

Beyond Aggregate ESG: Stock Price Crash Risk in China's Post-Dual-Carbon Era

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Article

Keywords: ESG ratings, stock price crash risk, dimension decomposition, Social dimension, heavy-polluting industries, China

Posted Date: October 23rd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11164998/v1>

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Additional Declarations: No competing interests reported.

Abstract

Aggregate ESG ratings may conceal which dimensions of sustainability are actually associated with extreme downside risk. This study examines the relationship between overall and pillar-level ESG performance and future stock price crash risk among 3,264 Chinese A-share firms during the post-“dual carbon” period of 2021–2024. Using NCSKEW and DUVOL, we find no significant association between the composite ESG score and future crash risk. Pillar decomposition, however, shows that the Social score is negatively associated with both crash-risk measures, consistent with a possible stakeholder-monitoring and reputational-capital interpretation, while the Environmental and Governance scores are statistically insignificant. The negative Social association is evident among heavy-polluting firms and state-owned enterprises, although cross-group differences are not statistically established. At the aggregate level, higher ESG performance is associated with a lower cost of debt, but this financing channel does not extend to crash risk. Using alternative Wind ratings leaves the composite result unchanged, while the Social effect weakens and Governance becomes positive and significant. Overall, composite ESG scores may mask economically relevant differences across sustainability dimensions, making pillar-level analysis important for assessing extreme downside risk.

JEL Classification: G12, G34, M14, Q56

Introduction

The global surge in Environmental, Social, and Governance (ESG) investing has fundamentally reshaped how market participants assess corporate risk. In China, the implementation of the “dual carbon” strategy since 2021 and the subsequent introduction of mandatory sustainability disclosure guidelines by the Shanghai, Shenzhen, and Beijing stock exchanges in 2024 have accelerated ESG integration into the capital market infrastructure. These institutional developments raise the pressing question of whether ESG performance is associated with lower extreme downside risk in the Chinese stock market.

Stock price crash risk, defined as the likelihood of extreme negative firm-specific returns arising from the sudden release of accumulated bad news (Lee et al., 2020), represents one of the most consequential forms of downside risk for investors. The theoretical link between ESG and crash risk operates through several channels. First, high ESG ratings may reflect more transparent information environments, reducing the scope for managers to hoard bad news (Feng et al., 2022). Second, ESG-related disclosure can be more effective when firms face stronger external supervision, highlighting the role of monitoring in constraining managerial opportunism (Hao et al., 2025). Third, strong ESG performance may build reputational capital that provides an “insurance-like” mechanism during adverse events (Fiorillo et al., 2024).

However, the empirical evidence remains far from conclusive. Feng et al. (2022) document a significant negative relationship between ESG ratings and crash risk for Chinese A-share firms over the 2009–2020 period. Wang (2026) confirms the negative relationship in a more recent Chinese A-share sample and identifies corporate intelligent transformation as a mediating mechanism. In contrast, Hao et al. (2025)

show that mandatory ESG disclosure per se has no significant unconditional effect on crash risk, as heterogeneity analyses indicate risk-reducing effects for firms with higher corporate governance levels or stronger external supervision, while further analysis identifies ESG ratings as a key factor in reducing crash risk. Li et al. (2026) shift the focus from ESG levels to ESG rating uncertainty, demonstrating that disagreement among rating agencies increases crash risk through higher financing costs, managerial myopia, and information asymmetry. Wang et al. (2023) adopt a network perspective and find that low-ESG-rated firms act as net transmitters of crash risk spillovers, with the Social dimension playing a particularly important role in reducing crash-risk connectivity.

Despite the growing literature on ESG and stock price crash risk, several unresolved questions remain. First, much of the firm-level ESG–crash-risk literature evaluates ESG as a composite construct (Feng et al., 2022; Gao et al., 2022; Wang, 2026). Although this approach is useful for identifying the overall ESG–crash-risk association, it may conceal heterogeneous relationships across the three pillars because each dimension captures a different aspect of corporate behavior. For example, Environmental performance reflects firms’ environmental compliance and disclosure practices (Ding et al., 2022), Social performance captures stakeholder-oriented activities and social responsibility (Wang et al., 2023), and Governance performance reflects internal monitoring and shareholder oversight (Kim et al., 2014). These differences imply that E, S, and G need not convey the same information to market participants or relate to crash risk through the same mechanisms. Existing pillar-level evidence provides some support for this view, but it addresses related rather than identical questions. Fiorillo et al. (2024) examine E, S, and G as moderators of the relationship between geopolitical risk and crash risk, whereas Wang et al. (2023) analyze pillar-specific patterns in a network framework of crash-risk spillovers. As a result, it remains unclear whether the firm-level relationship observed for aggregate ESG reflects a common ESG effect or instead combines distinct pillar-level associations with subsequent crash risk. We address this question by examining aggregate ESG together with the E, S, and G dimensions within the same firm-level crash-risk framework.

