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"Market Noise" or "Governance Blessing"? —A Study of How ESG Rating Discrepancy Affects the Risk of Stock Price Crash

Xiaoyang Zhang

Carey Business School, Johns Hopkins University, Baltimore, USA
sfruczhangxiaoyang@163.com

Abstract. This paper focuses on the emerging phenomenon of ESG rating discrepancy, using Chinese A-share listed companies from 2015 to 2023 as the research sample, and employs a fixed effects model to empirically examine the impact of ESG rating discrepancy on stock price crash risk, its mechanism of action, and its heterogeneity. The study finds that ESG rating discrepancy can significantly inhibit stock price crash risk, and this conclusion remains valid after a series of robustness tests. Heterogeneity analysis shows that this inhibitory effect is more significant in non-state-owned firms, low-pollution firms, firms with low ESG scores, and firms with low media attention. Mechanism analysis confirms that ESG rating discrepancy mainly exerts its role through the "information effect": it promotes more prudent decision-making by market participants by improving stock liquidity, stabilizing investor sentiment, and intensifying analyst forecast divergence, thereby effectively weakening the herd effect and reducing crash risk. This study provides empirical evidence and policy implications for objectively viewing the market role of ESG rating discrepancy, improving the ESG rating ecosystem, and preventing and resolving financial risks.

Keywords: ESG Rating Discrepancy, Stock Price Crash Risk, Information Effect

1. Introduction

Against the background of the deepening global concept of green development and sustainable finance, Environmental, Social, and Governance (ESG) has turned into a key dimension for measuring enterprises' non-financial performance and long-term value, which is crucial for stabilizing the real economy and preventing financial risks. As China's "dual-carbon" goals have progressed and information disclosure methods have improved, the market and regulators have been increasingly interested in the ESG performance of companies. However, differences in standards and methodologies among domestic and foreign ESG rating systems lead to divergent ESG scores for the same enterprise. The information contradictions contained in such rating discrepancy pose new challenges to the information circumstance of the capital market and investors' decision-making. This study focuses on the economic effects of ESG rating discrepancy from the viewpoint of stock

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price crash risk (the Crash Risk) in an effort to offer new empirical proof for comprehending its market significance.

This paper's primary objective is to figure out how ESG rating discrepancy affects the Crash Risk. The following are the research's marginal contributions in relation to the body of existing studies: ① It expands the research sample and time horizon. Since valid data on mainstream ESG rating discrepancy have been available only since 2015, this paper uses panel data from 2015 to 2023 for empirical analysis, which expands the sample size compared with existing studies, thereby enhancing the reliability of the conclusions. ② It deepens the discussion on the mechanism of action. On the basis of existing literature that mainly focuses on channels such as heterogeneous beliefs and information search [1, 2], this study identifies three new and effective mediating paths: investor sentiment, stock liquidity, and analyst forecast divergence. ③ It provides a positive interpretation of rating discrepancy. Different from most literature that regards it as market noise, this paper argues that given the inherent subjectivity of the ESG concept, a moderate degree of rating discrepancy is reasonable and has positive significance for the healthy development of the market, which offers a more flexible viewpoint for the ESG system's further development.

The remaining parts of this paper are arranged as follows: Section 2 presents theoretical hypotheses; Section 3 explains the model setting and source of data; Section 4 analyzes empirical results and heterogeneity; Section 5 performs mechanism tests; and the sixth section makes conclusions and policy suggestions.

2. Theoretical hypotheses

The theoretical root of the Crash Risk lies in information asymmetry; namely, a concentrated breakout of unfavorable information that management conceal triggers market panic [3]. In addition to the company's own transparency, external factors such as investors' herd behavior and analyst forecast bias can also exacerbate this risk [4, 5]. As emerging non-financial information, ESG should inhibit crash risk by reducing information asymmetry [6]. However, substantial rating variance sends confusing or even conflicting signals to the market because there is no universal rating system. Although this discrepancy increases investors' information processing costs, constitutes a new type of information opacity, and may intensify fluctuations in investor sentiment and amplify potential risks [7, 8], some studies believe that discrepancy has a positive effect [1]. As the classic theory of information asymmetry argues that rating discrepancy exacerbates the complexity and noise of the information environment, there may also be information revealed by the discrepancy. Therefore, this paper holds that its positive effect may dominate. In light of this, the basic hypothesis is put forth:

Hypothesis 1: By influencing investor sentiment, stock liquidity, and analyst forecast bias, ESG rating discrepancy lowers the Crash Risk.

