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Research article

Climate policy uncertainty: A catalyst for stock price crash?[☆]

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ABSTRACT

This study investigates the impact of climate policy uncertainty (CPU) on stock price crash risk. Using a panel dataset of 94,573 U.S. firm-year observations from 1989 to 2024, and employing panel regression with industry fixed effects and firm-clustered standard errors, we find that elevated CPU significantly increases firms' susceptibility to stock price crashes. Our channel tests confirm that bad news hoarding and investor heterogeneity are key mechanisms through which CPU leads to price crashes. Specifically, CPU incentivizes management to adopt aggressive accounting practices and withhold adverse information for extended periods, while also exacerbating heterogeneities among investors, thereby making stocks more crash-prone. Further analyses reveal that these effects are more pronounced in firms with higher information asymmetry and, to some extent, weaker governance structures.

1. Introduction

Over the past decades, climate change phenomena, including rising temperatures, sea-level rises, and extreme weather events, have imposed significant challenges on the global economy.[1] In response, governments worldwide have pursued ambitious net-zero emission targets and adopted a broad range of climate policies to facilitate a low-carbon and climate-resilient transition. These policy measures are vital for directing capital toward sustainable development; however, the uncertainty surrounding their scope, enforcement, and long-term commitment can create considerable compliance burdens and distort market expectations. This emerging challenge, termed climate policy uncertainty (CPU), may significantly alter firm behavior and investor decisions, with potential implications for financial market stability.

While the importance of regulatory clarity in climate policy has been recognized, limited research has directly explored the financial market consequences associated with CPU. After Gavriilidis (2021) introduces a newspaper-based measure of climate policy uncertainty (CPU) for the U. S. market, subsequent studies extend the evolving research on CPU by examining its impact on corporate dividends (Ayed et al., 2024), tax avoidance (Amin et al., 2023), banks' risk-taking behaviors (Dai and Zhang, 2023), firm-level total factor productivity (Ren et al., 2022), corporate social responsibility (Vo et al., 2024). However, a critical gap remains in understanding how market participants respond to the increased regulatory costs and information frictions associated with CPU, particularly whether such uncertainty manifests in stock price crashes. Addressing this question is crucial, as stock price crashes not only reflect extreme downside risk but also pose systemic threats to capital markets.

Our study aims to bridge this gap by investigating the relationship between CPU and firm-level stock price crash risk. We draw on two well-established theoretical channels for crash risk: (i) the bad news hoarding hypothesis, which suggests that managers delay the release of unfavorable information until it accumulates and triggers a crash, and (ii) investor heterogeneity, where diverse beliefs and disagreement among investors under uncertainty can amplify price volatility and crash risk. We hypothesize that CPU amplifies both mechanisms by increasing information asymmetry and reducing managerial predictability.

To empirically test this, we utilize a sample of 94,573 U.S. firm-year observations, spanning the period from 1989 to 2024. Our proxy for CPU is the news-based CPU measure adopted from Gavriilidis (2021), which captures the frequency of searches on eight leading U.S. newspapers for

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[1] https://edition.cnn.com/2024/04/17/business/climate-change-disasters-economic-cost/index.html The price tag carried by extreme weather catastrophes is stunning: an average 19 % reduction in global income over the next 25 years. The projected global economic damages caused by climate change until 2049, estimated at $38 trillion, are 6 times more than the mitigation costs required to comply with the Paris Climate Agreement and restrict global warming to 2 °C.

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terms related to climate change and climate policy. Firm-level stock price crash risks are measured by the skewness of weekly stock returns (*NCSKEW*) and down-to-up volatility of weekly returns (*DUVOL*), consistent with Jin and Myers (2006), and Kim et al. (2011a, 2011b). Our baseline results document a positive and economically meaningful relationship between CPU and crash risk. Specifically, the standard deviation of crash risk as measured by NCSKEW and DUVOL increases by 5.79 % and 5.5 %, respectively, for every standard deviation increase in CPU. These findings are robust across multiple alternative specifications, including variable definitions, estimation techniques, exclusion of crisis periods, and endogeneity tests.

Our extended analysis supports the proposed theoretical channels. We find that higher CPU intensifies managerial bad news hoarding through earnings smoothing and aggressive accounting practices, while also exacerbating investor disagreement. Both effects contribute to the increased likelihood of stock price crashes, as well established in prior literature. In addition, our cross-sectional results reveal that firms with higher information asymmetry are more vulnerable to CPU-induced crashes, while the moderating role of governance is somewhat more nuanced—strong internal governance, such as active institutional ownership, appears to mitigate the effect, whereas evidence for external audit quality is less consistent.

This study makes several novel contributions to the growing literature on environmental economics. While previous research has primarily examined the impact of CPU on firm operations and aggregate market volatility, our work is the first to establish a direct link between CPU and firm-level stock price crash risk, thereby shedding new lights on the destabilizing effects of regulatory uncertainty on financial markets.

First, we extend the CPU literature by shifting the focus from conventional corporate financial decisions—such as dividend payouts (Ayed et al., 2024), tax behavior (Amin et al., 2023), green innovation (Sun et al., 2024; Attílio, 2025), and risk-taking behavior (Dai and Zhang, 2023)—to the extreme downside risk embedded in stock price crashes, which have direct implications for both market stability and investor protection.

Second, while prior studies have explored CPU's role in driving volatility and spillover dynamics across green financial markets at the macro level (e.g., Wang et al., 2023; Ozkan et al., 2024; Raza et al., 2024), our analysis adopts a firm-level lens. A study closely related to ours is Olasehinde-Williams et al. (2023), which investigates the impact of CPU on the returns and volatility of sustainable investments[2]; however, we differ by focusing on crash risk and identifying the underlying micro-level transmission mechanisms through which CPU exerts its effects. Specifically, we show that CPU intensifies two well-established drivers of stock price crashes: managerial bad news hoarding and investor heterogeneity.

Finally, the study yields important policy insights. We demonstrate that elevated CPU, if not properly addressed, can contribute to fragility in financial markets by increasing firms' crash susceptibility. This underscores the importance of consistent and transparent climate policy communication from regulators, as well as improved firm-level disclosure practices to mitigate information asymmetries. Collectively, our contributions advance the environmental finance literature by identifying a previously underexplored transmission channel through which climate policy uncertainty affects financial market outcomes—thereby providing new evidence to guide both corporate strategies and public policy design.

The remainder of the paper proceeds as follows: section 2 provides the theoretical foundations and hypothesis development, section 3 describes the sample and research design, section 4 discusses our main empirical results, and section 5 provides concluding remarks.

2. Related literature

2.1. Mechanisms of stock price crash

Stock price crash risk refers to the probability of an abrupt and extreme decline in stock price (Jin and Myers, 2006; Callen & Fang, 2013; J.-B. Kim et al., 2011b; Habib et al., 2018). Since market crashes erode investor wealth and disrupt capital market operations, understanding the determinants and consequences of price crashes holds substantial implications for strategic asset allocation and portfolio diversification decisions. Existing literature has well established that crash risk takes its root from both within the firm (through managers' bad news hoarding mechanism) and from outside the firm (through investor heterogeneity mechanism) (Andreou et al., 2021; Hutton et al., 2009; Zhang et al., 2022).

Rooted in the agency theory perspective, the *bad news hoarding mechanism* posits that self-interested managers possess both the incentives and the capacity to conceal adverse information. Influenced by reward packages and empire-building motivations, and facilitated by an asymmetric information environment between corporate insiders and external stakeholders, managers are prone to deliberately withhold unfavorable information to avoid immediate backlash from shareholders. However, there exists a threshold to how much negative news management can hide. When the stockpiled bad news reaches a tipping point and can no longer be concealed, they are disclosed all at once to the market, sending the company's shares into a plunge (Jin and Myers, 2006; Hutton et al., 2009). This agency theory-based explanation is empirically supported by a substantial body of crash risk literature. For instance, prior studies have attributed price crashes to managerial equity-based compensation (Kim et al., 2011a), excess perks (Xu et al., 2014), and the separation of a firm's voting and cash flow rights, which results in value expropriation from controlling shareholders (Boubaker et al., 2014). Consistent with this reasoning, firms can partially mitigate the propensity for crashes through agency-mitigating mechanisms such as CEO inside debt holdings (He, 2015), green bond issuance (Ge et al., 2024), institutional investor stability and dedication (Callen and Fang, 2013; An and Zhang, 2013), conditional reporting conservatism (Kim and Zhang, 2016), mandatory IFRS adoption (DeFond et al., 2015), annual report readability (Ertugrul et al., 2017), corporate social responsibility (Kim et al., 2014), take-over threats (Bhargava et al., 2017), intensive media coverage (Aman, 2013), and social trust (Cao et al., 2016; Li et al., 2017), among others. Previous studies have also identified opaque financial reporting (accrual earnings management, real earnings management), and corporate tax avoidance as the primary techniques utilized by managers to engage in opportunistic bad news hoarding practices (Hutton et al., 2009; Kim et al., 2011a; Francis et al., 2016).

