Risk in Focus, Information in Shadow: Managerial Attention of Climate Risks and Private Information Intensity

Abstract We analyze the relationship between managerial attention to climate risk and private information intensity using Chinese A-share listed firms from 2003 to 2023. We find that heightened managerial attention to climate risk is associated with greater private information intensity, with the association being stronger for physical risks than for transition risks. Policy interventions generally diminish the private information intensity; but their impacts are mitigated for high-risk enterprises, where attention-driven influences prevail. Governance analysis reveals divergent moderating effects: concentrated ownership attenuates the positive association, consistent with stronger shareholder monitoring; higher audit reputation amplifies it, as managers appear to exploit audit reputation as a legitimacy shield; broader external market monitoring proves largely ineffective. These findings offer implications for the design of climate governance and corporate disclosure regulation.

Keywords managerial attention of climate risk · private information intensity · corporate governance · information environment

JEL Classification G30, G38, M41, M48, Q54

1. Introduction

The climate crisis has emerged as a systemic risk to the global economy in the 21st century. The World Economic Forum predicts that by 2050, climate-related health impacts on food and agriculture, the built environment, and health and medical care sectors could result in at least $1.5 trillion in global productivity losses[1]. For businesses and financial systems, climate risks pose unprecedented threats and volatility (Painter, 2020; Huynh & Xia, 2021), and the accurate pricing of these risks in capital markets remains a central challenge (Bernstein et al., 2019; Ilhan et al., 2021). In response, regulators worldwide are advancing standardized climate disclosure requirements with unprecedented momentum, reflecting a broad consensus that improving corporate information transparency is essential for directing capital toward a sustainable future (Dye, 2001; Krueger et al., 2020; Amiraslani et al., 2023; Ilhan et al., 2023; Frankel et al., 2025).

These regulatory efforts rest on an intuitive premise. As climate risks become more salient, firms should respond with greater transparency, thereby reducing information asymmetry and lowering financing costs (Verrecchia, 1983; Szydlowski, 2021). Managers with superior risk awareness can further use disclosure to demonstrate their capabilities and stabilize market confidence (Fu & Trigilia, 2024). Yet this optimistic prediction assumes that heightened risk awareness translates straightforwardly into more informative disclosure. For conventional business risks, this assumption may hold. Climate risk, however, is characterized by deep uncertainty about timing and magnitude, extended time horizons, and significant reputational stakes. These features give managers considerable latitude in how they present climate-related exposures to the market. Managers, as self-interested agents, may exploit this latitude to conceal or obfuscate information in order to protect their personal reputation, compensation, and career prospects (Watts & Zimmerman, 1978; Fama, 1980; Gibbons & Murphy, 1992). Research on decision-making under uncertainty further suggests that individuals facing

[1]For more details, please refer to https://www.weforum.org/publications/building-economic-resilience-to-the-health-impacts-of-climate-change/

potential losses tend toward risk-seeking behavior and avoidance of threatening information (Kahneman & Tversky, 1979), which in a corporate setting may manifest as a preference for opacity over transparency. Indeed, prior literature has documented that firms engage in strategic impression management in environmental reporting rather than straightforwardly reducing information asymmetry (Rodrigue et al., 2013; Cho et al., 2015; Liu et al., 2025). This evidence points to a fundamental tension: as climate risk becomes more salient, firms may move toward less, rather than more, transparent information environments.

Resolving this tension requires understanding the cognitive process through which managers interpret climate risk and translate it into disclosure decisions. Yet this micro-foundation remains largely unexplored. Prior research has established that personal experience shapes climate beliefs (Myers et al., 2012; Zaval et al., 2014) and that attention influences market responses to climate events (Choi et al., 2020), but few studies have examined how managerial attention to climate risk shapes firm-level information management. We address this gap by drawing on the Attention-Based View (ABV), which holds that organizational actions are shaped not by objective environmental conditions alone, but by how decision-makers selectively attend to, interpret, and prioritize those conditions (Ocasio, 1997; Ocasio, 2011). Building on the ABV, we argue that corporate disclosure strategies, particularly those that rely on situational judgment, are fundamentally products of managerial attention (Wade & Griffiths, 2022). Objective climate risks translate into specific firm behaviors only after being perceived and interpreted by management. This argument leads to our central research question: does heightened managerial attention to climate risk reduce or increase the role of private information in firm-level price discovery?

We study this question in the context of China's A-share market over the period 2003 to 2023. As the world's largest carbon emitter and an economy facing significant transition pressures, China provides a particularly relevant setting for examining how managerial attention to climate risk shapes the corporate information environment (Chen et al., 2025; Xiong et al., 2025). Through textual analysis of corporate annual

reports, we construct a proxy for managerial attention to climate risk (ACR), measured by the relative frequency of climate-risk-related terms, to capture the salience of this topic in managerial communication. We measure private information intensity (PII) using the price–volume sensitivity metric of Kim and Verrecchia (2001), which captures the degree to which stock price discovery relies on heterogeneous private information among investors rather than on public disclosure. When a firm's public information environment is inadequate, investors engage in private information acquisition, leading to greater dispersion in beliefs and higher sensitivity of price changes to trading volume. A higher PII thus indicates that private information plays a more dominant role in price discovery, reflecting a less transparent information environment. We adopt this market-based measure rather than a climate-specific disclosure metric because our theoretical argument implies that heightened climate-risk attention may affect managers' general information strategy, not merely their climate-related disclosures. A manager who attends to significant climate risk may adjust the overall informativeness of the firm's communication with the market, for example by increasing the complexity of financial reports or reducing the precision of forward-looking guidance.

Our baseline results show that firms whose annual reports contain more climate-risk-related language exhibit significantly higher private information intensity. This positive association is stronger for physical risk terms than for transition risk terms, and various robustness tests support the baseline findings. In terms of economic magnitude, a one-standard-deviation increase in ACR is associated with a 1.55% standard-deviation increase in PII, suggesting an economically meaningful relationship.

A natural concern is that this association may reflect underlying climate exposure rather than managerial attention. We address this through two identification strategies. For physical risk, we construct an instrumental variable that interacts region-level extreme weather events with pre-determined industry-level climate sensitivity. The region-level weather shocks provide exogenous variation in the physical salience of climate risk to managers, while the industry-level sensitivity captures

differential attention across sectors. Their interaction generates variation in managerial attention to physical climate risk that is plausibly exogenous to firm-level information management decisions. The IV estimates are consistent with the baseline results. For transition risk, we exploit the 2012 Green Credit Guidelines as a quasi-natural experiment using a difference-in-difference-in-differences (DDD) design. We find that while the policy generally reduced private information intensity, this effect reversed for firms with high managerial attention to climate risk, where private information intensity instead increased.

We further explore how the relationship between ACR and private information intensity varies across governance settings. Concentrated ownership attenuates the positive association, consistent with the monitoring role of large shareholders in constraining managerial opportunism (Diaz-Rainey et al., 2024). In contrast, higher audit reputation does not mitigate the effect but instead amplifies it, suggesting that managers in firms with reputable auditors may use audit reputation as a legitimacy signal that facilitates rather than constrains strategic information management. This finding contrasts with Lamoreaux et al. (2025) but is consistent with Aobdia and Yoon (2025).

This study contributes to the corporate finance literature in three ways. First, we complement the extensive research on the economic consequences of climate risk by examining how climate risk shapes the corporate information environment from the supply side. Prior studies have documented climate risk's impact on asset pricing (Bernstein et al., 2019; Sautner et al., 2023), firm valuation (Wang et al., 2025), fixed income securities (Painter, 2020; Huynh & Xia, 2021), bank lending (Brown et al., 2021), and corporate financial policies (Ginglinger & Moreau, 2023). Scholars have also shown that institutional investors view these risks as critical (Krueger et al., 2020; Stroebel & Wurgler, 2021) and that market reactions vary with investor beliefs (Hong et al., 2019; Ilhan et al., 2021), the quality of disclosures (Matsumura et al., 2024), and non-financial signals such as shareholder votes (He et al., 2023) and extreme weather events (Fich & Xu, 2025). While this body of work documents how markets respond to

climate risk, it less directly addresses why firms adopt particular disclosure stances. We provide evidence on this earlier stage of the causal chain, showing that managerial attention of climate risk is a meaningful determinant of the corporate information environment.

Second, we contribute to corporate disclosure research by introducing a behavioral micro-foundation through the ABV (Ocasio, 1997, 2011; Wade & Griffiths, 2022). Prior work has shown that personal experience shapes climate beliefs (Myers et al., 2012; Zaval et al., 2014) and that attention drives market behavior (Choi et al., 2020), but has not examined how managerial attention shapes firm-level disclosure decisions. We build on Cho et al. (2015) by moving beyond the debate over competing disclosure motives to directly model the role of selective managerial attention, offering an integrated perspective that connects climate-risk attention to firm-level information management.

