilities and protect the environment and public interest. Moreover, the government should enhance the review procedures for corporate ESR reports to ensure the accuracy and authenticity of their content, increasing information transparency for the public and investors. To prevent "greenwashing", it is imperative to improve the transparency and openness of corporate environmental responsibility information.

Companies need to understand the non-linear relationship between ESR and TFP, paying attention to moderate ESR to avoid overcommitment that can decrease productivity. Companies should actively engage in ESR initiatives, avoiding "greenwashing" by taking genuine environmental actions to enhance their image and efficiency. Small companies and high-tech companies should be more focused on the level of ESR. Since the conclusions obtained in this article are general, listed companies need to pay close attention to the relationship with their own total factor productivity and stabilize their environmental social responsibility levels around their own thresholds, thereby maintaining a high level of production.

In summary, the collaboration between the government and listed companies will support sustainable economic, social, and environmental development. The government can establish a comprehensive and scientific evaluation system, strengthen the review of corporate reports, and ensure companies genuinely fulfill their social responsibilities and protect the environment. Economic incentives and reward mechanisms will encourage companies to actively participate in ESR, promoting sustainable industry development. Tailored policies for different company sizes and industry needs will further encourage the use of green technologies and products, promoting balanced economic, social, and environmental development. Governments can provide green bonds, loans, and tax incentives to encourage green investment. Carbon pricing mechanisms should be promoted to foster sustainable development. Support could be provided to small companies through green technology subsidies and technical assistance to reduce the cost of adopting sustainable practices. Listed companies should be required to disclose their environmental, social, and governance performance, and third-party audits should be introduced to prevent 'greenwashing'. Emission standards should be set for highly polluting industries, while sustainable practices should be encouraged in areas such as agriculture. The government could also promote a circular economy and resource reuse through extended producer responsibility systems and waste-to-energy programs. Finally, corporate social responsibility activities and public awareness programs should be launched to involve all sectors in environmental protection. Strengthening the enforcement of environmental laws and regulations, imposing heavy penalties on companies that violate regulations, and rewarding companies with outstanding performance will help encourage companies to actively fulfill their social responsibilities and achieve coordinated and sustainable development.

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Appendix A

Before TFP estimation, the form of the production function needs to be set, with the Cobb–Douglas function used as the production function. Douglas, P. H. (1976) [61] supposed that the Cobb–Douglas function reflects the production activities of the company well.

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} \tag{A1}$$

The variables used need to be defined before the OP estimation. By using Equation (A3), we define the relationship between the firm's cost and investment.

$$K_{it+1} = (1-\delta)K_{it} + I_{it} \tag{A2}$$

where K denotes firm cost, and I denotes company investment.

According to the idea of the OP method, there exists an upper limit to the technological critical value ϖ. The higher the level of technology in this period, the higher the level of investment in the current period.

$$i_{it} = i_t(\varpi, k_{it}) \tag{A3}$$

Assuming that h is an inverse function of i, then ϖ can be expressed as follows:

$$\varpi_{it} = h_{it}(i_{it}, k_{it}) \tag{A4}$$

Then we linearize Equation (A5) and take the natural logarithm of both the left and right sides.

$$y_{it} = \beta k_{it} + \alpha l_{it} + \varepsilon_{it} \tag{A5}$$

Substituting Equation (A4) into Equation (A5) gives the following:

$$y_{it} = \beta k_{it} + \alpha l_{it} + h_{it}(i_{it}, k_{it}) + u_{it} \tag{A6}$$

The contribution of capital to production can be defined as ϕ through Equation (A7):

$$\phi_{it} = \gamma k_{it} + h_{it}(i_{it}, k_{it}) \tag{A7}$$

$$y_{it} = \alpha l_{it} + \phi_{it} + u_{it} \tag{A8}$$

Equation (A8) allows the estimation of the coefficient of labor, α. Next, it is necessary to estimate the coefficient of capital, γ. We assume V_{it} in order to estimate γ.

$$V_{it} = \ y_{it} - \hat{\alpha} l_{it} \tag{A9}$$

It is sufficient to finally estimate Equation (A10):

$$V_{it} = \ \gamma k_{it} + g(\phi_{it-1} - \gamma k_{it-1}) + \mu_{it} + u_{it} \tag{A10}$$

Equation (A10) contains lagged variables that are constantly iterated and cannot be estimated by simple linear regression. After Equation (A11) is estimated, TFP can be calculated based on the Cobb–Douglas function.