Alternatively, from a market-based perspective, market crashes can occur through the *investor heterogeneity mechanism*. Under this mechanism, investors' divergent opinions are further exacerbated by short-selling constraints, which impede investors' ability to express their views on overvalued stocks. As short sellers are informed investors (Senchack and Starks, 1993; Christophe et al., 2004; Griffin et al., 2016), they play a crucial role in providing market liquidity and identifying mispricing. The restriction of short selling, therefore, causes mispricing (overvaluation) to persist for longer periods, leading to more pronounced price corrections when they are eventually resolved upon the surface of previously hoarded negative news (Hong and Stein, 2003). This triggers a sudden and substantial decline in stock prices. It is important to highlight that the body of literature exploring the market-based explanation is considerably less extensive compared to that of the agency-based perspective (Habib et al., 2018).

[2] We thank an anonymous reviewer for suggesting the inclusion of this paper, which has strengthened the contextual framing and positioning of our study within the existing literature.

2.2. Uncertainty and stock price crash risk

The evolving uncertainty of the global economic landscape and the resultant fragility of capital markets have prompted extensive literature exploring various types of uncertainty and their impacts on stock price crash risk. The consensus view is that crash risk is higher during uncertain times, with managerial incentives to withhold bad news and increased investor disagreements clearly contributing to this phenomenon. This body of research can be broadly categorized into two main domains based on the scope of uncertainty: macro-level and firm-level.

The first domain addresses macro-level uncertainty, examining the impacts of economic policy uncertainty (EPU) and various other economy-wide uncertainties related to the political environment, carbon pricing policies, and oil prices on crash risk (e.g., Ren et al., 2023; Jin et al., 2019; Lei and Song, 2022; Yuan et al., 2022; Han et al., 2023; Xiao et al., 2022). Specifically, Zhou et al. (2024) assert that EPU constrains corporate green technology innovation by exacerbating financing constraints. In the same vein, Lei and Song (2022) argue that elevated EPU incentivizes firms to postpone investments and elevate their capital costs, thereby lowering stock returns. Consequently, investors may liquidate their stock holdings, increasing the risk of crashes. Jin et al. (2019) construct a novel Chinese newspaper-based EPU index, distinct from the original index by Baker et al. (2016), to investigate the unique institutional setting influencing crash risk. Their findings highlight the pivotal role played by state-owned enterprises in amplifying the positive EPU-crash risk relationship. Similarly, Yuan et al. (2022) validate that EPU elevates the financial and credit risks of commercial banks by increasing the default risks of borrowing firms. This dynamic strengthens bank management's incentive to hoard bad news, leading to increased crash risk. Ren et al. (2023) and Xiao et al. (2022) document similar results and channels when examining the impacts of carbon price uncertainty and oil price uncertainty on crash risk. Collectively, the authors underscore the presence of various sources of risk premiums in stock returns and highlight the downside risk to corporate share values.

Studies within the second strand of literature, albeit relatively scant compared to the first, utilize a quantified firm-level policy uncertainty exposure, following the methodology pioneered by Hassan et al. (2019). In contrast to Baker et al. (2016), which constructs a market-level uncertainty index by capturing the time-series frequency of specific terms in a country's leading newspapers, Hassan et al. (2019) adopt a more granular approach. They conduct textual analysis of quarterly earnings conference-call transcripts, utilizing a pattern-based sequence-classification method to measure firm-level risk exposure over time. One relevant study is Wang et al. (2023). The authors explore the management discussion and analysis sections (MD&A) in Chinese firms' annual reports to construct a firm-level EPU index. They argue that their index captures the firm-specific perception of overall EPU, with a higher index indicating greater management anticipation, preparedness, and information disclosure concerning economic policy uncertainty. Given this interpretation, it is not surprising that they find empirical evidence indicative of a negative association between EPU and crash risk.

2.3. Climate policy uncertainty and stock price crash risk

The primary mechanism driving the economy towards a low-carbon energy transition is climate policy settings. These typically encompass carbon pricing, fossil fuel subsidy removal, renewable energy subsidy introduction, low-carbon energy technologies development, and green finance policies, among others. However, the imperfections and unpredictability of these government-formulated policies may introduce substantial compliance costs for market participants. Research indicates that newly introduced environmental requirements carry significant macro- and micro-level implications. At the macro level, these impacts may manifest as labor market frictions, capital depreciation, and sovereign debt. At the micro level, transition risks include inefficient green capital infusion, stranded assets (i.e., fossil fuel infrastructure deemed environmentally inappropriate), shifting consumer demand (as consumers switch to more environmentally friendly products), increased operational costs (as firms are forced to reduce their carbon footprint and invest in greener technologies), and legal transition liabilities, among other vulnerabilities[3] (Bose et al., 2021; Griffin et al., 2017; Huang et al., 2021). We build our hypothesis on this line of micro-level implications of environmental policies and explore a potential positive externality of CPU, firm-specific stock price crash risk.

We hypothesize that an increase in CPU would result in a higher chance of stock price crash through both mechanisms: bad news hoarding and investor heterogeneity. There are two reasons that justify management's incentives to withhold bad news under elevated CPU. First, uncertainties have long been associated with less transparent information settings (Rehse et al., 2019; Zeng et al., 2024), which enables managers to suppress bad news. This occurs because, under investors' skepticism, firms with unfavorable news can blend in with non-disclosing firms (Dye, 1985; Jung and Kwon, 1988; Bao et al., 2022). Additionally, management may withhold bad news in the hope that future policy changes will turn in their favor and allow them to conceal the bad news (Bao et al., 2019). Second, increased uncertainty makes the performance of vulnerable firms more volatile, which further facilitates managerial withholding behaviors since higher volatility correlates with a less transparent information environment for external stakeholders (Li et al., 2018). We argue that climate policy uncertainties, either in the form of price-based interventions (i.e., higher carbon pricing, emissions trading schemes) or quantity-based interventions (i.e., outright quantitative limits on the use of carbon-intensive energy sources), render firm performance significantly more volatile. Collectively, these conditions incentivize management to *hoard bad news*, increasing the likelihood of future crashes.

Alternatively, we conjecture that CPU conveys risk-driving signals that magnify behavioral biases and disagreements among investors, hence the increased possibility of crashes. This is central to the *investor heterogeneity* mechanism. As environmental awareness grows, investors increasingly factor climate-related risks into their decisions (Fahmy, 2022), highlighting the need for firms to disclose their climate policy exposure and mitigation strategies. While such disclosures make the market more informed about potential risks and enhance asset pricing efficiency, they risk exposing proprietary, strategic information (Ilhan et al., 2023) and subject firms to increased scrutiny from investors and other stakeholders (Zhang et al., 2022). Given the intricate nature of climate transition policies and the lack of mandates for disclosing climate exposure,[4] firms are believed to avoid providing detailed public disclosures. This behavior increases information asymmetry, exacerbates disagreements over corporate fundamentals, heightens valuation uncertainties, and ultimately renders stocks more susceptible to crashes. We then propose our main hypothesis as follows.

Hypothesis 1. Increased climate policy uncertainty results in a higher risk of stock price crash.

[3] "*V20 Debt review: An account of debt in the Vulnerable group of twenty*", report available for download at https://www.v-20.org/resources/publications/v20-debt-review-2nd-edition.

[4] It was not until March 6, 2024, that the SEC finally adopted final rules aimed at enhancing disclosures by public companies regarding climate-related risks, with these rules set to take effect no earlier than 2026. However, these new regulations have yet to address the risks associated with the uncertainty aspect of climate policy. https://viewpoint.pwc.com/dt/us/en/pwc/in_briefs/2024/2024-in-brief/ib202402.html and https://www.sec.gov/news/press-release/2024-31.

