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Environment-specific political risk discourse and expected crash risk: The role of political activism☆

Sohanur Rahman *, Elisabeth Sinnewe, Larelle Chapple

School of Accountancy, Queensland University of Technology, Brisbane, QLD, Australia

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ABSTRACT

This study examines whether greater discourse on environment-specific political risk (EPR) in earnings conference calls (ECCs) has a favourable effect on firms' information environment affecting stock price crash risk. Under *the risk mitigation hypothesis*, EPR discourse lowers crash risk, whereas, under *the risk escalation hypothesis*, management may exploit information asymmetry leading to greater crash risk. Results from US firm-year observations reveal that the EPR discourse of the current year reduces the crash risk of the following year, thus supporting *the risk mitigation hypothesis*. Further, this study shows that the effect of EPR discourse on crash risk is more pronounced for politically active firms, potentially due to their proximity to the political decision-making process and better access to associated information. Additionally, the results suggest that the negative association between EPR discourse and crash risk is stronger in the democrat regimes and for the firms with more institutional monitoring and characterised by a higher level of integrity. Random Forest and Extreme Gradient Boosting machine learning algorithms support the effectiveness of EPR discourse in predicting crash risk. The primary results remain robust to potential endogeneity concerns.

1. Introduction

This study empirically examines the effect of environment-specific political risk (EPR) discourse on firm-level stock price crash risk (hereafter crash risk). EPR is a significant component of political risk due to growing political attention to climate change issues (Gorbatikov, van Lent, Naik, Sharma, & Tahoun, 2019; Huynh & Xia, 2020). To see how discourse on EPR in earnings conference calls (ECCs) affects crash risk, this study is built on two competing hypotheses: *the risk mitigation hypothesis* and *the risk escalation hypothesis*. Under *the risk mitigation hypothesis*, EPR discourse mitigates information asymmetry by providing decision-useful information, reducing the possibility of investors' future surprise and mitigating crash risk. Alternatively, under *the risk escalation hypothesis*, management may opportunistically manipulate the ECC discourse and exploit information asymmetry, leading to greater crash risk.

EPR discourse in ECCs is important as a voluntary disclosure mechanism. Existing literature suggests that conversation with analysts and investors in conference calls generally reduces information asymmetry by providing value-relevant information (Brown, Hillegeist, & Lo, 2004), and ECCs are considered to be a reliable information source (Fei, Xu, & Zhang, 2023; Heinrichs, Park, & Soltes, 2019; Jung, Wong, & Zhang, 2018). Management tends to provide additional information about uncertain events in ECCs, which cannot be reliably measured and recognised in written reports (Frankel, Johnson, & Skinner, 1999). However, the unstructured and unregulated nature of such calls provides a greater opportunity for managers to manipulate the information dissemination in ECCs (Davis, Ge, Matsumoto, & Zhang, 2015), especially where information related to risk, such as political risk, has uncertain outcomes.

This research plays out against such tension: revealing new risk factors in the ECC previously unknown to investors and competitors provides the opportunity for managers to signal that they are optimally managing risk (Kravet & Muslu, 2013). When managers provide risk-related information in an ECC, it signals that they are transparent and sincere in navigating and managing such risks. Existing literature finds that firms voluntarily disclose unfavourable information in ECCs (Baginski, Hassell, & Kimbrough, 2004). Matsumoto, Pronk, and

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* Corresponding author.
E-mail address: s5.rahman@qut.edu.au (S. Rahman).

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Roelofsen (2011) show that management provides more detailed disclosures on unfavourable information in the discussion segment, particularly upon questioning by analysts.

In contrast, if management withholds or opportunistically manipulates information about potential risks, an information gap exists, and stakeholders may not be able to adequately assess a firm's risk profile (Linsley & Shrives, 2006). In an untransparent information environment, managers can hide unfavourable information for an extended period to maximise managerial compensation or protect their employment (Kothari, Shu, & Wysocki, 2009). It is possible that management may restrain themselves from detailed disclosures of EPR information in ECCs if it exposes new risks and management cannot reliably predict the outcome of new information arrival (Hollander, Pronk, & Roelofsen, 2010).

EPR is the perceived political uncertainty associated with environmental issues (Hassan, Hollander, van Lent, & Tahoun, 2019), such as potential government policies mandating cap and trade schemes or changing existing environmental regulations. A higher level of EPR indicates a higher level of exposure to political uncertainty and reflects a firm's sensitivity to environmental violations, litigation, or environmental regulations. As a stock price crash is attributed to an overreaction to the sudden release of stockpiled unfavourable information (Hutton, Marcus, & Tehranian, 2009; Jin, Chen, & Yang, 2019; Qiao, Adegbite, & Nguyen, 2022), this study proposes that if EPR discourse reduces information asymmetry either by providing value-relevant information to the market or desensitising investors to an upcoming risk factor, future crash risk will be reduced (i.e., *the risk mitigation hypothesis*); alternatively, if management opportunistically exploits EPR discourse, future crash risk will be increased (i.e., *the risk escalation hypothesis*).

There have been a growing number of environmental policies and regulations globally, which have a pervasive impact on firms' environmental strategies, operations, and performance (Meng & Rode, 2019; Wu, Li, Wu, Li, & Zhong, 2022). EPR has distinctive resonance with respect to crash risk in the US market because, in recent years, US environmental policies have become more unpredictable, exposing firms to higher EPR. For instance, the US joined the Paris Agreement in 2015, while the Trump administration withdrew from the Accords in 2017. However, although the Biden government re-joined the Paris Agreement in 2021, the administration's immediate action in cancelling the Keystone XL pipeline[1] increased political uncertainty in the oil and gas industry.

To test the potential association between EPR discourse and crash risk, this study examines 28,933 firm-year observations covering 2002 to 2020. We utilise Hassan et al.'s (2019) political risk measure as a representation of EPR discourse, which captures the proportion of conference call conversations concentrating on EPR. A higher EPR reflects a higher level of discourse on EPR in an ECC. In the tests, we primarily examine two measures of crash risk: negative skewness (NSKEW) and down-to-up volatility (DUVOL). Higher NSKEW and DUVOL indicate a higher level of crash risk. The results support *the risk mitigation hypothesis* that the EPR discourse of the current year reduces the crash risk of the following year. Thus, the findings suggest that greater EPR discourse in ECCs reduces crash risk by reducing information asymmetry and unwanted future surprises. We employ an entropy-balanced sample approach to address potential self-selection bias while addressing omitted variable bias through the Oster (2019) test. Two-stage least squares (2SLS) regression analysis provides further robustness to the baseline findings. Using alternative measures of crash risk confirms that the baseline findings are not sensitive to the choice of crash risk measures. Random Forest and Extreme Gradient Boosting machine learning algorithms provide further support that EPR discourse plays an important role in predicting future crash risk.

This study has several contributions to the existing literature. First, this study extends the literature on the effectiveness of climate change risk disclosure, such as Lin and Wu (2023) and Kim, Wang, and Wu (2022), by demonstrating the importance of EPR discourse in mitigating crash risk. Our study is closely related to but distinct from Au, Qiu, & Wu, 2023, who show that mandatory risk factor disclosures in 10-K reports reduce future crash risk, but voluntary risk factor disclosures have no such effects. In contrast, we show that EPR discourse in ECCs, which is voluntary in nature and partially interactive, reduces future crash risk. Our findings are attributable to the tendency of management to be more cautious in voluntarily disclosing information in regulated disclosures (Matsumoto et al., 2011), where more incremental EPR information is spontaneously disclosed by management in ECCs, leading to lower crash risk. Our study also extends Lin and Wu (2023), who find that climate change risk disclosures in quarterly and annual reports of Chinese firms are useful in reducing crash risk. While climate change risk arises from global environmental changes, including temperature rise and adverse shifts in weather patterns, our EPR arises from the US national and regional political and regulatory landscape. Therefore, this study adds to Lin and Wu (2023) by focusing on a different aspect of risk disclosures in a distinct regulatory setting.

Second, this study assesses the relevance of policy uncertainty and risk issues to crash risk. For instance, Luo and Zhang (2020) and Jin et al. (2019) show that the impact of macro-level broader policy uncertainty on China's national economy instigates management to hide information and increase crash risk. We demonstrate that EPR directly affecting a particular firm is important from the crash risk perspective, and more discourse on these issues reduces expected crash risk. Interestingly, our findings show that investors find politically active (through lobbying) firms' EPR discourse more informative, further reducing crash risk. This result aligns with existing knowledge: lobbying firms are considered to have better access to upcoming environmental policies through their political channels (Christensen, Morris, Walther, & Wellman, 2023; Wellman, 2017), and lobbying indicates that upcoming policy changes will be more aligned with firms' interests (Meng & Rode, 2019). This, in turn, is likely to boost investors' confidence in EPR management and be effective in reducing crash risk.

Third, this study shows that EPR discourse in ECCs appears to be a crash risk mitigation strategy protecting investors' wealth, further confirming the informativeness of discussions in ECCs (Heinrichs et al., 2019; Matsumoto et al., 2011). This identifies a new factor in the literature on the determinants (Hutton et al., 2009; Jin et al., 2019; Qiao et al., 2022) and mitigation strategies (Fiordelisi, Ricci, & Santilli, 2023; Yu, Liang, Liu, & Wang, 2023; Zhou, Tang, & Luo, 2023) of crash risk.

The paper proceeds as follows. Section 2 develops the hypothesis, and Section 3 outlines the research design. Section 4 describes the main empirical results. Section 5 details the robustness tests, and Section 6 discusses the additional analysis. Finally, Section 7 provides a conclusion.

2. Literature review and hypothesis development

ECCs, while not obligatory, are a common practice among US firms, often accompanying quarterly earnings releases. Prior literature suggests that ECCs are a material information source for investors, financial analysts and other stakeholders (Brown et al., 2004; Frankel et al., 1999; Heinrichs et al., 2019; Jung et al., 2018). ECC conversations contain incremental information (Matsumoto et al. (2011): management can share information more freely than in the financial reports, and analysts can engage in two-way conversations with management during the discussion segment.

However, the unstructured and unregulated nature of ECCs allows managers to control the information flow (Davis et al., 2015). In traditional disclosures as part of company reporting, management is

[1] The Keystone XL pipeline was initially approved and subsequently rejected by the Obama administration in 2015. In 2017, the Trump administration revived it, but this was revoked by the Biden administration in 2021.

motivated to conceal or manipulate unfavourable information from outside investors to protect their interests, such as maximising compensation and protecting employment (Kothari et al., 2009). They may manipulate disclosures when they have incentives to support stock prices (Bao, Kim, Mian, & Su, 2019). In these disclosures, management may attempt to influence the market response by making the information costly to analyse or refraining from detailed disclosures due to the risk of litigation and governmental enforcement actions (Bao & Datta, 2014). In contrast, management can provide additional favourable information through ECCs that is not allowed to be recognised in financial reports because it cannot be reliably measured (Lee, 2016).