ESG rating discrepancy's effect on the Crash Risk is not invariable, and its intensity is likely to be significantly moderated by specific company characteristics and the external information environment. Existing literature has initially explored such differences from the perspectives of ownership nature, industry characteristics, ESG performance itself, and media attention [9, 10, 8]. For example, in enterprises with higher information asymmetry and relatively weaker external supervision, the negative impact of rating discrepancy may be more serious. In general, in environments with differences in market constraints, information transparency, and investor expectations, the effect of rating discrepancy should vary and be more prominent under specific conditions. According to the analysis above, the second hypothesis is put forth:

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Hypothesis 2: ESG rating discrepancy has more significant influences on the Crash Risk of non-state-owned firms, firms in low-pollution industries, firms with low ESG scores, and firms with low media attention.

3. Model setting and source of data

3.1. Model setting

This research studies the impact of ESG rating discrepancy on the Crash Risk and analyzes its internal path of action and heterogeneity. Considering the recognition and availability of data, this paper selects rating data from 4 mainstream institutions (Sino-Securities, Wind, SynTao Green Finance, and China Alliance of Social Value Investment (CASVI)) to calculate the degree of discrepancy. Since rating discrepancy began to appear only after 2015, the sample is panel data of Shanghai and Shenzhen A-share from 2015 to 2023, and the following model for baseline regression is constructed:

$$\mathrm{Crash}_{i,t} = \alpha_0 + \alpha_1 \mathrm{ESG\_Dis}_{i,t} + \mathrm{Controls}_{i,t} + \mathrm{Year} + \mathrm{Firm} + \varepsilon_{i,t} \tag{1}$$

Among them, $\mathrm{Crash}_{i,t}$ represents stock price crash risk; $\mathrm{ESG\_Dis}_{i,t}$ represents the independent variable ESG rating discrepancy; $\mathrm{Controls}_{i,t}$ represents the conventional control variables affecting stock price crash risk. Furthermore, time (Year) and individual (Firm) fixed effects are controlled as well.

3.2. Variable definition

3.2.1. Crash risk

This paper uses the negative skewness coefficient of returns (NCSKEW) and the up-down volatility ratio (DUVOL) first proposed by Chen et al. as metrics of the Crash Risk [11].

First, regress the weekly return of individual stocks on the weekly market return:

$$R_{i,t} = \beta_0 + \beta_1 R_{M,t-2} + \beta_2 R_{M,t-1} + \beta_3 R_{M,t} + \beta_4 R_{M,t+1} + \beta_5 R_{M,t+2} + \varepsilon_{i,t} \tag{2}$$

Among them, $R_{i,t}$ represents the weekly return of individual stock i in week t, and $R_{M,t}$ represents the market return weighted by tradable market value in week t. To account for the effects of non-synchronous trading, the model incorporates two leading terms and two lagged terms of market return. The residual term $\varepsilon_{i,t}$ represents the part that is unable to explain with the five-period market return, and is used to calculate $W_{i,t}$, the idiosyncratic weekly return of individual stock i in week t:

$$W_{i,t} = \ln\left(1 + \varepsilon_{i,t}\right) \tag{3}$$

Then, $W_{i,t}$ can be used to calculate $NCSKEW_{i,t}$ and $DUVOL_{i,t}$ respectively:

$$NCSKEW_{i,t} = -\frac{n(n-1)^{\frac{3}{2}} \sum W_{i,t}^3}{(n-1)(n-2)\left(\sum W_{i,t}^2\right)^{\frac{3}{2}}} \tag{4}$$

DOI: 10.54254/2754-1169/2025.BL29255

$$DUVOL_{i,t} = \log\left(\frac{(n_u-1)\Sigma_{DOWN}R_{i,t}^2}{(n_d-1)\Sigma_{UP}R_{i,t}^2}\right) \tag{5}$$

Among them, n represents the number of trading weeks of individual stock i in a year; n_u and n_d represent the number of weeks when the idiosyncratic return of individual stock i is greater than and less than the average annual return, respectively. Both indicators have a positive correlation with the Crash Risk.

