Forecasting Under Climate Uncertainty: How Extreme Weather Shapes Managerial Disclosure Behavior

Xiaolin Xue

School of Economics and Finance, Xi'an Jiaotong University, Shaanxi, China

xiaolin_xue@163.com

Zeyong Cao*

School of Management, Xi'an Jiaotong University, Shaanxi, China

corecao@stu.xjtu.edu.cn

***Corresponding author: Zeyong Cao**

E-mail address: corecao@stu.xjtu.edu.cn; Full postal address: Xi'an Jiaotong University, NO.28 Xianning West Road, Xi'an, Shaanxi, 710049, China; Phone numbers: +86-15129031729

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Abstract: This study investigates how managers adjust their earnings forecast practices in response to the increased corporate opacity induced by extreme weather. Using typhoons as a proxy for extreme weather, we find that firms located in neighborhood areas issue more frequent, precise, and accurate earnings forecasts following such events. Further analysis suggests that these effects are not driven by psychological biases or strategic disclosure incentives, but rather by managers' motivations to reduce heightened information asymmetry caused by extreme weather. Heterogeneity analyses reveal that the effect is more pronounced among firms with younger executives, higher levels of fixed assets, and non-state ownership. In addition, we find that firms located in disaster zones issue fewer, less precise, and less accurate forecasts following typhoon events, suggesting that the more severe physical damage in these areas hampers managers' ability to collect information and evaluate future performance. Overall, this study contributes to our understanding of the link between extreme weather and managerial disclosure, offering practical implications for regulators and investors concerned with the information environment under climate risk.

Keywords: Extreme weather; management earnings forecasts; climate risk; managerial disclosure; information asymmetry

1. Introduction

Amid growing concerns about climate change, the impacts of extreme weather events have become an increasingly prominent focus in academic research. Existing studies have examined the impact of extreme weather on firm performance, corporate real activities, and capital market outcomes (Bird et al., 2023; Addoum et al., 2023). With regard to financial reporting quality and managerial disclosure, prior research finds that extreme weather events can lead to increased earnings management, financial fraud, and ESG disclosures, driven by incentives to mask poor performance and shifts in managerial perceptions of climate risk (Ding et al., 2021; Dessaint and Matray, 2017). However, despite the central role of management earnings forecasts as a key component of voluntary disclosure and a vital source of firm-specific information for capital markets (Chen et al., 2021), little is known about how extreme weather influences such forecasts. This study addresses this gap by examining the impact of extreme weather on managerial earnings forecast practices.

The relationship between extreme weather and management earnings forecasts is not straightforward. Extreme weather can exacerbate corporate opacity, obstruct information gathering and performance evaluation, amplify strategic disclosure incentives, and trigger psychological biases—all of which may influence managerial forecasting decisions (Kong et al., 2021; Huang et al., 2022). According to the voluntary disclosure literature, increased information asymmetry motivates managers to disclose more firm-specific information to reduce adverse selection, enhance stock liquidity, and lower the cost of external financing (Balakrishnan et al., 2014). However, such disclosure is also constrained by costs, including information processing difficulties, litigation risks, and reputational concerns, which may limit the extent of voluntary disclosure (Nagar et al., 2019; Kim et al., 2016). Strategic disclosure theory further suggests that managers often withhold bad news while selectively releasing good news to shape investor expectations and dampen negative market reactions (Chen et al., 2024). Additionally, behavioral accounting research indicates that managerial forecasts may be biased due to psychological factors such as mood and risk aversion (Alok et al., 2020). Taken together, the effect of extreme weather on the frequency and characteristics of management earnings forecasts is ultimately an empirical question.