3. Sample and empirical model

3.1. Sample construction

Our sample is constructed from several data sources: accounting data from Compustat; stock return data from CRSP; CPU and EPU data from the website htttp://www.policyuncertainty.com; election data from the Database of Political Institutions (2020) (DPI2020). Similar to earlier research, we exclude financial firms (SIC 6000–6999) and observations with insufficient data values to construct crash risk measures or control variables, and winsorize all continuous variables at the 1st and 99th percentiles. Our final sample consists of 94,573 firm-year observations, spanning the period from 1989 to2024.[5] The definitions and data sources of all variables employed in our analysis are furnished in Appendix A.

3.2. Model specification

3.2.1. Measuring stock price crash risk

We draw upon the market model pioneered in prior studies to construct two firm-specific crash risk measures: *NCSKEW* and *DUVOL* (Chen et al., 2001; Jin and Myers, 2006; Kim et al., 2011a, 2011b). The former estimates the negative coefficient of skewness of weekly stock returns while the latter measures down-to-up volatility of weekly returns. The procedures to estimate variables are as follows:

First, we regress firms' weekly stock return on the current week return as well as lead and lag returns of the U.S. market:

$$r_{i,t} = \alpha_i + \beta_{1,i} r_{m,t-2} + \beta_{2,i} r_{m,t-1} + \beta_{3,i} r_{m,t} + \beta_{4,i} r_{m,t+1} + \beta_{5,i} r_{m,t+2} + \varepsilon_{i,t} \tag{1}$$

where, return of stock i at week t and CRSP value-weighted market return at week t are denoted as $r_{i,t}$ and $r_{m,t}$, respectively and $\varepsilon_{i,t}$ represents the error term. Then the firm-specific weekly return, denoted as $R_{i,t}$, is obtained by taking the natural logarithm of one plus the error term from Eq. (1):

$$R_{i,t} = ln(1 + \varepsilon_{i,t}) \tag{2}$$

The first measure of stock price crash risk – *NCSKEW* – is then computed by taking the negative coefficient of the third moment of firm-specific weekly returns:

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

where n is the number of available weekly returns of stock i in year t. The negative sign is added to the ratio to facilitate interpretation of crash risk, where a more negative skewed return distribution indicates a higher likelihood of crash.

Our second measure of stock price crash risk is down-to-up volatility of returns (*DUVOL*). For a given stock i over one year, we label the weekly returns below annual mean as "down" and those above annual mean as "up" then calculate the standard deviations of "up"sample and "down" sample separately. *DUVOL* is calculated as taking the natural logarithm of down weeks' standard deviation to the up weeks' standard deviation. Similar to *NCSKEW*, an increase in *DUVOL* corresponds to a higher possibility of crash.

$$DUVOL_{i,t} = \log\left(\frac{(n_{up} - 1)\sum_{down} R_{i,t}^{2}}{(n_{down} - 1)\sum_{up} R_{i,t}^{2}}\right) \tag{4}$$

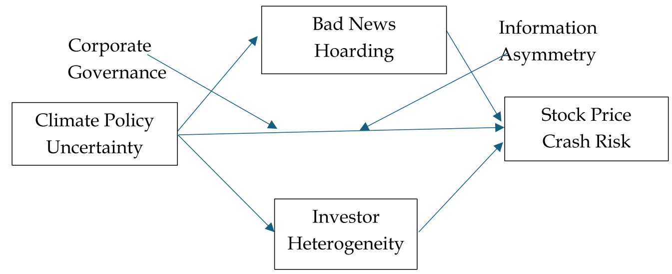

Fig. 1. Conceptual framework: Climate Policy Uncertainty and Stock price crash risk.

In the formula, n is the number observations of $R_{i,t}$ over period t, and n_{up} and n_{down} are the number of up weeks and down weeks, respectively.

3.2.2. Model specification

Our baseline model to examine the relationship between CPU and stock price crash risk is established as follows:

$$\begin{aligned}\mathbf{CrashRisk_{i,t}} &= \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{CPU_{i,t-1}} + \boldsymbol{\pi}\mathbf{Firm - specific\ variables_{i,t-1}} \\ &+ \Phi\ \mathbf{Macroeconomic\ variables_{i,t-1}} + \mathbf{IndustryFE} + \mathbf{Time\ trend} \\ &+ \boldsymbol{\varepsilon_{i,t}}\end{aligned} \tag{5}$$

where *i* and *t* index firms and years, respectively. We alternate two measures of crash risk, *NCSKEW* and *DUVOL*, as dependent variable. Our main explanatory variable of interest, CPU, is the natural logarithm of the monthly average Gavriilidis (2021)'s CPU index in a given year. The index is constructed using text-mining of terms associated with climate-related policy uncertainty in eight major U.S. newspapers and is available from 1989. We include a list of firm-level and macro-level control variables that are well established as predictors of crash risk following previous studies (Chen et al., 2001; Hutton et al., 2009; Kim et al., 2011a, 2011b). Firm-level control variables include: *Size, Leverage, ROA* (Return on assets)*, MTB* (Market-to-book)*, DTURN* (the yearly change in average monthly share turnover), *Past return* (firm--specific average of monthly returns)*, Stock return vol* (Stock return volatility), *Cash flow vol* (Cash flow volatility), *Opaque* (Earnings smoothness), *NCSKEW_lag* (lagged NCSKEW). Our set of macro control variables includes Baker et al. (2016)'s EPU (Economic policy uncertainty) and *Election* dummy. The inclusion of the *EPU* and *Election* dummy in our model is to separate the impact that CPU has on stock price crash risk from those brought about by either a different sort of uncertainty or an election. We include industry fixed effect[6] and a time trend in our regressions to control for unobserved time-invariant heterogeneities across industries and to capture the linear time effects of systematic changes, respectively. We conduct clustered standard errors by firms. We do not control for year fixed effects because for any given year, CPU index is universal across all firms. Variable definitions and measures are further detailed in Appendix A.

Fig. 1 illustrates the framework underpinning our analysis of the relationship between climate policy uncertainty and stock price crash risk.

4. Main empirical results

4.1. Descriptive statistics

Panel A of Table 1 shows summary statistics and Panel B reports the pairwise correlation matrix for the variables involved in our study. As

[5] We begin our sample in 1989 because data on CPU is available since that year.

[6] The results remain qualitatively similar if we use firm fixed effects instead of industry fixed effects.

can be seen, the mean of CPU is 4.518 with a standard deviation of 0.384. The two measures of crash risk, *NCSKEW* and *DUVOL*, are highly correlated at 0.957. Furthermore, the correlations between these two proxies and CPU are also significantly and positively correlated – an early indication that CPU positively affects stock price crash risks. Other than that, none of the correlations between any pairs of variables is high enough to raise concerns about multicollinearity.

4.2. Baseline results

Table 2 reports the estimation results of our baseline model, as specified in Eq. (5). Both measures of crash risks, *NCSKEW* and *DUVOL*, are positively associated with CPU, and this relationship is always positive and statistically significant at 1 %. In terms of economic magnitude, in column (1) the coefficient of *NCSKEW* is 0.127 and that of *DUVOL* is 0.054, implying that one standard deviation increase in CPU leads to 5.79 % (=0.127*0.384/0.843) increase in standard deviation of *NCSKEW* and 5.5 % (=0.054*0.384/0.377) increase in standard deviation of *DUVOL*, respectively. This result lends strong credence to our initial argument that the possibility of crashes increases when uncertainty related to climate policies increases.

The relationship between control variables and crash risk is generally consistent with what has been documented in prior studies. For example, the significant positive coefficients of *Opaque, DTURN,* and *Past return* confirm previous notions that higher accruals management, higher trading volume (proxy for opinion divergence), and higher historical returns all contribute to subsequent crash risk (Chen et al., 2001; Hutton et al., 2009).

4.3. Robustness tests

We conduct a series of robustness tests using alternative model estimations and alternative definitions for both CPU and crash risk. We also perform placebo analysis. The results are reported in Table 3.

4.3.1. Alternative measures of variables/model specifications and placebo analysis

First, to verify that the selection of CPU proxies has no bearing on our baseline findings, in Panel A of Table 3, we consider four alternative measures of CPU: *CPU_Raw*, weighted CPU (*WCPU*), median CPU (*CPU_Med*), and *CPU_OECD* (obtained from Berestycki et al., 2022 [7]). The coefficients of CPU remain positive and statistically significant at 1 % across all eight regressions for both *NCSKEW* and *DUVOL*.