3.2.2. ESG rating discrepancy

Due to the incompatibility in rating systems among various rating institutions, this paper first uniformly converts their ratings into values in the range of 0-1. Subsequently, the standard deviation of scores from various institutions (ESGSDi,t) and the average value of the absolute differences between each pair of scores (ESGDIFFi,t) are used to measure ESG rating discrepancy.

3.2.3. Control variables

Common factors affecting the Crash Risk constitute control variables. The particular variable names, meanings, and measurements are exhibited in Table 1 [2, 11]. Table 1 also lists investor sentiment, stock liquidity, and analyst forecast divergence, which are used as mediating variables in the mechanism test later.

Table 1. Variable names, meanings and measurements

Variable Name	Variable Meaning	Calculation Method
NCSKEW	The Crash Risk	Current negative return skewness coefficient
DUVOL	The Crash Risk	Current return up-down volatility ratio
Sigma	Volatility of single stock	Standard deviation of the weekly idiosyncratic return of individual stock i in year t
Ret	Return of single stock	Average value of the weekly idiosyncratic return of individual stock i in year t
Size	Firm size	Natural logarithm of total assets
MB	Market-to-book ratio	Market value of equity / Book value of equity
Lev	Asset-liability ratio	Total liabilities / Total assets
ROA	Return on assets	Net profit / Average value of total assets at the beginning and end of the period
Top1	The largest shareholder ratio	Number of the largest shareholder's shares / Total shares
SENTIMENT	Investor sentiment	Standardized residual value of firm size, leverage ratio, and profitability
ILLIQ	Stock illiquidity	Amihud measure [12]
FDISP	Analyst forecast divergence	Standard deviation of analysts' EPS forecasts / Initial stock price [13]

DOI: 10.54254/2754-1169/2025.BL29255

3.3. Source of data

The ESG rating data used in this paper are public releases from various rating institutions. The media attention data are from the CNRDS database. The rest listed company data are from the CSMAR database and the annual reports of various enterprises.

4. Regression analysis

On the basis of the aforementioned conceptual study, the following section uses a fixed effects model for empirical testing, aiming to examine the immediate effect of ESG rating discrepancy on the Crash Risk and run robustness tests for the results.

4.1. Baseline regression analysis

To examine the effect of ESG rating discrepancy on the Crash Risk, this paper constructs Model (1) shown in 3.1. for baseline regression, and outcomes are exhibited in Table 2. Time and individual fixed effects are controlled for all models. Column (1) includes the core independent variable ESG rating discrepancy itself, and its coefficient is significantly negative at the 1% level (-0.020), initially indicating that ESG rating discrepancy can inhibit the Crash Risk. Column (2) adds individual stock market risk variables, and the inhibitory effect remains robust. Subsequently, Columns (3) to (5) gradually include firm-level control variables such as firm size, market-to-book ratio, and asset-liability ratio, and the coefficient of ESG rating discrepancy stabilizes around -0.024 and is highly significant. Finally, Column (6) includes all control variables and adds the largest shareholder ratio, and the outcomes are mostly in line with the prior models, confirming the robustness again. In conclusion, the outcomes in Table 2 consistently reveal the fact that a significant and robust negative correlation lies between ESG rating discrepancy and the Crash Risk, and the expansion of ESG rating discrepancy reduces the probability of enterprise crash.

Table 2. Baseline regression outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	DUVOL	DUVOL	DUVOL	DUVOL	DUVOL	DUVOL
ESGdif4	-0.020***	-0.025***	-0.025***	-0.024***	-0.024***	-0.024***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Sigma		-4.308***	-4.326***	-4.324***	-4.373***	-4.369***
		(0.243)	(0.244)	(0.244)	(0.243)	(0.243)
Ret		-9.212***	-9.498***	-9.507***	-9.232***	-9.276***
		(0.604)	(0.633)	(0.633)	(0.636)	(0.636)
size			0.021*	0.024*	0.032**	0.032**
			(0.012)	(0.013)	(0.013)	(0.013)
mbratio			-0.073**	-0.074**	-0.081**	-0.085**
			(0.033)	(0.033)	(0.033)	(0.033)
Lev				-0.037	-0.079	-0.079
				(0.045)	(0.049)	(0.049)
roa					-0.143**	-0.148**

DOI: 10.54254/2754-1169/2025.BL29255

Table 2. (continued)

					(0.069)	(0.070)
top1						0.001*
						(0.001)
Firm_FE	YES	YES	YES	YES	YES	YES
Year_FE	YES	YES	YES	YES	YES	YES
N	20032	20032	20032	20032	20032	20032
r2	0.025	0.117	0.117	0.117	0.118	0.118

Note: Standard errors of coefficients are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively. The same applies to the following tables.