Olley and Pakes (1996) [49] suggested that the firm's optimal decision-making can be measured using a Bellman equation (Bellman, 1966 [62]), which is shown in Equation (A11). The problem of selectivity bias can be well addressed using Bellman's equation.

$$V_{it}(K_{it}, a_{it}, \omega_{it}) = Max\left\{\Phi, Sup_{I_{it\geq 0}} \Pi_{it}(K_{it}, a_{it}, \omega_{it}) - C(I_{it}) + \rho E[V_{i,t+1}(K_{i,t+1}, a_{i,t+1}, \omega_{i,t+1})|J_{it}]\right\} \tag{A11}$$

where π is the profit function, C is the cost of investment, ρ is the discount factor, and E denotes the expectation of the future at time t. If ϕ is greater than the expected return, then the firm will withdraw from the market and cease production activities. The exit function is shown in Equation (A12).

$$\chi_{it} = \begin{cases} 1\ if\ \omega_{it} \geq \underline{\omega}_{it}(K_{it}, a_{it}) \\ 0 \qquad\qquad\quad others \end{cases} \tag{A12}$$

When χ is 1, the firm continues its production activities; when χ is 0, the firm withdraws from them. A firm's exit decision relies on a technological threshold $\underline{\omega}$. If real productivity is above this threshold, the firm will remain in business; otherwise, it will exit the industry.

Since the variable contains only 1s and 0s, the exit variable can be measured using the probit function.

$$Probit(\chi_{it} = 1|J_{i,t-1}) = Probit\left(\chi_{it}\middle|\omega_{it-1}, \widehat{\omega_{it}(k_{i,t+1}}\right)) = \varphi(i_{i,t-1}, k_{i,t-1}) \tag{A13}$$

After performing all the above steps, the regression in Equation (A14) allows the measurement of the cost of investment in listed companies i.

$$V_{it} = \gamma k_{it} + g\left(\phi_{it-1} - \gamma k_{it-1}, \widehat{Probit}_{t-1}\right) + \mu_{it} + u_{it} \tag{A14}$$

Despite sample selection bias, this treatment yields consistent estimates of the capital term.

The specific model for measuring TFP using the OP method is shown in Equation (A15). This calculation references Olley and Pakes (1996) [49] and Loecker (2007) [52].

$$\begin{gathered} lnY_{it} = \beta_0 + \beta_k lnK_{it} + \beta_l lnL_{it} + \beta_a age_{it} + \beta_s state_{it} + \beta_e EX_{it} \\ + \sum_m \delta_m year_m + \sum_n \lambda_n reg_n + \sum_k \zeta_k ind_k + \varepsilon_{it} \end{gathered} \tag{A15}$$

In Equation (A15), i represents the company, j represents the industry, age represents the age of the company, state is a dummy variable indicating whether it is a state-owned enterprise or not, and EX is also a dummy variable reflecting whether the company is involved in import and export activities. Due to simultaneity bias and sample selection bias in the least squares estimation process, we use the Olley–Pakes three-step semi-parametric estimation method. In this calculation, the state variables are represented by state, which contains lnK and *age*; the control variables contain state and EX; the proxies are lnL; *year*, *reg*, and *ind* are free variables; and the exit variable, *exit*, is generated based on the firm's operations.

After performing all the above steps, the total factor productivity is calculated as shown in Equation (A16).

$$lnTFP_{it} = lnY_{it} - \beta_k lnK_{it} - \beta_l lnL_{it} \tag{A16}$$

Appendix B

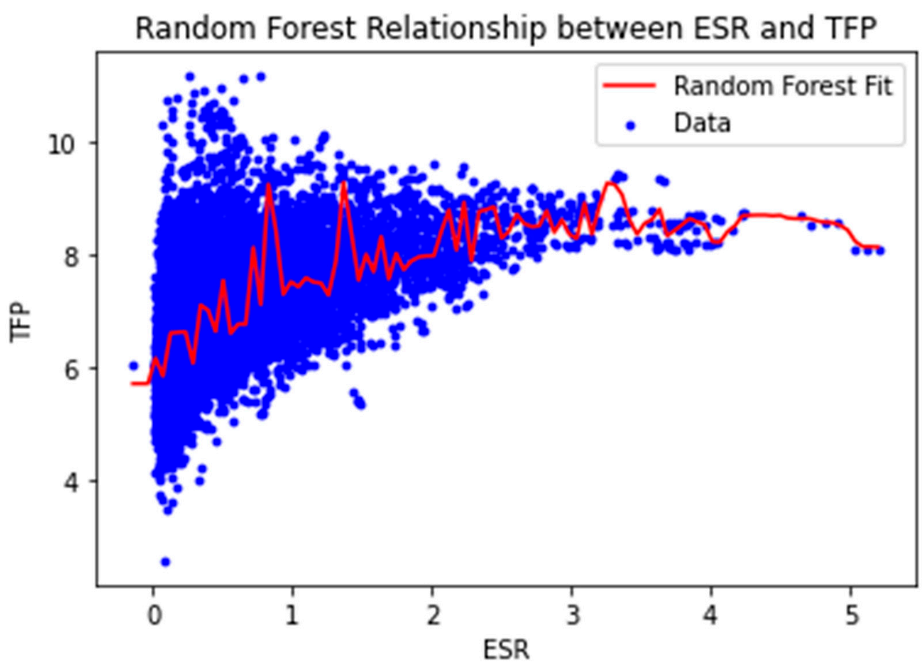

Figure A1. Random forest fit.