Third, our findings inform the design of climate governance. The divergent effects of ownership concentration and audit reputation suggest that standard oversight tools can produce heterogeneous and sometimes unintended outcomes. Effective climate governance should account for how managers attend and strategically respond to climate risks, rather than assuming a uniform relationship between risk awareness and transparency.

The rest of the paper is structured as follows. Section 2 reviews the related literature and develops our research questions. Section 3 describes the research design. Section 4 presents empirical results and robustness tests. Section 5 evaluates policy shock effects. Section 6 examines internal and external governance mechanisms. Section 7 summarizes findings, offers policy recommendations, and outlines directions for future research.

2. Related Literature and Research Questions

This paper sits at the intersection of three strands of literature. The first examines how climate risk affects corporate behavior and capital markets. The second

investigates the determinants of corporate disclosure strategies. The third explores how governance mechanisms shape the information environment. We review each strand below, identify the gaps that motivate our research questions, and develop empirical predictions grounded in the Attention-Based View (ABV).

2.1. Climate Risk and the Corporate Information Environment

A rapidly growing body of research documents the economic consequences of climate risk for firms and financial markets. Studies have shown that climate risk affects asset pricing (Bernstein et al., 2019; Sautner et al., 2023), fixed income securities (Painter, 2020; Huynh & Xia, 2021), and corporate financial policies such as investment, financing, and cash management (Ginglinger & Moreau, 2023). Institutional investors increasingly view climate risk as material to firm value (Krueger et al., 2020; Ilhan et al., 2021), and the demand for climate-related information has intensified across capital markets.

In parallel, a growing literature examines climate-related disclosure. Traditional disclosure theory predicts that firms with favorable private information will disclose voluntarily to reduce information asymmetry and lower the cost of capital (Verrecchia, 1983; Dye, 2001). Applied to climate risk, this perspective suggests that firms facing material climate exposures should disclose proactively to demonstrate preparedness and attract sustainability-oriented capital (Lins et al., 2017; Krueger et al., 2020). However, empirical evidence paints a more complex picture. Cho et al. (2015) document that environmental disclosures often serve impression management purposes rather than genuine information provision, and Rodrigue et al. (2013) show that corporate environmental governance frequently takes on a symbolic rather than substantive character. These findings suggest that the relationship between climate risk and corporate information quality is not straightforward.

Despite this progress, an important gap remains. Most studies treat climate risk as an exogenous condition and examine its downstream consequences for firm outcomes or market responses. Far less attention has been paid to the upstream question of how

managers internalize climate risk and translate it into information management decisions. This supply-side question matters because the informational content available to investors is ultimately shaped by managerial choices about what, when, and how to disclose (Beyer et al., 2010). Understanding these choices requires a framework that connects environmental conditions to managerial cognition and behavior.

2. 2. Managerial Attention, Behavioral Incentives, and Disclosure Strategy

We address this gap by drawing on the Attention-Based View (ABV), which holds that organizational actions are shaped not by objective environmental conditions alone, but by how decision-makers selectively attend to, interpret, and prioritize those conditions (Ocasio, 1997, 2011). The ABV implies that the same objective climate risk can lead to different disclosure outcomes depending on how managers allocate attention to it and what interpretive frame they apply (Wade & Griffiths, 2022). This insight provides a micro-foundation for understanding disclosure behavior that purely structural or incentive-based models do not offer.

A natural starting point is the expectation that heightened managerial attention to climate risk would lead to greater transparency. Managers who attend closely to climate risk are better positioned to understand their firm's exposures and can use disclosure to demonstrate preparedness, reduce information asymmetry, and lower financing costs (Verrecchia, 1983; Spence, 1973). Under this view, attention should translate into more informative public communication, reducing investors' need for private information acquisition and thereby lowering private information intensity (Kim & Verrecchia, 2001).

However, this expectation rests on the assumption that managers who attend to a risk will choose to communicate it transparently. Climate risk has several distinctive features that undermine this assumption. First, climate risk involves deep uncertainty about timing, magnitude, and firm-level impact, which gives managers considerable latitude in how they characterize their exposures (Christensen et al., 2018). Unlike financial risks with established measurement conventions, climate exposures are

difficult to quantify and verify, creating space for strategic framing. Second, the time horizon of climate risk extends well beyond typical managerial tenure, weakening the alignment between managers' personal incentives and long-term value creation (Jensen & Meckling, 1976). Third, climate risk carries significant reputational stakes. Candid disclosure of material climate exposures may be interpreted by the market as evidence of managerial failure or strategic vulnerability, threatening managers' professional standing and compensation (Fama, 1980; Gibbons & Murphy, 1992).

These features create conditions under which attention to climate risk may trigger self-protective rather than transparency-enhancing responses. Research on decision-making under uncertainty suggests that individuals facing potential losses tend toward risk-seeking behavior and avoidance of threatening information (Kahneman & Tversky, 1979). In a corporate setting, managers who attend to climate risk and recognize its threatening implications may prefer to meet minimum regulatory requirements while providing vague or boilerplate disclosures that obscure material information rather than reveal it (Hutton et al., 2009; Roychowdhury et al., 2019; Cho et al., 2015). Hood (2002) identifies this pattern as "blame avoidance," where decision-makers facing ambiguous threats prioritize reputational protection over transparency. When the quality of public information declines in this way, investors must rely more heavily on private information acquisition to assess firm value, increasing the role of private information in price discovery (Kim & Verrecchia, 2001).

We therefore examine whether managerial attention to climate risk increases private information intensity. While the conventional disclosure logic predicts a negative association, the distinctive features of climate risk and the behavioral incentives they activate lead us to predict a positive association.

2. 3. Governance Structures and the Climate-Opacity Relationship

If managerial attention to climate risk increases private information intensity through the behavioral mechanism described above, the strength of this relationship should depend on the governance structures that constrain or facilitate managerial

discretion. We focus on two governance mechanisms that have received extensive attention in the literature but whose roles in the climate disclosure context remain underexplored.

Ownership concentration. When ownership is concentrated, large shareholders have both the incentive and the ability to monitor managerial behavior, because they internalize a larger share of the costs of managerial opportunism (Shleifer & Vishny, 1986; Jensen & Meckling, 1976). Unlike dispersed shareholders who face collective action problems, concentrated owners can exert direct influence through board representation and access to internal information. In the context of climate risk, concentrated owners with long-term investment horizons have strong incentives to ensure that managerial attention translates into substantive communication rather than strategic obfuscation. This is because concealed climate vulnerabilities increase the risk of sudden value corrections when they eventually materialize, directly harming large shareholders' wealth (Diaz-Rainey et al., 2024; Ilhan et al., 2021). By reducing managerial latitude to engage in selective disclosure, ownership concentration should constrain the behavioral mechanism that links climate risk attention to increased opacity. We therefore examine whether concentrated ownership attenuates the positive association between managerial attention to climate risk and private information intensity.

An alternative possibility, however, deserves consideration. Concentrated owners may develop private communication channels with management, satisfying their own information needs without improving the public information environment (Boone & White, 2015; Müller et al., 2023). If large shareholders are co-opted into management's information strategy, concentrated ownership could reinforce rather than constrain opacity. Our empirical analysis adjudicates between these competing predictions.

Audit reputation. The conventional view holds that high-quality external audits serve as a disciplinary mechanism that constrains managerial opportunism across the firm's entire information environment (DeAngelo, 1981; Francis et al., 2013). Under this view, hiring reputable auditors raises the reputational cost of information

manipulation, thereby limiting the ability of managers to increase opacity in response to climate risk attention. Lamoreaux et al. (2025) provide evidence consistent with this disciplinary perspective.

However, this logic presupposes that auditors can effectively scrutinize the information domain in question. Climate-related disclosures are predominantly narrative, forward-looking, and non-standardized, placing them largely outside the scope of traditional financial audits (Aobdia & Yoon, 2025). This creates an asymmetry that self-interested managers can exploit. Managers who attend to climate risk and recognize its threatening implications may strategically employ the firm's audit reputation as a form of reputational cover (Campa & Laguecir, 2025). By associating the firm with a reputable auditor, managers can enhance the perceived credibility of their overall information environment while simultaneously providing climate-related disclosures that are technically compliant but substantively uninformative (Cho et al., 2012; Matsumura et al., 2024). This use of audit reputation as a legitimacy device is consistent with the broader literature on symbolic environmental governance, where corporate actions are designed to manage stakeholder perceptions rather than achieve substantive improvements (Rodrigue et al., 2013). In such cases, high-quality audits do not constrain strategic opacity in the climate domain but instead facilitate it by providing a credibility buffer that shields management from scrutiny. We therefore examine whether audit reputation amplifies the positive association between managerial attention to climate risk and private information intensity.

