

ESG Rating Disagreement and Corporate Total Factor Productivity: Inference and Prediction

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Abstract

This paper examines how ESG rating disagreement (*Dis*) affects corporate total factor productivity (TFP) in China based on data of A-share listed companies from 2015 to 2022. We find that *Dis* reduces TFP, especially in state-owned, non-capital-intensive, and low-pollution firms. Mechanism analysis shows that green innovation strengthens the dampening effect of *Dis* on TFP, and that *Dis* lowers corporate TFP by increasing financing constraints. Furthermore, XGBoost regression demonstrates that *Dis* plays a significant role in predicting TFP, with SHAP showing that the dampening effect of ESG rating disagreement on TFP is still pronounced in firms with large *Dis* values.

JEL Codes: G32, G24, C54.

Keywords: ESG rating disagreement; Total factor productivity; Green innovation; Financing constraints; Machine learning

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1 Introduction

Since 1987, the United Nations has reinforced its commitment to sustainable development, and introduced the concept of ESG (Environmental, Social, and Governance) by then-UN Secretary-General Kofi Annan in 2004. Since then, ESG principles have been increasingly integrated into global investment strategies and corporate assessments, with their specific meanings evolving over time. In recent years, China is prominently advocating the philosophy that "green mountains and clear waters are as valuable as mountains of gold and silver", and promoting sustainable development both domestically and internationally. On December 27, 2023, the *Guidelines for the Comprehensive Advancement of Beautiful China Construction* was issued by the Central Committee of the Communist Party of China and the State Council clearly clarified the exploration and development of ESG assessment frameworks, which shows a strong will of establishing ESG Evaluation System with Chinese Characteristics.

Despite the implementation of various ESG policies in recent year, there are still significant disagreement in ESG rating system. From the moment the ESG concept was introduced in China, multiple rating agents have independently published their ESG rating reports. However, these reports often display significant discrepancies in ratings, which undoubtedly has a substantial impact on the companies being evaluated. Examining the economic consequences of these ESG rating disagreements is of considerable value for both enterprises and regulatory bodies. The main recent studies are: Wang et al. (2024); Zhao et al. (2024) argue that disagreements in ESG ratings are significantly negatively correlated with stock returns; ESG rating disagreement increase analyst forecast errors(Liu et al., 2024); ESG rating disagreement drives firms towards green innovation (Hou and Xie, 2024; Geng et al., 2024; Chen et al., 2024a); Moreover, increased disagreement in ESG ratings leads to higher levels of real earnings management both in the current period and over the next one to two years (Li and Cheng, 2024); The firms with agreed high ESG rating can benefit through cost reduction and larger amount debt-financing(Guo et al., 2024); Besides,the disagreement in ESG ratings may poses a potential risk of stock price collapse(Luo et al., 2023); What's more, ESG rating disagreement significantly increases audit fees due to information asymmetry(Ling et al., 2024).

However, the focus of most recent studies has been less on exploring the impact of ESG rating disagreements on the overall development of a company. Therefore, we select TFP as the subject of our analysis in this study, as it serves as an indicator of a company's high-quality development.

2 Theoretical Analysis and Research Hypotheses

According to information asymmetry theory, ESG rating disagreements can confuse stakeholders and contribute to the degree of information asymmetry between companies and investors. ESG ratings, as non-financial information, provide stakeholders with a more comprehensive insight into companies, thereby alleviating information asymmetry (Xiaohong and Zhenghan, 2023). Conversely, significant ESG rating disagreements can intensify information asymmetry, creating a noise effect that leads to investor misjudgments (Berg et al., 2022). Thereby, increasing financing constraints and ultimately resulting in a decline in total factor productivity. Simultaneously, based on stakeholder theory, companies may take certain remedial measures in response to ESG rating disagreements to balance the interests of various stakeholders. For example, companies might intensify green innovation under the stimulus of ESG rating disagreements (Hou and Xie, 2024; Geng et al., 2024; Chen et al., 2024a); However, as this initiative cannot cater to all stakeholders under noise effect caused by ESG rating disagreement, it may lead some groups to perceive "greenwashing" behaviors, which ultimately undermines the company's financing efforts and results in a decline in total factor productivity (Peng and Xie, 2024).

In summary, we propose the research hypothesis **H1**: ESG rating disagreement reduces corporate TFP.

3 Data and Empirical Design

3.1 Sample Selection

We utilize financial data of A-share listed companies in China from 2015 to 2022¹, alongside ESG ratings from four agencies: Huazheng, Wind, SynTao Green Finance, and MioTech. The data processing procedures follow these steps: (1) excluding companies in the financial and real estate industries; (2) excluding ST, *ST, and delisted companies; (3) excluding companies with only one ESG rating in a given year; (4) excluding companies with missing key indicators; and (5) applying Winsorization at the 1% level on both tails. All data is sourced from the CSMAR database, the CNRDS database, and the four rating agencies, resulting in 13417 samples in baseline regression.

¹Before 2015, the only more well-known local ESG rating agencies in China were Huazheng

3.2 Model Specification

To test the hypotheses presented earlier, we conduct the following baseline regression model²:

$$TFP_{i,t+1} = \alpha_0 + \alpha_1 Dis_{i,t} + \alpha_2 Control_{i,t} + Year_t + Id_i + \epsilon_{i,t} \quad (1)$$

where $TFP_{i,t+1}$ is the total factor productivity of company i in year $t + 1$, $Dis_{i,t}$ is the ESG rating discrepancy, $Control_{i,t}$ represents the control variables, $Year_t$ and Id_i denote year and company fixed effects, respectively, and $\epsilon_{i,t}$ is the error term.