This study examines this question using typhoon events and data from the Chinese capital market. Given our objective to investigate whether managers respond to the exacerbation of corporate opacity caused by extreme weather through increased disclosure of firm-specific information, this setting provides three key advantages. First, due to their highly destructive nature and the difficulty in predicting and assessing their occurrence and impact, typhoons have been widely used as a setting in research on salient risk, climate risk, and uncertainty (Dessaint and Matray, 2017; Binz, 2022). Second, the impact of a typhoon exhibits spatial attenuation, with the most severe effects concentrated at the landfall location and gradually diminishing with increasing distance from the point of landfall. This allows us to gauge the degree to which firms are affected by typhoon shocks based on their geographic proximity to the landfall location, and to distinguish between informed and uninformed managers. Third, typhoons in China predominantly occur between July and October, while 99.5 percent of management earnings forecasts of Chinese firms are issued after late October. This pattern allows us to examine the effect of typhoons on forecasts issued within the same year. Given that the underlying mechanism of the managerial disclosure incentive is to reduce information asymmetry by voluntarily providing additional firm-specific information, focusing on a narrow event window mitigates the confounding influence of other information entering the market and better identifies the role of management forecasts as a key source of information.

Following Dessaint and Matray (2017) and Kong et al. (2021), we classify regions into three categories based on their proximity to typhoon landfall sites: disaster zones, neighborhood areas, and other areas. Using a sample from 2010 to 2021, we find that firms located in the neighborhood areas issue more frequent earnings forecasts, with improved precision and accuracy following typhoon events. These results remain robust after controlling for other natural disasters and conducting a propensity score matching (PSM) analysis.

We further conduct mechanism analyses. We argue that the mechanism underlying the baseline results is that extreme weather heightens information asymmetry, prompting managers to issue more frequent and higher-quality forecasts in an effort to enhance market transparency. Using bid-ask spreads and illiquidity measures as proxies for market opacity (Nagar et al., 2019; Amihud, 2002), we find empirical support for this mechanism.

An alternative explanation for the above findings may lie in managers' strategic disclosure motives. Following typhoon events, managers may have stronger incentives to issue more precise "good news" forecasts in order to influence investors' expectations about the firm's future earnings. As a result, the observed positive relationship between extreme weather and the frequency and precision of forecasts in our baseline regressions may reflect strategic disclosure behavior rather than a genuine intention to enhance corporate transparency. Moreover, managers affected by extreme weather may overreact to risk and issue pessimistically biased forecasts. To address these concerns, we further examine the impact of extreme weather on forecast bias and the nature of the news conveyed. The results show that extreme weather has no significant effect on either forecast bias or the likelihood of "good news" forecasts. These findings help rule out alternative explanations such as strategic motives or psychological biases, lending support to our main interpretation.

Heterogeneity tests show that the effects are more pronounced in firms with younger executives, greater fixed assets, and non-state ownership. These findings suggest that career concerns, climate risk exposure, and financing constraints amplify managers' disclosure incentives.

Finally, we examine how firms located in disaster zones adjust their earnings forecast decisions following typhoon events. As these areas experience direct shocks from typhoons, their communication and transportation infrastructure are more likely to be disrupted. This hampers the collection of relevant information, making it more difficult to assess firms' prospects and issue earnings forecasts. Consistent with this expectation, we find that firms in disaster zones issue fewer earnings forecasts, and these forecasts tend to be less precise and less accurate after typhoon events. Moreover, we find no evidence that these firms are more likely to issue pessimistically biased or "good news" forecasts. These findings provide further insight into the impact of extreme weather on management earnings forecasts.

This study makes several contributions to the existing literature. First, it enriches the research on the impact of extreme weather on corporate activities, particularly in the areas of financial reporting quality and voluntary disclosure. In the context of real losses, prior studies have shown that firms exposed to extreme weather are more likely to engage in earnings management and financial fraud to obscure poor performance (Ding et al., 2021; Chen et al., 2024). In terms of managerial perceptions of climate risk, extreme weather has been found to increase the disclosure of ESG and climate-related information (Huang et al., 2022; Griffin et al., 2023; Dessaint and Matray, 2017). This study contributes a novel angle by exploring how uncertainty induced by extreme weather influences managerial earnings forecast behavior, thereby extending the literature on extreme weather and corporate disclosure.