3. Data and Methodology

3. 1. Data and Sample Construction

This paper uses Chinese A-share listed firms from 2003 to 2023 as the research sample. This period covers the evolution of China's economic landscape. Financial and corporate governance data are sourced from the CSMAR database. The following data screening procedures are applied: (1) Exclusion of firms in the financial industry, as

their unique business models and financial reporting standards may have differential impacts on disclosure quality; (2) Exclusion of firms treated as ST or *ST during the observation period, as well as those with IPOs in the same year, to avoid interference from samples in financial distress or with strategic peculiarities; (3) Exclusion of observations with missing key variables. After these screenings, we obtain an unbalanced panel dataset comprising 25,520 firm-year observations from 261 cities. To mitigate the influence of outliers, continuous variables are winsorized at the 1% and 99% levels.

3. 2. Variable Definition

3. 2. 1. Private Information Intensity

The dependent variable is private information intensity, measured following Kim & Verrecchia (2001). Their framework is grounded in the premise that when a firm's public disclosure is insufficient to resolve uncertainty about firm value, investors must engage in costly private information acquisition. As a result, trading becomes the primary channel through which heterogeneous private information is incorporated into prices, and stock price movements become more sensitive to changes in trading volume (Atiase & Bamber 1994; Bamber et al., 2011; Dutta et al., 2017). Model (1) provides the formal specification for this measure.

$$Ln\left|\frac{P_t-P_{t-1}}{P_{t-1}}\right| = \alpha_0+\alpha(Vol_t-Vol_0)+\varepsilon \quad (1)$$

Here, P_t and Vol_t represent the stock closing price and trading volume on day t, respectively, and Vol_0 is the average daily trading volume over the study period. The α value obtained from OLS regression for each listed firm serves as the *PII* indicator in this paper. This indicator captures the sensitivity of price volatility to trading volume beyond what public information can explain. Higher PII values indicate that private information plays a more dominant role in price discovery, reflecting a less transparent information environment.

3. 2. 2. Attention of Climate Risk

The primary independent variable is managerial attention of climate risk (ACR). Some prior studies use earnings call transcripts as the basis for word frequency statistics (Sautner et al., 2023; Ginglinger & Moreau, 2023; Li et al., 2024), which provides a certain forward-looking perspective. However, in earnings calls, the lack of analyst questions may lead to sample selection bias and estimation noise (Ball et al., 2012; Kim & Pae, 2023). Furthermore, in the Chinese context, earnings call resources are often difficult to access. Given these challenges, we turn to annual reports as a more suitable data source. The language in these documents is carefully deliberated by management and offers traceable characteristics, making textual analysis based on them a more scientifically robust method for this study.

Specifically, we adopt the dictionary developed by Du et al. (2023). The dictionary development involves the following key steps: First, acquire annual reports from all A-share listed firms and manually read over 600 reports to analyze texts mentioning climate risk. Combine information disclosed by the China National Meteorological Science Data Center, the China Meteorological Disaster Yearbook, and the working paper by Li et al. (2024) to screen relevant terms based on Chinese semantic features and construct an initial dictionary. Next, to enhance the dictionary's objectivity and comprehensiveness, draw on Bengio et al. (2003) and LeCun et al. (2015) by employing machine learning techniques to train annual report corpora. Use the word vector CBOW model to expand the dictionary with the top ten words similar to the seed set based on similarity rankings. Finally, incorporate opinions from several experts to finalize the dictionary[2]. The frequency of these climate risk terms in the management's discussion and analysis section of corporate annual reports, as a proportion of the total word frequency in the report, serves as the *ACR* indicator. Higher values indicate that climate risk features more prominently in managerial communication, reflecting greater managerial attention to this topic. Adhering to this established and validated procedure,

[2] The specific dictionary is in Appendix A.

we expand and update the dataset for use in this study.

Given that firm size and debt structure often subject firms to higher scrutiny and regulatory pressure (Lang & Lundholm, 1993), and that business models and growth capabilities also affect the information environment (Edelen et al., 2012; Ginglinger & Moreau, 2023), this paper includes firm size (*Size*), leverage ratio (*Lev*), book-to-market ratio (*BM*), return on total assets (*ROA*), current ratio (*Liquid*), and operating revenue growth rate (*Growth*) as control variables. Additionally, considering the important supervisory roles of corporate governance and audit reputation in information transparency (Jensen & Meckling, 1976; Kausar et al., 2016; Lamoreaux et al., 2025), the paper further incorporates whether the chairman and general manager are the same person (*Dual*) and whether one of the Big Four audit firms is engaged (*Big4*) as control variables.

3. 3. Summary Statistics and Correlation Analysis

Table 1 presents the descriptive statistics for the main variables, reporting the number of observations, mean, median, standard deviation, minimum, and maximum values. The minimum value of *PII* is 0.0001952; given the small numerical scale of this variable, its actual magnitude is noted here. For scaling consistency, ACR is multiplied by 100. The standard deviation of Liquid is 2.166, indicating substantial differences in current ratios across firms due to varying business models. The mean of Dual is 0.265, meaning that 26.5% of firms have the chairman and CEO as the same person. Similarly, 6.3% of firms engage international Big Four auditors. The distribution of other variables in the sample is relatively uniform.

Fig. **1** displays the correlation heatmap for the main variables. Large-scale firms are often in mature development stages, with lower market expectations for future earnings growth, resulting in a certain positive correlation between *BM* and *Size* (coefficient 0.4995). On the other hand, high-leverage operating models typically involve substantial interest-bearing debt, which crowds out freely disposable cash resources and weakens firm liquidity. Therefore, *Liquid* and *Lev* exhibit a strong

negative correlation of -0.6679. Apart from these, there are no strong correlations among the main variables, indicating no high degree of redundancy among categories.

3. 4. Empirical Model

This paper examines the relationship between managerial attention to climate risk and private information intensity, with the theoretical analysis in Section 2 predicting a positive association. To test this prediction, we construct Model (2):

$$PII_{it}=\alpha_0+\alpha_1 ACR_{it}+Controls+City+Year+\varepsilon \quad (2)$$

Here, PII_{it} and ACR_{it} denote private information intensity and managerial attention to climate risk for firm i in year t, respectively. *Controls* represent the control variables, and ε is the unobservable random disturbance term. To account for potential unobserved regional climate and macroeconomic policy shocks, as well as time-invariant factor differences, we include city (*City*) and year (*Year*) fixed effects. Furthermore, standard errors are clustered at the city level to address potential correlations in the error terms among firms operating within the same city, which may arise from shared macroeconomic fluctuations, environmental regulations, or physical climate events. Based on the theoretical argument developed in Section 2, we predict that α_1 is positive, indicating that heightened managerial attention to climate risk is associated with greater private information intensity.

4. Empirical Results and Analysis

4. 1. Variable Validity Check

Before deriving the primary findings, we assess the validity of the key variables.

To validate that the *PII* measure effectively captures private information intensity in the Chinese market, we conduct regressions associating it with established proxies of earnings management and information asymmetry. As shown in Table 2, *PII* exhibits a significant positive correlation with real earnings management (*REM*) at the 1% level, confirming that *PII* captures the informational consequences of operational

manipulations that evade accrual detection, consistent with Roychowdhury (2006). However, *PII* shows no significant association with discretionary accruals (*DA*), demonstrating that *PII* isolates market-based information frictions without contamination from accounting manipulations, aligning with Ascioglu et al. (2005), who highlight how disclosure quality metrics avoid biases inherent in accrual-based earnings management proxies. Furthermore, *PII* is positively correlated with effective spread (*EffSpread*) at the 1% level, verifying that *PII* captures information asymmetry that directly inflates trading costs, in line with Leuz & Verrecchia (2000). Finally, *PII* correlates positively with ESG rating divergence (*ESG_uncertainty*) at the 10% level, affirming that *PII* identifies disclosure inadequacies contributing to inconsistent sustainability assessments, as evidenced in Avramov et al. (2022).

Taken together, these results provide robust evidence that *PII* possesses strong construct validity and reliably captures the degree to which private information dominates the price discovery process in the Chinese capital market.

To affirm the robustness of *ACR* as a proxy for managerial attention of climate risk, we perform two validation tests. First, *ACR* should be elevated in climate-vulnerable industries. Table 3 ranks the top 15 industries by mean *ACR*, corroborating this expectation because industries most exposed to climate impacts—such as ecological protection (mean 0.770), gas supply (0.662), and electricity production (0.513)—exhibit the highest values, indicating heightened managerial attention in sectors directly facing environmental disruptions and regulatory pressures.