Second, an important link between the ESG–crash-risk and debt-financing literature remains unresolved. Existing crash-risk studies identify financing costs, managerial myopia, and information asymmetry as channels through which ESG rating uncertainty is associated with crash risk (Li et al., 2026). Hao et al. (2025) further show that ESG-related crash-risk outcomes depend on corporate governance quality and external supervision, while Wang (2026) identifies corporate intelligent transformation as a mediating mechanism. In parallel, debt-financing research shows that sustainability-related information can affect creditors’ pricing decisions. Ding et al. (2022) find that environmental penalties increase subsequent debt costs through deterioration in environmental disclosure quality, while Zhang et al. (2022) show that green credit policy affects firms’ debt-financing costs. More directly, Shi et al. (2024) find that stronger ESG performance is associated with lower debt-financing costs among Chinese listed firms. These findings make debt pricing a plausible link between ESG and crash risk, but they do not establish whether realized COD connects firm-level ESG performance to subsequent stock price crash risk. Li et al. (2026) provide the closest related evidence by showing that ESG rating uncertainty increases broader financing costs and, in turn, crash risk, but their analysis concerns disagreement among rating providers rather than ESG

performance levels and does not isolate realized debt costs. We therefore examine whether aggregate ESG is associated with COD and whether COD, in turn, is associated with subsequent crash risk.

Third, it remains uncertain whether ESG–crash-risk relationships documented largely in earlier Chinese samples generalize to the post-“dual carbon” institutional environment. Much of the existing evidence is based on observations ending in 2020 (Feng et al., 2022; Gao et al., 2022; Hao et al., 2025), when China’s ESG framework was at an earlier stage of development. Since 2021, greater policy attention to sustainability, expanding ESG-related regulation, evolving disclosure practices, and growing investor interest in non-financial information have changed the setting in which ESG ratings are produced and interpreted. These developments may affect both firms’ incentives surrounding ESG performance and the information that market participants extract from ESG ratings. The question, therefore, is not whether the “dual carbon” policy itself caused changes in crash risk, but whether ESG–crash-risk relationships established predominantly in pre-2021 samples remain evident in this more recent institutional environment. By focusing on 2021–2024, we provide contemporary evidence on the external validity of earlier findings.

Fourth, the role of industry and ownership characteristics in shaping the ESG–crash risk relationship remains insufficiently understood. Existing evidence suggests that these institutional characteristics matter for different dimensions of corporate risk. Wang (2026) finds that the association between ESG performance and crash risk is more pronounced in non-heavy-polluting industries, while Wang et al. (2023) highlight the relevance of state ownership for ESG-related crash risk spillovers. Related evidence from the green finance literature further shows that the effects of green credit policy on default risk among heavy-polluting firms vary with state ownership (Qiu and Yu, 2024). Thai et al. (2023) similarly demonstrate that corporate governance characteristics can moderate crash-risk relationships, while Qi and Diao (2020) show that diversification-related crash risk differs between SOEs and non-SOEs. Taken together, these studies point to the importance of both industry pollution intensity and ownership structure, yet their respective roles in shaping the firm-level ESG–crash-risk association remain underexplored.

This study addresses these gaps by making the following contributions. First, we systematically decompose ESG ratings into their E, S, and G components and examine their individual associations with future crash risk. Our key finding is that only the Social dimension is significantly negatively associated with crash risk, while the E and G dimensions are not. This finding highlights the limitations of treating ESG as a unified construct and provides direct firm-level evidence on dimensional heterogeneity in China. Second, we examine the cost of debt as a potential transmission channel in the ESG-crash risk relationship. Although we find that ESG is negatively and significantly associated with COD, the estimated indirect association involving COD is not statistically significant. Thus, the results do not provide evidence that COD constitutes a statistically significant channel linking aggregate ESG to crash risk. Third, we provide new evidence from China’s post-“dual carbon” period (2021–2024), examining the ESG–crash-risk relationship within an institutional environment characterized by expanding ESG regulation and sustainability-disclosure practices, which distinguishes this period from those covered by earlier studies.

This temporal focus is critical because the institutional environment may substantially shape how ESG information is produced, disseminated, and priced. Fourth, we examine whether the ESG–crash-risk relationship varies across industry pollution intensity and ownership structure, two important institutional characteristics of Chinese listed firms. This analysis extends existing evidence by identifying the contexts in which ESG-related crash-risk associations may differ across firms.

The remainder of this paper is organized as follows. The Literature Review and Hypotheses Development section reviews the relevant literature and develops the hypotheses. The Research Design section describes the sample, variable definitions, and empirical models. The Empirical Results section presents the baseline, dimension-decomposition, and channel-analysis results, followed by the Heterogeneity Analysis. The Endogeneity and Robustness section reports the endogeneity tests and robustness checks. The paper concludes with a discussion of the main findings, implications, limitations, and directions for future research.

Literature Review and Hypotheses Development

ESG and Stock Price Crash Risk

A central theoretical explanation for firm-specific stock price crash risk is the bad-news-hoarding mechanism of Jin and Myers (2006), whereby managers may strategically withhold negative firm-specific information. When the accumulated bad news reaches a tipping point and is released simultaneously, stock prices experience sharp declines. Managerial incentives such as career concerns and compensation contracts can further encourage such behavior (Kim et al., 2011). Consistent with this mechanism, Hutton et al. (2009) show that firms with more opaque financial reporting are more prone to future stock price crashes. Xu et al. (2013) further show that greater analyst coverage is associated with higher future stock price crash risk in China, particularly when analysts are more optimistic.

ESG performance may mitigate crash risk through three primary channels. The information transparency channel suggests that high-quality ESG disclosure reduces information asymmetry between managers and outside investors, limiting managers' ability to conceal adverse information (Feng et al., 2022). Firms with strong ESG practices are more likely to maintain comprehensive, timely, and credible disclosure practices that extend beyond financial reporting. The external monitoring channel suggests that the effects of ESG-related disclosure can be stronger when firms face greater external supervision (Hao et al., 2025), providing additional scrutiny that complements traditional shareholder monitoring. The reputational capital channel argues that firms with strong ESG performance accumulate goodwill that functions as an insurance mechanism, cushioning the stock price impact when negative events occur (Fiorillo et al., 2024).