3.3 Variable Descriptions

(1) Dependent Variable

The dependent variable in this study is Corporate Total Factor Productivity. Considering the robustness of the empirical process, we use three methods to measure TFP, they are LP introduced by Levinsohn and Petrin (2003) and adopted by Lu and Lian (2012), OP by Olley and Pakes (1992) and GMM by Blundell and Bond (1998). In the prediction task, we use TFP measured by LP method as the dependent variable (Xue et al., 2024).

(2) Independent Variable

The independent variable in this study is ESG Rating Disagreement. Domestic ESG rating agencies have advantages in terms of time and spatial proximity that foreign agencies cannot match, making them more likely to influence the behavior of domestic firms. Therefore, this study uses ESG rating data from four Chinese agencies: Huazheng, Wind, SynTao Green Finance, and MioTech. Following Avramov et al. (2022), the ratings were assigned positive values according to their rating levels, with a difference of 1 between levels. We define the rankings as the values normalized to the range $[0, 1]$ for the given rating agency in a given year, and the pairwise standard deviation of these rankings is used as the measure of Dis .

$$Dis_{i,t} = \sqrt{\frac{1}{n-1} \sum_{k \neq j}^n (rank_{i,t,k} - rank_{i,t,j})^2} \quad (2)$$

where $rank_{i,j,k}$ represents the normalized ranking of corporate i in year t given by agency k , n represents the number of pairs, k and j represent different ESG rating agencies.

(3) Control Variables

²Considering the time required for information to be transmitted and for the market to react, TFP is lagged by one period

Based on the characteristics of our research and with reference to the works of Yang et al. (2024) and Xue et al. (2024), the control variables include firm value, top 10 shareholders' ownership percentage, years listed, leverage ratio, firm size, revenue per capita, and ownership ratio. The main variables are defined in Table 1.

Table 1: Definition of Main Variables

Symbol	Source	Description
<i>TFP</i>	CSAMR	Estimated using the LP, OP and GMM method
<i>Dis</i>	ESG Rating Agencies	Calculated based on the method described above
<i>TobinQ</i>	CSAMR	Tobin's Q ratio
<i>Top10</i>	CSAMR	Shareholding of top 10 shareholders / total shares
<i>ListAge</i>	CSAMR	Natural logarithm of years since the firm's IPO
<i>Lev</i>	CSAMR	Total liabilities at year-end / total assets at year-end
<i>Size</i>	CSAMR	Natural logarithm of total assets at year-end
<i>Avg</i>	CSAMR	Natural logarithm of operating income / number of employees
<i>Der</i>	CSAMR	Total liabilities at year-end / total equity at year-end
<i>EI</i>	CNRDS	Natural logarithm of the number of green patents obtained in a given year
<i>FC</i>	CSAMR	WW and KZ indices, the larger they are the more constrained the financing is

4 Empirical Analysis

Table 2: Descriptive Statistics of Main Variables

Variables	Count	Mean	SD	Min	25%	50%	75%	Max
TFP_{LP}	13417	8.51	1.04	6.38	7.79	8.40	9.14	11.28
TFP_{OP}	13417	6.83	0.85	5.14	6.24	6.72	7.33	9.17
TFP_{GMM}	13417	5.72	0.80	4.09	5.18	5.63	6.18	8.12
Dis	13417	0.26	0.19	0.01	0.11	0.24	0.34	0.83
$TobinQ$	13417	2.03	1.32	0.83	1.22	1.61	2.31	8.34
$Top10$	13417	56.77	15.15	23.59	45.91	56.95	67.87	90.89
$ListAge$	13417	2.34	0.68	1.10	1.79	2.40	3.00	3.37
Lev	13417	0.43	0.19	0.06	0.28	0.43	0.57	0.88
$Size$	13417	22.52	1.34	20.09	21.54	22.32	23.31	26.41
Avg	13417	4.79	0.80	3.07	4.25	4.69	5.25	7.17
Der	13417	1.05	1.07	0.07	0.39	0.74	1.31	6.75
EI	13417	1.30	1.49	0.00	0.00	1.10	2.30	7.74
WW	10059	-1.03	0.08	-1.24	-1.08	-1.03	-0.98	-0.86
KZ	13417	1.17	1.94	-4.35	0.02	1.36	2.49	6.22

Note: The data in the table are descriptive statistics for deleting missing values after lagging one period of TFP.

4.1 Baseline Regression

Table 3 reports the results of the baseline regression, with clustering at the individual and time levels. The results indicate that ESG rating disagreement reduces corporate total factor productivity, providing preliminary support for the validity of Hypothesis H1.