Second, we align annual dictionary-based climate risk word frequencies with China's meteorological disaster losses and evaluate transition risk fluctuations around pivotal events. In this analysis, Climate_loss represents direct economic losses caused by climate disasters, while Physical_mean represents the average frequency of all words in the dictionary encompassing physical risks and Transit_mean denotes the average for transition risks. Fig. **2** depicts these trends from 2003 to 2023, where Physical_mean displays spikes aligning with major disaster years and Transit_mean accelerates around key policy milestones, closely mirroring Climate_loss volatility and thereby validating

ACR's capture of managerial attentions responsive to real-world physical and transitional climate developments.

4. 2. Main Results

Based on the theoretical analysis, we examine the relationship between *ACR* and *PII*. Table 4 presents the baseline regression results. In column (1), the coefficient of *ACR* on *PII* is approximately 0.005 and statistically significant at the 5% level. Column (2) incorporates city-level clustering, yielding qualitatively similar findings. After controlling for other variables, a one-standard-deviation increase in *ACR* (0.186) leads to a 1.55% increase in the standard deviation of *PII* (0.00093/0.060). These results suggest that heightened managerial attention to climate risk is associated with greater private information intensity, consistent with the prediction developed in Section 2; however, although the statistical effect is significant, its economic magnitude is modest, indicating that increased managerial attention raises opacity without dramatically altering the overall information environment.

Notably, the coefficient of *Big4* among the control variables is significantly positive, indicating that firms audited by Big Four firms exhibit higher private information intensity. The coefficient on Big4 suggests that firms audited by Big Four auditors exhibit higher information opacity by 0.013 units, which represents about 36% of the mean level of IO and roughly 22% of its standard deviation. This magnitude is economically meaningful and supports the interpretation that high-reputation auditors may act as a reputational shield, allowing managers to obscure climate-related information without severely undermining market confidence. Given recent controversies involving PwC, one of the Big Four, we conduct a robustness check by excluding it from the *Big4* measure[3]; the results in column (3) remain robust. To explore

[3] According to the administrative penalty decision issued by the Ministry of Finance, PwC and its Guangzhou branch knowingly failed to identify material misstatements in Evergrande Real Estate's financial statements during the audits for 2018–2020, issued inappropriate audit opinions, and produced false audit reports. The case caused significant disruption to China's capital market. The China Securities Regulatory Commission (CSRC) subsequently imposed administrative penalties on PwC for failing to exercise due diligence in its audits of Evergrande Real Estate's annual reports and bond issuances. Under the Securities Law of the People's Republic of China, PwC's business income related to the case, totaling

this counterintuitive finding, we replace Big4 with whether the audit opinion is unqualified (*Opinion*). Column (4) shows that the coefficients of *ACR* and *Opinion* remain significantly positive, indicating that this result is not due to measurement error in *Big4* but rather an effect systematically related to high audit reputation. The most plausible explanation is that management exploits audit reputation (Aobdia & Yoon, 2025). This finding provides empirical evidence relevant to the concerns raised by Campa & Laguecir (2025) regarding the potential unintended consequences of audit practices[4].

We disaggregate the climate risk dictionary into physical risks (further subdivided into acute and chronic risks) and transition risks. As presented in Table 5, attentions to acute and chronic risks are both positively and significantly associated with *PII* at the 1% level, with coefficients substantially larger than those for transition risks or overall *ACR*. This suggests that managerial attention varies across risk categories, manifesting more prominently in response to physical risks, which impose direct and substantive threats to firm assets and operations (Bernstein et al., 2019; Ginglinger & Moreau, 2023). Such immediate risks may precipitate market volatility and valuation erosion, thereby intensifying incentives for information concealment. Conversely, the long-term and indirect nature of transition risks appears to attenuate these motives.

4. 3. Robustness Test

4. 3. 1. Instrumental Variable

The baseline regression may face endogeneity issues in two aspects: (1) Omitted variable bias, for example, certain unobserved firm characteristics may simultaneously lead to heightened managerial sensitivity to risks and a tendency toward strategic information disclosure; (2) Reverse causality, firms planning information manipulation may intentionally increase discussions of climate risk in annual reports to divert

RMB 27.74 million, was confiscated, and the firm was also given the maximum fine of RMB 297 million, resulting in a total penalty of RMB 325 million. For details of the penalty, please refer to https://www.csrc.gov.cn/csrc/c100028/c7506541/content.shtml.

[4] We will further examine this result in Section 6.2.

attention from regulators and investors, thereby elevating *ACR* (Kim & Pae, 2023).

To address these concerns, we employ an interaction-based instrumental variable (IV) approach, focusing on the physical dimension of climate risk. The identification strategy rests on the insight that extreme weather events do not uniformly affect managerial attention across all firms. Rather, their impact on climate risk attention is amplified in industries that are inherently more sensitive to climate-related concerns. We exploit this differential response to construct our instrument.

Specifically, the IV consists of two components and their interaction. The first component is a region-level extreme climate indicator (*CPRI*), computed from the dataset of Guo et al. (2024) as a weighted average of days experiencing extreme temperatures (high and low), rainfall, and drought at the city level in each year (details on its construction are provided in Appendix B). *CPRI* is determined by meteorological conditions beyond the control of individual firms, providing the exogenous source of variation in our instrument. The second component is the base-period industry-average *ACR*, which measures the pre-existing climate sensitivity of each industry, that is, the degree to which climate risk was already a topic of attention within the industry before the sample period unfolds. We multiply *CPRI* by the base-period industry-average *ACR* to form the interaction term (*HSY*), serving as our IV.

The rationale for this interaction is straightforward. Consider a severe drought that strikes a particular region. This event is likely to heighten climate risk attention far more strongly for managers in agriculture or water-intensive manufacturing than for managers in financial services or technology, because climate risk is inherently more salient in the former industries. The interaction of region-level weather shocks with pre-determined industry-level climate sensitivity thus generates variation in the intensity of the attention-triggering effect of weather shocks across firms. This variation is plausibly exogenous to firm-level information management decisions, because neither the weather shock nor the base-period industry characteristic is determined by any individual firm's contemporaneous disclosure strategy.

Relevance. The IV satisfies the relevance condition, as evidenced by the first-stage

OLS results in Table 6. The coefficient on *HSY* is 0.020 and significant at the 1% level, with an F-statistic exceeding 10, alleviating weak instrument concerns. This confirms that the interaction of regional weather shocks and industry-level climate sensitivity is a strong predictor of firm-level *ACR*.

Exclusion restriction. For the IV to be valid, *HSY* must affect *PII* only through its influence on *ACR*. A potential threat to this condition arises if regional physical shocks directly alter *PII* through economic consequences, such as supply chain disruptions or asset impairments, without any change in managerial attention.

This concern is mitigated in our research setting for three main reasons. First, *PII* is constructed as the sensitivity of price changes to trading volume over the entire fiscal year, which captures the systematic quality of the annual information environment rather than immediate responses to short-term physical disasters. Second, city fixed effects control for time-invariant regional differences, year fixed effects account for common temporal variations in macroeconomic and climate conditions, and control variables absorb contemporaneous changes in firm financial condition that could result from such shocks. Third, the key identifying variation comes from the interaction term, not from *CPRI* alone. The direct economic impact of weather shocks on firm fundamentals does not necessarily vary with pre-determined industry-level climate sensitivity. By contrast, the attention-triggering effect of weather shocks is expected to be concentrated in industries where climate risk was already a topic of managerial concern. This distinction supports the interpretation that *HSY* captures variation in managerial attention to climate risk rather than direct economic exposure.

Table 6 reports the second stage 2SLS results, the fitted value of the instrument *ACRiv* is significantly positively associated with *PII* at the 5% level, with a coefficient of 0.012. The instrumental variable approach not only mitigates potential endogeneity issues but also corrects estimation biases from measurement errors, revealing a stronger positive effect closer to the true situation.

4. 3. 2. Alternative Variable Measurements

As a supplementary test, this paper focuses here on measurement issues with the variable itself.

First, given that *ACR* relies on textual analysis, we substitute it with an objective, exogenous indicator of physical climate shocks to ensure the results are not driven by the specific measurement approach. We collect typhoon data for the sample period from the Tropical Cyclone Data Center of the China Meteorological Administration and compute the annual number of typhoon-strikes within 200 kilometers of each firm's location as the replacement variable (*Typhoon*). As reported in Table 6, *Typhoon* enters significantly positive in the regression, consistent with our main prediction and bolstering the reliability of the inferences.

Second, our primary measure of private information intensity uses the correlation between stock returns and absolute changes in trading volume, but firm-level differences in tradable shares could introduce bias. We therefore adopt a relative measure of private information intensity, as specified in Model (3), which scales trading volume changes by the initial value. Table 6 presents the OLS results; after the replacement, *PII_r* is the new measure, and the significance of *ACR* rises to the 1% level with a coefficient of 0.017, leaving the main conclusions unchanged.

$$Ln\left|P_t-\frac{P_{t-1}}{P_{t-1}}\right|=\alpha_0+\alpha\left(\frac{Vol_t}{Vol_0}-1\right)+\varepsilon \tag{3}$$

4. 3. 3. Model Adjustments

The baseline model employs city and year fixed effects to control for time-invariant regional factors and common temporal shocks. To ensure the results are insensitive to alternative specifications that address potential firm-level heterogeneity and residual dependence, we perform a series of supplementary estimations.