ECCs can be suitable channels for disseminating information on environmental sustainability (Eccles & Serafeim, 2013), even though they are considered venues for disseminating earnings forecast information with a short-term focus (Setterberg & Sjöström, 2021). Nevertheless, firms increasingly disclose environmental information in ECCs due to the demand for such information (Elaine, Xi, & Andrea, 2021). Investors are sensitive to corporate environmental risk (Zhou et al., 2023), and they want to know about the environmental impact and associated risks (De Villiers & Van Staden, 2010). An examination of Hassan et al.'s (2019) EPR ECC data reveals that there has been a greater discourse on environmental political risks since 2010 due to key events such as the Kyoto Protocol in 2009 and BP's oil spill in 2010, which saw corporate environmental issues receiving intensified political attention (Cavezzali, Hussain, & Rigoni, 2016).

While many companies may find disclosing environmental issues in ECCs difficult because of the uncertain outcome (Dzieliński, Eugster, Sjöström, & Wagner, 2022; Setterberg & Sjöström, 2021), this challenge may motivate them to strategically manipulate the information presented in these conversations (Cicon, 2017; Matsumoto et al., 2011). Motivation to disclose environmental risks can be more complex because firms are expected to present viable risk mitigation strategies. Failure to demonstrate a risk mitigation strategy may expose a firm to more uncertainty, leading to higher stock return volatility (Kravet & Muslu, 2013). Hence, management may refrain from disclosing material risk information if they cannot demonstrate how they plan to mitigate the risk they face (Kang & Gray, 2019). However, by relinquishing a certain degree of control over the information disclosures in the interactive Q&A section, management faces the inherent possibility of accidentally exposing a risk to investors (Lee, 2016). To mitigate unintended exposures, management often relies on predetermined scripted responses and prefers to invite analysts with supportive views of the firm (Lee, 2016; Mayew, 2008).

Although no prior research specifically examined the association between EPR discourse and crash risk, closely related literature examines: i. the association between conversations on overall environmental discourse and the cost of capital (Elaine et al., 2021); ii. environmental, social, and governance (ESG) performance and discourse tone (DeLisle, Grant, & Mao, 2021); iii. Analyst questions and management's greenwashing attitude (Hail, Shawn, & Zhang, 2021); iv. climate talk and carbon emissions (Dzieliński et al., 2022); and iv. the extent of financial analysts' demand and management's willingness to provide sustainability information (Cavezzali et al., 2016; Eccles & Serafeim, 2013). In the traditional disclosure literature, studies generally support the view that firms provide more environmental disclosures to maximise firm value by reducing information asymmetry in the market (Cormier, Ledoux, & Magnan, 2011; Verrecchia, 2001). In the ECC literature, these findings are challenged: greater environmental discourse in ECCs is associated with greater market uncertainty, leading to adverse capital market consequences such as lower share prices and higher capital costs (Elaine et al., 2021), especially for firms with poor environmental performance (Dzieliński et al., 2022). These findings suggest that analysts penalise management for greater disclosure by seeing through strategically manipulated information or forcing management to disclose unfavourable information.

In theory, as management is privileged with incremental information on political decisions, information asymmetry between management and investors will likely increase in the face of the growing climate change agenda unless it is communicated regularly to the investors. The possibility of a future crash is reduced once the market is fully informed about the risk and its adverse consequences. For instance, research has found that disclosing penalties for environmental violations or unfavourable environmental news reduces the probability of future crash risk (Zaman, Atawnah, Haseeb, Nadeem, & Irfan, 2021). Although a higher level of EPR signals that firms operate in an uncertain environment, it also indicates greater discourse that can reduce information asymmetry and future crashes if management can convince analysts of its ability to manage its known political risk.

Generally, management responds to higher government policy uncertainty by increasing voluntary disclosures (Nagar, Schoenfeld, & Wellman, 2019). Therefore, we would expect greater ECC discourse on EPR to help maintain investors' confidence in environmental decisions made by management, reducing information asymmetry and future crash risk. This study refers to this prediction as *the risk mitigation hypothesis* for convenience.

In contrast, management may not wish to provide regular updates due to the inherent uncertainty around policy outcomes. For instance, Hollander et al. (2010) find that managers withhold information during conference calls if they presume litigation risk from a specific issue. However, when the potential effect of policy decisions on a firm's operation becomes evident, its stock price crashes. Instead of stockpiling bad news, managers may use other strategic communication choices since silence in ECCs can be interpreted as the presence of unfavourable information (Chen, Matsumoto, & Rajgopal, 2011). They might decide: i. not to engage in the Q&A section management or rely on the predetermined scripted responses to analysts (Lee, 2016); ii. to be strategic in the selection of analysts they allow to participate (Mayew, 2008); iii. to present unfavourable information in a period when investors pay less attention (Miller & Skinner, 2015); iv. or de-emphasise negative information (Pei, 2021). In such situations, even in the presence of EPR discourse, information asymmetry persists, leading to a future crash. This alternate prediction is what this study refers to as *the risk escalation hypothesis*. Given these two opposing predictions, the association between EPR and stock price crash risk is an empirical question as represented in the following non-directional hypothesis:

H_1: EPR discourse in ECCs affects stock price crash risk.

3. Research design and summary statistics

3.1. Sample selection

This study employs four sample selection criteria for all US firms (2002–2020). First, similar to Kim and Zhang (2016), the sample includes firms with total assets and book values of equity greater than zero, and the year-end stock price is greater than $1. Second, the sample firm must have at least 26 weekly returns for each fiscal year. Third, firms must have their headquarters in any state in the USA. Fourth, we eliminated firm-years with missing data for the variables used in the regressions. After applying the selection criteria, stock return data from CRSP, firm-level EPR data from the Economic Policy Uncertainty (EPU) database, and historical accounting data from the Compustat are merged. Following the prior literature (Pang & Xie, 2024; Yu et al., 2023), the continuous variables are winsorised at both the 1st and 99th percentiles to mitigate the effect of outliers. Conditional on the inclusion of relevant data required for analysis in different models, the final sample comprises 29,109 firm-year observations. As crash risk measures ($NSKEW_{t+1}$ and $DUVOL_{t+1}$) and the moving sum of discretionary accruals involve lead and lag variables, this study does not have observations for 2002 and 2020 in the main analysis.

3.2. Variable construction

This section discusses the dependent variables (*NSKEW* and *DUVOL*), independent variable (*EPR*), and firm-specific control variables.

3.2.1. Crash risk measures

Following existing literature (Hasan, Taylor, & Richardson, 2021; Kim, Li, & Zhang, 2011; Qiao et al., 2022; Zhou et al., 2023), this study primarily employs two firm-level crash risk measures based on firm-specific weekly returns estimated as the residuals from the market model. Specifically, the extended market model regression is estimated as follows:

$$r_{i,t} = \alpha_{i,t} + \beta_{1i} r_{m,t-2} + \beta_{2i} r_{m,t-1} + \beta_{3i} r_{m,t} + \beta_{4i} r_{m,t+1} + \beta_{5i} r_{m,t+2} + \varepsilon_{i,t} \quad (1)$$

where $r_{i,t}$ is the stock return on firm i in week t, $r_{m,t}$ is the CRSP value-weighted market index in week t, and $\varepsilon_{i,t}$ is an error term. In the estimation, the lead and lag terms for the market index account for non-synchronous trading (Dimson, 1979). The firm-specific weekly return ($R_{i,t}$) for firm i in week t is calculated as the natural log of one plus the residual return from Eq. (1):

$$R_{i,t} = log(1 + \varepsilon_{i,t}) \quad (2)$$

The first proxy of crash risk is *NSKEW*, which captures the negative conditional skewness of firm-specific weekly returns for each year. This study computes the negative third moment of firm-specific weekly return $R_{i,t}$ for the individual sample year over the standard deviation of firm-specific weekly return raised to the third power as follows:

$$NSKEW_{i,t} = -\frac{\left(n(n-1)^{\frac{3}{2}} \sum R_{i,t}^3\right)}{\left((n-1)(n-2)\left(\sum R_{i,t}^2\right)^{3/2}\right)} \quad (3)$$

The second proxy of crash risk is *DUVOL,* which measures the down-to-up volatility of the crash likelihood. The firm-specific weekly returns are divided into 'down weeks' and 'up weeks' groups. The 'down weeks' correspond to the below annual mean return, and the 'up weeks' represent the above annual mean return. The standard deviation of firm-specific returns for individual groups is then calculated. Finally, to capture *DUVOL*, this study applies the natural logarithm of the ratio of standard deviation in down weeks divided by the standard deviation in up weeks:

$$DUVOL_{i,t} = log\left[\frac{\left(n_u - 1\right)\sum_d R_{i,t}^2\right)}{\left(n_d - 1\right)\sum_u R_{i,t}^2\right)}\right] \quad (4)$$

where 'n_u' is the number of 'up weeks' and 'n_d' is the number of 'down weeks.' A higher value of *NSKEW* and *DUVOL* reflects a higher crash risk.

3.2.2. EPR discourse

EPR discourse is measured by utilising Hassan et al. (2019). Their text-based measure of firm-level political risk is based on computational linguistics: the proportion of the quarterly ECCs that firms attribute to political risks. More discussion on a political topic between management and conference call participants indicates higher political risk. Among various topic-specific political risks, the environment-specific political risk is utilised:

$$EPR_{i,t} = \frac{\sum_b^{Bit}\left(1[b \in P_E \backslash N] \times 1[|b-p| < 10] \times \frac{f_{p,P}}{B_P} \times \frac{f_{b,P_E}}{B_{P_E}} log\left(\frac{Z}{f_{b,z}}\right)\right)}{B_{i,t}} \quad (5)$$

where $EPR_{i,t}$ is the measure of discourse on environment-specific political risk, *1[•]* is an indicator function, $P \backslash N$ is the set of bigrams related to EPR contained in political bigram, P, but not in non-political bigram, N, p is the position of the nearest synonym of EPR, $f_{p,P}$ is the frequency of bigram p in the political training library P, B_P is the total number of bigrams in the political training library, E indicates the bigram related to EPR, $f_{b,z}$ is the number of libraries in z that contain bigram b, $log(z/f_{b,z})$ adjusts each bigram's weighting for how unique its use is to the discussion on the environment compared to all the other political topics, and $B_{i,t}$ is the total number of bigrams b in the conference call transcript t.