4.2. Robustness tests

(1) Replacing the dependent variable indicator. The baseline regression uses the up-down volatility ratio calculated by Formula (5) to measure the Crash Risk. This part replaces the dependent variable indicator with the negative skewness coefficient calculated by Formula (4). The outcomes are exhibited in Column (1) of Table 3. The estimated coefficient of the independent variable is still significant at the 1% level, and its absolute value further increases, indicating that ESG rating discrepancy produces an even stronger negative influence on the Crash Risk measured by the negative skewness coefficient. This confirms the robustness of the relationship between the two.

(2) Changing the rating institutions for the independent variable indicator. To eliminate the impact of the rating institutions themselves, this part first increases the number of ESG scores used to calculate ESG rating discrepancy from 4 to 6, that is, adds the scores of FTSE Russell and Rankins CSR Ratings (RKS) to the original scores from 4 rating institutions to recalculate ESG rating discrepancy, denoted as ESGdif6. Then, the scores of CASVI and RKS are removed, and the ESG rating discrepancy is still computed with the scores from 4 rating institutions, denoted as ESGdif4_1. The outcomes are exhibited in Columns (2) to (3) of Table 3, respectively. The significance and sign of the estimated coefficient of the independent variable are not affected, and its value is basically stable, which fully suggests that the inhibitory effect of ESG rating discrepancy on the Crash Risk does not depend on the specific combination of rating institutions or their quantity, and is quite robust.

(3) Changing the computation method for the independent variable indicator. The baseline regression uses the standard deviation method to calculate ESG rating discrepancy. This part replaces the independent variable indicator with ESG rating discrepancy calculated using the range method. The new indicator is denoted as ESGrange4. The outcomes are exhibited in Column (4) of Table 3. The estimated coefficient of the independent variable is still significant, though the absolute value is somewhat lower than that in the baseline regression, it is sufficient to prove that the reducing impact of ESG rating discrepancy on the Crash Risk does not disappear due to the change of its calculation method.

DOI: 10.54254/2754-1169/2025.BL29255

Table 3. Robustness test outcomes

	(1)	(2)	(3)	(4)
	NCSKEW	DUVOL	DUVOL	DUVOL
ESGdif4	-0.032***			
	(0.012)			
ESGdif6		-0.021***		
		(0.007)		
ESGdif4_1			-0.044***	
			(0.007)	
ESGrange4				-0.013***
				(0.005)
Controls	YES	YES	YES	YES
Firm_FE	YES	YES	YES	YES
Year_FE	YES	YES	YES	YES
N	20032	20032	33862	20032
r2	0.121	0.118	0.115	0.118

4.3. Heterogeneity analysis

The previous results consistently demonstrate that ESG rating discrepancy significantly inhibits the Crash Risk. This section tests its heterogeneity: grouping from four dimensions, namely ownership nature, industry pollution level, comprehensive ESG performance, and media attention, as shown in Table 4. First, in terms of ownership nature, Columns (1) to (2) of Table 4 show that the inhibitory effect mainly exists in non-state-owned firms, while it is not significant in state-owned firms. The potential explanation is that non-state-owned firms more frequently trigger external supervision; while state-owned firms have higher credibility due to political connections and implicit guarantees, resulting in weaker information asymmetry, and the marginal impact of rating discrepancy is limited. Second, in terms of industry pollution level, referring to previous studies, industries B07, B08, B09, C25, C26, C28, C29, C30, C31, C32, and D44 are defined as high-pollution industries, and the others are low-pollution industries. Columns (3) to (4) of Table 4 show that the negative impact is significant in low-pollution industries, but not in high-pollution industries; industries with large volumes of pollution are usually subject to more stringent supervision as well as mandatory disclosure constraints, resulting in limited space for concealing information, so the information governance role of rating discrepancy is restricted. Third, based upon the average ESG score for the current periods, all firms are split into high and low groups in terms of ESG performance. Columns (5) to (6) of Table 4 illustrate that the inhibitory effect is concentrated in firms with low scores; firms with high scores have better governance and transparency, and stronger investor confidence, so a small amount of rating differences can hardly disturb stock prices, while the discrepancy of firms with low scores can better reveal potential risks. Finally, based upon the average amount of media attention for the current periods, all firms are split into high and low groups in terms of media attention. Columns (7) to (8) of Table 4 indicate that the effect is highly significant in firms with low attention, but weakens in firms with high attention; media, as an external supervision, improves

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information transparency and reduces the space for concealment, making the incremental information of rating discrepancy limited in firms with high attention.