We first substitute firm fixed effects for city fixed effects while keeping year fixed effects, which eliminates all time-invariant firm heterogeneity and bases estimation solely on within-firm variation over time. The coefficient on *ACR* remains positive and

significant, suggesting that the documented relationship stems from temporal changes in climate risk attention within the same firm rather than from cross-sectional differences across firms. We next retain the baseline fixed effects but cluster standard errors at the firm level to accommodate arbitrary serial correlation and heteroskedasticity within firms. We finally combine these approaches by estimating the firm and year fixed effects model with firm-clustered standard errors. In all cases, the positive association between *ACR* and *PII* persists with statistical significance at the 10% level or better and magnitudes comparable to the main results, as reported in Appendix C.

5. External Policy Shock Test

To provide more robust identification evidence and delve deeper into how private information intensity evolves when firms face transition risks and external environmental regulatory pressures, we utilize the "Green Credit Guidelines" issued by the China Banking Regulatory Commission in 2012 as a quasi-natural experiment. This policy aims to promote the development of green credit by banking financial institutions, supporting a green economy, low-carbon economy, and circular economy, while effectively identifying, measuring, monitoring, and controlling environmental and social risks in credit operations, explicitly including climate change-related environmental issues. The policy requires banking institutions to implement stricter credit approval and management for high-pollution, high-energy-consumption, and overcapacity industries[5]. This constitutes an exogenous shock of financing constraints and regulatory pressures for high-pollution firms, providing a powerful setting to identify how managers' disclosure strategies evolve under external environmental constraints, especially when they already devote considerable attention to climate risks.

5. 1. The Difference-in-Differences-in-Differences (DDD) Model

We construct a triple-difference model to test our prediction in this experimental

[5] For details, please refer to https://www.gov.cn/gongbao/content/2012/content_2163593.htm.

framework, as specified in Model (4):

$$PII_{it}=\beta_0+\beta_1(Treat\times Post)+\beta_2(Treat\times ACR_{it})+\beta_3(Post\times ACR_{it}) +\beta_4(Treat\times Post\times ACR_{it})+Firm+Year+\varepsilon \quad (4)$$

Here, *Treat* indicates whether the firm is a high-pollution firm affected by the policy, and *Post* indicates whether the year is after the policy implementation. The model includes firm and year fixed effects and focuses on the direction of the coefficient β_4, which reflects how *ACR* influences *PII* under policy pressure.

The DDD design addresses a different identification challenge than the IV approach. While the IV exploits exogenous variation in physical climate salience, the DDD examines how an exogenous regulatory shock differentially affects firms based on their level of climate risk attention. The key identifying assumption is that, absent the Green Credit Guidelines, the difference in *PII* trends between high-*ACR* and low-*ACR* firms would have evolved similarly in treated and control industries. This assumption is testable through pre-trend analysis, which we present below.

The DDD is also informative for our theoretical argument. If *ACR* merely captured objective climate exposure, we would expect the policy to reduce private information intensity, not less, for high-exposure firms, because these firms face stronger regulatory incentives to improve transparency. A positive β_4 would instead suggest that managers with heightened climate risk attention respond to regulatory pressure by strategically managing their information environment, consistent with the behavioral mechanism predicted by our framework.

5. 2. Results and Dynamic Effects

Table 7 reports the DDD regression results. Column (1) presents the results from Model (4), where the coefficient of *Treat* × *Post* is -0.009 and significant at the 1% level. This suggests that the introduction of the green credit policy significantly reduced private information intensity for treated firms on average, consistent with the policy's intent to enhance environmental transparency. However, the coefficient of *Treat* × *Post* × *ACR* is 0.051 and significant at the 1% level, indicating that for firms with high managerial attention to climate risk, the policy effect reversed. Rather than reducing

private information intensity, the policy was associated with increased private information intensity among high-ACR treated firms. Column (2) shows the results using dual clustering at the firm and city levels. Additionally, we apply entropy balancing matching (EBM) to improve covariate balance between treated and control groups, with results displayed in column (3). The main conclusions from all specifications remain largely unchanged, implying that a one-size-fits-all policy approach may not be effective.

This finding supports the prediction developed in Section 2. Managers who are more attentive to climate risk appear to respond to heightened regulatory pressure not by embracing transparency, but by strategically managing their information environment to mitigate perceived threats. The policy, while effective on average, inadvertently triggered defensive behavior among precisely those firms whose managers were most attentive to climate-related vulnerabilities.

Furthermore, we employ an event study approach to examine the dynamic effects, as shown in Fig. **3** (a). Before the policy implementation, all coefficient confidence intervals include zero, indicating no systematic differences between the treatment and control groups prior to the policy and validating the parallel trends assumption. Starting from the second year after implementation, all coefficients are significantly positive and remain at high levels. This suggests that when firms face higher financing constraints and regulatory pressures, managers who already devote considerable attention to climate risks are more inclined to increase private information intensity to conceal potential vulnerabilities, forming a strategic response mechanism. Additionally, to further ensure result robustness, we conduct a placebo test. Fig. **3** (b) displays the simulated distribution from 1000 random samples, where the true t-value is far from the 95% and 99% confidence intervals. This implies that the observed positive effect is highly unlikely to stem from random noise but rather from the genuine impact of the policy shock. Overall, these dynamic and robustness analyses reinforce the conclusions of the baseline DDD model.

6. Mechanism Analysis

Thus far, this paper has demonstrated that managerial attention to climate risk increases private information intensity, even under external policy interventions. This section examines the conditions under which the main effect is mitigated or amplified, focusing on the moderating roles of ownership concentration and audit reputation as developed in Section 2, along with extended governance analyses.

6. 1. The Role of Ownership Concentration

We test the prediction that ownership concentration attenuates the positive association between *ACR* and *PII*. Columns (1) and (2) in Table 8 use the shareholding ratio of the top ten shareholders (*Top10*) and the Herfindahl index (*Herfindahl10*) as proxies for ownership concentration, respectively. In column (1), the coefficient of *Top10* × *ACR* is -0.0003 and significant at the 1% level. This indicates that Top10 significantly weakens the positive effect of *ACR* on *PII*. In column (2), we conduct a robustness test using *Herfindahl10*; the coefficient of *Herfindahl10* × *ACR* is -0.031 and significantly negative at the 5% level, with conclusions remaining consistent. Both results are consistent with the monitoring prediction developed in Section 2.3 Rather than forming insider alliances with management through private communication channels to sacrifice disclosure quality (Boone & White, 2015), concentrated owners act as active monitors. The more concentrated the ownership, the stronger this monitoring power, thereby more effectively constraining management's strategic response to climate risk attention.

6. 2. The Role of Audit Reputation

Recent research indicates that auditors often fail to detect material weaknesses in information disclosures when clients encounter negative ESG events (Aobdia & Yoon 2025). We test the prediction that audit reputation amplifies the positive association between *ACR* and *PII*, using auditor industry expertise (*MSA*) and audit fees (*AuditFee*).

Table 8 column (3) shows the coefficient on *MSA* × *ACR* as 0.153 significant at the 1% level. Superior expertise amplifies the link between *ACR* and *PII*. Column (4) uses *AuditFee* and shows *AuditFee* × *ACR* at 0.006 significant at the 5% level. These results are consistent with the prediction developed in Section 2.3. High-quality audits provide managers with reputational cover in climate risk areas where verification proves difficult, facilitating rather than constraining strategic information management (Aobdia & Yoon, 2025). This finding complements Lamoreaux et al. (2025) who view auditors as reducers of information asymmetry. In this context, however, audit reputation functions as a legitimacy shield that enables opacity rather than curbing it. The main effect of ACR turns negative and significant in columns (3) and (4), suggesting that firms with low audit resources face greater market scrutiny and compensate by improving transparency to counter perceived risks.

6. 3. Extended Analysis: Ownership, Auditor Choice, and Market Monitoring

6. 3. 1. Deepening Internal Governance

We extend the internal governance analysis to include control rights management incentives minority shareholder monitoring and management stability. Table 9 reports the results.