Feng et al. (2022), using 24,193 firm-year observations of Chinese A-share firms from 2009 to 2020, document a statistically and economically significant negative association between ESG ratings and future stock price crash risk. Their analysis considers competing stakeholder- and agency-theory explanations for the ESG–crash-risk relationship. Gao et al. (2022), examining Chinese A-share firms over

2010–2020, similarly find that stronger ESG performance is associated with lower crash risk and identify greater green-investor attention, improved analyst competency, and constraints on managerial behavior as channels underlying this relationship. Wang (2026), using a more recent sample of Chinese A-share firms from 2011 to 2022, also documents a negative ESG–crash-risk relationship and identifies corporate intelligent transformation as a mediating mechanism, while green innovation efficiency strengthens the risk-mitigating association. In contrast, Hao et al. (2025), using Chinese A-share firms from 2006 to 2020, find no significant unconditional effect of mandatory ESG disclosure on stock price crash risk, although the risk-reducing association is stronger among firms with better corporate governance or external supervision. They also show that higher ESG ratings are associated with lower crash risk.

From a different angle, Li et al. (2026) demonstrate that ESG rating uncertainty, defined as disagreement among rating agencies, significantly increases crash risk through higher financing costs, managerial myopia, and greater information asymmetry. This finding underscores that it is not merely the level but also the consistency of ESG signals that matters for market stability. Wang et al. (2023), adopting a network spillover framework, find that low-ESG-rated firms are net transmitters of crash risk, indicating strong risk interconnectedness across ESG tiers.

The Importance of ESG Dimension Decomposition

A critical limitation of the existing literature is its reliance on composite ESG scores. The E, S, and G dimensions capture fundamentally different aspects of corporate behavior. The Environmental dimension relates to pollution control, resource efficiency, and climate risk management. The Social dimension encompasses labor practices, community engagement, product safety, and supply chain responsibility. The Governance dimension reflects board structure, executive compensation, shareholder rights, and internal controls.

Fiorillo et al. (2024), in their study of 4,402 firms across 64 countries from 2010 to 2021, provide important evidence on dimensional heterogeneity: while both the E and S dimensions significantly mitigate the effect of geopolitical risk on crash risk, the G dimension shows no significant moderating effect. Wang et al. (2023) find that in the Chinese context, the Social (S) dimension is particularly effective in reducing crash risk spillover connectivity, whereas the Environmental (E) dimension, due to possible “greenwashing” behaviors, may actually increase risk transmission from high-rated firms.

In the Chinese post-“dual carbon” context, we argue that dimensional effects are likely to diverge for several institutional reasons. The Environmental dimension, despite receiving the most policy attention, may suffer from signal quality issues because firms in this regulatory spotlight face incentives to engage in symbolic environmental compliance without substantive behavioral change. The Governance dimension in China exhibits limited cross-sectional variation due to regulatory convergence in board structures and the dominance of controlling shareholders, reducing its discriminative power. The Social dimension, however, captures aspects of stakeholder management such as labor relations, community

trust, and the social license to operate that are becoming increasingly salient in China's evolving social contract between firms and society.

The Role of Cost of Debt as a Mediating Channel

The cost of debt (COD) represents the effective borrowing cost borne by the firm and reflects the pricing of credit risk by lenders. Prior evidence from China indicates that environmental regulation and disclosure-related factors can affect firms' debt-financing costs (Ding et al., 2022; Zhang et al., 2022). Li et al. (2026) further show that ESG rating uncertainty increases broader financing costs, which in turn contribute to higher crash risk. Taken together, these studies point to financing costs as a plausible link between ESG-related information and stock price crash risk. Building on this literature, we focus specifically on COD and examine whether ESG rating levels are associated with lower debt-financing costs and whether COD, in turn, is associated with lower subsequent crash risk. Higher ESG ratings may signal lower default risk and stronger risk management to creditors, potentially reducing borrowing costs. Lower debt-financing costs may alleviate financial pressure and reduce managers' incentives to withhold adverse information in order to preserve favorable borrowing terms. In addition, creditor monitoring associated with debt contracts may constrain managerial opportunism.

The Moderating Role of Industry and Ownership

Heavy-polluting industries face heightened environmental regulation, greater public scrutiny, and higher exposure to sustainability-related risks. In these industries, ESG practices carry greater information value because stakeholders are more attentive to firms' environmental and social compliance. Thai et al. (2023), examining corporate tax avoidance and crash risk, show that specific corporate governance mechanisms can moderate crash-risk effects, underscoring the importance of governance context.

Ownership structure introduces another layer of heterogeneity. State-owned enterprises (SOEs) in China operate under implicit government guarantees and established governance frameworks, potentially reducing the marginal value of ESG as a governance mechanism. Non-SOEs, facing higher information asymmetry and tighter financing constraints, may benefit more from ESG's signaling function. However, SOEs also face greater political scrutiny and social obligations, which may amplify the relevance of the Social dimension. Qi and Diao (2020) find that diversification increases crash risk more strongly in non-SOEs and that stronger external monitoring mitigates this relationship, suggesting that the ESG-crash risk relationship may similarly vary by ownership type.