Table 3: Baseline Regression Results

Variables	TFP					
	TFP_{LP}	TFP_{OP}	TFP_{GMM}	TFP_{LP}	TFP_{OP}	TFP_{GMM}
<i>Dis</i>	-0.0675*** (-2.7452)	-0.0536** (-2.1838)	-0.0536** (-2.2098)	-0.0447*** (-2.9449)	-0.0357** (-2.2503)	-0.0373** (-2.2395)
<i>TobinQ</i>				-0.0032 (-0.5471)	-0.0017 (-0.3953)	-0.0007 (-0.1795)
<i>Top10</i>				-0.0010 (-0.9976)	-0.0009 (-0.9496)	-0.0005 (-0.4838)
<i>ListAge</i>				0.0989** (2.4952)	0.0855** (2.3667)	0.0160 (0.4241)
<i>Lev</i>				-0.1697 (-1.5121)	-0.1557 (-1.5361)	-0.1481 (-1.4348)
<i>Size</i>				0.3737*** (13.129)	0.2581*** (14.214)	0.2245*** (10.939)
<i>Avg</i>				0.2292*** (2.7852)	0.2695*** (2.8274)	0.2671*** (2.7426)
<i>Der</i>				-0.0210** (-2.0405)	-0.0190* (-1.8342)	-0.0211** (-1.9816)
Controls	NO	NO	NO	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Id	YES	YES	YES	YES	YES	YES
Doubel Clustering	YES	YES	YES	YES	YES	YES
<i>N</i>	13417	13417	13417	13417	13417	13417
<i>R</i> ²	0.0015	0.0011	0.0011	0.1785	0.1670	0.1409

Note: t-statistics are in parentheses. * p<0.1, ** p<0.05, *** p<0.01. The same applies below.

4.2 Robustness Tests

To ensure the robustness of the baseline regression results, the following robustness tests were conducted.

First, to verify whether Hypothesis H1 holds when only leading *Dis* by one period, we lead the it by one period(see table8).

Second, since the total factor productivity of firms in this study is influenced by regional productivity levels, to mitigate endogeneity issues arising from omitted variable bias, we include the provincial-level New quality productivity measured by Lu et al. (2024) as a control variable (see table9).

Third, following Yang et al. (2022), we calculate the industry average of ESG rating disagreements by year and industry, and use the cube of the difference between the industry average and the ESG rating disagreements as an instrumental variable. A two-stage least squares (2SLS) estimation is then conducted to further mitigate potential

endogeneity issues (see table10).

Fourth, we denote disagreements under 20% as non-existent and the remainder as present. Propensity scores are computed via logistic regression, followed by 1:1 nearest-neighbor matching and subsequent regression (see table11).

4.3 Mechanism Analysis

4.3.1 The Role of Green Innovation

Myriad existing researches demonstrate that ESG rating disagreement can drive firms to enhance green innovation(Hou and Xie, 2024; Geng et al., 2024; Chen et al., 2024b). However, does this green innovation truly contribute to substantial corporate development? This study introduces green innovation as a mechanism variable, measured by the natural logarithm of the number of green patents held by a company. To examine the role of green innovation in the relationship between ESG rating disagreement and TFP, an interaction term between green innovation and ESG rating disagreement is constructed, with other settings remaining consistent with Equation 1.

Table 4 and figure1 reports the results. The results show that when there are no ESG rating discrepancies, green innovation promotes the improvement of TFP. Conversely, when there are ESG rating discrepancies, it strengthens the dampening effect of ESG rating disagreement on TFP. Dose this contradicts exiting researches that show firms tend to increase their green innovation efforts when ESG rating disagreement is present(Hou and Xie, 2024; Geng et al., 2024; Chen et al., 2024b). This observation is very likely caused by a remedial action taken by firms in response to ESG rating disagreement, as Hou and Xie (2024) mentioned, such ESG rating disagreement is negatively correlated with the quality of corporate green innovation. According to stakeholder theory, firm’s remedial green innovations may be seen as "greenwashing" when there is disagreement over ESG ratings, which will lead to higher costs of debt financing for corporations, ultimately bringing about a decline in TFP(Peng and Xie, 2024).

Table 4: Green Innovation Mechanism

Variables	TFP					
	TFP_{LP}	TFP_{OP}	TFP_{GMM}	TFP_{LP}	TFP_{OP}	TFP_{GMM}
<i>Dis</i>	-0.0264 (-1.2045)	-0.0205 (-1.0114)	-0.0199 (-0.9590)	-0.0167 (-0.8367)	-0.0130 (-0.7014)	-0.0136 (-0.7069)
<i>EI</i>	0.0412*** (8.4064)	0.0283*** (6.2383)	0.0253*** (5.4522)	0.0223*** (4.9596)	0.0142*** (3.3848)	0.0126*** (2.8967)
<i>Dis * EI</i>	-0.0366*** (-3.1706)	-0.0292*** (-2.7348)	-0.0296*** (-2.7184)	-0.0249** (-2.3693)	-0.0199** (-2.0401)	-0.0207** (-2.0432)
<i>TobinQ</i>				-0.0030 (-0.7895)	-0.0016 (-0.4611)	-0.0007 (-0.1778)
<i>Top10</i>				-0.0010* (-1.7413)	-0.0010* (-1.7832)	-0.0005 (-0.8682)
<i>ListAge</i>				0.1012*** (3.4856)	0.0869*** (3.2139)	0.0172 (0.6122)
<i>Lev</i>				-0.1692*** (-3.2834)	-0.1550*** (-3.2318)	-0.1472*** (-2.9594)
<i>Size</i>				0.3664*** (28.243)	0.2537*** (21.017)	0.2208*** (17.632)
<i>Avg</i>				0.2297*** (22.666)	0.2698*** (28.608)	0.2673*** (27.331)
<i>Der</i>				-0.0210*** (-3.1573)	-0.0190*** (-3.0646)	-0.0211*** (-3.2805)
Controls	NO	NO	NO	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Id	YES	YES	YES	YES	YES	YES
<i>N</i>	13417	13417	13417	13417	13417	13417
<i>R</i> ²	0.0092	0.0052	0.0042	0.1806	0.1680	0.1417