The number of discussions around environmental but not non-political environmental topics is captured by the first two terms in the numerator. The final term assigns a score to each bigram, indicating how strongly the bigram is connected to the discussion of EPR. Overall, $EPR_{i,t}$ captures the proportion of the conversations devoted to risks associated with environment-specific political topics, adjusted by the total number of bigrams contained in the transcripts. Thus, a higher percentage measure of $EPR_{i,t}$ implies more discussion on environment-specific political risk. Following Choi, Chung, and Wang (2021) and Rahman, Sinnewe, Chapple, and Osborne (2023), this study employs the annualised EPR, standardised by mean.

3.2.3. Control variables

This study follows prior literature to include control variables in the regression models. As Chen, Hong, and Stein (2001) demonstrate that stock return volatility *(Sigma),* past stock returns *(RET),* and differences in investors' opinion, measured by detrended stock trading volume (*DTURN*), increase crash risk, this study also considers these in the models. Hutton et al. (2009) show that a firm's size and growth opportunities are positively associated with crash risk, and this study also controls for firm size by employing a firm's market capitalisation *(Size)* and growth opportunities using the market-to-book ratio *(MTB)*. Following Qiao et al. (2022) this study also controls for leverage *(Leverage)* and return on assets *(ROA)*, which are positively associated with future crash risk. Discretionary accruals *(DisAcc)* are also controlled, as Hutton et al. (2009) suggest that firms with higher levels of discretionary accruals are more prone to crashes. Similar to Hutton et al. (2009), the moving sum of absolute discretionary accruals is calculated using the modified Jones model (Dechow, Sloan, & Sweeney, 1995). Following Zaman, Bahadar, and Mahmood (2021), this study also controls for analyst coverage *(Analyst)* as the proxy of external monitoring, which reduces crash risk. Finally, this study controls for $NSKEW_{t+0}$, as according to Chen et al. (2001), stock return skewness persists over time. Further, firm, year, and state fixed effects are included in the regressions to control the impact of the unobserved firm, year, and state-specific factors. Detailed definitions of the control variables are in Appendix A.

3.3. Summary statistics

In Table 1, Panel A presents the descriptive statistics. The mean values of $NSKEW_{t+1}$ and $DUVOL_{t+1}$ are 0.091 and 0.053, respectively, which are qualitatively similar to the prior literature (Kim, Li, & Li, 2014; Krishnamurti, Chowdhury, & Han, 2021; Li & Zeng, 2019). *NSKEW* and *DUVOL* have a mean value of 0.112 and 0.057, respectively. The mean values suggest that, on average, the sample firm-specific weekly returns are more right-skewed and slightly more volatile in down weeks than in up weeks. The mean EPR is −0.049 after standardising the raw values (mean of zero and standard deviation of 1). The average of *RET* is 31.3%, indicating a favourable stock market performance, and *ROA* is 9.60%, reflecting the profitability of the sample firms. On average, the sample covers moderately large (*Size* = 25.689), leveraged (*Leverage* = 0.546), and more volatile (*Sigma* = 0.046) firms, and they have high levels of growth opportunities (*MTB* = 3.112). In addition, the average differences in investors' opinion (*DTURN*) and the moving sum of absolute discretionary accruals (*DisAcc*) are 0.082 and 0.172, respectively. The mean value of the log of the number of analysts following (*Analyst*) the sample firms is 2.081, which is relatively higher than Hasan et al. (2021). On average, the descriptive results of the

Table 1
Summary statistics and correlation matrix.

Panel A: Descriptive statistics

	N	Mean	SD	p25	Median	p75
$NSKEW_{t+1}$	28,933	0.091	0.851	−0.384	0.028	0.492
$DUVOL_{t+1}$	28,933	0.053	0.266	−0.122	0.041	0.215
EPR	28,933	−0.049	0.510	−0.327	−0.221	0.022
NSKEW	28,933	0.112	0.842	−0.376	0.041	0.509
DUVOL	28,933	0.057	0.264	−0.119	0.044	0.219
RET	28,933	0.313	0.834	−0.108	0.317	0.726
DTURN	28,933	0.082	4.746	−1.542	−0.017	1.545
Sigma	28,933	0.046	0.026	0.027	0.039	0.056
Size	28,933	25.689	1.773	24.454	25.604	26.834
ROA	28,933	0.096	0.158	0.052	0.112	0.170
Leverage	28,933	0.546	0.254	0.358	0.542	0.713
MTB	28,933	3.112	5.066	1.349	2.164	3.705
DisAcc	28,933	0.172	0.167	0.067	0.121	0.212
Analyst	28,933	2.081	0.732	1.558	2.100	2.651

Panel B: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) $NSKEW_{t+1}$	1.000													
(2) $DUVOL_{t+1}$	0.899*	1.000												
(3) EPR	−0.035*	−0.035*	1.000											
(4) NSKEW	0.020*	0.017*	0.007	1.000										
(5) DUVOL	0.023*	0.021*	0.002	0.898*	1.000									
(6) RET	0.022*	0.019*	0.002	−0.320*	−0.329*	1.000								
(7) DTURN	0.016*	0.025*	−0.008	0.050*	0.059*	0.011	1.000							
(8) Sigma	−0.019*	0.020*	−0.024*	0.120*	0.164*	0.017*	0.197*	1.000						
(9) Size	0.040*	0.020*	0.059*	0.011	−0.011	−0.011	0.007	−0.554*	1.000					
(10) ROA	0.021*	0.004	−0.039*	0.010	−0.005	−0.016*	−0.011	−0.416*	0.323*	1.000				
(11) Leverage	−0.018*	−0.022*	0.067*	−0.012*	−0.018*	0.024*	0.045*	−0.100*	0.216*	−0.024*	1.000			
(12) MTB	0.021*	0.026*	−0.038*	−0.037*	−0.035*	0.131*	0.018*	−0.041*	0.146*	0.002	−0.034*	1.000		
(13) DisAcc	0.008	0.033*	−0.024*	0.011	0.035*	0.016*	0.032*	0.414*	−0.301*	−0.288*	−0.111*	0.079*	1.000	
(14) Analyst	0.017*	0.010	0.020*	0.038*	0.025*	−0.041*	−0.030*	−0.341*	0.772*	0.219*	0.123*	0.118*	−0.192*	1.000

Panel A of this table presents the descriptive, and Panel B presents the pairwise correlation matrix for the key variables. * Indicates the statistical significance of coefficient estimates at the 5% level. Variables are defined in Appendix A.

control variables agree with the prior studies (Jia, 2018).

Panel B of Table 1 shows the correlation results. Crash risk measures, *NSKEW* and *DUVOL*, have a strong positive correlation, consistent with the existing literature (Hasan et al., 2021; Luo & Zhang, 2020). *EPR* is negatively associated with a one-year lead of both crash risk measures (0.035 and 0.035, respectively), which offers some support for the hypothesis that EPR discourse is related to crash risk. The association between the crash risk measures and controls are largely consistent with prior literature (Krishnamurti et al., 2021; Li & Zeng, 2019). The variance inflation factor (VIF) values (untabulated) in any model do not exceed 5, and the condition indices are <10 (Hair, Anderson, Tatham, & Black, 1995).[2] Thus, the concern for multicollinearity does not appear to be significant.

4. Empirical analysis

4.1. Univariate analysis

Following Chang, Chen, and Zolotoy (2017), we begin by plotting $NSKEW_{t+1}$ and $DUVOL_{t+1}$ against *EPR*. First, we divide the entire sample into deciles by EPR. Then, for each EPR decile, we determine the mean values of the crash risk measures. Finally, we plot the mean values against deciles from lowest to highest. A trend in the negative skewness, as EPR increases, is presented in Fig. 1. We observe a similar pattern for down-to-up volatility. For both measures, the difference between the mean values of crash risk for firms in the 1st versus 10th deciles of EPR is statistically significant (untabulated *t*-statistics). This univariate analysis results further support the negative association between EPR discourse and crash risk. However, more refined multivariate tests are required for conclusive evidence, which we turn to next.

4.2. Baseline results: EPR and crash risk

For the empirical analysis, the following regression model is estimated to see whether EPR discourse reduces future crash risk:

$$StockPriceCrash_{i,t+1} = \alpha_0 + \beta_1 EPR_{i,t} + \beta_2 Controls_{i,t} + \gamma_i + \delta_t + \in_{i,t} \qquad (6)$$

where the dependent variable is the stock price crash risk measured by *NSKEW* and *DUVOL* of firm *i* in one year ahead from year *t*. The main variable of interest is *EPR*. Control variables include *NSKEW*, *RET*, *DTURN*, *Sigma*, *Size*, *ROA*, *Leverage*, *MTB*, *DisAcc*, and *Analyst* (see Appendix A for variable definitions). Firm and year fixed effects are included in all regressions.

Table 2 presents the multivariate OLS regression results for the associations between EPR discourse and crash risk measures with within-firm clustering. Column (1) shows the effect of EPR on $NSKEW_{t+1}$, and the coefficient is −0.067, which is negative and significant. Similarly, Column (2) presents the association between EPR and $DUVOL_{t+1}$, and the results show a negative and statistically significant coefficient of −0.019. The associations between control variables and crash risk measures are broadly consistent with the existing literature (Chen, Kim, & Yao, 2017; Hasan et al., 2021; Kim et al., 2014; Qiao et al., 2022). Although some literature indicates a positive association between *NSKEW* and $NSKEW_{t+1}$/DUVOL $_{t+1}$, similar to Chen et al. (2017) and Wu and Lai (2020), the results of this study show a negative association, which is inconsistent with our prediction. The discrepancy is attributable to the inclusion (exclusion) of firm fixed effects in this study (prior studies) (Chen et al., 2017). If firm fixed effects are excluded in the models, the association between *NSKEW* and $NSKEW_{t+1}$ is positive (Untabulated).[3] One of the plausible explanations is that firm-specific unobserved characteristics are correlated with *NSKEW*. *RET* and *SIZE* are positively associated with $NSKEW_{t+1}$/DUVOL $_{t+1}$, as in Chen et al. (2017). This study also finds a positive association between *ROA* and $NSKEW_{t+1}/DUVOL_{t+1}$, similar to Qiao et al. (2022) and Hasan et al. (2021). *Analyst* is negatively associated with $NSKEW_{t+1}/DUVOL_{t+1}$, consistent with Xu, Jiang, Chan, and Yi (2013).

Overall, the results in all columns suggest that EPR discourse mitigates future crash risk, supporting *the risk mitigation hypothesis*. The findings are consistent with the view that more discussion on perceived political risk topics in ECCs is useful in reducing information asymmetry surrounding that topic (Matsumoto et al., 2011). Even if we compare our results with the view that, in general, limited but entirely new information is disclosed in ECCs because of the continuous disclosure obligations (Westbrook, 2014), the way existing information is presented can increase the level of EPR discourse, facilitating a robust understanding of investors about EPR. Thus, such discourse can boost their confidence in firms' sincerity and capabilities in navigating EPR and reduce the likelihood of future investors' surprise upon related information disclosure, leading to lower crash risk.