Hypotheses

Hypothesis 1

(Aggregate Effect): Higher composite ESG ratings are associated with lower future stock price crash risk.

Hypothesis 2

(Dimensional Heterogeneity): The E, S, and G dimensions are differentially associated with future crash risk.

Hypothesis 3

(COD Channel): The association between ESG ratings and future stock price crash risk is partly transmitted through the cost of debt.

Hypothesis 4

(Industry Moderation): The negative association between ESG ratings and crash risk is stronger in heavy-polluting industries.

Hypothesis 5

(Ownership Moderation): The association between ESG ratings and crash risk varies between state-owned and non-state-owned enterprises.

Research Design

Sample and Data

Our sample comprises Chinese A-share listed firms over the period 2021–2024, corresponding to the post-“dual carbon” policy era. ESG data are obtained from the Huazheng ESG rating system, which provides both composite ESG scores and individual E, S, and G dimension scores on a 1–9 scale. For robustness, we also employ Wind ESG ratings as an alternative measure. Stock price crash risk is computed from weekly stock return data sourced from the China Stock Market and Accounting Research (CSMAR) database, following the standard firm-specific crash-risk framework originating in Chen et al. (2001) and its subsequent weekly-return applications (Hutton et al., 2009; Kim et al., 2011). Financial and corporate governance data are also obtained from CSMAR.

Consistent with common screening practices in the Chinese crash risk literature (e.g., Feng et al., 2022; Li et al., 2026), the CSMAR extraction was pre-filtered to exclude financial-industry firms and firms with ST, *ST, or PT designations. Observations with missing values for key variables are subsequently excluded during sample construction. Continuous variables are winsorized at the pooled 1st and 99th percentiles to mitigate the influence of outliers, with COD treated separately within the channel-analysis sample as described below. The final baseline sample contains 9,327 firm-year observations from 3,264 unique firms, with explanatory variables measured over 2021–2023 and dependent variables measured over the exact corresponding lead years 2022–2024.

Variable Definitions

The definitions and measurement of all variables used in the empirical analysis are summarized in Table 1. Following Chen et al. (2001) and subsequent firm-level applications using weekly returns (Hutton et al., 2009; Kim et al., 2011), we construct two measures of firm-specific crash risk. For each firm-year, we estimate an expanded market model in which the firm's weekly return is regressed on the value-weighted market return in weeks $w - 2$, $w - 1$, w , $w + 1$, and $w + 2$ to accommodate nonsynchronous trading. The firm-specific weekly return is defined as $W = \ln(1 + \epsilon)$, where ϵ is the OLS residual. NCSKEW (Negative Conditional Skewness) captures the third moment of the firm-specific weekly return distribution, while DUVOL (Down-to-Up Volatility) compares the volatility of down-week returns with up-week returns. Higher values of both measures indicate greater crash risk. We require at least 30 valid weekly observations after constructing the expanded-market-model regressors.

The core explanatory variables are the Huazheng ESG composite score (ESG) and its three sub-dimension scores: Environmental (E), Social (S), and Governance (G), each measured on a 1–9 scale. The cost of debt (COD) is measured as interest expense divided by total liabilities. Observations with missing interest expense are excluded from the COD channel analysis, and COD is winsorized once at the pooled 1st and 99th percentiles within the channel-analysis sample.

Following prior crash-risk research (e.g., Feng et al., 2022; Wang, 2026), we control for: firm size (SIZE), leverage (LEV), return on assets (ROA), book-to-market ratio (BM), Tobin's Q, tangibility (TANG), firm age (AGE), largest shareholder ownership (TOP1), board independence (Indep), managerial ownership (Mshare), dividend per share (DPS), and state ownership (SOE).

Table 1
Variable Definitions

Type	Variable	Symbol	Definition
Dependent	Negative skewness	NCSKEW _{$t+1$}	Chen et al. (2001) measure
Dependent	Down-to-up volatility	DUVOL _{$t+1$}	Chen et al. (2001) measure
Independent	ESG composite	ESG	Huazheng composite score (1–9)
Independent	Environmental	E	Huazheng E dimension score
Independent	Social	S	Huazheng S dimension score
Independent	Governance	G	Huazheng G dimension score
Intermediate	Cost of debt	COD	Interest expense / total liabilities
Moderator	Heavy pollution	HeavyPollute	1 = heavy-polluting industry, 0 = otherwise
Moderator	State ownership	SOE	1 = state-owned, 0 = non-state-owned
Control	Firm size	SIZE	ln(total assets)
Control	Leverage	LEV	Total debt / total assets
Control	Profitability	ROA	Net income / total assets
Control	Book-to-market	BM	Book value / market value
Control	Tobin's Q	TobinQ	Market value / replacement cost
Control	Tangibility	TANG	Tangible assets / total assets
Control	Firm age	AGE	Years since IPO
Control	Ownership concentration	TOP1	Largest shareholder stake (%)
Control	Board independence	Indep	Independent directors / board size (%)
Control	Managerial ownership	Mshare	Management shareholding (%)
Control	Dividends	DPS	Cash dividend per share

Empirical Models

The baseline, channel, and heterogeneity regressions include industry and year fixed effects, with standard errors clustered at the firm level. Dependent variables are matched to explanatory variables by firm and exact calendar year, so that an observation measured in year t is paired only with crash risk in year $t + 1$; gaps in firm-year coverage are not treated as one-year leads. This timing structure helps mitigate reverse-causality concerns.