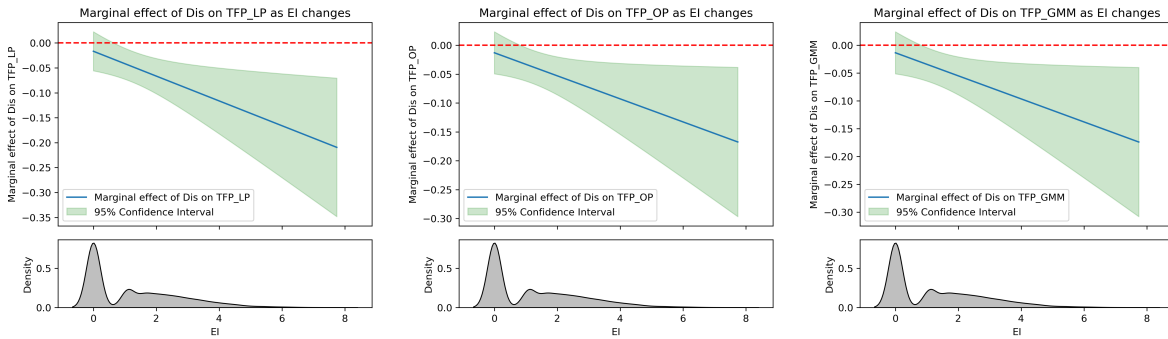


Figure 1: Marginal Effect

4.3.2 The Role of Financing Constraints

Undoubtedly, ESG investment plays a crucial role in promoting ESG development, making it essential to examine the impact of ESG rating disagreement on corporate financing. According to the information asymmetry theory discussed in the previous section, ESG rating disagreement introduces noise, potentially contributes financing constraints for firms. This study focuses exclusively on data from domestic ESG rating agencies in China, in contrast to Li et al. (2024), which also includes data from foreign rating agencies to explore this mechanism. Hence, we employ the WW and KZ indices from CSAMR to enhance the robustness of the empirical evidence. Furthermore, we follow Jiang (2022)’s research on the transmission mechanism, to avoid financing constraints being both exogenous and endogenous. We only use independent variable to regress with Financing constraints, since numerous researches have demonstrated that financing constraints are detrimental to TFP improvement (Hopenhayn, 2014; Zhang et al., 2021; Piao et al., 2023).

Table 5 reports the regression results. The *Disb* is the variable by one period. So we concludes that increased ESG rating disagreement reduces corporate financing constraints, thereby lowering TFP.

Table 5: Financing Constraints Mechanism

Variables	WW							
	WW	WW	KZ	KZ	WW	WW	KZ	KZ
<i>Dis</i>		0.0122*** (4.7408)		0.2166*** (3.0974)		0.0089*** (3.6730)		0.1815*** (2.6598)
<i>Disb</i>	0.0122*** (4.7691)		0.2142*** (3.0604)		0.0074*** (3.3430)		0.1392** (2.2547)	
<i>TobinQ</i>					-0.0022*** (-3.9269)	-0.0006 (-0.9530)	0.2724*** (19.528)	0.0237 (1.4433)
<i>Top10</i>					-0.0007*** (-8.8614)	-0.0006*** (-6.9840)	0.0011 (0.4783)	-0.0061** (-2.3496)
<i>ListAge</i>					0.0204*** (6.1906)	0.0143*** (2.9544)	0.5530*** (6.5333)	1.2048*** (9.5882)
<i>Lev</i>					0.0370*** (5.0820)	0.0359*** (4.5416)	6.7446*** (32.842)	3.1453*** (14.109)
<i>Size</i>					-0.0614*** (-36.832)	-0.0455*** (-22.973)	-0.4512*** (-9.5683)	-0.2274*** (-4.0781)
<i>Avg</i>					-0.0260*** (-18.835)	-0.0113*** (-7.3282)	-0.5288*** (-13.531)	-0.0107 (-0.2432)
<i>Der</i>					0.0030*** (3.4646)	0.0011 (1.2994)	0.0191 (0.6820)	-0.0027 (-0.0931)
Controls	NO	NO	NO	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
Id	YES	YES	YES	YES	YES	YES	YES	YES
<i>N</i>	10059	10059	13417	13417	10059	10059	13417	13417
<i>R</i> ²	0.0034	0.0034	0.0010	0.0010	0.2647	0.1221	0.2250	0.0517

Note: Similar to the robustness tests, *Dis* corresponds to regressions on ESG rating disagreement in year t and financing constraints in year t+1, while *Disb* corresponds to regressions on ESG rating disagreement in year t-1 and financing constraints in year t.

4.4 Heterogeneity Analysis

To further explore whether the dampening effect of ESG rating disagreement on TFP exhibits heterogeneity, this study conducts a subgroup regression analysis. Given that the sample size decreases after subgrouping, making the results more susceptible to the influence of outliers, the data was Winsorized at the 2% level on both ends before performing the subgroup regression and conducting a Chow Test on *Dis*.