4.3. Role of political activism

Generally, corporate firms become politically active for numerous reasons, including but not limited to reducing existing or potential political risk and drawing favourable policy outcomes (Hassan et al., 2019; Rahman et al., 2023; Shang, Lin, & Saffar, 2021). Prior research suggests that politically active firms seem to possess an informational edge compared to their counterparts, enabling them to anticipate and respond more promptly to policy changes (Christensen et al., 2023, Christensen et al., 2023; Wellman, 2017). Shang et al. (2021) suggest that economic policy uncertainty instigates firms to lobby policymakers for access to upcoming policy information. Wellman (2017) also highlights that politically active firms gain differential access to information through their political channels. The ability to gain an information advantage from political activism arises from the fact that members of Congress are legally allowed to selectively reveal political information to external stakeholders (see, e.g., Bainbridge, 2011; Nagy & Painter, 2012). Accordingly, this study is interested to see if political activism plays a role in the association between EPR discourse and crash risk based due to the information advantage. As politically active firms have better access to political information, we predict that investors find incremental information in ECCs if the firms are politically active. If the prediction holds true, it indicates that incremental information gained through private political channels is, at least in part, shared in ECCs, leading to reduced information asymmetry and crash risk, which is consistent with our findings on *the risk mitigation hypothesis*. In addition, political activism indicates a firm's proximity to political power and decision-making. Such proximity boosts investors' confidence because it signals that management is sincerely navigating the potential policy changes and acting on drawing favourable outcomes for their interest (Gounopoulos, Mazouz, & Wood, 2021; Hill, Kubick, Lockhart, & Wan, 2013).

To assess the role of political activism in the association between EPR discourse and crash risk, we subgroup the sample based on lobbying expenditures. We employ lobbying expenditures as a proxy of political activism, and the data is sourced from the Center for Responsive Politics (CRP) database, as in prior literature (Rahman et al., 2023; Unsal, Hassan, & Zirek, 2016). CRP gathers data from the disclosure reports filed with the Secretary of the US Senate Office of Public Records. Since the CRP does not employ specific firm identifiers such as CUSIP, ISIN,

[2] The untabulated results discussed in this study are available upon request.

[3] As the explanatory power (R^2) of the models significantly increases after controlling for the firm fixed effects, following prior research (Callen & Fang, 2015; Chen et al., 2017; Wu & Lai, 2020), all models include firm fixed effects.

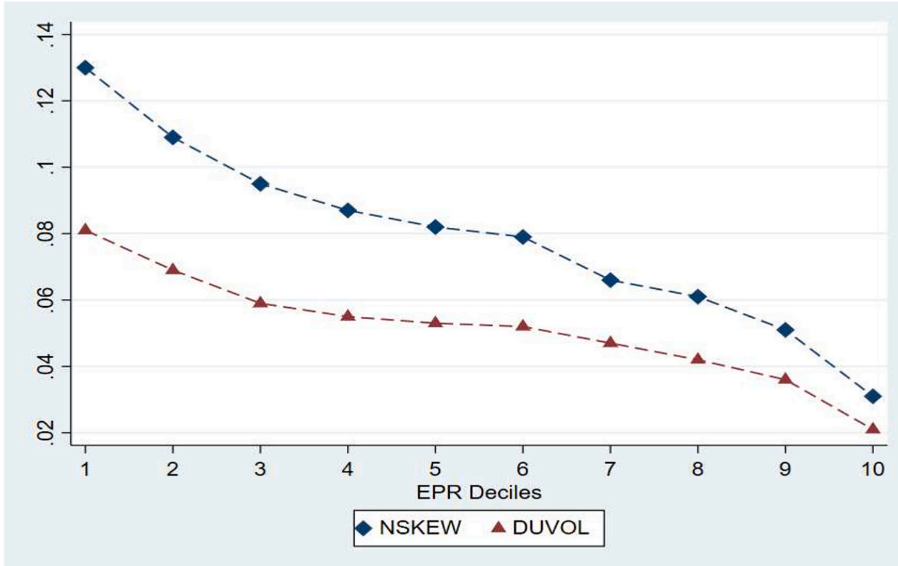

Fig. 1. Plot of crash risk measures for EPR deciles.
This graph presents the mean values of $NSKEW_{t+1}$ and $DUVOL_{t+1}$ against *EPR Deciles* from lowest to highest. The figure is produced in STATA.

Table 2
Baseline results.

	Expected sign	(1)	(2)
		$NSKEW_{t+1}$	$DUVOL_{t+1}$
EPR	+/−	−0.067***	−0.019***
		(−4.609)	(−4.274)
NSKEW	+	−0.088***	−0.025***
		(−10.895)	(−10.406)
RET	+	0.047***	0.018***
		(5.392)	(6.546)
DTURN	+	−0.000	0.000
		(−0.108)	(0.184)
Sigma	+	−0.351	0.121
		(−0.762)	(0.867)
Size	+	0.264***	0.080***
		(15.510)	(15.595)
ROA	+	0.215**	0.070**
		(2.045)	(2.268)
Leverage	+	0.017	0.016
		(0.280)	(0.919)
MTB	+	−0.002	−0.000
		(−1.433)	(−1.176)
DisAcc	+	0.006	0.009
		(0.090)	(0.441)
Analyst	−	−0.085***	−0.018**
		(−3.346)	(−2.541)
Constant	+/−	−0.067***	−0.019***
		(−4.609)	(−4.274)
Firm fixed effects		Yes	Yes
Year fixed effects		Yes	Yes
Observations		28,933	28,933
R^2		0.182	0.180

This table presents the baseline regression results of EPR discourse on stock price crash risk. *NSKEW* and *DUVOL* are the dependent variables, where $t + 1$ refers to a one-year lead. *EPR* is the independent variable. The control variables include *NSKEW*, *RET*, *DTURN*, *Sigma*, *Size*, *ROA*, *Leverage*, *MTB*, *DisAcc*, and *Analyst*. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. Variables are defined in Appendix A. *, **, and ***, indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

GVKEY, or PERMNO, our process involves manual confirmation of firm names. We then cross-reference these firm names with those in the Compustat database to obtain the corresponding GVKEY identifiers. Subsequently, we utilise the GVKEY as the main key to combine CRP data with information obtained from CRSP, Compustat, and various other databases.

We perform the analysis by creating two subgroups: if a firm lobby in a given year belongs to the Politically active group; otherwise, it belongs to the Politically non-active group. Firstly, we examine whether there exists any difference in EPR discourse between politically active and non-active firms. Our *t*-test results reveal that there are significant differences in mean values of EPR discourse between the two groups.[4] Secondly, we perform the regression analysis, and the results are resented in Table 3. In Columns (1) and (3), the coefficients on EPR discourse are negative and significant at a 1% level for the politically active firms. The coefficient on EPR discourse in Columns (2) and (4) are also negative at the 5% and 10% significance level, respectively, for the politically non-active firms. However, in terms of magnitude, the coefficients for the politically active groups are larger than the politically non-active groups,[5] and untabulated *F*-tests indicate that coefficients for the subsamples are significantly different at conventional levels.

Overall, the negative coefficients on EPR discourse are statistically significant at different levels, confirming our baseline results that greater EPR discourse is generally negatively associated with crash risk. In addition, if the firms are politically active, EPR discourse has a greater effect on reducing crash risk by potentially making the EPR discourse informative because of the excess access to political information (Wellman, 2017), boosting investors' confidence in firms dealing with relevant policy changes.

5. Robustness test

5.1. Evidence from machine learning

To provide further evidence that EPR discourse is a driver of crash risk, we employ two machine learning techniques: Random Forest and Extreme Gradient Boosting algorithms, as in recent accounting and

[4] The *t*-test results show a t-statistic of −7.474 (Pr(|T| > |t|) = 0.000), significant at the 1% level.

[5] The coefficient of $NSKEW_{t+1}$ regressing on *EPR* is 15% higher for politically active firms compared to the same coefficient for non-active firms. Similarly, the coefficient of $DUVOL_{t+1}$ regressing on *EPR* is 43% higher for politically active firms compared to the same coefficient for non-active firms.

Table 3
Role of political lobbying.

	Lobbying = 1	Lobbying = 0	Lobbying = 1	Lobbying = 0
	(1)	(2)	(3)	(4)
	$NSKEW_{t+1}$	$NSKEW_{t+1}$	$NSKEW_{t+1}$	$NSKEW_{t+1}$
EPR	−0.068***	−0.058**	−0.021***	−0.012*
	(−3.411)	(−2.381)	(−3.540)	(−1.718)
NSKEW	−0.003	0.003	−0.000	0.001
	(−1.268)	(1.374)	(−0.674)	(1.335)
RET	0.705	−1.323*	0.464**	−0.286
	(1.001)	(−1.882)	(2.153)	(−1.322)
DTURN	0.291***	0.265***	0.087***	0.081***
	(11.498)	(9.823)	(11.453)	(9.775)
Sigma	0.210	0.154	0.062	0.069
	(1.258)	(0.956)	(1.246)	(1.473)
Size	0.120	0.021	0.038	0.024
	(1.294)	(0.215)	(1.380)	(0.817)
ROA	−0.002	−0.003	−0.001	−0.000
	(−1.112)	(−1.110)	(−1.202)	(−0.653)
Leverage	0.157	−0.191**	0.048	−0.053**
	(1.420)	(−2.257)	(1.466)	(−2.016)
MTB	−0.084**	−0.056	−0.018*	−0.011
	(−2.232)	(−1.589)	(−1.678)	(−1.126)
DisAcc	−0.068***	−0.058**	−0.021***	−0.012*
	(−3.411)	(−2.381)	(−3.540)	(−1.718)
Analyst	−0.106***	−0.080***	−0.031***	−0.022***
	(−9.295)	(−5.959)	(−8.863)	(−5.495)
Constant	−7.253***	−6.254***	−2.189***	−1.936***
	(−11.543)	(−9.641)	(−11.499)	(−9.665)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	11,557	17,376	11,557	17,376
R^2	0.264	0.247	0.255	0.250

This table presents the regression results of EPR discourse on stock price crash risk by splitting the sample between the politically active and non-active groups. If a firm has at least $1 of lobbying expenditures in a given year, it belongs to the politically active group (Lobbying = 1); otherwise, it belongs to the politically non-active group (Lobbying = 0). *NSKEW* and *DUVOL* are the dependent variables, where $t+1$ refers to a one-year lead. *EPR* is the independent variable. The control variables include *NSKEW*, *RET*, *DTURN*, *Sigma*, *Size*, *ROA*, *Leverage*, *MTB*, *DisAcc*, and *Analyst*. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. Variables are defined in Appendix A. *, **, and ***, indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

finance literature (Jones, Moser, & Wieland, 2023; Leippold, Wang, & Zhou, 2022). The Random Forest is an ensemble learning method proposed by Breiman (2001), building multiple decision trees and combining them to enhance the overall performance of the model. Using bootstrap sampling, each individual decision tree produces a prediction for a class. The overall prediction of the random forest is determined by the class that accumulates the highest number of votes across all individual trees. Extreme Gradient Boosting algorithm (here XGBoost) is also a tree ensemble method, but it provides more robust results. While Random Forest averages over random trees ("bagging"), the Gradient Boosting technique focuses on examples that previous trees find problematic ("boosting"). In general, boosting produces better forecasts than bagging if misclassified instances exist in the previous models (Bogousslavsky, Fos, & Muravyev, 2024).