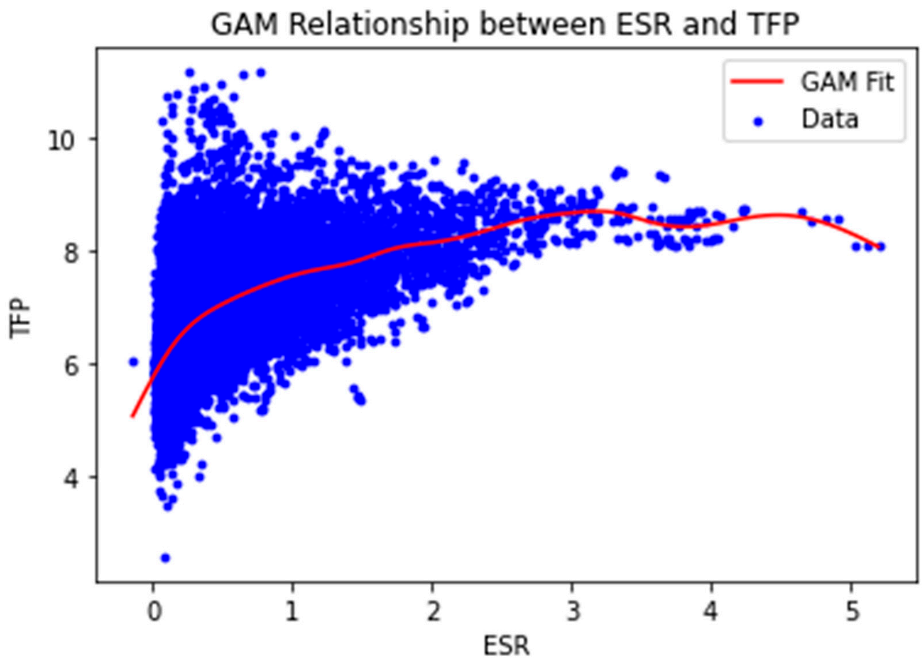

Figure A2. GAM fit.

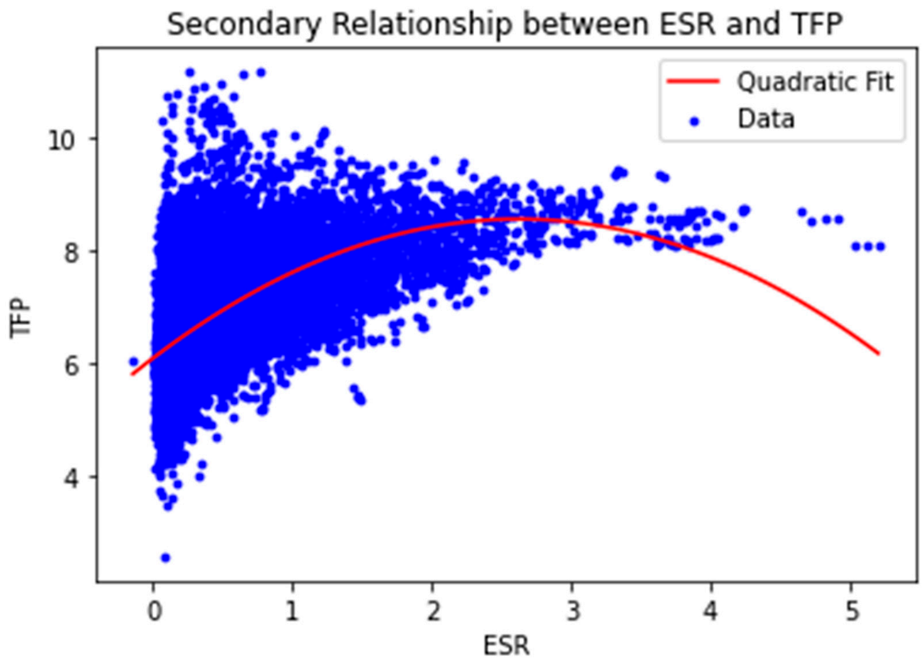

Figure A3. Quadratic fit.

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