Table 6 reports the results of the heterogeneity analysis. The results indicate that the effect is more significant in state-owned firms, non-capital-intensive firms, and low-pollution firms. The above heterogeneity may exist because, first, there is a greater willingness to engage in ESG construction among non-state-owned firms due to the fact that they tend to focus more on ESG performance to attract more investment; second, usually capital-intensive firms are less affected by market forces due to their own low variable costs and high fixed costs; third, in the case of highly polluting firms that are susceptible to a variety of environmental policies and regulations in their financing, such firms are less likely to invest in ESG performance, and therefore the impact of divergent ESG ratings is less significant.

Table 6: Heterogeneity Analysis

Variables	TFP					
	State-Owned	Non-State-Owned	Capital-Intensive	Non-Capital-Intensive	High-Pollution	Low-Pollution
<i>TFP_{LP}</i>						
<i>Dis</i>	-0.0622** (-2.0516)	-0.0310* (-1.8294)	-0.0322 (-1.1009)	-0.0462*** (-2.8884)	-0.0239 (-1.0401)	-0.0481*** (-2.7959)
Chow Test	500.19***		289.12***		544.57***	
<i>R</i> ²	0.1573	0.1886	0.1741	0.1817	0.2010	0.1754
<i>TFP_{OP}</i>						
<i>Dis</i>	-0.0553* (-1.8608)	-0.0268 (-1.5208)	-0.0097 (-0.3229)	-0.0458*** (-2.6338)	-0.0070 (-0.3149)	-0.0493** (-2.4735)
Chow Test	529.58***		269.31***		534.66***	
<i>R</i> ²	0.1759	0.1593	0.1672	0.1663	0.1930	0.1595
<i>TFP_{GMM}</i>						
<i>Dis</i>	-0.0618** (-2.1381)	-0.0310* (-1.6745)	-0.0278 (-0.9906)	-0.0471*** (-2.6889)	-0.0134 (-0.6185)	-0.0519** (-2.5484)
Chow Test	498.97***		248.15***		475.42***	
<i>R</i> ²	0.1607	0.1254	0.1504	0.1377	0.1691	0.1321
Controls	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Id	YES	YES	YES	YES	YES	YES
Double Clustering	YES	YES	YES	YES	YES	YES
<i>N</i>	4416	9001	2342	11075	3900	9517

5 Further Discussion

In the above analysis we can get that ESG rating disagreement brings about a decrease in TFP, which is obtained based on linear regression. In order to further explore the relationship between ESG rating divergence and TFP under the nonlinear assumption, we consider a regression analysis using a machine learning approach that can be interpreted with SHapley Additive exPlanations(SHAP) introduced by Scott et al. (2017), which can observe whether ESG rating disagreement is crucial for explaining TFP under the assumption of nonlinear system and explore the nonlinear influence relationship between the two variables.

Following Xue et al. (2024), we use the XGBoost machine learning model introduced by Chen and Guestrin (2016) to predict TFP_{LP} . XGBoost is an ensemble learner based on gradient boosted trees (GBDT) that has demonstrated excellent performance in many applications, even outperforming deep neural networks in some tasks. In this

paper, the Optuna library developed by Akiba et al. (2019), combed with early stopping and cross-validation strategies is employed for parameter selection. After that, we adopt the SHAP (SHapley Additive exPlanations) method proposed by Scott et al. (2017) to explain XGBoost. The variables include the ESG rating disagreement (Dis & $Disb$), all control variables, and institutional ownership percentage ($Inst$).

We use 80% of the dataset for training and 20% for testing and conducted three rounds of training: the first round included ESG rating disagreement, the second round added ESG rating disagreement from the previous period, and the third round did not include ESG rating disagreement. Table 7 reports the evaluation metrics for the three rounds of training. It can be observed that using R^2 as the evaluation metric, the model's predictive performance improved by **4.3%** and **6.23%** respectively compared to the model without ESG rating disagreement, indicating that ESG rating disagreement aids in the short-term prediction of TFP_{LP} .

Table 7: Performance Metrics for Training and Test Sets

Metric	Training Set 1	Training Set 2	Training Set 3	Test Set 1	Test Set 2	Test Set 3
MSE	0.2609	0.2274	0.2818	0.3492	0.3300	0.3835
RMSE	0.5108	0.4769	0.5309	0.5909	0.5744	0.6192
MAE	0.3995	0.3729	0.4145	0.4589	0.4523	0.4818
MAPE	4.7786%	4.4569%	4.9457%	5.4649%	5.3644%	5.7293%
R²	0.7685	0.7969	0.7500	0.7045	0.7176	0.6755

To analyze the influence of ESG rating disagreement on TFP_{LP} in the predictive task, SHAP was used to interpret the XGBoost model. SHAP values, rooted in game theory, quantify each feature's contribution to the model output by treating features as "players" in a game. The Shapley value ϕ_i for a feature i is calculated as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|! \cdot (|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \quad (3)$$

where S is a subset excluding i , $f(S)$ is the model output for S , and $f(S \cup \{i\})$ is the output after adding i to S .