Figure 2 ranks the importance of key variables, including the additional controls, used in this study to predict crash risk based on machine learning techniques.[6] According to the Random Forest algorithm in Panel A, EPR discourse appears as the third strongest factor in predicting future crash risk. When we estimate the Extreme Gradient Boosting model in Panel B, EPR discourse appears as the fourth important indicator for expected crash risk. Overall, both machine learning techniques provide robust evidence that EPR discourse plays an important role in predicting future crash risk, which is consistent with our baseline regression results.

5.2. Entropy-balanced sample

Since the choice to be engaged in EPR discourse can be endogenous, it is a concern that this self-selection bias drives the findings. To provide evidence that the results are robust to possible self-selection bias, following prior literature (Christensen, Jin, et al., 2023; Li & Liu, 2023), we re-estimate Eq. (6) based on the entropy balancing approach developed by Hainmueller (2012). Entropy balancing is considered a rigorous weighting method because of its ability to estimate weights through optimisation, thus reducing coefficient bias. This method ensures appropriate covariate balance between treatment and control groups by weighing observations such that the post-weighing means, variances, and skewness for treatment and control firms are equal for each matching dimension, adjusting for random and systematic inequalities in the variable. The results are presented in Table 4. We first divide the sample into two groups. The treatment group includes firms with EPR discourse above the median (−0.224); otherwise, it belongs to the control group.

The mean, variance, and skewness of all covariates in the treatment and control groups are presented in Panel A (before entropy balancing) and Panel B (after entropy balancing). The regression results are presented in Columns (1) and (2) of Panel C. The results are robust to the use of entropy balancing: the coefficient on crash risk measures for EPR discourse remains negative and significant.

5.3. Addressing omitted variable bias

In the baseline regression models, we control for the standard set of variables to minimise the concern that other sources of crash risk do not drive the results. Following prior research (Andreou, Louca, & Petrou, 2017; Hasan et al., 2021; Kim et al., 2014; Zaman, Bahadar, & Mahmood, 2021), we now incorporate additional control variables in the models to address potential omitted variable bias and present the results in Panel A, Table5. First, since CEO characteristics appear as the significant factors for crash risk in the prior studies (Andreou et al., 2017), we include CEO duality, CEO age, and CEO gender in the models, and the results are presented in Columns (1) and (5). Second, as existing literature suggests that competitive pressures from the product market exaggerate crash risk (Li & Zhan, 2019), we include product market competition in the model. Product market competition is measured by the Herfindahl–Hirschman Index (HHI). As a higher HHI value implies a lower product market competition, we use the opposite number of HHI (i.e., 1 – HHI) so that a higher value indicates higher competition. The results, including HHI as a control, are presented in Columns (2) and (6). Finally, following Zaman, Bahadar, and Mahmood (2021), we control for a state's economic condition (GDP) by considering where the firm headquarters are located. The results are presented in Columns (3) and (7). Columns (4) and (8) include all the additional controls along with the standard controls used in the baseline. We continue to observe the significant and positive effect of EPR on crash risk for both $NSKEW_{t+1}$ and $DUVOL_{t+1}$. Overall, the baseline findings persist and remain robust after including additional control variables in the baseline model.

Although including additional control variables provides evidence of the robustness of the baseline results, we cannot completely rule out the omitted variable bias. To test further that the regression models are not plagued by unobserved variables, following prior literature (Daines, Li, & Wang, 2021; Hossain & Masum, 2022), we employ Oster's (2019) estimation technique as the coefficient stability test approach. According to Oster (2019), the stability of coefficients of the variable of interest

[6] We have employed only $NSKEW_{t+1}$ as the crash risk measure for brevity purposes in this analysis.

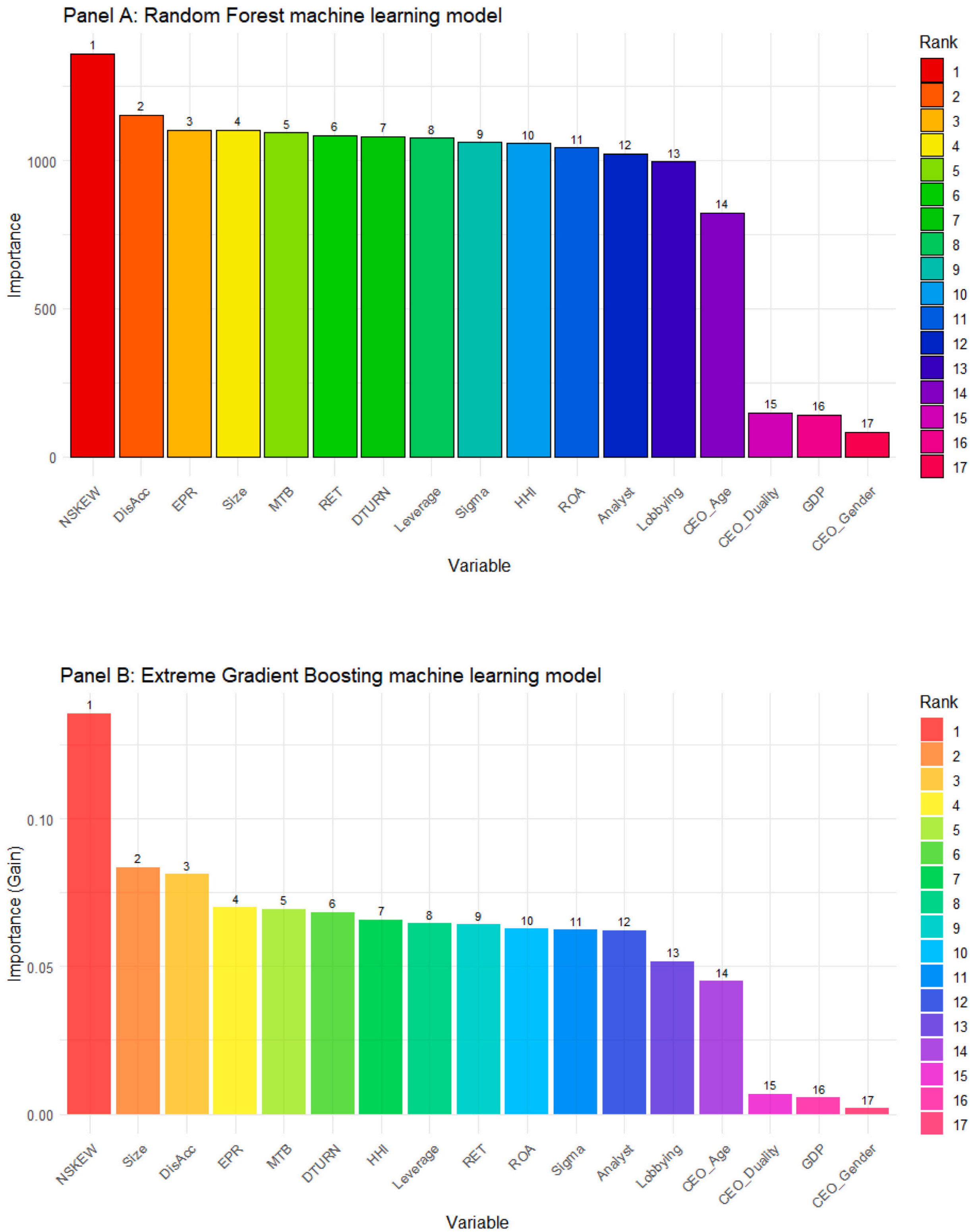

Fig. 2. Variable importance plot using machine learning techniques.
This figure displays the variable importance plot for predicting crash risk ($NSKEW_{t+1}$) using Random Forest and Extreme Gradient Boosting machine learning techniques in Panel A and B, respectively. The figures are produced in R studio.

in the model, including and excluding the set of controls, can be used to construct an identifiable set. We can reject the null hypothesis that omitted variable bias is responsible for the outcome if the identifiable set does not contain a zero (Altonji, Elder, & Taber, 2005). The identified set is defined as: $[\widetilde{\beta}, \beta^*]$, where $\widetilde{\beta}$ represents the coefficient estimate of the variable of interest with all controls in the baseline model and β^* is derived from the following formula, which uses the coefficient estimate of the variable of interest and R-squared from the baseline model including (controlled) and excluding (uncontrolled) control variables.

Table 4
Addressing endogeneity: entropy balancing.