In columns (1) and (3), the interaction terms *Mshare* × *ACR* for management shareholding ratio (*Mshare*) and *STMT* × *ACR* for top management team stability (*STMT*) are both insignificant. This indicates that mechanisms aimed at alleviating agency conflicts through interest alignment (Jensen & Meckling, 1976) or maintaining governance continuity fail to effectively curb management's strategic behavior in response to climate risk attention. The results lean more toward supporting the entrenchment perspective (Gibbons & Murphy, 1992), suggesting that these internal governance tools may falter when addressing novel and complex non-financial risks. In column (2), the coefficient of *Holders* × *ACR* is significantly positive, indicating that more dispersed ownership strengthens the positive effect of *ACR* on *PII*. This result

complements the monitoring effect of ownership concentration in Section 6.1; dispersed ownership exacerbates free-rider problems, creating a monitoring vacuum that provides space for management's strategic information management.

6. 3. 2. Deepening External Audit

The findings above suggest that high audit reputation may serve as a legitimacy shield. An important follow-up question is whether other features of the audit process and firms' audit choice behaviors also contain important information.

In columns (1) and (2) of Table 10, the interaction terms for audit report lag (*AudLag*) and auditor change (*Change*) are both insignificant, indicating that these variables primarily capture operational or tenure factors rather than strategic adjustments. In column (3), the coefficient of the interaction term for upgrading auditor change (*UpChange*) is significantly negative, indicating that upgrading auditors weakens the positive effect of *ACR* on *PII*. While this result appears to contrast with the shield effect documented in Section 6.2, it also reveals the complex dynamics of audit choice. One possible explanation is that upgrading auditors may stem from regulatory requirements or predecessor resignation rather than pure firm initiative; the unfamiliarity effect of new auditors promotes stricter scrutiny (DeAngelo, 1981) or mitigates potential risks of predecessor complacency, thereby indirectly activating the disciplinary function of auditing.

6. 3. 3. The Failure of Broad External Monitoring

Beyond internal governance and audit reputation mechanisms, this section explores the effectiveness of external market monitoring; the results are detailed in Appendix D. The evidence suggests that broad external monitoring mechanisms tend to be ineffective, while management exploits specific strategic positions and weak links in the information environment to amplify opportunistic behavior.

Specifically, institutional investor holdings fail to curb management's opportunism. However, when the firm itself holds shares in financial institutions, the positive effect

of *ACR* on *PII* is significantly amplified. This implies that what matters is not passive external shareholding monitoring but the strategic financial connections actively established by the firm. Such connections may reduce the expected costs of management's strategic behavior. Management may anticipate more stable credit support through these financial ties in the face of climate-related negative shocks, thereby weakening market discipline constraints for maintaining high transparency.

Second, analyst coverage fails to effectively moderate management's behavior, indicating that the quantity of monitoring does not equate to quality. However, in firms with higher analyst earnings forecast errors—those with greater uncertainty in the information environment—the positive association between *ACR* and *PII* is significantly amplified. This suggests that management does not increase private information intensity indiscriminately but selectively exploits informational weaknesses, strengthening strategic information management precisely when the market already struggles to assess firm value accurately.

7. Conclusion and Discussion

This paper examines how managerial attention to climate risk shapes the corporate information environment, using Chinese A-share listed firms from 2003 to 2023. We find that firms with more climate-risk-related language in annual reports exhibit higher private information intensity. These findings are robust to both an interaction-based instrumental variable approach and a DDD design based on the 2012 Green Credit Guidelines, suggesting that regulatory pressure can sometimes trigger strategic information management among managers already attentive to climate risk. Governance mechanisms show mixed effects: concentrated ownership weakens this association, reflecting the monitoring role of large shareholders, while higher audit reputation strengthens it, implying that managers may leverage audit reputation to enhance legitimacy in areas where climate verification is limited. Broader external monitoring mechanisms have limited impact. Overall, greater risk awareness does not automatically lead to more transparent disclosure; climate risk can also activate

behavioral incentives that reduce public information quality.

The results have important implications for practice and policy. Broad environmental regulations may have unintended effects on firms with managers highly attentive to climate risk, highlighting the need for governance mechanisms that address micro-level managerial behavior. Board-level climate risk management committees can help ensure that regulatory pressure translates into substantive action. Their roles may include overseeing risk assessments, reviewing disclosures for genuine engagement, formalizing decision-making, and incorporating climate expertise to enhance oversight and accountability.

Future research could explore how managerial attention to climate risk interacts with organizational culture, leadership values, and professional norms to shape disclosure behavior. Comparative studies across institutional settings could assess the generalizability of these patterns, while in-depth case studies and mixed-method approaches may shed light on the mechanisms through which attention translates into either strategic concealment or responsible climate communication. Such work will provide a deeper understanding of how governance and managerial incentives can foster transparent and effective climate risk disclosure.

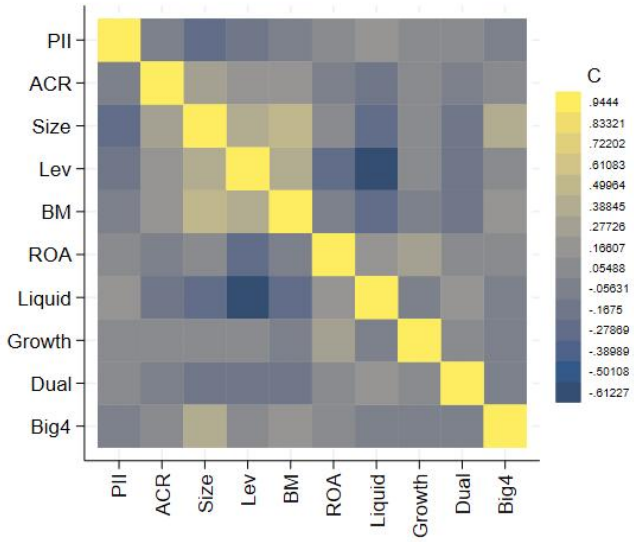


Fig. 1 The correlation between variables

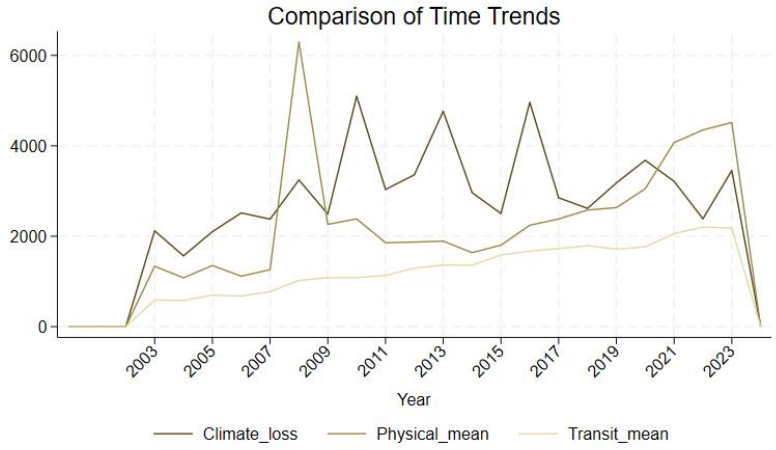


Fig. 2 Comparison of time trends

Note: Physical risk frequencies peak during major events like China's 2008 extreme cold disaster, 2010 drought-flood extremes with heatwaves, and 2016 severe floods and typhoons, validating the indicator's sensitivity to physical threats. Transition risk turning points coincide with the 2015 Paris Agreement and 2021 dual-carbon policy implementation plus national carbon market launch, confirming its capture of policy-driven shifts. Notably, physical mentions surged in 2015 and 2021 annual reports, underscoring how global low-carbon imperatives amplify perceived immediate physical urgencies. Collectively, these patterns affirm the indicator's efficacy in gauging managerial climate risk attention.

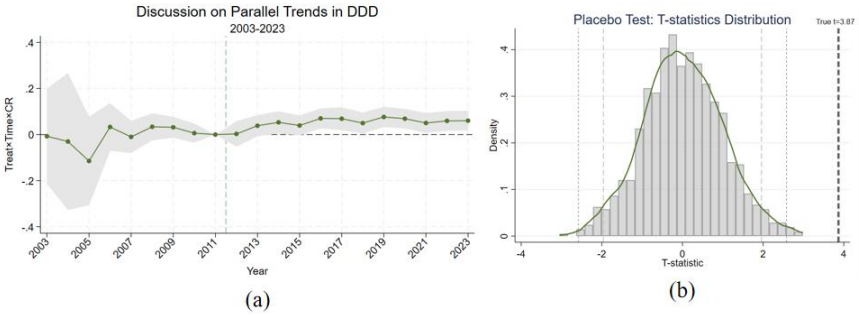


Fig. 3 Event study

Table 1 Descriptive statistics

VarName	Obs	Mean	Median	SD	Min	Max
PII	25520	0.036	0.015	0.060	0.000	0.446
ACR	25520	0.167	0.108	0.188	0.007	1.086
Size	25520	22.166	21.964	1.336	15.577	28.697
Lev	25520	0.439	0.436	0.204	0.059	0.898
BM	25520	0.632	0.634	0.247	0.112	1.182
ROA	25520	0.036	0.036	0.076	-1.542	1.285
Liquid	25520	2.287	1.592	2.166	0.245	13.383
Growth	25520	0.165	0.102	0.417	-0.592	2.632
Dual	25520	0.265	0.000	0.441	0.000	1.000
Big4	25520	0.063	0.000	0.242	0.000	1.000