Second, this study contributes to the literature on the determinants of management earnings forecasts, particularly the influence of uncertainty and exogenous shocks. Prior research has shown that economic policy and political uncertainty affect voluntary managerial disclosures, including earnings forecast decisions (Nagar et al., 2019; Bird et al., 2023). Other studies find that unexpected events—such as terrorist attacks and the COVID-19 pandemic—can shape disclosure behavior by altering managerial sentiment and incentives (Chen et al., 2022; Chen et al., 2021). Building on this line of inquiry, our study shows that extreme weather events influence managerial forecasting behavior by heightening investor uncertainty about firms' future performance. These findings deepen our understanding of how uncertainty and external shocks shape managerial decisions on earnings forecasts.

Third, this paper contributes to the literature on how extreme weather shapes the corporate information environment, which is jointly influenced by managerial disclosure, private information acquisition, and intermediaries such as analysts and the media. Prior studies have shown that extreme weather affects investor trading behavior (Alok et al., 2020; Huynh and Xia, 2023), analyst forecasts (Kong et al., 2021; Addoum et al., 2023), and managerial misconduct (Ding et al., 2021; Chen et al., 2024), all suggesting a decline in market transparency. Focusing on management earnings forecasts as a key source of firm-specific information, this study finds that firms located in neighborhood areas respond to heightened uncertainty induced by extreme weather by increasing both the frequency and quality of earnings forecasts. In contrast, firms in disaster zones experience a further deterioration in their information environment, characterized by a reduction in both the quantity and quality of forecasts. These findings provide important insights into the dynamics of the corporate information environment under climate risks.

2. Literature review and hypothesis development

2.1. The impacts of extreme weather

This paper provides a review of the existing literature on how extreme weather events influence firm performance, managerial voluntary disclosures, financial reporting practices, and the overall corporate information environment.

Changes in firm performance following extreme weather events stem from both direct operational disruptions and managerial responses. The empirical evidence, however, remains mixed. Some studies find that natural disasters adversely affect firm outcomes (Hsu et al., 2018; Pankratz et al., 2023). Additionally, Addoum et al. (2023) report that extreme temperatures impact firm performance—positively or negatively—in more than 40% of industries. In contrast, other studies document no significant effects. For example, Kong et al. (2021) find that earthquakes have no measurable impact on the profitability or stock returns of nearby firms, while Addoum et al.

(2020) report no clear relationship between temperature shocks and firms' sales, productivity, or profitability. Treating extreme weather as an exogenous shock to uncertainty, Binz (2022) shows that managers respond by reducing revenues and expenditures, ultimately improving short-term profitability.

Beyond operating performance, extreme weather events also significantly affect firms' disclosure behavior and financial reporting quality. Prior research shows that climate risk is associated with heightened earnings management, as firms attempt to smooth earnings and mitigate investor concerns (Ding et al., 2021). Additionally, exposure to climate risk increases the likelihood of corporate fraud, driven by intensified pressures related to performance, financing, and shareholder expectations (Chen et al., 2024). Extreme weather events also encourage firms to enhance their ESG disclosures, especially among firms located near disaster areas, as managers seek to respond to heightened risk salience and investor demand for transparency (Huang et al., 2022). Moreover, studies show that firms often include more voluntary risk-related disclosures in their filings following natural disasters, although such disclosures remain relatively rare and may even lower firm valuation (Griffin et al., 2023; Dessaint and Matray, 2017). Finally, climate vulnerability has been linked to increased stock price crash risk due to aggressive bad news hoarding and weakened fundamentals (Ni et al., 2022).