	Treatment group			Control group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Panel A: Before entropy balancing						
NSKEW	0.122	0.685	0.636	0.102	0.733	0.572
RET	0.311	0.698	0.254	0.316	0.694	0.161
DTURN	0.070	23.220	0.705	0.095	21.830	0.251
Sigma	0.046	0.001	1.891	0.046	0.001	1.767
Size	25.820	3.292	0.141	25.550	2.959	0.199
ROA	0.085	0.027	–2.239	0.107	0.023	–2.412
Leverage	0.569	0.063	0.184	0.523	0.064	0.520
MTB	2.950	24.720	2.080	3.274	26.570	1.939
DisAcc	0.170	0.030	2.487	0.175	0.026	2.385
Analyst	2.110	0.534	–0.170	2.051	0.535	–0.042
Panel B: After entropy balancing						
NSKEW	0.122	0.685	0.636	0.122	0.685	0.636
RET	0.311	0.698	0.254	0.311	0.698	0.254
DTURN	0.070	23.220	0.705	0.070	23.220	0.705
Sigma	0.046	0.001	1.891	0.046	0.001	1.891
Size	25.820	3.292	0.141	25.820	3.291	0.141
ROA	0.085	0.027	–2.239	0.085	0.027	–2.239
Leverage	0.569	0.063	0.184	0.568	0.063	0.184
MTB	2.950	24.720	2.080	2.952	24.750	2.080
DisAcc	0.170	0.030	2.487	0.170	0.030	2.487
Analyst	2.110	0.534	–0.170	2.110	0.534	–0.170

Panel C: Entropy balancing regression results

	(1)	(2)
	$NSKEW_{t+1}$	$DUVOL_{t+1}$
EPR	−0.066***	−0.018***
	(−3.628)	(−3.302)
NSKEW	−0.091***	−0.026***
	(−9.084)	(−8.572)
RET	0.042***	0.016***
	(3.326)	(4.137)
DTURN	−0.000	0.000
	(−0.144)	(0.066)
Sigma	−0.446	0.100
	(−0.591)	(0.425)
Size	0.257***	0.077***
	(3.878)	(3.649)
ROA	0.227	0.076
	(0.709)	(0.801)
Leverage	−0.013	0.010
	(−0.079)	(0.202)
MTB	−0.002	−0.000
	(−0.802)	(−0.484)
DisAcc	0.012	0.011
	(0.105)	(0.314)
Analyst	−0.089**	−0.018
	(−2.148)	(−1.464)
Constant	−6.208***	−1.879***
	(−3.627)	(−3.457)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	28,933	28,933
R^2	0.188	0.184

This table presents the results of entropy balancing estimates of Eq. (6). Panels A and B report the means, variance, and skewness for the covariates of the treatment groups and the control groups before and after balancing, respectively. We reach convergence or perfect balancing using Hainmueller's Stata code, given that there is no mean, variance or skewness difference between the treatment and control groups after the balancing. Panel C presents the regression based on the entropy balancing method. The control variables include *NSKEW*, *RET*, *DTURN*, *Sigma*, *Size*, *ROA*, *Leverage*, *MTB*, *DisAcc*, and *Analyst*. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. Variables are defined in Appendix A. *, **, and ***, indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

$$\beta^{*} = \widetilde{\beta} - \left[\beta' - \widetilde{\beta}\right] \frac{R_{max} - \tilde{R}}{\tilde{R} - R'} \tag{7}$$

where β' represents the coefficient estimates of the variable of interest from the uncontrolled regression. $\widetilde{R}$ and R' are the R-squared values from the controlled and uncontrolled regressions. We rely on Oster's (2019) argument that the proper upper bound for δ is 1, implying that the omitted variables need to be as significant as the included variables to make the coefficient value of interest equal to zero. For the upper Oster bound of the identified sets, first, we utilise the more conservative Mian and Sufi (2014) value of $R_{\max} = \min(2.2\,\widetilde{R}, 1)$, and later, we utilise the extreme one from Oster (2019) of $R_{max} = 1$. We display the results in Panel B of Table 5 and find that the identified sets do not include zero. Therefore, we conclude that the inferences from the OLS specifications presented in Table 2 are not plagued by omitted variable bias. More importantly, the results remain robust irrespective of the use of $R_{\max} = \min(2.2\,\widetilde{R}, 1)$ or $R_{max} = 1$.

5.4. Two-stage least squares (2SLS) regression analysis

Our baseline regressions are estimated using one-year lead crash risk measures. Therefore, it is unlikely that baseline results are plagued by the reverse causality problem because there is little chance that future crash risk will affect current EPR discourse. However, since other endogeneity concerns may remain, we perform a 2SLS analysis with an instrumental variable (IV) approach. An IV focuses on variations in the dependent variable that are uncorrelated with the error term and disregards the variations in the dependent variable that bias the OLS coefficients due to endogeneity problems. A valid instrument should also be uncorrelated with the error terms in the regression equation. This study uses the industry average political risk discourse as the instrument, which is not related to the error term reported in the baseline eq. (6), as used in prior literature (Ahmed, Muttakin, & Khan, 2023; Yu et al., 2023). Since firm-level EPR discourse is idiosyncratic, the industry EPR discourse is likely to influence a firm's own EPR discourse but not its crash risk. Therefore, industry average EPR discourse appears as a valid instrument for firm-level EPR discourse.

The results are presented in Table 6. The first-stage regression results are presented in Column (1), showing the significant association between *IndAvgEPR*, the instrument variable, and *EPR*, the key independent variable. The Cragg–Donald Wald F statistic is larger than the Stock–Yogo's weak identification critical value of 16.38, which confirms the relevance requirement of the instrument. The statistical significance of the chi-square value in the under-identification test confirms that the model is correctly identified. An over-identification test also supports the validity of the instrument. Columns (2) and (3) present the second-stage regression results controlling for the endogenous relationship between crash risk measures ($NSKEW_{t+1}$ and $DUVOL_{t+1}$) and firm-level EPR discourse. Our results show that the independent variable, the predicted value of EPR, has a significant negative association with both crash risk measures. Therefore, 2SLS results reinforce our findings based on the baseline estimates that EPR discourse mitigates expected crash risk.

Table 5
Addressing endogeneity: additional controls and Oster (2019) test.

Panel A: Additional controls for omitted variable bias

	$NSKEW_{t+1}$				$DUVOL_{t+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EPR	−0.067***	−0.067***	−0.067***	−0.067***	−0.018***	−0.019***	−0.019***	−0.018***
	(−4.579)	(−4.595)	(−4.604)	(−4.565)	(−4.241)	(−4.259)	(−4.266)	(−4.223)
CEO_Duality	0.116***			0.116***	0.031***			0.031***
	(5.214)			(5.221)	(4.719)			(4.735)
CEO_Gender	0.113**			0.110**	0.024			0.023
	(2.183)			(2.138)	(1.501)			(1.449)
CEO_Age	−0.006***			−0.006***	−0.002***			−0.002***
	(−3.381)			(−3.408)	(−3.544)			(−3.581)
HHI		0.172**		0.169**		0.052**		0.052**
		(2.060)		(2.036)		(1.973)		(1.977)
GDP			0.104	0.125			0.057	0.063
			(0.661)	(0.785)			(1.123)	(1.239)
Constant	−5.886***	−6.325***	−8.990**	−9.324**	−1.796***	−1.939***	−3.416**	−3.509***
	(−14.330)	(−15.510)	(−2.128)	(−2.193)	(−14.274)	(−15.602)	(−2.524)	(−2.578)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,933	28,933	28,933	28,933	28,933	28,933	28,933	28,933
R^2	0.184	0.183	0.182	0.185	0.182	0.180	0.180	0.182

Panel B: Oster (2019) test for omitted variable bias

Dependent variable	Variable of interest	Controlled		Uncontrolled		Identified set	Includes zero
		Beta	R-squared	Beta	R-squared		
Assume $\delta = 1$; $R_{max} = \min(2.2\tilde{R}, 1)$							
$NSKEW_{t+1}$	EPR	−0.0672	0.182	−0.0584	0.001	−0.0785, −0.0672	No
$DUVOL_{t+1}$	EPR	−0.0186	0.180	−0.0180	0.001	−0.0194, −0.0186	No
Assume $\delta = 1$; $R_{max} = 1$							
$NSKEW_{t+1}$	EPR	−0.0672	0.182	−0.0585	0.001	−0.1142, −0.0673	No
$DUVOL_{t+1}$	EPR	−0.0186	0.180	−0.0180	0.001	−0.0218, −0.0186	No

Panel A of this table presents the regression results of EPR on stock price crash risk after including additional control variables: *CEO_Duality*, *CEO_Gender*, *CEO_Age*, *HHI*, and *GDP*. *NSKEW* and *DUVOL* are the dependent variables in Columns (1)–(5) and (6)–(10), respectively, where $t+1$ refers to a one-year lead. *EPR* is the independent variable. Other controls include *NSKEW*, *RET*, *DTURN*, *Sigma*, *Size*, *ROA*, *Leverage*, *MTB*, *DisAcc*, and *Analyst*. All regressions include firm and year fixed effects. Panel B of the table presents the Oster (2019) bounds for the variable of interest as depicted in baseline analysis in Table 2. The variable of interest is *EPR*, and the dependent variable is $NSKEW_{t+1}$ ($DUVOLt_{+1}$). The results generated using the assumption of Mian and Sufi (2014) of Oster bounds using $\delta = 1$ and $RMAX = \min(2.2\tilde{R}, 1)$ are presented first, followed by the results using the extreme case of $RMAX = 1$. As R-squared cannot be >1, this is the most diligent testing of any omitted variables bias based on Oster (2019). Standard errors are clustered at the firm level where applicable. t-statistics are reported in parentheses. Variables are defined in Appendix A. *, **, and ***, indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Addressing endogeneity: 2SLS estimation.

	(1)	(2)	(3)
	1st Stage regression	2nd Stage regression	2nd Stage regression
	EPR	$NSKEW_{t+1}$	$DUVOL_{t+1}$
EPR		−0.064**	−0.019**
		(−2.246)	(−2.082)
NSKEW	0.003	−0.088***	−0.025***
	(1.054)	(−11.653)	(−11.125)
RET	−0.009**	0.047***	0.018***
	(−2.446)	(5.767)	(6.997)
DTURN	−0.000	−0.000	0.000
	(−0.498)	(−0.115)	(0.196)
Sigma	0.391*	−0.352	0.121
	(1.853)	(−0.816)	(0.927)
Size	−0.012	0.264***	0.080***
	(−1.636)	(16.574)	(16.668)
ROA	0.038	0.215**	0.070**
	(0.896)	(2.185)	(2.424)
Leverage	−0.011	0.017	0.016
	(−0.397)	(0.299)	(0.983)
MTB	−0.000	−0.002	−0.000
	(−0.849)	(−1.531)	(−1.257)
DisAcc	0.008	0.006	0.009
	(0.325)	(0.096)	(0.471)
Analyst	−0.008	−0.085***	−0.018c
	(−0.746)	(−3.576)	(−2.717)
IndAvgEPR	0.958***		
	(15.656)		
Constant	0.301	−6.377***	−1.957***
	(1.627)	(−16.377)	(−16.576)
Firm fixed effects	Yes	Yes	
Year fixed effects	Yes	Yes	
Observations	28,933	28,933	
R^2	29.040	.	.
F statistics		11.25***	10.40***
Test of weak instrument			
(Cragg-Donald Wald F statistic)	88.113***		
(Stock-Yogo weak ID test critical value at 10%)	16.380		
Test of under-identification			
(Anderson canon. Corr. LM statistic)	69.417***		
Over-identification	No		

This table presents results from 2SLS (IV) regressions. In the first stage of regression, a firm's industry average EPR discourse (*IndAvgEPR*) is the instrument for EPR, where *IndAvgEPR* is the key independent variable, and *EPR* is the dependent variable. In the second stage of regression, the dependent variables are $NSKEW_{t+1}$ in Column (2) and $DUVOL_{t+1}$ in Column (3), where $t+1$ refers to a one-year lead. The control variables include *NSKEW*, *RET*, *DTURN*, *Sigma*, *Size*, *ROA*, *Leverage*, *MTB*, *DisAcc*, and *Analyst*. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. Variables are defined in Appendix A. *, **, and ***, indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

5.5. *Alternative measures of crash risk*

To identify the sensitivity of the findings, we use alternative measures of crash risk. First, following prior literature (Andreou et al., 2017; Hasan et al., 2021), we employ extreme sigma (ExSigma) measured by the negative of the worst deviation of firm-specific weekly returns ($W_{j,\omega}$) from the average firm-specific weekly returns scaled by the standard deviation of firmspecific- weekly returns (σ_w) for a given year, as follows:

$$ExSigma = -Min\left[\frac{W_{j,\omega} - \overline{W}}{\sigma_w}\right] \tag{8}$$

Second, similar to the existing literature (Hutton et al., 2009; Kim et al., 2011), we use *Crash_Dummy*, which is coded as one if a firm has at least one firm-specific weekly return falling at least 3.09 standard deviations below its mean value in a given year, and zero otherwise. The cut-off of 3.09 standard deviations is selected to produce 0.1% of the distribution (Hutton et al., 2009).