Table 2 Variable validity check(a)

	(1)	(2)	(3)	(4)
	REM	*DA*	*EffSpread*	*ESG_uncertainty*
PII	0.084***	0.011	0.830***	0.140*
	(2.61)	(1.21)	(5.98)	(1.87)
Size	-0.001	-0.001	0.034***	0.009***
	(-0.57)	(-1.25)	(8.52)	(4.71)
Lev	0.081***	0.035***	0.018	-0.028*
	(6.64)	(6.61)	(0.64)	(-1.94)
BM	-0.080***	-0.026***	-0.275***	-0.012
	(-6.80)	(-8.30)	(-10.11)	(-1.27)
ROA	0.330***	-0.133***	0.351***	0.069***
	(9.54)	(-7.95)	(5.61)	(2.71)
Liquid	0.002*	0.001***	0.008**	0.002
	(1.83)	(4.63)	(2.12)	(1.14)
Growth	0.059***	0.022***	0.028***	-0.007
	(12.46)	(13.43)	(5.55)	(-1.45)
Dual	0.009**	-0.000	0.022***	0.003
	(2.58)	(-0.15)	(3.63)	(0.80)
Big4	-0.000	-0.005***	0.008	-0.023***
	(-0.05)	(-3.35)	(0.42)	(-3.78)
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
N	21398	22994	25520	7689
r2_a	0.112	0.108	0.077	0.053

Note: *REM* denotes the absolute value of real earnings management; *DA* represents the absolute value of discretionary accruals; *EffSpread* is the effective spread; *ESG_uncertainty* measures divergence in ESG ratings across institutions. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3 Variable validity check(b)

rank	Industry	*ACR*_mean	N
1	Ecological Protection and Environment Governance Industry	0.770	218
2	Gas Production and Supply Industry	0.662	127
3	Science and Technology Promotion and Application Services Industry	0.628	5
4	Comprehensive Utilization of Waste Resources Industry	0.541	21
5	Electric Power and Heat Production and Supply Industry	0.513	608
6	Petroleum and Natural Gas Extraction Industry	0.413	45
7	Water Production and Supply Industry	0.382	115
8	Coal Mining and Washing Industry	0.372	139
9	Non-metallic Ore Mining and Dressing Industry	0.291	4
10	Mining Professional and Auxiliary Activities	0.262	97
11	Electrical Machinery and Equipment Manufacturing	0.262	1565
12	Professional Technical Services Industry	0.252	247
13	Ferrous Metal Smelting and Rolling Processing Industry	0.250	264
14	Petroleum Processing, Coking and Nuclear Fuel Processing Industry	0.227	125
15	Chemical Raw Materials and Chemical Products Manufacturing	0.220	1661

Table 4 Baseline regression

	(1) *PII*	(2) *PII*	(3) *PII*	(4) *PII*
ACR	0.005**	0.005**	0.005**	0.004*
	(2.43)	(1.99)	(2.01)	(1.95)
Size	-0.015***	-0.015***	-0.015***	-0.014***
	(-37.63)	(-21.34)	(-20.03)	(-17.34)
Lev	0.020***	0.020***	0.019***	0.019***
	(7.62)	(5.32)	(5.14)	(5.20)
BM	0.027***	0.027***	0.027***	0.026***
	(14.06)	(10.61)	(10.46)	(10.08)
ROA	0.094***	0.094***	0.094***	0.089***
	(17.95)	(12.66)	(12.60)	(11.60)
Liquid	0.004***	0.004***	0.004***	0.004***
	(19.43)	(8.11)	(8.06)	(8.23)
Growth	0.005***	0.005***	0.004***	0.004***
	(5.26)	(5.54)	(5.49)	(5.34)
Dual	0.009***	0.009***	0.009***	0.009***
	(11.06)	(7.83)	(7.83)	(7.81)
Big4	0.013***	0.013***		
	(8.27)	(6.63)		
Big3			0.012***	
			(6.95)	
Opinion				0.006***
				(3.96)
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
N	25520	25520	25520	25520
r2_a	0.182	0.182	0.182	0.180

Note: All variables in the regressions have variance inflation factors well below 10, indicating no severe multicollinearity. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5 Risk subdivision

	(1)	(2)	(3)	(4)
	PII	*PII*	*PII*	*PII*
Physical	0.615***			
	(6.00)			
Acute		0.624***		
		(3.52)		
Chronic			0.828***	
			(5.90)	
Transit				0.004*
				(1.78)
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
N	25520	25520	25520	25520
r2_a	0.184	0.183	0.184	0.182

Note: *Physical* represents physical risk, *Acute* and *Chronic* represent acute and chronic risks, respectively, and *Transit* represents transition risk. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6 Robustness test

	2SLS		Replace variables	
	First stage	Second stage	Replace *ACR*	Replace *PII*
	ACR	*PII*	*PII*	*PII _r*
HSY	0.020***			
	(31.22)			
ACRiv		0.012**		
		(2.54)		
Typhoon			0.001*	
			(1.91)	
ACR				0.017***
				(2.90)
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
N	25523	25523	12952	25528
r2_a	0.444	0.183	0.158	0.129

Note: Due to typhoons primarily affecting China's southeastern coastal regions, the sample size for typhoon paths is reduced compared to the baseline regression. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7 DDD test

	(1)	(2)	(3)
	PII	*PII*	*PII*
Treat	0.002	0.002	0.003
	(0.48)	(0.54)	(0.86)
Post	0.000	0.000	0.000
	(.)	(.)	(.)
Treat×Post	-0.009***	-0.009**	-0.010***
	(-2.70)	(-2.48)	(-2.85)
ACR	0.007	0.007	0.006
	(0.70)	(0.79)	(0.62)
Treat×ACR	-0.019	-0.019	-0.017
	(-1.35)	(-1.40)	(-1.25)
Post×ACR	-0.012	-0.012	-0.009
	(-1.19)	(-1.26)	(-0.94)
Treat×Post×ACR	0.051***	0.051***	0.047***
	(3.87)	(3.81)	(3.43)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
N	25484	25484	25484
r2_a	0.400	0.400	0.390

Note: Although some prior literature uses PSM methods, they have been criticized in frontier research for sample loss and potential manipulation of results. Based on this, this paper adopts the EBM method. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8 Mechanism Analysis (a)

	(1)	(2)	(3)	(4)
	PII	*PII*	*PII*	*PII*
Top10	0.001***			
	(30.21)			
ACR	0.022***	0.010***	-0.006*	-0.085*
	(3.71)	(2.90)	(-1.68)	(-1.93)
Top10×ACR	-0.000***			
	(-3.07)			
Herfindahl10		0.061***		
		(11.99)		
Herfindahl10×ACR		-0.031**		
		(-1.98)		
MSA			-0.012	
			(-1.27)	
MSA×ACR			0.153***	
			(3.75)	
AuditFee				-0.001
				(-1.02)
AuditFee×ACR				0.006**
				(2.05)
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
N	25528	25528	25528	24908
r2_a	0.233	0.193	0.184	0.183

Note: In the table, *Top10* sums the top ten shareholders' ownership ratios. *Herfindahl10* sums the cubes of the top ten shareholders' ownership ratios. *MSA* equals 1 if the auditor has industry expertise and 0 otherwise. *AuditFee* is the natural logarithm of annual audit fees. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 9 Mechanism Analysis (b)

	(1)	(2)	(3)
	PII	*PII*	*PII*
Mshare	0.000***		
	(8.14)		
ACR	0.004	-0.082**	0.002
	(1.15)	(-2.18)	(0.32)
Mshare×ACR	0.000		
	(0.28)		
Holders		-0.034***	
		(-43.30)	
Holders×ACR		0.008**	
		(2.38)	
STMT			0.004
			(1.45)
STMT×ACR			0.003
			(0.35)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
N	24735	25527	25258
r2_a	0.195	0.295	0.184

Note: *Mshare* sums management shareholding ratios. *Holders* is the natural logarithm of total shareholders. *STMT* equals 1 for top management team changes in the year and 0 otherwise. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 10 Mechanism Analysis (c)

	(1)	(2)	(3)
	PII	*PII*	*PII*
AudLag	-0.004		
	(-1.42)		
ACR	-0.053	0.005**	0.005**
	(-1.15)	(2.25)	(2.16)
AudLag×ACR	0.013		
	(1.26)		
Change		-0.002	
		(-1.16)	
Change×ACR		-0.002	
		(-0.34)	
UpChange			-0.002
			(-0.70)
UpChange×ACR			-0.012*
			(-1.86)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
N	25413	25528	25528
r2_a	0.181	0.182	0.182