Model 1 (Baseline — H1):

$$\text{NCSKEW}_{i,t+1} = \alpha + \beta_1 \text{ESG}_{i,t} + \gamma X_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t} \quad (1)$$

Model 2 (Dimension Decomposition — H2):

$$\text{NCSKEW}_{i,t+1} = \alpha + \beta_1 E_{i,t} + \beta_2 S_{i,t} + \beta_3 G_{i,t} + \gamma X_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t} \quad (2)$$

Model 3 (Channel Analysis — H3): Following the traditional Baron and Kenny (1986) stepwise procedure, supplemented by the Sobel test (Sobel, 1982): Step 1 regresses COD on ESG; Step 2 regresses NCSKEW on ESG; Step 3 regresses NCSKEW on ESG and COD.

Model 4 (Moderation — H4, H5):

$$\text{NCSKEW}_{i,t+1} = \alpha + \beta_1 \text{ESG}_{i,t} + \beta_2 \text{ESG}_{i,t} \times \text{Moderator}_{i,t} + \beta_3 \text{Moderator}_{i,t} + \gamma X_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t} \quad (3)$$

where Moderator is either HeavyPollute or SOE. When HeavyPollute is used as the moderator, its main effect is absorbed by the industry fixed effects because the indicator is constant within industries and is therefore not separately estimated.

Empirical Results

Descriptive Statistics

Table 2 reports descriptive statistics for the main variables. The mean values of NCSKEW and DUVOL are -0.2851 and -0.1511, respectively. The mean ESG composite score is 4.19, with E, S, and G dimension scores averaging 2.15, 4.85, and 5.17, respectively. The E dimension has the lowest average score among the three pillars in our sample. In the COD channel-analysis sample, the mean cost of debt is 1.48% (std = 1.17%).

Table 2
Descriptive Statistics

Variable	N	Mean	Std	Min	P25	Median	P75	Max
NCSKEW ₊₁	9,327	-0.2851	0.7700	-2.6145	-0.7119	-0.2516	0.1780	1.6324
DUVOL ₊₁	9,327	-0.1511	0.4810	-1.2802	-0.4801	-0.1573	0.1688	1.0569
ESG	9,327	4.1937	0.8117	2.0000	4.0000	4.0000	5.0000	6.0000
E	9,327	2.1536	1.1231	1.0000	1.0000	2.0000	3.0000	6.0000
S	9,327	4.8473	0.8876	3.0000	4.0000	5.0000	5.0000	7.0000
G	9,327	5.1717	1.1034	2.0000	5.0000	5.0000	6.0000	7.0000
COD	8,811	0.0148	0.0117	0.0001	0.0050	0.0129	0.0218	0.0540
SIZE	9,327	22.4331	1.3119	20.1109	21.4638	22.2255	23.2298	26.3890
LEV	9,327	0.4283	0.2059	0.0615	0.2656	0.4189	0.5754	0.9415
ROA	9,327	0.0303	0.0698	-0.2308	0.0069	0.0321	0.0649	0.2285
BM	9,327	0.6462	0.2569	0.1278	0.4544	0.6390	0.8220	1.2506
TobinQ	9,327	1.9309	1.1801	0.7996	1.2165	1.5650	2.2005	7.8246
TANG	9,327	0.1945	0.1486	0.0018	0.0784	0.1619	0.2795	0.6493
AGE	9,327	25.9355	5.8529	13.0000	22.0000	26.0000	30.0000	41.0000
TOP1	9,327	30.8027	14.8224	0.0000	20.2600	29.1600	40.1350	70.2900
Indep	9,327	38.1083	5.4137	33.3300	33.3300	36.3600	42.8600	57.1400
Mshare	9,327	12.6403	18.0412	0.0000	0.0032	0.9863	22.7424	66.4842
DPS	9,327	0.1731	0.2925	0.0000	0.0000	0.0700	0.2000	1.8000
SOE	9,327	0.3331	0.4714	0.0000	0.0000	0.0000	1.0000	1.0000
<i>Note: All continuous variables are winsorized at the 1st and 99th percentiles. COD statistics are based on the 8,811-observation channel-analysis sample after excluding observations with missing interest expense.</i>								

The untabulated correlation and multicollinearity diagnostics indicate that pairwise associations among the main regressors are modest and do not suggest severe multicollinearity concerns. The regression analysis below therefore focuses on the multivariate associations after controlling for firm characteristics and fixed effects.

Baseline Regression Results

Table 3 presents the baseline regression results. Columns (1) and (2) report the coefficients on the ESG composite score for NCSKEW and DUVOL, respectively. Columns (3) and (4) report the dimension decomposition results.

Table 3
Baseline Regression Results

Variable	(1) NCSKEW _{<i>t</i>+1}	(2) DUVOL _{<i>t</i>+1}	(3) NCSKEW _{<i>t</i>+1}	(4) DUVOL _{<i>t</i>+1}
ESG	-0.0013	0.0031		
	(0.0120)	(0.0076)		
E			0.0094	0.0076
			(0.0090)	(0.0057)
S			-0.0256**	-0.0163**
			(0.0104)	(0.0065)
G			0.0070	0.0066
			(0.0091)	(0.0057)
Controls	Yes	Yes	Yes	Yes
Industry + Year FE	Yes	Yes	Yes	Yes
N	9,327	9,327	9,327	9,327
Adj. R ²	0.0226	0.0336	0.0230	0.0342
<i>Note: Standard errors clustered at the firm level are reported in parentheses. *p < 0.1, **p < 0.05, ***p < 0.01.</i>				

Column (1) shows that the ESG composite score has a coefficient of - 0.0013 ($p = 0.917$) on NCSKEW, which is statistically indistinguishable from zero. Column (2) confirms this insignificant result for DUVOL ($\beta = 0.0031$, $p = 0.678$). These findings indicate that H1 is not supported: aggregate ESG is not significantly associated with future crash risk in the baseline specification.