The regression results using alternative crash risk measures are reported in Table 7. Column (1) shows that the association between *EPR* and *ExSigma* is negative and significant. Similarly, in Column (2), the association between *EPR* and *Crash_Dummy* is also negative and significant. Thus, these results confirm that the baseline results continue to hold for the alternative measures of the dependent variable and are not dependent on the choice of crash risk measures.

6. Additional analysis

In this section, we perform additional cross-sectional and median analyses. This analysis helps us understand different factors affecting the association between EPR discourse and crash risk.

6.1. *Role of political regimes*

We explore the moderating role of US political regimes for two primary reasons. First, generally, the Democrats appear more pro-environmental than the Republicans, favouring stringent environmental policies (Bergquist & Warshaw, 2020). Second, a greater level of environmental policy uncertainty is observed during the republican administration in recent regimes (Noailly, Nowzohour, & Van Den Heuvel, 2022). They have more frequently reversed environmental policies, particularly in the last two decades, as part of a broader trend of partisan polarization in environmental politics (Kim & Urpelainen, 2017). Both stringency and uncertainty surrounding environmental

Table 7
Robustness test: alternative measures of crash risk.

	(1)	(2)
	$ExSigma_{t+1}$	$CRASH\_Dummy_{t+1}$
EPR	−0.059***	−0.124***
	(−4.308)	(−4.345)
NSKEW	−0.058***	0.072***
	(−8.856)	(4.139)
RET	0.039***	0.063***
	(5.569)	(3.163)
DTURN	−0.001	−0.003
	(−1.175)	(−0.851)
Sigma	0.388	3.464***
	(1.034)	(4.357)
Size	0.160***	0.028*
	(11.839)	(1.786)
ROA	0.093	0.297***
	(1.107)	(2.865)
Leverage	−0.094*	−0.343***
	(−1.903)	(−5.882)
MTB	−0.001	0.001
	(−0.748)	(0.466)
DisAcc	0.013	0.314***
	(0.270)	(3.424)
Analyst	−0.027	−0.057*
	(−1.469)	(−1.794)
Constant	−0.059***	−0.124***
	(−4.308)	(−4.345)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	28,933	28,933
R^2/Pseudo R^2	0.177	0.016

The table presents the regression results analysing the effect of EPR discourse on $Crash\_Dummy_{t+1}$ and $ExSigma_{t+1}$ as the alternative measures of crash risk. *EPR* is the independent variable. The large control variables include *NSKEW*, *RET*, *DTURN*, *Sigma*, *Size*, *ROA*, *Leverage*, *MTB*, *DisAcc*, and *Analyst*. All regressions include firm, and year fixed effects. *t*–statistics are reported in parentheses. Standard errors are clustered at the firm level. Variables are defined in Appendix A. *, **, and ***, indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

policy are likely to affect firms' ability to navigate political risk and strategies to disseminate associated information, affecting crash risk. Therefore, it is plausible that the negative association between EPR discourse and crash risk will be stronger in the democrat regimes.

Panel A, Table 8, presents the regression results splitting the sample based on political regimes, where *Democratic* indicates the presence of the Democratic party and *Republican* indicates the Republican party in power in a given year. The results suggest that EPR discourse has a negative association with crash risk in Columns (1) and (3), significant at the 1% level, for the democrat regimes. The plausible explanation of these results is that as the Democrat party is more pro-environmental, firms present more information in ECCs to show their sincerity in addressing policy-related concerns. However, EPR discourse does not reduce crash risk in Columns (2) and (4), perhaps due to the added tension and uncertainty of whether laxer environmental policy by the current administration will pass through Congress or survive in a future administration.

6.2. Role of institutional monitoring

An important argument for the relationship between EPR discourse and crash risk is that firms with strong monitoring are unlikely to conceal valuable information from investors in ECCs. Therefore, we explore whether strong monitoring moderates the association between EPR discourse and crash risk. We use institutional investors as the proxy of monitoring.

Prior literature suggests that, generally, institutional investors tend to improve a firm's information environment (Choi & Chung, 2023), thereby reducing crash risk (Callen & Fang, 2013). Specifically, institutional investors having large stockholding and monitoring relationships with firms contribute to increased transparency and decreased information asymmetry (Heinrichs et al., 2019). These investors also play a key role in shaping discourse in ECCs, ensuring more informative discussions (Jung et al., 2018). It is likely that the negative association between EPR discourse and crash risk will be stronger for firms with a greater level of institutional investors.

Panel B, Table 8, presents the regression results. We create subsamples based on the median value of the number of institutional investors. If the number of institutional investors is greater than the median value, the firm is categories as *High monitoring,* otherwise *Low monitoring.* Our results reveal that there is a stronger negative association between EPR discourse and crash risk for *High monitoring* firms in Columns (1) and (3). Our results are not statistically significant for the *Low monitoring* firms in Columns (2) and (4). Thus, our findings support the role of institutional monitoring in driving informative discussions in ECCs and reducing future crash risk.

6.3. Role of management integrity

The extent of informativeness of discourse in ECCs is largely influenced by management intention (Hope & Wang, 2018). If the management is characterised by a higher level of integrity, it is expected that information will be presented more objectively in ECCs, and potential challenges and risks will be acknowledged by them in the course of discussion with the investors. This kind of attitude demonstrates a commitment to openness and accountability, enhancing investors' engagement in conversation, boosting investors' confidence, and leading to a more informative discussion (Dzieliński, Wagner, & Zeckhauser, 2017). Thus, it is plausible that a higher level of management integrity will demonstrate a stronger negative association between EPR discourse and crash risk.

We examine the role of management integrity in the association between EPR discourse and crash risk based on subsamples. We measure integrity as in Li, Mai, Shen, and Yan (2021) and identify a firm as having *High integrity* if the integrity score of a firm is above the median value. Otherwise, the firm is categorised as *having Low integrity* in a given

Table 8
Cross-sectional analysis.

Panel A: Role of political regime

	Democratic	Republican	Democratic	Republican
	(1)	(2)	(3)	(4)
	$NSKEW_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$	$DUVOL_{t+1}$
EPR	−0.112***	−0.028	−0.031***	−0.010
	(−5.420)	(−1.239)	(−5.029)	(−1.392)
Constant	−10.339***	−4.858***	−3.296***	−1.350***
	(−12.241)	(−7.867)	(−12.672)	(−7.132)
All controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	13,691	15,242	13,691	15,242
R^2	0.274	0.292	0.265	0.284

Panel B: Role of monitoring

	High monitoring	Low monitoring	High monitoring	Low monitoring
	(1)	(2)	(3)	(4)
	$NSKEW_{t+1}$	$DUVOL_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
EPR	−0.070***	−0.017	−0.018***	−0.008
	(−3.290)	(−0.793)	(−2.880)	(−1.307)
Constant	−6.490***	−7.661***	−2.050***	−2.240***
	(−9.851)	(−10.840)	(−9.939)	(−10.786)
All controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	14,044	14,889	14,044	14,889
R^2	0.203	0.289	0.204	0.272

Panel C: Role of management integrity

	High integrity	Low integrity	High integrity	Low integrity
	(1)	(2)	(3)	(4)
	$NSKEW_{t+1}$	$DUVOL_{t+1}$	$NSKEW_{t+1}$	$DUVOL_{t+1}$
EPR	−0.076***	−0.028	−0.021***	−0.007
	(−3.717)	(−1.268)	(−3.551)	(−0.985)
Constant	−6.786***	−6.025***	−2.038***	−1.893***
	(−10.715)	(−9.647)	(−10.803)	(−9.796)
All controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	14,668	14,265	14,668	14,265
R^2	0.272	0.239	0.267	0.236

This table presents the regression results of EPR discourse on stock price crash risk based on cross-sectional analyses. In Panel A, sample firms are split based on the Democrat and Republican political regimes. In Panel B, sample firms are split based on the number of institutional investors; a firm belongs to the *High Monitoring* group if the number of institutional investors is above the sample median value; otherwise, it belongs to the *Low monitoring* group. In Panel C, sample firms are split based on management integrity; a firm belongs to the *High integrity* group if the firm's integrity score is above the sample median value; otherwise, it belongs to the *Low integrity* group. *NSKEW* and *DUVOL* are the dependent variables, where $t + 1$ refers to a one-year lead. *EPR* is the independent variable. The control variables include *NSKEW*, *RET*, *DTURN*, *Sigma*, *Size*, *ROA*, *Leverage*, *MTB*, *DisAcc*, and *Analyst*. All regressions include firm and year fixed effects. Standard errors are clustered at the firm level. *t*-statistics are reported in parentheses. Variables are defined in Appendix A. *, **, and ***, indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

year. The regression results are presented in Panel C, Table 8. The results reveal that while there is a significant and negative association between EPR discourse and crash risk for the *High integrity* group in Columns (1) and (3), no significant association exists for the *Low integrity* group in Columns (2) and (4). Our plausible explanation is that investors experience informative discussions with management characterised by high integrity that eventually helps reduce crash risk by reducing future speculation in the stock market.

6.4. Mediating role of earnings forecast dispersion

As information asymmetry plays an important role in driving crash risk (Jin & Myers, 2006; Kothari et al., 2009), in this section, we empirically test whether EPR discourse can reduce crash risk by improving the information environment or lowering the information gap in the market. We posit that firms with higher EPR discourse are characterised by less hoarding of unfavourable news by management, leading to less information asymmetry in the market. If EPR discourse reduces information asymmetry, crash risk should be reduced, as in existing literature (Jin & Myers, 2006; Kothari et al., 2009).