Table 4. Heterogeneity analysis results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non-state-owned Firms	State-owned Firms	Low-pollution Industries	High-pollution Industries	Low ESG Score	High ESG Score	Low Attention	High Attention
ESGdif4	-0.020**	-0.027	-0.029***	-0.011	-0.022**	-0.013	-0.021***	-0.058*
	(0.009)	(0.017)	(0.008)	(0.017)	(0.011)	(0.013)	(0.008)	(0.035)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm_FE	YES	YES	YES	YES	YES	YES	YES	YES
Year_FE	YES	YES	YES	YES	YES	YES	YES	YES
N	13244	4418	15423	4609	9596	10436	17345	2521
R^2	0.125	0.125	0.121	0.116	0.123	0.124	0.118	0.202

5. Mechanism analysis

This section further examine the internal mechanism by which the Crash Risk is impacted by ESG rating discrepancy, conducting a mediating effect test from three perspectives: investor sentiment, stock liquidity, and analyst forecast divergence.

5.1. Investor sentiment

The immediate cause of the stock price crash lies in investors' concentrated selling of stocks due to panic, so investor sentiment is a key transmission link. Drawing on the method developed by Rhodes-Kropf et al., a proxy variable for investor sentiment (SENTIMENT) is constructed through Model (6) [14]:

$$Q_{i,t} = \beta_0 + \beta_1 size_{i,t} + \beta_2 lev_{i,t} + \beta_3 roa_{i,t} + \varepsilon_{i,t} \tag{6}$$

Among them, size represents firm size, lev represents leverage ratio, and roa represents return on assets. These three constitute the most important factors for fitting the intrinsic value of the company. Therefore, the fitted value $Q^f_{i,t}$ calculated using the coefficients obtained from the above regression can be roughly considered the company's intrinsic value. The gap between the actual value and the fitted value, $Q^e_{i,t}$, after Z-standardization, can be used as a substitute variable for investor sentiment (SENTIMENT). Subsequently, the effect of ESG rating discrepancy on SENTIMENT is tested, as shown in (7):

$$SENTIMENT_{i,t} = \alpha_0 + \alpha_1 ESG\_Dis_{i,t} + Controls_{i,t} + Year + Firm + \varepsilon_{i,t} \tag{7}$$

DOI: 10.54254/2754-1169/2025.BL29255

The regression outcomes in Column (1) of Table 5 illustrate that the coefficient of ESG rating discrepancy is significantly positive at the 1% level. This indicates that the expansion of rating discrepancy significantly boosts investor sentiment, thereby inhibiting the Crash Risk. The internal logic could be: when ratings consistently point to negative, it is easy to trigger investors' irrational selling; while when there is discrepancy in ratings, it will prompt investors to conduct more prudent evaluation of information, thereby curbing the herd effect to a certain extent. Therefore, investor sentiment is an important mediating channel by which stock price crash risk is impacted by ESG rating discrepancy.

5.2. Stock liquidity

According to the study of Shen Jiafeng, by cutting investors' holding costs and alleviating information asymmetry, increased stock liquidity can lower the Crash Risk [15]. This research uses the illiquidity indicator (ILLIQ) proposed by Amihud as a reverse proxy variable for stock liquidity, as shown in (8) [12]:

$$\mathrm{ILLIQ}_{i,t} = \frac{1}{D_{i,t}} * \sum_{d=1}^{D_{i,t}} \frac{|R_{i,t,d}|}{V_{i,t,d}} \tag{8}$$