The insignificant aggregate ESG result contrasts with Feng et al. (2022) and Gao et al. (2022), who document significant negative associations between ESG performance and stock price crash risk in earlier Chinese samples, but is broadly consistent with Hao et al. (2025), who find no significant unconditional effect of mandatory ESG disclosure on crash risk.

The dimension decomposition in Columns (3) and (4) provides evidence of pillar-level heterogeneity. The Social dimension is significantly negatively associated with future crash risk: $\beta = -0.0256$ ($p = 0.013$) for NCSKEW and $\beta = -0.0163$ ($p = 0.012$) for DUVOL. In economic terms, a one-unit increase in the S score is associated with approximately a 0.033-standard-deviation decrease in NCSKEW and a 0.034-standard-deviation decrease in DUVOL. The Environmental dimension is positive but insignificant ($\beta = 0.0094$, $p =$

0.292), and the Governance dimension is also insignificant ($\beta = 0.0070$, $p = 0.445$) in the NCSKEW specification.

These results partially support H2: the S dimension shows the only statistically significant negative association with future crash risk, while the E and G coefficients are not statistically significant. This finding resonates with Wang et al. (2023), who find that the Social dimension is particularly important in reducing crash-risk spillover connectivity in China.

Potential Cost-of-Debt Channel

Table 4 reports the channel analysis examining whether COD represents a potential pathway linking ESG to crash risk (H3).

Table 4 Potential COD Channel: ESG, COD, and NCSKEW			
Variable	Step 1: COD	Step 2: NCSKEW ₊₁	Step 3: NCSKEW ₊₁
ESG	−0.0021*** (0.0002)	−0.0032 (0.0122)	−0.0004 (0.0124)
COD	—	—	1.3541 (0.8580)
Controls	Yes	Yes	Yes
Industry + Year FE	Yes	Yes	Yes
N	8,811	8,811	8,811
Adj. R ²	0.3294	0.0231	0.0232
<i>Note: The channel-analysis sample excludes observations with missing interest expense. COD is constructed as B001211101/A002000000 and winsorized once at the pooled 1st and 99th percentiles within the channel-analysis sample. Standard errors clustered at the firm level are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Sobel test: indirect effect = − 0.0028, $Z = - 1.5574$, $p = 0.1194$.</i>			

Step 1 shows that ESG is negatively and significantly associated with the cost of debt ($\beta = -0.0021$, $p < 0.001$). Using the same 8,811-observation channel-analysis sample, Step 2 yields an insignificant ESG–NCSKEW association ($\beta = -0.0032$, $p = 0.795$). In Step 3, ESG remains statistically insignificant ($\beta = -0.0004$, $p = 0.976$), while COD is positively but not significantly associated with NCSKEW ($\beta = 1.3541$, $p = 0.115$). Consistent with these results, the Sobel test indicates that the indirect association through COD is not statistically significant (indirect effect = − 0.0028; $Z = - 1.5574$, $p = 0.119$). Therefore, H3 is not supported.

Heterogeneity Analysis

Heavy-Polluting Industries

The results of the heterogeneity analysis for heavy-polluting and non-heavy-polluting industries are reported in Table 5. To test H4, we first interact ESG with HeavyPollute and then estimate separate subsample regressions with the full E/S/G dimension decomposition. Because HeavyPollute is constant within industries, its main effect is absorbed by the industry fixed effects and is not separately estimated in the full-sample moderation model.

Table 5
Heterogeneity: Heavy-Polluting vs. Non-Heavy-Polluting Industries

Variable	(1) Full Sample	(2) Heavy-Polluting	(3) Non-Heavy-Polluting
ESG	0.0038		
	(0.0134)		
ESG × HP	−0.0208		
	(0.0239)		
E		−0.0092	0.0145
		(0.0199)	(0.0101)
S		−0.0678***	−0.0072
		(0.0180)	(0.0126)
G		0.0022	0.0086
		(0.0192)	(0.0104)
Controls	Yes	Yes	Yes
Industry + Year FE	Yes	Yes	Yes
N	9,327	2,014	7,313
Adj. R ²	0.0225	0.0222	0.0229
<i>Note: Standard errors clustered at the firm level are reported in parentheses. The main effect of HeavyPollute is absorbed by industry fixed effects and is therefore not separately estimated. *p < 0.1, **p < 0.05, ***p < 0.01.</i>			

In heavy-polluting industries (Column 2), the S dimension is negatively and significantly associated with crash risk ($\beta = -0.0678$, $p < 0.001$), while neither E ($\beta = -0.0092$, $p = 0.642$) nor G ($\beta = 0.0022$, $p = 0.909$) is statistically significant. In non-heavy-polluting industries (Column 3), none of the three dimensions is individually significant. Thus, the subgroup estimates indicate that the negative S association is concentrated in the heavy-polluting subsample.