Second, our robustness check involves alternative crash risk measures. We adopt three additional proxies for crash risk from previous works by Andreou et al. (2023), Bhargava et al. (2017), Bradshaw et al. (2010), and Chowdhury et al. (2020). These are *COUNT* – the number of "crash weeks" minus the number of "jump weeks" over a fiscal year; *EXTR_SIGMA* – the negative of the worst deviation of firm-specific weekly returns from its annual mean, scaled by the standard deviation of firm-specific weekly returns; and *CRASH COMPOSITE* – a composite proxy representing the first principal component derived from the three variables *COUNT*, *NCSKEW*, and *DUVOL*. Referring to Panel B of Table 3, we consistently observe strong positive coefficients of CPU regardless of the crash risk measures used.

Third, we subject our baseline regression to alternative model estimations and report the results in Panel C of Table 3. The alternative specifications are: (1) replacing industry fixed effects with firm fixed effects; (2) replacing industry classifications under two-digit SIC2 by Fama French's 48 industry group; and (3) estimating the baseline regression for the period that excludes the Global Financial Crisis (2007–2008) and COVID year (2020). As can be seen, the reported coefficients and their significances persist regardless of the model estimations employed.

We further examine the robustness of our results to changes in the broader political and regulatory regime by estimating our baseline model separately for the Obama (2009–2016) and Trump (2017–2021) administrations.[8] As reported in Table OA1 of the Online appendix, while the CPU coefficients remain positive and significant in both periods, the magnitude of the coefficient is notably higher during the Trump era, consistent with increased policy uncertainty and reduced regulatory transparency observed during this period.

Fourth, we augment our baseline regression by incorporating additional firm-level climate-related control variables to address potential omitted variable bias. Specifically, we include environmental, social, and governance (*ESG*) *scores*,[9] corporate social responsibility (CSR) scores[10], and carbon intensity[11] as additional covariates.[12] Due to data availability constraints, the inclusion of these variables reduces the sample size to 19,906, 34,807, and 14,700 observations, respectively. The results, presented in Panel D of Table 3, show that the estimated coefficients on CPU remain statistically significant and consistent with our baseline findings.

Finally, we conduct placebo tests using a random sampling approach, following the methodologies of Ghoul et al. (2021) and Berger et al. (2022), to further validate our findings. If CPU is randomly assigned, we would not expect to observe a significant positive relationship between CPU and stock price crash risk. To test this, we generate 1000 random samples in which the actual CPU variable is replaced with placebo CPU variables randomly drawn from the sample distribution of CPU. We then re-estimate the baseline model specified in Eq. (5) using these placebo variables. In Panel E of Table 3, we report the average, min, max, and standard deviation of the coefficient estimates and t-statistics obtained from these 1000 estimations. The mean coefficients (t-values) for the placebo CPU are 0.000096 (0.01226) for *NCSKEW* and −0.00000437 (−0.00216) for *DUVOL*, suggesting that the relationship is neither economically nor statistically significant. Out of the 1000 estimations, only 33 and 34 statistically significant CPU coefficients are observed for *NCSKEW* and *DUVOL,* respectively. This distribution of coefficients generated by the placebo tests differs substantially from the actual estimated coefficients, lending further support to our main findings.

4.3.2. Addressing endogeneity concerns

To address the possibility that the observed positive association between CPU and stock price crash risk may be influenced by the differences in covariate distributions among the sample firms, we employ two matching techniques: entropy balancing, following Hainmueller (2012), and propensity score matching (PSM), following Shipman et al. (2017). For the purpose of matching, we categorize the sample into two groups based on the median CPU. The treatment (control) group consists of observations whose *CPU* is above (below) the sample median. Using the entropy balancing approach, we adjust the weight of firm-year

[7] We thank the authors, especially Tobias Kruse, for providing us with their data on CPU. Their CPU index, which we label CPU_OECD in our work, is developed using the text-mining methodology pioneered by Baker et al. (2016). The index is constructed using a search of over 60 key terms related to climate, policy, and uncertainty in 3 major U.S. newspapers: The New York Times, The Washington Post, and The Wall Street Journal

[8] We thank an anonymous reviewer for the insightful suggestion to explore the role of political and regulatory regimes. This motivated our additional analysis comparing the Obama and Trump administrations, which strengthened the empirical basis for our policy-related conclusions.

[9] Data on *ESG scores* are available for the period 2002–2024.

[10] Data on *CSR scores* are available for the period 1993–2019.

[11] *Carbon Intensity* data for the 2002–2021 period are obtained from Bai and Ru (2024).

[12] We thank an anonymous reviewer for highlighting the need to account for broader firm-level climate exposure, which guided the inclusion of these additional covariates.

Table 1
Descriptive statistics and correlation matrix.

Panel A: Summary statistics

Variable	Obs	Mean	Std.Dev	25th pct	Median	75th pct
	(1)	(2)	(3)	(4)	(5)	(6)
Crash risk measures						
NCSKEW	94,573	0	0.843	−0.461	−0.029	0.407
DUVOL	94,573	−0.062	0.377	−0.311	−0.071	0.171
Climate Policy Uncertainty						
CPU	94,573	4.518	0.384	4.212	4.430	4.680
Firm-level control variables						
Size	94,573	5.784	2.222	4.105	5.713	7.376
Leverage	94,573	0.192	0.215	0.005	0.117	0.312
ROA	94,573	−0.036	0.236	−0.036	0.031	0.071
MTB	94,573	2.943	4.787	1.146	1.927	3.439
DTURN	94,573	0.004	0.107	−0.023	0	0.025
Past return	94,573	0.159	0.660	−0.225	0.054	0.361
Stock return vol	94,573	0.143	0.093	0.080	0.119	0.177
Cash flow vol	94,573	0.092	0.138	0.020	0.042	0.100
Opaque	94,573	0.227	0.210	0.096	0.164	0.279
NCSKEW_lag	94,573	0.009	0.813	−0.447	−0.027	0.400
Macro-level control variables						
Economic policy uncertainty (EPU)	94,573	4.573	0.336	4.273	4.528	4.861
Election	94,573	0.489	0.500	0	0	1

Panel B. Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) NCSKEW	1.000													
(2) DUVOL	0.957*	1.000												
(3) CPU	0.026*	0.036*	1.000											
(4) Size	0.110*	0.161*	0.235*	1.000										
(5) Leverage	−0.045*	−0.044*	0.031*	0.285*	1.000									
(6) ROA	0.042*	0.088*	−0.081*	0.349*	0.048*	1.000								
(7) MTB	0.049*	0.049*	0.045*	0.010*	−0.204*	−0.052*	1.000							
(8) DTURN	0.016*	0.014*	−0.016*	−0.013*	−0.003	−0.006	0.044*	1.000						
(9) Past return	0.062*	0.072*	−0.058*	−0.014*	−0.160*	0.165*	0.197*	0.187*	1.000					
(10) Stock return vol	−0.038*	−0.091*	0.001	−0.409*	−0.031*	−0.399*	0.041*	0.181*	0.189*	1.000				
(11) Cash flow vol	−0.025*	−0.067*	0.051*	−0.385*	−0.175*	−0.626*	0.100*	0.019*	−0.014*	0.431*	1.000			
(12) Opaque	−0.029*	−0.062*	0.015*	−0.338*	−0.144*	−0.411*	0.064*	0.006*	−0.003	0.347*	0.573*	1.000		
(13) NCSKEW_lag	0.042*	0.044*	0.047*	0.124*	0.014*	−0.001	−0.017*	0.008*	−0.204*	−0.080*	−0.031*	−0.027*	1.000	
(14) EPU	−0.040*	−0.039*	0.552*	0.037*	0.063*	−0.038*	−0.012*	−0.005	0.005	0.099*	0.026*	0.019*	−0.006*	1.000

This table reports descriptive statistics and correlation matrix for the key variables used in our study. The sample contains 94,573 U.S. firm-year observations, spanning the period 1989–2024. All continuous variables are winsorized at the 1 % and 99 % levels. Variable definitions and data sources are provided in Appendix A. ***Panel A*** presents summary statistics, while ***Panel B*** shows the Pearson correlation matrix for each pair of variables. *$p < 0.05$.

Table 2
Climate policy uncertainty and stock price crash risk - Baseline results.