Extreme weather further influences the behavior of key information intermediaries—such as investors, auditors, and analysts—who, together with managers, shape the corporate information environment. Alok et al. (2020) and Huynh and Xia (2023) find that investors tend to overreact to extreme weather events, resulting in declines in bond and equity valuations for affected firms. Yu et al. (2023) show that auditors perceive higher audit risk in regions exposed to extreme weather and respond by charging increased audit fees. Kong et al. (2021) document a decline in analyst optimism in earnings forecasts following climate-related disasters. Addoum et al. (2023) find that although analysts often fail to react immediately to temperature shocks, they eventually incorporate these effects into their quarterly forecasts across multiple industries.

In sum, extreme weather events heighten investor uncertainty about firms' future performance, either directly through operational disruptions or indirectly through managerial responses. Moreover, the corporate information environment may further deteriorate due to behavioral biases from capital market participants in the wake of climate shocks.

2.2. Determinants of management earnings forecasts

Prior studies suggest that the costs and benefits of voluntary disclosure, strategic disclosure incentives, and managerial characteristics—including behavioral biases—jointly influence both the likelihood of issuing management earnings forecasts and the features of those forecasts.

Management earnings forecasts are a central component of voluntary disclosure. Both theoretical and empirical research indicate that managers assess the trade-offs between the costs and benefits of disclosure when deciding whether and how to issue earnings forecasts. The potential benefits include reducing information asymmetry, improving stock liquidity, and lowering the cost of capital (Verrecchia, 1983; Balakrishnan et al., 2014; Lang and Maffett, 2011). Consistent with this view, prior studies find that conditions associated with increased information opacity and heightened demand for public information—such as economic and political uncertainty—are often associated with more disclosure (Nagar et al., 2019; Bird et al., 2023).

However, disclosure also entails significant costs. The process of gathering and analyzing the necessary information to make accurate earnings forecasts can be resource-intensive. Moreover, inaccurate or misleading forecasts may expose managers to litigation and reputational risks (Verrecchia, 2001; Addoum et al., 2023). Kim et al. (2016) document a negative relationship between economic uncertainty and the likelihood of issuing management forecasts, attributing this to the increased cost of disclosure under uncertain conditions.

Research further indicates that managers often engage in strategic disclosure behavior. Specifically, they tend to release good news while withholding bad news (Kothari et al., 2009), especially when investors are uncertain about whether managers possess material private information. In such cases, managers may strategically issue optimistic forecasts to shape investor expectations. For instance, Chen et al. (2024) find that managers are more likely to issue optimistic and precise earnings forecasts in an attempt to obscure the negative consequences of climate risk exposure and maintain favorable stock valuations.

In addition, managerial behavioral biases can significantly influence disclosure decisions, particularly the tone and directional bias of earnings forecasts. Chen et al. (2022) find that managers who have experienced terrorist attacks are more likely to issue pessimistic forecasts. Similarly, Dessaint and Matray (2017) and Kong et al. (2021) show that managers and analysts affected by natural disasters tend to overestimate climate-related risks, leading to increased disclosure of risk-related concerns in financial reports and the issuance of less optimistic analyst forecasts.

2.3. Hypothesis development

Managers may be more inclined to issue earnings forecasts following extreme weather events due to heightened external uncertainty. Natural disasters create significant ambiguity surrounding a firm's operations and future performance—uncertainty that external investors are often poorly equipped to assess (Ding et al., 2021; Alok et al., 2020). In contrast, managers possess superior information regarding the consequences of such events.

This dynamic is particularly relevant in the context of typhoons, a highly disruptive form of extreme weather common in coastal and East Asian economies. Typhoons can cause immediate and localized damage to infrastructure, production capacity, and supply chains, while simultaneously raising investor concerns about firm resilience and future earnings potential (Chen et al., 2024; Gao et al., 2022). Such events increase corporate opacity and amplify demand for public information. In response, managers may choose to issue earnings forecasts to enhance firm transparency, reduce information asymmetry, improve liquidity, and ultimately lower the cost of capital (Balakrishnan et al., 2014; Lang and Maffett, 2011).