The aggregate ESG × HeavyPollute interaction is not statistically significant ($\beta = -0.0208$, $p = 0.384$), and therefore H4 is not supported. The subgroup estimates nevertheless reveal a descriptive pattern in which

the S coefficient is negative and statistically significant in the heavy-polluting subsample but not in the non-heavy-polluting subsample. Subgroup significance alone does not establish a statistically significant cross-group difference. This pattern is consistent with the possibility that stakeholder-oriented social performance is particularly salient in industries subject to greater environmental regulation and public scrutiny.

State Ownership

The results of the heterogeneity analysis by state ownership are presented in Table 6. The interaction term $ESG \times SOE$ is negative and marginally significant ($\beta = -0.0390$, $p = 0.056$), indicating weak evidence that the aggregate ESG–crash-risk association differs by ownership type. In the subsample analysis, the S coefficient is negative and statistically significant in SOEs ($\beta = -0.0426$, $p = 0.011$) but negative and not statistically significant in non-SOEs ($\beta = -0.0141$, $p = 0.296$). The subgroup estimates provide descriptive evidence consistent with the interaction result, although they do not constitute a formal test of the difference between the two S coefficients.

Table 6
Heterogeneity: State-Owned vs. Non-State-Owned Enterprises

Variable	(1) Full Sample	(2) SOE	(3) Non-SOE
ESG	0.0134		
	(0.0142)		
ESG × SOE	−0.0390*		
	(0.0204)		
SOE	0.1649*		
	(0.0874)		
E		−0.0034	0.0143
		(0.0149)	(0.0114)
S		−0.0426**	−0.0141
		(0.0167)	(0.0135)
G		−0.0048	0.0100
		(0.0167)	(0.0111)
Controls	Yes	Yes (SOE excluded)	Yes (SOE excluded)
Industry + Year FE	Yes	Yes	Yes
N	9,327	3,107	6,220
Adj. R ²	0.0228	0.0319	0.0212
<i>Note: Standard errors clustered at the firm level are reported in parentheses. SOE is excluded from the SOE and non-SOE subsample controls because it is constant within each subsample. *p < 0.1, **p < 0.05, ***p < 0.01.</i>			

The interaction evidence provides weak support for H5 at the 10% level. The ownership split also reveals a distinct subsample pattern for the S dimension. Two interpretations may help explain why the S coefficient is significant among SOEs. First, SOEs face greater political scrutiny and social-accountability pressures, making Social performance a potentially more salient signal of the fulfillment of social mandates. Second, SOEs' larger workforces and deeper community embeddedness may make labor relations, employee welfare, and stakeholder communication particularly relevant to operational stability and reputation (Remeikienė et al., 2025).

Endogeneity and Robustness

Endogeneity Concerns

We examine potential endogeneity using two complementary approaches, with the results reported in Table 7. First, we replace ESG with its exact one-year lagged value, while retaining the exact one-year-ahead crash-risk outcome. The lagged specification yields a positive but statistically insignificant coefficient ($\beta = 0.0248$, $p = 0.125$, $N = 6,063$), providing no evidence of a robust negative aggregate ESG association under the longer timing structure.

Second, we use the leave-one-out industry-year mean ESG score as an instrumental variable and estimate the model using proper two-stage least squares with firm-clustered inference. The excluded instrument is strongly associated with ESG in the first stage ($\beta = -0.3619$, $SE = 0.0782$, $t = -4.6256$, cluster-robust Wald $F = 21.40$, $p < 0.001$). The second-stage coefficient on instrumented ESG is -0.1173 ($SE = 0.2407$, $p = 0.626$), which is negative but not statistically significant. The IV results are therefore consistent with the baseline inference of no statistically significant aggregate ESG association. Because the exclusion restriction cannot be tested directly, the IV estimates are interpreted as complementary rather than definitive causal evidence.

Table 7 Endogeneity Tests					
Method	Variable	Coefficient	SE	N	First-stage Wald F
Exact-year lagged ESG	ESG_lag	0.0248	0.0162	6,063	—
IV first stage	IV_ESG	−0.3619***	0.0782	9,315	21.40
IV second stage (2SLS)	ESG	−0.1173	0.2407	9,315	—
Note: The lagged specification uses exact calendar-year matching. The IV model is estimated by proper 2SLS with firm-clustered inference. The first-stage diagnostic is the cluster-robust Wald F for the excluded instrument; it is not a Stock–Yogo, Cragg–Donald, or Kleibergen–Paap statistic. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.					

Robustness Checks

We conduct five additional robustness tests, summarized in Table 8.

Table 8
Robustness Checks

Test	Variable	Coefficient	SE	N	Adj. R ² / Within R ²
(1) Wind ESG (composite)	WindESG	−0.0093	0.0113	9,369	0.0225
(2) Wind E dimension	WindE	0.0000	0.0047	9,369	0.0230
Wind S dimension	WindS	−0.0095*	0.0056		
Wind G dimension	WindG	0.0239**	0.0107		
(3) Shortened sample (X: 2022–2023)	ESG	−0.0014	0.0153	6,332	0.0322
(4) Firm + year fixed effects	ESG	−0.0457**	0.0204	9,327	0.0319
(5) Industry-clustered SE	ESG	−0.0013	0.0152	9,327	0.0226
<i>Note: All regressions include control variables and the fixed effects appropriate to each specification. In the firm-and-year fixed-effects specification, AGE is excluded because it is absorbed by the fixed effects; the model is estimated using two-way within transformation with firm-clustered standard errors. Standard errors are clustered at the firm level except in test (5), where they are clustered at the industry level. *p < 0.1, **p < 0.05, ***p < 0.01. For the Wind pillar specification, E, S, and G are estimated jointly; the reported N and fit statistic therefore apply to all three coefficients.</i>					

Several findings merit discussion. First, the Wind composite score remains statistically insignificant, indicating that the absence of a significant aggregate ESG association is not specific to the Huazheng rating system. Second, the pillar-level results are more sensitive to the choice of rating provider. The Wind E coefficient is essentially zero, the Wind S coefficient is negative and significant at the 10% level ($\beta = -0.0095$, $p = 0.091$), and the Wind G coefficient is positive and significant at the 5% level ($\beta = 0.0239$, $p = 0.025$). These differences suggest that pillar-level ESG ratings from different providers should not be treated as interchangeable.