Dependent variable = Stock price crash risk (proxied by NCSKEW or DUVOL)		
Variable	NCSKEW	DUVOL
	(1)	(2)
CPU	0.127***	0.054***
	(0.015)	(0.007)
Size	0.052***	0.027***
	(0.002)	(0.001)
Leverage	−0.225***	−0.122***
	(0.016)	(0.007)
ROA	0.005	0.031***
	(0.018)	(0.008)
MTB	0.003***	0.001***
	(0.001)	(0.000)
DTURN	0.042	0.027**
	(0.029)	(0.012)
Past return	0.074***	0.039***
	(0.005)	(0.002)
Stock return vol	0.016	−0.121***
	(0.039)	(0.017)
Cash flow vol	0.086***	0.025*
	(0.033)	(0.014)
Opaque	−0.022	−0.013*
	(0.018)	(0.008)
NCSKEW_lag	0.037***	0.016***
	(0.004)	(0.002)
EPU	−0.169***	−0.070***
	(0.011)	(0.005)
Election	−0.022***	−0.011***
	(0.006)	(0.003)
Time trend (t)	−0.003***	−0.001***
	(0.001)	(0.000)
Obs	94,573	94,573
Adj. R^2	0.03	0.05
Industry FE	Yes	Yes

This table displays the estimation results for the baseline regressions in Eq. (5). The dependent variable is *Crash risk,* either proxied by *NCSKEW* or *DUVOL. CPU* is the news-based index developed by Gavriilidis (2021). Firm-level control variables include *Size, Leverage, ROA, MTB, DTURN, Past return, Stock return vol, Cash flow vol, Opaque, NCSKEW_lag.* Macro-level control variables are *EPU* and *Election.* All variables are winsorized at the 1 % and 99 % levels. Variable definitions and data sources are provided in Appendix A. We include industry fixed effects and a time trend to capture unobserved industry heterogeneities and time effects of systematic changes. Standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at 1 %, 5 %, and 10 %, respectively.

observations in the control group to ensure that the distribution of covariates (mean values) aligns with those of the treatment group. For the PSM technique, we employ a one-to-one matching strategy without replacement, based on propensity scores, and retain matches that fall within a caliper distance of 0.1. This matching process reduces the size of our sample to 70,049 observations. We then re-estimate the baseline relationship using the refined samples obtained from both matching methods and report the results in Panel A of Table 4. As demonstrated, both entropy balancing and PSM approaches yield consistent results, further supporting the robustness of our findings.

Furthermore, to address the concern that the baseline finding is a spurious correlation driven by unobservable and omitted confounding factors that themselves simultaneously affect CPU and crash risk, we conduct an instrumental variable (IV) analysis to address potential endogeneity. We use the global land-ocean temperature index[13] as an instrumental variable for CPU. Rising global temperatures intensify concerns about climate change, prompting regulatory actions and debates related to climate policy, which, in turn, breeds uncertainty about future climate policies. Consequently, the global temperature index is likely to be correlated with CPU, satisfying the relevance criterion. As for the exclusion restriction, it is unlikely that global temperatures directly affect the crash risk susceptibility of U.S. firms, other than through their influence on CPU. Firm-specific crash risk is primarily driven by the accumulation and abrupt release of adverse information, which is influenced by corporate disclosure choices and investor behaviors. While acute weather events (e.g., hurricanes) might have direct, immediate operational impacts, the global land-ocean temperature index is a slow-moving, aggregate climate signal, rather than a localized shock. Its primary channel of influence on financial markets is thus through macro-level policy uncertainty, rather than direct firm-level effects. Taken together, the global temperature index meets the relevance and exogeneity requirements for a valid instrumental variable.

We report the IV results in Panel B of Table 4. In the first stage of the IV regression, we regress CPU of the U.S. on the global land-ocean temperature index and find a significant, positive relationship. The F-statistics of 15,983.68, which is well above 10, shows that the relevance condition of IV variable is satisfied. In the second stage, the coefficients on the instrumented CPU are significantly positive for both NCSKEW and DUVOL. Following the framework developed by Imbens and Angrist (1994), we interpret this estimate as a Local Average Treatment Effect (LATE). This means we view the significant coefficient on the instrumented CPU not as a universal average but as the causal effect for 'compliers'—firms whose climate risk exposure responds to our instrument, the global temperature index. This interpretation adds important details to our findings, acknowledging that the causal effect may differ for firms whose risk exposure does not react to broad climate shifts signals.

Our third endogeneity test involves evaluating the potential bias from unobserved omitted variables using a methodology developed by Oster (2019), which gauges the stability of the coefficients (β) and the inclusion of control variables in explaining outcome variations (R-squared). This method is largely employed in prominent works in accounting and finance literature (see, for example Call et al., 2018; Brogaard et al., 2023). Accordingly, the recommended cutoff Oster's delta (δ) of 1 means that the unobservables have to be at least as important as the observable control variables to invalidate the test results (i.e., reduce the coefficients to 0). Our (untabulated) δ values using $Rmax = 1.3^*R^2$ as suggested by Oster for our baseline regressions in Table 2 are substantially higher than the cut-off, being 3.5412 for *NCSKEW* and 1.7982 for *DUVOL* regressions – a reassuring indication that our test results are unlikely to be influenced by unobserved variables.

Collectively, our findings about the positive association between CPU and crash risk remain valid, even after addressing endogeneity concern.

4.4. Economic mechanisms: climate policy uncertainty and bad news hoarding/investor heterogeneity channels

Literature has long attributed stock price crashes to two primary economic channels: bad news hoarding and investors' heterogeneous beliefs (Jin and Myers, 2006; Hutton et al., 2009). It then follows that if CPU increases the probability of market crashes, the mechanism would be through either one of these channels. As previously discussed, we anticipate that increased CPU prompts managers to hold back adverse information, while also resulting in differential access to, and interpretation of information, which further widens the gap in perceptions, expectations, and hence asset valuations among market participants.

In order to test whether bad news hoarding or investor heterogeneity prevails in explaining our baseline relationship, we employ a set of established proxies for each channel. For bad news hoarding, we use: (1) earnings smoothness (*Opaque*), following Leuz et al. (2003) and Dak-Adzaklo and Wong (2024); (2) discretionary accruals derived from the modified Jones model (*Accruals)*, as in Dechow et al. (1995), Hutton

[13] Data for the global land-ocean temperature index are obtained from https://www.nasa.gov/stem-content/global-land-ocean-temperature-index-data-set/.

Table 3
Robustness tests.

Panel A. Alternative measures of CPU

Variable	Dependent variable = NCSKEW				Dependent variable = DUVOL			
	CPU_Raw	WCPU	CPU_Med	CPU_OECD	CPU_Raw	WCPU	CPU_Med	CPU_OECD
CPU_Raw	0.069***	0.146***	0.122***	0.168***	0.022***	0.062***	0.051***	0.085***
	(0.012)	(0.015)	(0.016)	(0.017)	(0.005)	(0.007)	(0.007)	(0.008)
Obs	94,573	94,573	94,573	81,627	94,573	94,573	94,573	81,627
Adj. R^2	0.03	0.03	0.03	0.03	0.04	0.05	0.05	0.05
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Alternative measures of stock price crash risk

Dependent variable = Stock price crash risk			
Variable	COUNT	EXTR_SIGMA	CRASH COMPOSITE
	(1)	(2)	(3)
CPU	0.294***	0.042***	0.395***
	(0.012)	(0.013)	(0.028)
Obs	94,573	94,573	94,573
Adj. R^2	0.05	0.03	0.04
Industry FE	Yes	Yes	Yes

Panel C. Alternative model estimations

Variable	Dependent variable = NCSKEW			Dependent variable = DUVOL		
	Firm FE	*FF48*	*Excluding GFC & COVID*	*Firm FE*	*FF48*	*Excluding GFC & COVID*
	(1)	(2)	(3)	(4)	(5)	(6)
CPU	0.150***	0.125***	0.145***	0.067***	0.053***	0.068***
	(0.017)	(0.015)	(0.017)	(0.008)	(0.007)	(0.007)
Obs	94,573	94,053	87,275	94,573	94,053	87,275
Adj. R^2	0.07	0.03	0.03	0.08	0.05	0.05
Firm FE	Yes	No	No	Yes	No	No
Industry FE	No	Yes	Yes	No	Yes	Yes