Among them, $D_{i,t}$ represents the number of effective trading days of stock i in year y; day d represents the d-th trading day in the year; $R_{i,d}$ represents the return of stock i on day d; $V_{i,d}$ represents the trading volume of stock i on day d. A bigger value of ILLIQ means that the stock price is deeper affected by per unit trading volume. Therefore, it can be seen that the Amihud measure actually measures the illiquidity of stocks, that is, a larger value of ILLIQ indicates lower stock liquidity. Use ILLIQ for regression in place of the baseline regression model's dependent variable, and the regression formula is shown in (9):

$$\mathrm{ILLIQ}_{i,t} = \alpha_0 + \alpha_1 \mathrm{ESG\_Dis}_{i,t} + \mathrm{Controls}_{i,t} + \mathrm{Year} + \mathrm{Firm} + \varepsilon_{i,t} \tag{9}$$

The outcomes in Column (2) of Table 5 illustrate that the coefficient of ESG rating discrepancy is significantly negative at the 1% level, which means that the expansion of rating discrepancy significantly reduces the illiquidity of stocks, that is, improves stock liquidity. This indicates that the market does not interpret ESG rating discrepancy as a pure risk signal, but as a reflection of increased information complexity. This complexity stimulates more diverse trading behaviors, thereby improving stock liquidity and ultimately inhibiting stock price crash risk.

5.3. Analyst forecast divergence

As professional information intermediaries, analysts' forecast divergence can better reflect the market's uncertainty about the company's future prospects. Drawing on the approach of Chu Jian et al., the analyst forecast divergence (FDISP) is measured as follows [13]:

$$\mathrm{FDISP} = \mathrm{SD(FEPS)/PRICE} \tag{10}$$

Among them, SD(FEPS) represents the standard deviation of all analysts' latest annual EPS forecasts, and PRICE represents the initial stock price. Use FDISP for regression in place of the baseline regression model's dependent variable, and the regression formula is shown in (11):

DOI: 10.54254/2754-1169/2025.BL29255

$$FDISP_{i,t} = \alpha_0 + \alpha_1 ESG\_Dis_{i,t} + Controls_{i,t} + Year + Firm + \varepsilon_{i,t} \quad (11)$$

The outcomes in Column (3) of Table 5 illustrate that the coefficient of ESG rating discrepancy is significantly positive at the 1% level. This confirms that ESG rating discrepancy will significantly intensify the forecast divergence among analysts. This forecast divergence caused by rating discrepancy will prompt investors to evaluate the company's value more cautiously, avoiding extreme actions due to misinterpretation of information, thereby stabilizing stock prices and reducing crash risk.

Table 5. Mechanism analysis outcomes

	(1)	(2)	(3)
	SENTIMENT	ILLIQ	FDISP
ESGdif4	0.057***	-0.028***	0.001**
	(0.015)	(0.009)	(0.000)
Controls	YES	YES	YES
Firm_FE	YES	YES	YES
Year_FE	YES	YES	YES
N	20032.000	20029.000	10310.000
r2	0.165	0.210	0.075

6. Conclusions

Against the current macro background of high-quality development, ESG rating discrepancy, as an important constituent of non-financial information, has far-reaching practical significance for mitigating the Crash Risk as well as preventing systemic financial risks by promoting information flow and public supervision. Through systematic theoretical and empirical analysis, multiple rigorous robustness tests support the conclusion that ESG rating discrepancy can greatly reduce the Crash Risk. Additionally, heterogeneity analysis shows that the inhibitory effect is particularly prominent in firms with relatively opaque information environments, such as non-state-owned firms, low-pollution firms, firms with poor ESG performance, and firms with low media attention. Mechanism tests finally confirm that ESG rating discrepancy mainly plays its role as a market stabilizer through three core paths: improving investor sentiment, enhancing stock liquidity, and increasing analyst forecast divergence.

The conclusions have significant revelations for both the long-term sound growth of China's capital market and ESG system construction. In the light of this, three policy suggestions are put forward: First, we should continue to strengthen and refine the institutional requirements for ESG information disclosure, especially for low-pollution industries that are currently under relatively loose supervision, to improve the overall transparency of the market and reduce potential risks from the source. Second, we should accelerate the construction of a multi-level and broad-coverage financial service system, adequately relieve the financing constraints of non-state-owned firms, and thus fundamentally weaken their inherent motivation to conceal negative information for obtaining financing. Third, we should not rush to force the unification of the ESG evaluation system at the current stage. We should fully recognize the somewhat subjective nature of ESG evaluation, and allow and encourage a reasonable range of rating discrepancy during the self-improvement stage of

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market development, given that it continues to be a crucial factor in the contemporary securities market's healthy functioning.

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