In this study, based on the previous training results, we chose the model with one-period lagged ESG rating disagreement for our SHAP analysis, and the SHAP values were calculated for the test set. Figure 2 reports the feature importance, showing that the contribution ratio of $Disb$ is 0.14, again indicating that $Disb$ is crucial for predicting total factor productivity. Figure 3 reports the SHAP beeswarm plot, it can be observed that high ESG rating divergence suppresses a company's total factor

productivity, while in companies with low ESG ratings and small divergences, ESG rating disagreement is even positively correlated with TFP in the prediction task. The reason for this phenomenon is that the investment market is more tolerant of small ESG rating divergence, and listed companies will not face significant financing pressure due to small divergence.

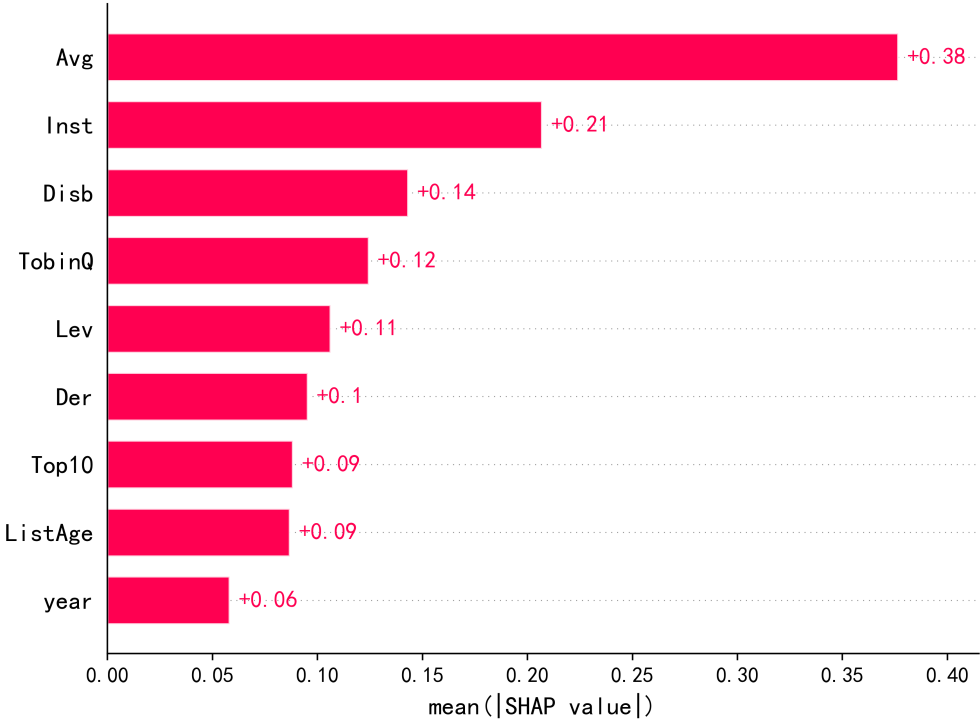


Figure 2: Feature Importance

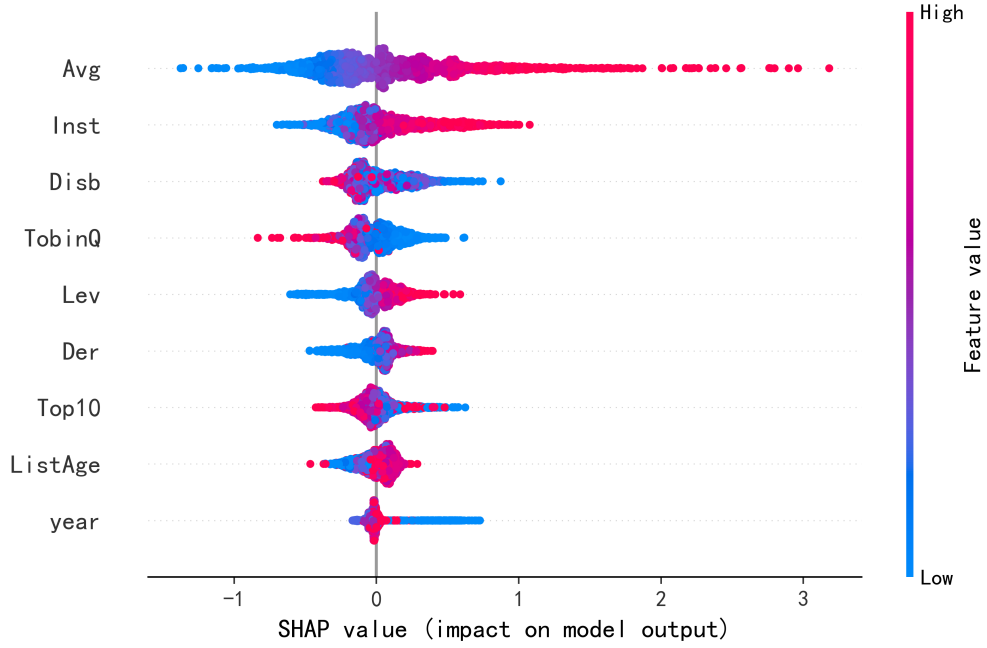


Figure 3: SHAP Beeswarm Plot

6 Conclusion

ESG rating disagreement poses challenges to the enhancement of corporate TFP. This study utilizes financial data from China’s A-share listed companies and ESG rating information from domestic ESG rating agencies between 2015 and 2022 to explore the relationship between ESG rating disagreements and firms’ TFP. The findings robustly indicate that ESG rating disagreements have a negative impact on firms’ TFP. The mechanism analysis reveals that green innovation instead strengthens the dampening effect of ESG rating disagreement on TFP; moreover, ESG rating disagreement strengthens firms’ financing constraints, thereby hindering the improvement of TFP. Heterogeneity analysis further indicates that the negative impact of ESG rating disagreements on TFP is more pronounced in state-owned enterprises, non-capital-intensive firms, and companies with lower levels of pollution. Additionally, an important finding from the analysis using machine learning methods suggests that ESG rating disagreements serve as a significant indicator for short-term predicting firms’ TFP, providing new insights for companies to engage in ESG risk management to enhance TFP.