However, disclosure is not always guaranteed. Managers may withhold earnings forecasts if they lack timely or reliable internal data. Typhoons often disrupt business operations and communication channels, making it difficult for managers to promptly assess the financial consequences. Under these conditions, the costs of issuing potentially inaccurate or misleading disclosures—including reputational damage and litigation risk—may outweigh the potential benefits (Verrecchia, 1983; Kim et al., 2016).

Geographic proximity to the disaster site plays a crucial role in shaping managerial information advantages. Firms located in disaster zones typically face more severe disruptions, which limit their ability to assess future performance with accuracy. In contrast, “neighborhood firms”—those situated in adjacent but less affected areas—experience fewer direct damages and are more likely to retain usable internal information about risk exposure and recovery prospects. Consequently, managers of neighborhood firms are better positioned to issue credible and informative earnings forecasts. This spatial variation forms the empirical basis for our focus on firms in the neighborhood area.

Beyond the decision to issue forecasts, managers also influence the content and quality of disclosures. Prior research shows that more precise and accurate forecasts convey richer information about firm fundamentals and elicit more favorable investor responses(Cheng et al., 2013). Managers with sufficient internal visibility may therefore not only be more likely to issue forecasts but may also provide higher-quality disclosures aimed at mitigating investor uncertainty and restoring market confidence.

These considerations lead to the following hypothesis:

Hypothesis: Firms in the neighborhood area issue more earnings forecasts and their forecasts are more precise and accurate after typhoon events.

However, prior literature suggests that managers may respond to extreme weather in divergent ways—either by providing more good news to influence investor expectations or by issuing more pessimistic forecasts due to behavioral biases triggered by climate shocks. These alternative or competing explanations pose potential challenges to our hypothesis. Therefore, how typhoon exposure shapes managerial forecasting behavior remains an open empirical question.

3. Data and research model

3.1. Sample and data

We employ a sample of Chinese A-share listed companies from 2010 to 2021[1], with all data sourced from the CSMAR database. Firms in the financial industry are excluded, and observations with missing values for key variables are removed. To examine the impact of extreme weather on the issuance of management earnings forecasts, we use the full sample. For analyses concerning the characteristics of such forecasts, we use a subsample comprising only firms that issue management earnings forecasts.

Our analysis focuses exclusively on voluntarily disclosed forecasts[2], excluding those that are mandatory. In instances of multiple disclosures within a forecasting period, only the initial disclosure is retained. To ensure that the forecasts follow typhoon events, we further restrict the sample to disclosures made after late October[3].

Regarding extreme weather, we focus on typhoon events with a landfall intensity classified as typhoon (TY), severe typhoon (STY), or super typhoon (SuperTY)[4]. Based on these criteria, we

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[1] We exclude the year 2020 from the sample due to the unavailability of typhoon data.

[2] China adopts a semi-mandatory management earnings forecast regime, under which firms are required to disclose forecasts under specific conditions: when net profit is negative, when earnings shift from a loss to a profit, when net profit changes by more than 50% compared to the same period in the previous year, when net assets are negative at the end of the period, or when annual operating revenue is less than 10 million yuan. In this study, we exclude earnings forecasts that fall under these mandatory disclosure requirements.

[3] All 36 typhoon events in our sample occurred between July and October. During the same period, only 0.5% of management earnings forecasts were issued before late October. Therefore, excluding forecasts issued prior to late October is unlikely to introduce significant selection bias into our analysis.

[4] According to the maximum sustained wind speed near the center, the China Meteorological Administration classifies tropical cyclones into six categories, from highest to lowest intensity: super typhoon, severe typhoon, typhoon, severe tropical storm, tropical storm, and tropical depression. Source: https://tcdata.typhoon.org.cn/dlrdqx.html

identify 36 relevant typhoon events during the sample period, with landfall locations distributed across 26 counties in six provinces[5].