Panel D. Additional controls: ESG scores, CSR scores, and Carbon intensity

Variable	Dependent variable = NCSKEW			Dependent variable = DUVOL		
	ESG scores	*CSR scores*	*Carbon Intensity*	*ESG scores*	*CSR scores*	*Carbon Intensity*
	(1)	(2)	(3)	(4)	(5)	(6)
CPU	0.218***	0.099***	0.119***	0.085***	0.040***	0.037*
	(0.043)	(0.024)	(0.043)	(0.019)	(0.011)	(0.019)
Obs	19,906	34,807	14,700	19,906	34,807	14,700
Adj. R^2	0.01	0.01	0.02	0.02	0.01	0.03
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel E. Placebo analysis

	Dependent variable = NCSKEW		Dependent variable = DUVOL	
	CPU coefficient	*t-stat*	*CPU coefficient*	*t-stat*
	(1)	(2)	(3)	(4)
Mean	0.000096	0.0122686	−0.00000437	−0.0021693
Max	0.021645	2.9773	0.0098915	3.179504
Min	−0.0213153	−2.939467	−0.0093152	−3.022031
Std.Dev	0.0071049	0.9812154	0.0029949	0.9673602

This table reports a battery of robustness tests for our empirical analyses. In ***Panel A***, we replace CPU with alternative measures: *CPU_Raw*, weighted CPU (*WCPU*), median CPU (*CPU_Med*), and *CPU_OECD (*see Berestycki et al., 2022). ***Panel B*** presents results for alternative measures of stock price crash risk: *COUNT* is the difference between the number of firm-specific weekly returns that are more than 3.09 standard deviations below the annual mean and the number of firm-specific weekly returns that are more than 3.09 standard deviations above the annual mean; *EXTR_SIGMA* is the negative of the worst deviation of firm-specific weekly returns from its annual mean, scaled by the standard deviation of firm-specific weekly returns; *CRASH COMPOSITE* is a composite proxy representing the first principal component derived from the three variables *COUNT*, *NCSKEW*, and *DUVOL*. ***Panel C*** reports results for alternative model specifications, including various fixed effects: Firm FE, and industry FE (classified under Fama French 48 industries instead of the two-digit SIC industry classification), and a sample excluding the Global Financial Crisis as well as COVID period. **Panel D** incorporate *ESG scores*, *CSR scores*, and *Carbon Intensity* as additional firm-level climate-related control variables. In the placebo test in ***Panel E***, we present the average, min, max, and standard deviation estimates for the coefficients and t-stats for the 1000 random samples of CPU drawn from the sample distributions of CPU. Control variables (unreported for brevity) include *Size, Leverage, ROA, MTB, DTURN, Past return, Stock return vol, Cash flow vol, Opaque, NCSKEW_lag, EPU,* and *Election*. Variable definitions and data sources are provided in Appendix A. We include industry fixed effects and a time trend, and cluster standard errors by firms. Standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at 1 %, 5 %, and 10 %, respectively.

Table 4
Endogeneity tests.

Panel A. Entropy balancing and PSM

Variable	Entropy balancing		PSM	
	NCSKEW	*DUVOL*	*NCSKEW*	*DUVOL*
	(1)	(2)	(3)	(4)
CPU	0.139***	0.057***	0.160***	0.068***
	(0.016)	(0.007)	(0.020)	(0.009)
Obs	94,573	94,573	70,049	70,049
Adj. R^2	0.03	0.05	0.03	0.05
Industry FE	Yes	Yes	Yes	Yes

Panel B. Instrumental variable regressions

Variable	First stage *CPU*	Second stage	
		NCSKEW	*DUVOL*
Temperature_index	1.778***		
	(0.014)		
Fitted CPU		0.220***	0.115***
		(0.051)	(0.022)
Industry FE	Yes	Yes	Yes
Obs	92,407	92,407	92,407
Weak identification test:			
Kleibergen-Paap Wald F statistic	15,983.68		

This table reports the results of the endogeneity tests we use in our analysis: (1) entropy balancing, (2) propensity score matching in ***Panel A***, and (3) instrumental variable test in ***Panel B***. The instrumental variable analysis is based on the two-stage least squares regression approaches, with the global land-ocean temperature index (*Temperature_index*) being the instrumental variable for the endogenous CPU variable. Control variables (unreported for brevity) include *Size, Leverage, ROA, MTB, DTURN, Past return, Stock return vol, Cash flow vol, Opaque, NCSKEW_lag, EPU,* and *Election*. Variable definitions and data sources are provided in Appendix A. We include industry fixed effects and a time trend, and cluster standard errors by firms. Standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at 1 %, 5 %, and 10 %, respectively.

et al. (2009), Hong et al. (2017), and Chen et al. (2017); and (3) managers' linguistic tone in corporate disclosures (*Netneg_comp_pres)*[14] (Edmans et al., 2018; Bushee et al., 2018; Pham & Nguyen, 2023).

For investor heterogeneity, we rely on three proxies: *Analyst forecast dispersion*, *Institutional ownership dispersion*, and *DTURN* – the yearly change in average monthly turnover (Chen et al., 2001; Hong and Stein, 2003).

Our results reported in columns (1)–(3) of Table 5 show significant, positive coefficients of *Opaque* and *Accruals,* suggesting that CPU is associated with higher income smoothing and manipulative accounting practices. The table also reports a negative coefficient for *Netneg_comp_pres,* which can be interpreted that managers in firms with higher CPU refrain from sharing negative opinions about their firms in the conference calls. Together, the results support our initial conjecture that higher CPU results in higher bad news hoarding from managers. Similarly, results in Columns (4)–(6) show that all three proxies for investor heterogeneity—*DTURN*, *analyst forecast dispersion*, and *institutional ownership dispersion*—are positively and significantly related to CPU.

In summary, these results about channel tests are in line with our expectations, confirming that higher CPU prompts managers to withhold negative news and widens the information gaps among market participants, thus predicting a higher chance of subsequent stock price crashes.

4.5. Subsample analyses

Thus far we have demonstrated that CPU increases a firm's susceptibility to crash risk. In what follows, we examine the cross-sectional variation in the relation between CPU and crash risk.

4.5.1. Monitoring mechanisms

There has been mounting evidence highlighting the role played by governance mechanisms in mitigating crash risks (An and Zhang, 2013; An et al., 2015; Ni et al., 2020). However, whether and how CPU influences a firm's crash risk in the presence of effective governing practices is still an open question. Theoretically, strong oversight might work as a deterrent to executive misconduct and opportunism. That is, active institutional investors or effective Big4 auditor can contribute to curtailing information asymmetry and preventing management from withholding negative news, which helps stabilize stock price movements. In line with this reasoning, we expect our baseline relationship to be weaker for firms with effective monitoring.

We employ two measures to proxy for governance: *institutional ownership* and *Big4 auditor dummy*. The full sample is divided into strong and weak corporate governance subsamples based on the median values of a firm's institutional ownership level, or whether the firm is audited by a Big4 auditor or not. The baseline regressions are re-estimated for each subsample. Results are reported in Table 6. To assess the differences in the estimated CPU coefficients across the two subsamples, we employ a standard Z-test, following the methodology of Clogg et al. (1995). For instance, in columns (3) and (6) of Panel A in Table 6, Z-test values of 2.664 and 3.588 indicate that the CPU coefficients in the low institutional ownership subsample are significantly higher than those in the high institutional ownership subsample for both *NCSKEW* and *DUVOL*. Similar results are observed in Panel B, where Big4 auditor dummy is used as the corporate governance proxy. These findings confirm our conjecture that the disciplinary role of governance helps reduce the risk of a crash in uncertain circumstances.

4.5.2. Information asymmetry

Previous works argue that stock market dynamics plays an important role in either expediting or mitigating impending crash risks. Chang et al. (2022) demonstrate that improved mandatory disclosure enhances information environment, which leads to less investors disagreement and reduced crash risk. Jin and Myers (2006) argue that enhanced transparency prevents management myopia and opportunism, thereby reducing hoarding behaviors and crash risk. Frijns et al. (2023) establish a direct relationship between uncertainty and informational efficiency at the firm level across a broad sample of U.S. stocks. Collectively, it stands for us to expect that less transparent environment, or higher information asymmetry will facilitate opinion divergence and, in turn, amplify the impact of CPU on crash risk.