Note: *AudLag* is the natural logarithm of the number of days delayed in the audit report. *Change* is 1 if the firm changes auditors, otherwise 0. *UpChange* is 1 if the firm upgrades to a higher-level auditor, such as from a domestic top eight to an international Big Four, otherwise 0. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendix A Climate Risk Dictionary

Table A1: Dictionary and Risk Classification

Panel A: Word Set Construction	
（1）Seed word	
Source	Li et al., (2024) working paper, National Meteorological Science Data Center, annual reports of listed firms
Word Set	energy saving, energy, clean, ecology, environment, transition, solar energy, upgrade, recycling, utilization rate, nuclear power, wind power, natural gas, efficiency improvement, fuel oil, efficiency, regeneration, emission reduction, environmental protection, green, low carbon, consumption reduction, fuel, water saving, photovoltaic, high efficiency, renovation, fuel consumption, electricity consumption, energy consumption, efficacy, intensification, disaster, earthquake, typhoon, tsunami, drought and flood, extreme, severe, waterlogging, strong wind, sand dust, hurricane, frost, flood disaster, storm, debris flow, landslide, freezing rain, snow disaster, drought disaster, flood and waterlogging, heavy rain, tornado, hail, flood catastrophe, rain and snow, freezing, blizzard, freeze injury, drought, drought condition, heavy rainfall, flood, severe cold, wind and sand, climate, weather, humidity, water temperature, temperature drop, cold, air temperature, rainfall, temperature, rainwater, rainy season, rainfall condition, precipitation, overcast and rain, rainy, extreme cold, winter, flood season, high humidity, water condition, water level, sunlight, water shortage, high cold, cold wave,

	settlement, groundwater, flood situation, surface, water storage
(2) Expanded Word Set	
Source	Expanded using word vector model to identify similar terms. Manually excluded terms that do not indicate climate risk (e.g., terms similar to 'electric energy' such as 'standard condition', 'meter box', 'pressure regulation') and terms that introduce noise in annual reports (e.g., terms similar to 'transition' such as 'upgrade', 'pace', 'strengthen').
Word Set	energy saving, energy, clean, ecology, environment, transition, solar energy, upgrade, recycling, utilization rate, nuclear power, wind power, natural gas, efficiency improvement, fuel oil, efficiency, regeneration, emission reduction, environmental protection, green, low carbon, consumption reduction, fuel, water saving, photovoltaic, high efficiency, renovation, fuel consumption, electricity consumption, energy consumption, wind power, photovoltaic, efficacy, intensification, disaster, earthquake, typhoon, tsunami, drought and flood, extreme, severe, waterlogging, strong wind, sand dust, hurricane, frost, flood disaster, storm, debris flow, landslide, freezing rain, snow disaster, drought disaster, flood and waterlogging, heavy rain, tornado, hail, flood catastrophe, rain and snow, freezing, blizzard, freeze injury, drought, drought condition, heavy rainfall, flood, severe cold, wind and sand, climate, weather, humidity, water temperature, temperature drop, cold, air temperature, rainfall, temperature, rainwater, rainy season, rainfall condition,

	precipitation, overcast and rain, rainy, extreme cold, winter, flood season, high humidity, water condition, water level, sunlight, water shortage, high cold, cold wave, settlement, groundwater, flood situation, surface, water storage
Panel B: Word Set Categorized by Risk Type	
Risk Category	Word Set
Physical Risk	
Acute Risk	disaster, earthquake, typhoon, tsunami, drought and flood, extreme, severe, waterlogging, strong wind, sand dust, hurricane, frost, flood disaster, storm, debris flow, landslide, freezing rain, snow disaster, drought disaster, flood and waterlogging, heavy rain, tornado, hail, flood catastrophe, rain and snow, freezing, blizzard, freeze injury, drought, drought condition, heavy rainfall, flood, severe cold, wind and sand
Chronic Risk	climate, weather, humidity, water temperature, temperature drop, cold, air temperature, rainfall, temperature, rainwater, rainy season, rainfall condition, precipitation, overcast and rain, rainy, extreme cold, winter, flood season, high humidity, water condition, water level, sunlight, water shortage, high cold, cold wave, settlement, groundwater, flood situation, surface, water storage
Transition Risk	energy saving, energy, clean, ecology, environment, transition, solar energy, upgrade, recycling, utilization rate, nuclear power, wind power, natural gas, efficiency improvement, fuel oil, efficiency, regeneration, emission reduction, environmental protection, green, low carbon, consumption reduction, fuel, water saving, photovoltaic, high efficiency, renovation, fuel consumption, electricity

	consumption, energy consumption, efficacy, intensification

Note: This word list draws on the research of Du et al. (2023). Due to the differences in semantics between Chinese and English, interested readers can contact the author of this article to obtain the original Chinese version of the word list.

Appendix B Calculation of the CPRI

As shown in Model (1), $LTD_{i,n}$ represents the number of extreme low-temperature days at station i in year n, constructed by weighting 365 daily (d) low-temperature indicators (LT). The calculation method for LT is shown in Model (2), where T_i^{10} is the historical 10th percentile value of the daily average temperature at station i. Similarly, $HTD_{i,n}$ denotes the number of extreme high-temperature days at station i in year n, and its calculation method is the same as that for LTD, as shown in Models (3) and (4). Furthermore, the system also includes the number of extreme rainfall days and extreme drought days, with calculation methods similar to those for LTD and HTD, as shown in Models (5) and (7). Slight differences are that R_i^{95} in Model (6) represents the 95th percentile of rainfall at station i, and H_i^5 in Model (8) represents the historical 5th percentile of daily humidity at station i. After calculating these indicators, the geographical locations of the stations are used to map them to the corresponding prefecture-level cities, computing the extreme indicator values for each city. Subsequently, the LTD, HTD, ERD, and EDD are aggregated into the $CPRI$ indicator for city i using a simple weighted average method.

$$LTD_{i,n}=\sum_{t=1}^{365} LT_{i,t,d} \tag{1}$$

$$LT_{i,t,d}=\begin{cases} 1 \ if \ T_{i,t,d}<T_i^{10} \\ 0 \ if \ T_{i,t,d}\geq T_i^{10} \end{cases} \tag{2}$$

$$HTD_{i,n}=\sum_{t=1}^{365} HT_{i,n,t} \tag{3}$$

$$HT_{i,t,d}=\begin{cases} 1 \ if \ T_{i,t,d}>T_i^{90} \\ 0 \ if \ T_{i,t,d}\leq T_i^{90} \end{cases} \tag{4}$$

$$ERD_{i,n}=\sum_{t=1}^{365} ER_{i,n,t} \tag{5}$$

$$ER_{i,t,d}=\begin{cases} 1 \ if \ R_{i,t,d}>R_i^{95} \\ 0 \ if \ R_{i,t,d}\leq R_i^{95} \end{cases} \tag{6}$$

$$EDD_{i,n}=\sum_{t=1}^{365} ED_{i,n,t} \tag{7}$$

$$ED_{i,t,d}=\begin{cases} 1 \ if \ H_{i,t,d}<H_i^{5} \\ 0 \ if \ H_{i,t,d}\geq H_i^{5} \end{cases} \tag{8}$$

Appendix C Model Adjustments

Table C1: Alternative Fixed Effects and Clustering

	(1)	(2)	(3)
	IO	*IO*	*IO*
PCR	0.008*	0.005**	0.008*
	(1.81)	(2.06)	(1.75)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
N	25476	25520	25476
r2_a	0.399	0.182	0.399

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendix D The Role of External Market Monitoring

Table D1 Additional Boundary Conditions

	(1)	(2)	(3)	(4)
	PII	*PII*	*PII*	*PII*
INST	0.000***			
	(10.16)			
ACR	0.010	0.004	0.003	-0.000
	(1.55)	(1.60)	(0.95)	(-0.08)
INST×ACR	-0.000			
	(-0.98)			
FinInst		-0.004***		
		(-3.07)		
FinInst×ACR		0.019***		
		(2.63)		
AnaAttention			0.001***	
			(6.50)	
AnaAttention×ACR			-0.000	
			(-0.43)	
FERR				-0.001***
				(-3.15)
FERR×ACR				0.002**
				(2.03)
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes
N	25528	25528	16922	16618
r2_a	0.194	0.182	0.191	0.180

Note：*INST* is the total shareholding proportion of institutional investors in the company.

FinInst equals 1 if the company holds shares in other financial institutions, and 0 otherwise. *AnaAttention* is the number of analyst teams covering the firm in a given year. *FERR* is the average error between analyst earnings forecasts and the actual values. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

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