3.2. Variable definitions

3.2.1. Dependent variables

In this study, we construct three dependent variables to capture different dimensions of management earnings forecast behavior: forecast issuance (*Forecast*), precision (*Precision*), and accuracy (*Accuracy*). First, *Forecast* is a binary indicator equal to 1 if a firm voluntarily issues an earnings forecast in a given year, and 0 otherwise. Second, following Cheng et al. (2013); Gong et al. (2013); Hribar and Yang (2016), we measure forecast precision as the ratio of the range between the highest and lowest forecasted net profits to the actual net profit. A lower value of *Precision* reflects a narrower forecast range, indicating greater precision. Third, we measure forecast accuracy, following Baginski et al. (2002); Hirst et al. (2008), as the absolute difference between the forecasted and actual net profits, scaled by the actual net profit. For range forecasts, we use the midpoint of the high and low forecast values as the predicted value. Accordingly, lower values of *Accuracy* indicate more accurate forecasts.

3.2.2. Independent variables

Following Dessaint and Matray (2017) and Kong et al. (2021), we identify firm exposure to typhoon events based on the geographical proximity of company headquarters to typhoon landfall sites. Prior research (Ye et al., 2020) and official data from the China Meteorological

[5] Among these provinces, Guangdong and Fujian experience the most frequent typhoon landfalls, followed by Zhejiang, Hainan, the Guangxi Zhuang Autonomous Region, and Jiangsu, in that order.

Administration[6] suggest that the impact radius of typhoons can extend up to 500 kilometers from the point of landfall. Accordingly, we classify regions into three categories: disaster zones (within 200 kilometers of landfall), neighborhood areas (between 200 and 500 kilometers), and other areas (beyond 500 kilometers).

We construct a dummy variable, *Neighbor*, which equals 1 if a firm is located in the neighborhood area in a year when at least one typhoon event occurs, and 0 otherwise. Firms located in the neighborhood area constitute the treated sample. These firms are plausibly subject to elevated uncertainty due to nearby typhoon activity, but typically do not suffer severe physical damage or major operational disruptions. As such, they provide a suitable setting for examining how managers respond to exogenous increases in information asymmetry. Firms located in other areas serve as the control group. To avoid potential confounding effects from extreme operational disruptions, we exclude firms in the disaster zones from our baseline analysis.

3.3. Empirical model

We begin by testing whether exposure to typhoon events affects the likelihood of issuing a management earnings forecast. For this purpose, we estimate the following Probit model, where the dependent variable, Forecast, is a binary indicator:

$$\Pr(Forecast_{it} = 1) = \Phi(\alpha + \beta \cdot Neighbor_{it} + \gamma \cdot X_{it} + \lambda_t + \theta_j + \delta_p + \varepsilon_{it}) \tag{1}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution. Subscripts i, t, j, and p refer to firm, year, industry, and province, respectively. The variable

[6] Source: https://www.cma.gov.cn/2011xwzx/2011xqxxw/2011xqxyw/202110/t20211030_40583-12.

Neighbor is defined as above. The vector X_{it} includes firm-level controls described below. The model includes year, industry, and province fixed effects.

Next, we examine how typhoon exposure affects the characteristics of earnings forecasts, specifically their precision and accuracy. These outcomes are modeled using the following linear specification:

$$MEF_{it} = \alpha + \beta \cdot Neighbor_{it} + \gamma \cdot X_{it} + \mu_i + \lambda_t + \delta_p + \varepsilon_{it} \tag{2}$$

where MEF_{it} refers to either *Precision* or *Accuracy*, both defined such that lower values indicate higher forecast quality. The explanatory variable $Neighbor_{it}$ is defined as above. This model controls for year, firm, and province fixed effects.