Following Derrien et al. (2016) and Autore and Kovacs (2010), we quantify information asymmetry using two measures: number of analysts (*Number_analysts)* and firm size (*Size)*. Greater analyst coverage enhances information flow, bridging the gap between insiders and external investors and reducing the risk of asset mispricing by mitigating information asymmetry. Likewise, larger firms benefit from reduced information asymmetry due to stricter reporting requirements and more rigorous scrutiny from regulators and investors. Also, their ample resources for compliance and public relations enable these firms to provide more comprehensive disclosures.

We partition the full sample into high and low information asymmetry subsamples using the median values of the information asymmetry proxies and re-estimate the baseline regressions for each subsample. The results are presented in Table 7. These findings indicate

[14] The variable ***Netneg_comp_pres***, adopted from Bushee et al. (2018), captures the overall tone of managerial communication during the presentation section of quarterly earnings conference calls. It is computed as the difference between the number of negative words and positive words, scaled by the total number of words in each transcript. A higher value indicates a more negative tone, and by implication, less concealment of bad news. This measure follows the tone analysis framework using the Loughran and McDonald (2011) dictionary of financial sentiment terms. The underlying transcript data and tone variable are made publicly available on the author's website, at https://danieltayloranalytics.com/data/.

Table 5
Economic mechanisms.

	Dependent variable = Bad news hoarding			**Dependent variable = Investor heterogeneity**		
Variable	*Opaque*	*Accruals*	*Netneg_comp_pres*	*DTURN*	*Analyst forecast dispersion*	*Institutional ownership dispersion*
	(1)	(2)	(3)	(4)	(5)	(6)
CPU	0.008*	0.031**	−0.108***	0.004**	0.014***	0.034***
	(0.004)	(0.012)	(0.020)	(0.002)	(0.002)	(0.004)
Obs	94,573	79,973	26,376	94,573	58,483	89,148
Adj. R^2	0.37	0.15	0.16	0.07	0.19	0.42
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the economic mechanisms through which CPU impacts stock price crash risk. The proxies for hypothesized channels, bad news hoarding and investor heterogeneity, are regressed on CPU. We employ three measures for bad news hoarding: *Opaque, Accruals, Netneg_comp_pres*. (1) *Opaque* is the negative correlation coefficient between the change in accruals and the change in cash flows from operations over the past five years, both scaled by lagged total assets. (2) *Accruals* is the cumulative sum of the absolute values of annual discretionary accruals over a three-year period, following the modified Jones model. (3) *Netneg_comp_pres* is the ratio of negative words minus positive words scaled by the total word count in a firm's quarterly earnings conference call. We employ three measures for investor heterogeneity – (1) *DTURN* - the yearly change in average monthly turnover. (2) *Analyst forecast dispersion*, and (3) *Institutional ownership dispersion*. Control variables (unreported for brevity) include *Size, Leverage, ROA, MTB, DTURN* (except col (4)), *Past return, Stock return vol, Cash flow vol, Opaque* (except col (1)(2)(3)), *NCSKEW_lag, EPU* and *Election*. Variable definitions and data sources are provided in Appendix A. We include industry fixed effects and a time trend, and cluster standard errors by firms. Standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at 1 %, 5 %, and 10 %, respectively.

Table 6
CPU and Stock price crash risk: High vs. Low monitoring mechanisms.

Panel A. Institutional ownership

Variable	**Dependent variable = NCSKEW**			**Dependent variable = DUVOL**		
	High institutional ownership subsample	*Low institutional ownership subsample*	*Z-test*	*High institutional ownership subsample*	*Low institutional ownership subsample*	*Z-test*
	(1)	(2)	(3)	(4)	(5)	(6)
CPU	0.115***	0.202***	2.664***	0.047***	0.098***	3.588***
	(0.021)	(0.025)		(0.009)	(0.011)	
Obs	45,150	45,150		45,150	45,150	
Adj.R^2	0.02	0.02		0.02	0.03	
Industry FE	Yes	Yes		Yes	Yes	

Panel B. Big4 auditor

Variable	**Dependent variable = NCSKEW**			**Dependent variable = DUVOL**		
	Big4 auditor	*Non Big4 auditor*	*Z-test*	*Big4 auditor*	*Non Big4 auditor*	*Z-test*
	(1)	(2)	(3)	(4)	(5)	(6)
CPU	0.075***	0.151***	2.283***	0.027**	0.065***	2.634***
	(0.028)	(0.018)		(0.012)	(0.008)	
Obs	31,653	62,873		31,653	62,873	
Adj.R^2	0.03	0.03		0.04	0.05	
Industry FE	Yes	Yes		Yes	Yes	

This table reports the effect of CPU on stock price crash risk, conditional on corporate governance. The dependent variable is either NCSKEW or DUVOL. CPU is the news-based index developed by Gavriilidis (2021). We divide the sample into high and low CG subsamples using the median corporate governance proxies. Two measures of corporate governance are employed: (1) *institutional ownership*, defined as the ratio of common shares held by institutional shareholders to the total common shares outstanding (*Panel A*), and (2) *Big4 auditor*, a dummy indicator equal to 1 if the firm is audited by a Big4 accounting firm, and 0 otherwise (*Panel B*). Control variables (not reported for brevity) include *Size, Leverage, ROA, MTB, DTURN, Past return, Stock return vol, Cash flow vol, Opaque, NCSKEW_lag, EPU,* and *Election*. Variable definitions and data sources are provided in Appendix A. We include industry fixed effects and a time trend, and cluster standard errors by firms. Standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at 1 %, 5 %, and 10 %, respectively.

that the CPU coefficients are significantly higher in the high information asymmetry subsamples, as proxied by *Size* (Panel A) and *Number_analysts* (Panel B), across both specifications involving *NCSKEW* and *DUVOL*.

To complement the subsample analyses above, we further estimate interaction regressions to examine whether the effect of CPU on crash risk varies systematically with firm-level governance and information asymmetry. Specifically, we interact CPU with institutional ownership and Big4 auditor status (governance proxies), as well as firm size and analyst coverage (information asymmetry proxies). The interaction terms for institutional ownership, firm size, and analyst coverage are statistically significant and in the expected directions, reinforcing the Z-test results reported in Tables 6 and 7 However, the interaction term for the Big4 auditor dummy is not statistically significant, suggesting that the influence of external audit quality as a moderating factor may be less consistent in our setting.

To aid interpretation, we plot the marginal effects of CPU conditional on firm size, institutional ownership, and analyst coverage in Online appendix Figure OA1. Since both institutional ownership and Big4 auditor status serve as governance proxies—and the former produced clearer and more consistent interaction effects—we choose to present only institutional ownership in the figure to avoid redundancy and streamline the visual narrative.

Table 7
CPU and Stock price crash risk: High vs. Low information asymmetry.

Panel A. Size

Variable	Dependent variable = NCSKEW			Dependent variable = DUVOL		
	Big size subsample	*Small size subsample*	*Z-test*	*Big size subsample*	*Small size subsample*	*Z-test*
	(1)	(2)	(3)	(4)	(5)	(6)
CPU	0.084***	0.201***	3.745***	0.031***	0.092***	4.534***
	(0.020)	(0.024)		(0.009)	(0.010)	
Obs	45,757	46,699		45,757	46,699	
Adj.R^2	0.01	0.02		0.02	0.03	
Industry FE	Yes	Yes		Yes	Yes	

Panel B. Number of analysts

Variable	Dependent variable = NCSKEW			Dependent variable = DUVOL		
	High analyst coverage subsample	*Low analyst coverage subsample*	*Z-test*	*High analyst coverage subsample*	*Low analyst coverage subsample*	*Z-test*
	(1)	(2)	(3)	(4)	(5)	(6)
CPU	0.101***	0.197***	3.156***	0.041***	0.088***	3.692***
	(0.022)	(0.021)		(0.009)	(0.009)	
Obs	43,858	50,715		43,858	50,715	
Adj.R^2	0.01	0.02		0.02	0.03	
Industry FE	Yes	Yes		Yes	Yes	

This table reports the effect of CPU on stock price crash risk, conditional on firm-level information asymmetry. The dependent variable is either *NCSKEW* or *DUVOL*. *CPU* is the news-based climate policy uncertainty index developed by Gavriilidis (2021). We divide the sample into high and low information asymmetry (IA) subsamples using the median IA proxies. Two measures of information asymmetry are employed: (1) *Size*, defined as the log value of market capitalization at the end of the fiscal year (*Panel A*), and (2) *Number_analysts*, defined as the log value of one plus the number of analysts that issue earnings forecasts for a given firm during the fiscal year (*Panel B*). Unreported control variables include *Size, Leverage, ROA, MTB, DTURN, Past return, Stock Return Vol, Cash Flow Vol, Opaque, NCSKEW_lag, EPU,* and *Election*. Variable definitions and data sources are provided in Appendix A. Unless otherwise stated, in the regressions we include industry fixed effects and a time trend to capture unobserved industry heterogeneities and time effects of systematic changes. Standard errors are reported in parentheses. The symbols ***, **, and * indicate statistical significance at 1 %, 5 %, and 10 %, respectively.