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A Appendix

A.1 Robustness Tests

Table 8: Robustness Tests (I)

Variables	TFP					
	TFP_{LP}	TFP_{OP}	TFP_{GMM}	TFP_{LP}	TFP_{OP}	TFP_{GMM}
<i>Dis</i>	-0.0662*** (-2.7472)	-0.0524** (-2.2660)	-0.0524** (-2.2781)	-0.0246** (-2.2085)	-0.0159** (-2.4677)	-0.0180** (-2.0769)
<i>TobinQ</i>				0.0218*** (6.8126)	0.0141*** (7.0455)	0.0150*** (6.1013)
<i>Top10</i>				0.0005 (0.8363)	0.0002 (0.5950)	0.0004 (0.8865)
<i>ListAge</i>				-0.0510** (-2.3362)	-0.0291** (-2.2563)	-0.0678*** (-4.0705)
<i>Lev</i>				0.1415 (1.8712)	0.0739 (1.5504)	0.0650 (1.2862)
<i>Size</i>				0.4212*** (21.576)	0.2448*** (18.539)	0.1800*** (11.207)
<i>Avg</i>				0.7135*** (38.466)	0.8172*** (64.699)	0.8193*** (55.668)
<i>Der</i>				-0.0257** (-2.0169)	-0.0113 (-1.3877)	-0.0135 (-1.5955)
Controls	NO	NO	NO	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Id	YES	YES	YES	YES	YES	YES
Doubel Clustering	YES	YES	YES	YES	YES	YES
<i>N</i>	13417	13417	13417	13417	13417	13417
<i>R</i> ²	0.0015	0.0011	0.0011	0.7027	0.8496	0.7734

Table 9: Robustness Tests (II)

Variables	TFP					
	TFP_{LP}	TFP_{OP}	TFP_{GMM}	TFP_{LP}	TFP_{OP}	TFP_{GMM}
<i>Dis</i>	-0.0647** (-2.5465)	-0.0519** (-1.9984)	-0.0510** (-2.0263)	-0.0419*** (-2.6444)	-0.0342** (-1.9838)	-0.0346** (-1.9658)
<i>TobinQ</i>				-0.0027 (-0.4030)	-0.0013 (-0.2619)	-0.0003 (-0.0725)
<i>Top10</i>				-0.0009 (-0.9777)	-0.0009 (-0.9697)	-0.0005 (-0.5039)
<i>ListAge</i>				0.0906** (2.4895)	0.0796** (2.3720)	0.0058 (0.1639)
<i>Lev</i>				-0.1555 (-1.3079)	-0.1408 (-1.2639)	-0.1334 (-1.1864)
<i>Size</i>				0.3762*** (14.285)	0.2596*** (13.442)	0.2262*** (10.036)
<i>Avg</i>				0.2277*** (2.6951)	0.2680** (2.7597)	0.2660** (2.6807)
<i>Der</i>				-0.0210* (-1.9537)	-0.0194 (-1.7844)	-0.0217 (-1.9273)
<i>N.TFP_{province}</i>				0.0993 (0.6302)	0.0847 (0.5857)	0.0403 (0.2531)
Controls	NO	NO	NO	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Id	YES	YES	YES	YES	YES	YES
Doubel Clustering	YES	YES	YES	YES	YES	YES
<i>N</i>	12893	12893	12893	12893	12893	12893
<i>R²</i>	0.0014	0.0011	0.0010	0.1793	0.1670	0.1406

Table 10: Robustness Tests (III)

Variables	Dependent Variable			
	<i>Dis</i>	<i>TFP_{LP}</i>	<i>TFP_{OP}</i>	<i>TFP_{GMM}</i>
<i>IV</i> (\hat{Dis})	-0.3336*** (-602.14)	-0.0479*** (-3.0748)	-0.0408** (-2.3966)	-0.0424** (-2.3533)
<i>TobinQ</i>	-0.0007 (-0.5971)	-0.0027 (-0.4037)	-0.0013 (-0.2634)	-0.0004 (-0.0756)
<i>Top10</i>	3.476e-05 (0.3084)	-0.0010 (-0.9808)	-0.0009 (-0.9708)	-0.0005 (-0.5052)
<i>ListAge</i>	-0.0056 (-0.9005)	0.0910** (2.4981)	0.0799** (2.3788)	0.0061 (0.1734)
<i>Lev</i>	-0.0029 (-0.3495)	-0.1554 (-1.3058)	-0.1407 (-1.2618)	-0.1333 (-1.1844)
<i>Size</i>	-0.0045** (-2.6017)	0.3760*** (14.301)	0.2594*** (13.453)	0.2260*** (10.029)
<i>Avg</i>	-0.0017 (-0.7314)	0.2278*** (2.6949)	0.2680** (2.7600)	0.2660** (2.6811)
<i>Der</i>	0.0037** (2.8094)	-0.0210* (-1.9412)	-0.0193 (-1.7701)	-0.0216 (-1.9119)
<i>N.TFP_{province}</i>	0.0100 (0.5583)	0.0999 (0.6350)	0.0851 (0.5902)	0.0408 (0.2565)
Controls	YES	YES	YES	YES
Year	YES	YES	YES	YES
ID	YES	YES	YES	YES
Double Clustering	YES	YES	YES	YES
<i>F</i>	2.983e+04	227.22	208.52	170.30
<i>N</i>	16907	12892	12892	12892
R²	0.9542	0.1794	0.1671	0.1408