Restricting the explanatory-variable period to 2022–2023, with crash-risk outcomes measured in 2023–2024, does not materially alter the insignificant aggregate ESG result ($\beta = -0.0014$, $p = 0.925$). Using firm and year fixed effects, however, yields a significant negative within-firm ESG coefficient ($\beta = -0.0457$, $p = 0.025$), indicating that within-firm increases in ESG ratings are associated with lower subsequent crash risk. The difference between this estimate and the baseline result is consistent with the possibility that time-invariant firm heterogeneity contributes to the contrast across specifications. The within-firm estimate, however, should not be interpreted as causal. Finally, clustering standard errors at the industry level leaves the aggregate ESG coefficient statistically insignificant ($\beta = -0.0013$, $p = 0.934$).

Conclusion

This study investigates the relationship between ESG ratings and stock price crash risk using a sample of Chinese A-share listed firms from 2021 to 2024. We move beyond the conventional approach of treating ESG as a monolithic construct by decomposing it into its Environmental, Social, and Governance dimensions and examining their individual associations with firm-level crash risk.

Our empirical analysis yields several key findings. First, the composite ESG score does not significantly predict future stock price crash risk, a result that may partly reflect the aggregation of heterogeneous pillar-level associations. This finding challenges the implicit assumption in much of the ESG literature that aggregate scores are informative for financial risk prediction and is consistent with evidence of ESG dimensional heterogeneity in Fiorillo et al. (2024) and Wang et al. (2023). Second, and central to our contribution, the Social dimension is the only pillar with a statistically significant negative association with future crash risk in the baseline Huazheng specification. Third, the heterogeneity evidence differs across the two moderators. In heavy-polluting industries, the S coefficient is negative and significant, but the aggregate $ESG \times HeavyPollute$ interaction is insignificant, so H4 is not supported and the subgroup pattern remains descriptive. For ownership, the $ESG \times SOE$ interaction is negative and marginally significant, providing weak support for H5; the S coefficient is also negative and significant among SOEs, but not among non-SOEs.

The exact-year lagged ESG coefficient and the proper 2SLS estimate are both statistically insignificant, consistent with the baseline absence of a robust aggregate ESG association. At the same time, the firm-and-year fixed-effects specification yields a significant negative within-firm ESG coefficient, suggesting that within-firm changes in ESG ratings are associated with lower crash risk.

Theoretical Implications

Our findings contribute to the literature in three ways. First, we extend prior dimension-level evidence in Fiorillo et al. (2024) and Wang et al. (2023) by showing that composite scores may mask dimension-specific associations. Second, we highlight the distinctive negative association of the Social dimension in the baseline Huazheng specification, enriching the understanding of how specific ESG attributes interact with institutional environments characterized by rapid social transformation and evolving stakeholder expectations. Third, our heterogeneity analyses suggest that ESG–crash-risk associations may vary across industry and ownership contexts, underscoring the importance of contextual analysis in ESG research (Wang et al., 2023; Erben, 2025).

Practical Implications

For investors, our results suggest that examining the Social dimension separately from the composite ESG score may provide additional information, particularly when evaluating firms in heavy-polluting industries. For corporate managers, stronger Social performance, particularly in community engagement, employee welfare, and stakeholder communication, is associated with lower tail-risk exposure. For regulators, the absence of a significant aggregate ESG–crash-risk association in our post-2021 sample

suggests that regulators and investors may benefit from greater attention to dimension-specific ESG information.

Limitations and Future Research

This study has several limitations. First, our sample is intentionally restricted to 2021–2024 to focus on the post-“dual carbon” institutional environment. This relatively short window limits our ability to examine longer-run dynamics. Second, our channel analysis examines COD as a potential pathway for aggregate ESG rather than for individual pillars. It therefore does not establish what accounts for the S-dimension association; future work could examine whether information asymmetry, analyst coverage, or social capital are associated with pillar-specific ESG–crash-risk patterns. Third, while we use Huazheng and Wind ESG ratings as alternative measures, both are domestic rating systems; cross-validation with international ESG providers (e.g., MSCI, Sustainalytics) would enhance generalizability. Fourth, lagged-variable and IV analyses mitigate, but do not eliminate, endogeneity concerns. Future research could strengthen causal identification by exploiting natural experiments or regulatory shocks.

Declarations

Competing interests

The authors declare no competing interests.

Ethics approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Author Contribution

Yinan Suo: Conceptualization; Investigation; Methodology; Writing – original draft; Writing – review & editing. Frederik Rech: Supervision; Writing – review & editing; Vladimir Zamorin: Formal analysis; Software; Data curation; Visualization; Validation; Writing – original draft; Writing – review & editing.

Acknowledgement

The authors gratefully acknowledge Prince Mohammad Bin Fahd University for its financial support of this research.

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