5. Conclusion

This study investigates the impact of climate policy uncertainty (CPU) on stock price crash risk using a comprehensive panel of 94,573 U.S. firm-year observations. We find robust evidence that elevated CPU is a significant catalyst for stock price crashes. We validate two key theoretical channels: bad news hoarding and investor heterogeneity – as mechanisms through which CPU operates. Specifically, CPU incentivizes managers to withhold adverse information through earnings smoothing and aggressive accounting, while simultaneously intensifying investor disagreement over firm value. These dynamics foster fragile conditions where crashes are more likely. Further, we find that these effects are more pronounced in firms with greater information asymmetry and, to a lesser extent, weaker governance structures. While the overall evidence supports the moderating role of governance mechanisms, the strength and consistency of these effects vary depending on the specific proxy employed.

The findings yield critical and actionable insights for policymakers, emphasizing that the process of policy-making—its clarity, predictability, and credibility—is as vital to financial stability as the substantive content of the policies themselves. Our results suggest two direct policy levers to mitigate the identified risks. First, to counteract the information asymmetry that amplifies crash risk, regulators should mandate and standardize comprehensive climate-related financial disclosures. Improved transparency would reduce opportunities for bad news hoarding and enhance investors' ability to make informed valuations. Second, to address the vulnerability from weak oversight, strengthening corporate governance standards for how firms manage and report on climate risks is essential.

While this study provides important insights, we recognize its limitations. Its focus on the U.S. means the results might not fully apply to emerging markets or countries with different institutional and regulatory environments. This opens several avenues for future research. Future studies could perform comparative cross-country analyses to examine how institutional quality influences outcomes, use event-study methods to identify the effects of specific policy announcements, or conduct more detailed sectoral analyses – for example, examining the heterogeneous effects across high-versus low-carbon industries.

In conclusion, by identifying and validating the key channels through which climate policy uncertainty destabilizes equity markets, this paper significantly contributes to the climate-finance literature. It highlights that credible, transparent policy and strong corporate oversight are crucial safeguards for building a resilient financial system capable of navigating the global transition to a low-carbon economy.

CRediT authorship contribution statement

Hong Vo: Writing – review & editing, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anh Phan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Quoc Dat Trinh:** Writing – review & editing, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation.

Declaration of competing interest

We have nothing to declare.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.126629.

Appendix A

Table A1
Definitions of variables.

VARIABLES	DEFINITIONS	SOURCES
Dependent Variable	Stock price crash risk (Crashrisk)	CRSP
NCSKEW	The negative conditional skewness of firm-specific weekly returns over a given year.	CRSP
DUVOL	Down-to-up volatility of returns, calculated as the natural logarithm of down weeks' standard deviation divided by the up weeks' standard deviation. We define up (down) weeks as all the weeks with firm-specific weekly returns above (below) the annual mean.	CRSP
COUNT	The difference between the number of firm-specific weekly returns that are more than 3.09 standard deviations below the annual mean and the number of firm-specific weekly returns that are more than 3.09 standard deviations above the annual mean.	CRSP
EXTR_SIGMA	The negative of the worst deviation of firm-specific weekly returns from its annual mean, scaled by the standard deviation of firm-specific weekly returns.	CRSP
CRASH COMPOSITE	A composite proxy representing the first principal component derived from the three variables COUNT, NCSKEW, and DUVOL.	CRSP
Key explanatory variable	Climate policy uncertainty index (CPU)	
CPU	The natural logarithm of the monthly average Gavriilidis (2021)'s CPU index in a given year, constructed using text-mining of terms associated with climate-related policy uncertainty in eight major US newspapers.	https://www.policyuncertainty.com/
CPU_Raw	The average of the monthly Gavriilidis (2021)'s CPU index in a given year divided by 100.	https://www.policyuncertainty.com/
WCPU	The natural logarithm of the weighted average CPU, where the more recent months' CPU carry more weight than the distant months' towards the calculation of the yearly CPU. In the formula, *m* is the last month of the year *t:* $WCPU_t = \ln([(CPU_m) \times 12 + (CPU_{m-1}) \times 11 + (CPU_{m-2}) \times 10 + (CPU_{m-3}) \times 9 + (CPU_{m-4}) \times 8 + (CPU_{m-5}) \times 7 + (CPU_{m-6}) \times 6 + (CPU_{m-7}) \times 5 + (CPU_{m-8}) \times 4 + (CPU_{m-9}) \times 3 + (CPU_{m-10}) \times 2 + (CPU_{m-11})]/78)$	https://www.policyuncertainty.com/
CPU_Med	The natural logarithm of the median of the monthly Gavriilidis (2021)'s CPU index over a year.	https://www.policyuncertainty.com/
CPU_OECD	The natural logarithm of the CPU index constructed using a search of over 60 key terms related to climate, policy, and uncertainty in three major US newspapers: the New York Times, the Washington Post, and the Wall Street Journal.	Berestycki et al. (2022)
Control Variables		
Size	Log value of total assets.	Compustat
Leverage	Long-term debts divided by (long-term debts plus market value of common shares outstanding).	Compustat
ROA	Ratio of income before extraordinary items to total assets	Compustat
MTB	Market value of common shares outstanding divided by the book value of common shares outstanding.	Compustat
Past return	The arithmetic average of the monthly returns of the firm during the year.	Compustat
DTURN	The yearly change in average monthly share turnover. Monthly share turnover is calculated by dividing monthly trading volume by the number of shares outstanding during the month.	Compustat
Stock return vol	The standard deviation of the monthly returns of the firm during the year.	Compustat
Cash flow vol	The standard deviation of the sum of income before extraordinary items plus depreciation and amortization scaled by total assets over the past five years.	Compustat
Opaque	The negative correlation coefficient between the change in accruals and the change in cash flows from operations over the past five years, both scaled by lagged total assets.	Compustat
NCSKEW_lag	The negative skewness of firm-specific weekly returns over the previous year.	
Election	A dummy variable that equals one if there was an executive election or a legislative election in a given year, and zero otherwise.	The Database of Political Institutions (2020) (DPI2020)
EPU	The natural logarithm of the monthly average Baker et al. (2016)'s EPU index in a given year, constructed using text-mining of terms associated with Economic policy uncertainty in ten large US newspapers by Baker et al. (2016).	https://www.policyuncertainty.com/
Carbon Intensity	The natural log of firm-level Greenhouse Gas (GHG) emissions	Bai and Ru (2024)
ESG scores	The sum of the adjusted scores of ESG components divided by 100	LSEG
CSR scores	The sum of the differences in the ratios of five CSR components. The ratio of each CSR component is calculated by dividing the raw strength (concern) scores by the number of items of the strength and concern of that component and then taking the difference between the ratio of concerns and the ratio of strength for each component.	MSCI ESG KLD STATS
Economic Mechanisms		
Opaque	The negative correlation coefficient between the change in accruals and the change in cash flows from operations over the past five years, both scaled by lagged total assets. A higher value of *Opaque* means a higher degree of earnings smoothing, hence higher bad news hoarding.	Compustat
Accruals	The cumulative sum of the absolute values of annual discretionary accruals over a three-year period. A higher value of *Accruals* means higher bad news hoarding.	Compustat
Netneg_comp_pres	The overall tone of managers, calculated as the ratio of negative words minus positive words scaled by the total word count in each quarterly conference call transcript. A higher value of *Netneg_com_pres* means lower bad news hoarding.	https://danieltayloranalytics.com/data/
DTURN	The yearly change in average monthly share turnover. Monthly share turnover is calculated by dividing monthly trading volume by the number of shares outstanding during the month.	CRSP
Analyst forecast dispersion	The standard deviations of analysts' earnings forecasts in prior month scaled by mean monthly price	I/B/E/S
Institutional ownership dispersion	The additive inverse of the sum of the squares of firms' percentage of each institutional ownership.	LSEG 13F Institutional Holdings

Data availability

The authors do not have permission to share data.

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