This study relies on analyst earnings forecast dispersion as a proxy for information asymmetry through which EPR discourse can reduce crash risk. If information asymmetry increases, dispersion among analysts' forecasts increases due to their access to varying levels of information about the firm (Au, Qiu, & Wu, 2023; Callen & Fang, 2015). Our conjecture is that greater EPR discourse is useful in reducing analyst earnings forecast dispersion by enabling analysts to gain a clearer understanding of a firm's business prospects, including the multi-faceted impacts of EPR. Such reduced dispersion indicates a more transparent information environment, reducing the likelihood of investors' surprises and potential crashes (Kim, Si, Xia, & Zhang, 2022). Reduced earnings forecasts can signal to the market that there's less uncertainty about the company's future performance (Barron & Stuerke, 1998; Diether, Malloy, & Scherbina, 2002). This reduced uncertainty can boost investors' confidence and lead to lower their risk perception, which may diminish the likelihood of a stock price crash due to panic selling or sudden shifts in market sentiment (Bird & Yeung, 2012).

We perform a mediation analysis to explore earnings forecast dispersion as a channel mechanism for the association between EPR and crash risk. Previous literature (e.g., Chen, Huang, Li, & Shevlin, 2019; Francis, Hasan, Liu, Wu, & Zhao, 2021) utilises this methodology in other settings. The following three conditions should be met to determine the mediation effect in this analysis. First, the independent variable (*EPR*) should significantly relate to the dependent variable ($NSKEW_{t+1}$). Second, the independent variable (*EPR*) should significantly relate to the mediator variable ($Dispersion_{t+1}$). Finally, the dependent variable ($NSKEW_{t+1}$) is regressed on both the independent variable (*EPR*) and the mediator ($Dispersion_{t+1}$). If the mediator variable mediates the association between $NSKEW_{t+1}$ and *EPR*, the mediator should be significant, and the significance of the independent variable of interest (*EPR*) is reduced after the mediator variable is added to the regression.

In Table 9, for the ease of comparison, Column (1) repeats the baseline regression results of Column (2) in Table 2, serving as the first stage benchmark for all potential channels. Column (2) shows the second-stage regression, keeping $Dispersion_{t+1}$ as the dependent variable, revealing a negative association with *EPR*. In Column (3), after adding the mediator ($Dispersion_{t+1}$) in the original regression, the coefficient (0.061) of *EPR* is still negative; however, it is smaller in magnitude than the coefficient of *EPR* in Column (1) (0.067). The decrease in the magnitude of the coefficient of *EPR* represents the mediation effect that arises from including *Dispersion* as an additional explanatory variable in the crash risk model. In Column (3), the Sobel test results confirm that the mediation effect is significant at the 1% level. Thus, the mediation analysis results support that EPR discourse affects crash risk through information asymmetry channel. The total effect of EPR on crash risk is 0.067 (Column (1)), and the direct effect is 0.060 (Column (3)). The indirect mediation effect is 0.006 (0.067–0.060), which is only 10.44% (0.007/0.067) of the total effect, suggesting that the earnings forecast dispersion acts as a mediator for the association between EPR discourse and future crash risk, but the mediation effect is not economically large.[7]

Table 9
Mediating role of earnings forecast dispersion.

	(1)	(2)	(3)
	$NSKEW_{t+1}$	$Dispersion_{t+1}$	$NSKEW_{t+1}$
EPR	−0.067***	−6.591**	−0.060***
	(−4.606)	(−2.380)	(−4.462)
$Dispersion_{t+1}$			0.002***
			(8.460)
NSKEW	−0.088***		−0.086***
	(−10.903)		(−10.748)
RET	0.047***	−5.126*	0.049***
	(5.394)	(−1.899)	(5.750)
DTURN	−0.000	0.156	−0.000
	(−0.105)	(0.418)	(−0.155)
Sigma	−0.353	−170.207	−0.301
	(−0.766)	(−1.208)	(−0.658)
Size	0.264***	−6.474	0.266***
	(15.510)	(−1.177)	(15.849)
ROA	0.215**	−23.021	0.224**
	(2.045)	(−0.766)	(2.152)
Leverage	0.017	−8.968	0.020
	(0.279)	(−0.573)	(0.339)
MTB	−0.002	0.094	−0.002
	(−1.439)	(0.308)	(−1.480)
DisAcc	0.005	15.145	−0.001
	(0.080)	(0.783)	(−0.012)
Analyst	−0.085***	−27.419***	−0.074***
	(−3.351)	(−2.991)	(−3.042)
Constant	−0.620***	50.715*	−6.588***
	(−5.393)	(1.914)	(−15.946)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	28,933	28,933	28,933
R^2	0.182	0.441	0.190
Sobel test (*p*-value)			<0.01

This table presents the results of the mediation effect of analyst earnings forecast dispersion on the relationship between EPR discourse and crash risk. The variable in the headline of each column is the dependent variable of the corresponding regression. *Dispersion* is measured as the ratio of the standard deviation of estimated EPS to the closing stock price of a given year multiplied by 100, where $t+1$ refers to a one-year lead. The control variables include *NSKEW* (apart from Columns (2)), *RET*, *DTURN*, *Sigma*, *Size*, *ROA*, *Leverage*, *MTB*, *DisAcc*, and *Analyst*. All regressions include firm and year fixed effects. *t*-statistics are reported in parentheses. Standard errors are clustered at the firm level. Variables are defined in Appendix A. *, **, and ***, indicate the statistical significance at the 10%, 5%, and 1% levels, respectively.

7. Conclusion

EPR has become a significant factor because of the global call for stricter environmental policies. Due to growing climate change policies at both the national and international levels, it is increasingly difficult for managers to predict the outcome of such policies, which leads to information asymmetry due to uncertain outcomes. This study adopts two competing hypotheses. According to *the risk mitigation hypothesis*, ECC participants either find meaningful information from EPR discourse or become relatively less sensitive to a forecasted risk issue strategically presented by management over time, leading to lower future crash risk. Alternatively, *the risk escalation hypothesis* argues that management tends to manipulate the EPR discourse in ECC opportunistically, leading

[7] Our untabulated results employing $DUVOL_{t+1}$ instead of $NSKEW_{t+1}$ as the crash risk proxy are qualitatively similar.

to greater information asymmetry and future crash risk. The results suggest that more discourse on EPR reduces crash risk, thus supporting the information asymmetry-reducing view and highlighting the favourable effect of more discussion on EPR in ECC from the crash risk perspective. The findings are consistent with the view that greater discourse on EPR signals better management in navigating uncertainty and transparent efforts to mitigate information asymmetry.

This study extends the existing literature by highlighting the effectiveness of voluntary risk disclosures in interactive settings, emphasising their importance in reducing future crash risk, and differentiating from previous research on climate change risk disclosure (Au, Qiu, & Wu, 2023; Lin & Wu, 2023). Further, this study contributes to the literature on broader political risk and uncertainty by highlighting the importance of firm-level exposure to political risk related to environmental issues in the context of crash risk (Jin et al., 2019; Luo & Zhang, 2020), showing that increased discourse on these issues reduces expected crash risk. In addition, our findings highlight the importance of political activism through lobbying in reducing crash risk because of the excess access of lobbying firms to political information (Christensen, Morris, et al., 2023; Wellman, 2017). Finally, the crash risk literature generates many findings on determinants of and mitigation strategies for crash risk (Fiordelisi et al., 2023; Yu et al., 2023), and this study identifies EPR discourse as a new crash risk mitigating factor.

This study has potential implications for investors, analysts, managers, and policymakers. Investors and management should be aware that greater EPR discourse is valuable in avoiding speculative trading and reducing the occurrence of stock price crashes. These findings suggest that regulated EPR disclosures in corporate fillings could be useful in providing comparable and decision-useful information to validate any discussions held in the ECC. As this study considers the US context, future research can adopt a global perspective encompassing different environmental policies to assess how the capital market reacts to EPR in other countries' political environments because how much discourse will be dedicated to the EPR issue might be derived by the national political decisions in a country.

Declaration of competing interest

None.

Data availability

No

Appendix A. Variable definition

Variable	Definition
NSKEW	The negative coefficient of skewness; see Eq. (3) for details. Source: Authors' calculation based on the CRSP data
DUVOL	The down-to-up volatility; see Eq. (4) for details. Source: Authors' calculation based on the CRSP data
EPR	The standardised value of average firm-level EPR discussion over the past four quarters; See Eq. (5) for details. Source: Economic Policy Uncertainty Database
RET	RET is calculated as the mean of firm-specific weekly returns during a given period multiplied by 100 (Chang et al., 2017). Source: CRSP
DTURN	The detrended trading volume is calculated as the average monthly stock turnovers over the current fiscal year minus those over the previous fiscal year. Monthly stock turnover is calculated as the ratio of monthly trading volume over the number of shares outstanding. Source: CRSP
Sigma	The standard deviation of firm-specific weekly returns over the fiscal year. Source: CRSP
Size	The natural logarithm of the market value of equity. Source: Compustat
ROA	The ratio of income before extraordinary items over the book value of total assets. Source: Compustat
Lev	The ratio of long-term debt over the book value of total assets. Source: Compustat
MTB	The ratio of the market value of equity over the book value of equity. The market value of equity is the product of stock price and the number of shares outstanding. Source: Compustat
DisAcc	The moving sum of discretionary accruals is calculated employing the modified Jones model (Dechow et al., 1995). Source: Authors' calculation based on the Compustat data
Analyst	The natural logarithm of 1 plus the average number of equity analysts following a firm in a given year. Source: I/B/E/S
ExSigma	The extreme sigma is measured as the negative value of the worst deviation of firm-specific weekly returns from the average firm-specific weekly return divided by the standard deviation of firm-specific weekly returns in a fiscal year. Source: Authors' calculation based on CRSP data
Crash_Dummy	Binary crash risk measure coded one if a firm experiences one or more firm-specific weekly returns falling at least 3.09 standard deviations below its mean value in a given year and zero otherwise (Hutton et al., 2009). Source: CRSP
CEO_Duality	A dummy variable coded one if there is CEO-Chair duality and zero otherwise. Source: BoardEx
CEO_Gender	A dummy variable coded one if the CEO is a female and zero otherwise. Source: BoardEx
CEO_Age	The natural logarithm of the age of the CEO. Source: BoardEx
HHI	The Herfindahl–Hirschman Index is calculated as the sum of squares of market shares in the industry $= \Sigma\ [s/S]^2$, where s is each firm's sales and S is the sum of sales for all firms in the industry (defined by the two-digit SIC codes). Source: Authors' calculation based on Compustat data
GDP	The natural logarithm of a state's real Gross Domestic Product (GDP) in a year. Source: Bureau of Economic Analysis
Dispersion	Computed as the ratio of the standard deviation of estimated EPS to year-end closing stock price multiplied by 100. Source: IBES/CRSP

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