Note: The second stage of 2SLS regression follows the baseline regression with a one-period lag.

Table 11: Robustness Tests (IV)

Variables	TFP					
	TFP_{LP}	TFP_{OP}	TFP_{GMM}	TFP_{LP}	TFP_{OP}	TFP_{GMM}
<i>Dis</i>	-0.1054*** (-3.0359)	-0.0959*** (-2.9849)	-0.0908*** (-2.7841)	-0.0730** (-2.3040)	-0.0676** (-2.2900)	-0.0645** (-2.1303)
<i>TobinQ</i>				0.0007 (0.0934)	0.0002 (0.0351)	-0.0026 (-0.3889)
<i>Top10</i>				0.0005 (0.5206)	0.0004 (0.3886)	0.0007 (0.6853)
<i>ListAge</i>				0.1119 (1.6127)	0.1001 (1.5470)	0.0149 (0.2245)
<i>Lev</i>				-0.0295 (-0.3276)	-0.0270 (-0.3216)	-0.0174 (-0.2021)
<i>Size</i>				0.3899*** (16.968)	0.2685*** (12.538)	0.2291*** (10.440)
<i>Avg</i>				0.2343*** (13.111)	0.2761*** (16.582)	0.2832*** (16.598)
<i>Der</i>				-0.0408*** (-3.4013)	-0.0368*** (-3.2928)	-0.0385*** (-3.3577)
Controls	NO	NO	NO	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
ID	YES	YES	YES	YES	YES	YES
Double Clustering	NO	NO	NO	NO	NO	NO
<i>N</i>	5368	5368	5368	5368	5368	5368
R²	0.0028	0.0027	0.0024	0.1739	0.1628	0.1455

A.2 Optuna Parameter Range & Correlation Coefficient

Table 13: Hyperparameters for XGBoost Model

Parameter	Range(optuna) / Value
loss_function	rmse
learning_rate	[0.005, 0.2] (log scale)
max_depth	[1, 3]
min_child_weight	[1, 5] (log scale)
subsample	[0.5, 0.8]
colsample_bytree	[0.5, 0.8]
reg_lambda	[1, 10] (log scale)
reg_alpha	[1, 10] (log scale)
tree_method	hist
device	cuda
num_boost_round	1000
nfold	20
early_stopping_rounds	5
seed	42

Table 12: Correlation Matrix

	TFP_{LP}	TFP_{OP}	TFP_{GMM}	Dis	$TobinQ$	$Top10$	$ListAge$	Lev	$Size$	Avg	Der	$N.TFP_{province}$	IV
TFP_{LP}	1.000	0.951	0.918	-0.066	-0.200	0.127	0.329	0.444	0.801	0.648	0.344	-0.037	0.082
TFP_{OP}	0.951	1.000	0.976	-0.054	-0.183	0.104	0.303	0.405	0.707	0.841	0.325	-0.036	0.067
TFP_{GMM}	0.918	0.976	1.000	-0.041	-0.132	0.080	0.244	0.356	0.583	0.823	0.295	-0.005	0.059
Dis	-0.066	-0.054	-0.041	1.000	0.014	-0.078	0.025	0.039	-0.071	-0.024	0.052	-0.015	-0.974
$TobinQ$	-0.200	-0.183	-0.132	0.014	1.000	-0.036	-0.094	-0.249	-0.283	-0.116	-0.173	0.012	-0.008
$Top10$	0.127	0.104	0.080	-0.078	-0.036	1.000	-0.364	-0.066	0.147	0.044	-0.052	0.038	0.087
$ListAge$	0.329	0.303	0.244	0.025	-0.094	-0.364	1.000	0.292	0.424	0.204	0.240	-0.184	-0.024
Lev	0.444	0.405	0.356	0.039	-0.249	-0.066	0.292	1.000	0.458	0.256	0.843	-0.044	-0.038
$Size$	0.801	0.707	0.583	-0.071	-0.283	0.147	0.424	0.458	1.000	0.413	0.359	-0.104	0.082
Avg	0.648	0.841	0.823	-0.024	-0.116	0.044	0.204	0.256	0.413	1.000	0.222	-0.041	0.027
Der	0.344	0.325	0.295	0.052	-0.173	-0.052	0.240	0.843	0.359	0.222	1.000	-0.047	-0.046
$N.TFP_{province}$	-0.037	-0.036	-0.005	-0.015	0.012	0.038	-0.184	-0.044	-0.104	-0.041	-0.047	1.000	0.014
IV	0.082	0.067	0.059	-0.974	-0.008	0.087	-0.024	-0.038	0.082	0.027	-0.046	0.014	1.000