Following prior studies (Huang et al., 2022; Maslar et al., 2021), the control variables in X_{it} include: (1) firm size (*Size*), measured by the natural logarithm of total assets at the end of the period; (2) book-to-market ratio (*BM*), calculated as the book value of equity divided by market value; (3) leverage (*LEV*), measured by total liabilities at the period end divided by total assets; (4) return on assets (*ROA*), calculated as net profit divided by total assets; (5) institutional investor ownership (*InsInvestorProp*), measured by the number of shares held by institutional investors divided by the total number of outstanding shares; (6) analyst coverage (*AnaNum*), measured by the natural logarithm of the number of analysts tracking the firm; (7) return volatility (*Volatility*), calculated as the annual variance of the firm's monthly return rates; (8) discretionary accruals (*DisAcc*), calculated based on the modified Jones model; and (9) forecast horizon (*Horizon*), defined as the number of days between the release date of the earnings forecast and the actual disclosure date of the annual report. The variable *Horizon* is excluded from Model (1) since it is undefined for firm-years without earnings forecasts.

All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. Standard errors are clustered at the firm level in all regressions. Detailed definitions and construction procedures for all variables are provided in the Appendix.

4. Empirical analyses

4.1. Descriptive statistics

Table 1 presents the summary statistics for the main variables used in our analysis. The mean value of forecast issuance is 0.487, indicating that approximately 48.7% of firm-year observations in the full sample issue management earnings forecasts. Among firms with forecast data, the average forecast precision is 0.266, suggesting that the typical forecast range spans 26.6% of the actual net profit, while the average forecast accuracy is 0.115, indicating an average deviation of 11.5% from the realized earnings. The mean value of *Neighbor* is 0.209, indicating that 20.9% of the sample firms are located in the neighborhood areas of typhoon landfall sites, and thus belong to the treatment group. Descriptive statistics for the control variables are consistent with prior studies.

Insert Table 1 about here

4.2. Baseline results

Table 2 presents the regression results examining how exposure to typhoon events affects firms' decisions to issue earnings forecasts and the characteristics of those forecasts, as measured by their precision and accuracy. Columns (1) and (2) report Probit model estimates where the dependent variable is a binary indicator (*Forecast*). The coefficient on *Neighbor* is positive and statistically significant in both specifications, indicating that firms located in neighborhood areas are more likely to issue earnings forecasts. Columns (3) to (6) report OLS estimates where the dependent variables are *Precision* and *Accuracy*, respectively. The coefficient on *Neighbor* is negative and statistically significant at the 1% level across all specifications, suggesting that forecasts issued by firms in the neighborhood area are more precise and accurate. Collectively, these findings are consistent with our hypothesis that firms in the neighborhood area issue more earnings forecasts and their forecasts are more precise and accurate after typhoon events..

Insert Table 2 about here

4.3. Robustness tests

4.3.1. Concerns of the effect of other extreme weather events

To ensure that our findings are not confounded by the presence of other extreme weather events, we conduct a robustness check using the Chinese Climate Physical Risk Index (CCPRI)[7]. The CCPRI provides annual province-level measures of climate physical risk from 1993 to 2023, including four components: extreme low temperature days (LTD), extreme high temperature days (HTD), extreme rainfall days (ERD), and extreme drought days (EDD), which are aggregated to reflect the overall degree of climate physical stress in each region.

Specifically, we exclude firm-year observations in the control group that are located in provinces experiencing extreme climate risk in the same year, defined as having total extreme weather days

[7] The CCPRI dataset is constructed by Guo et al. (2024) using daily meteorological records and includes data for 31 provinces and 229 prefectural cities in China.

(LTD + HTD + ERD + EDD) exceeding the 75th percentile across all province-year observations in our sample. This approach mitigates the concern that firms classified as "unexposed" may, in fact, be facing other forms of severe climate shocks that could affect managerial disclosure decisions.

Table 3 presents the results after applying this restriction. The coefficient on *Neighbor* remains statistically significant and directionally consistent across all model specifications, indicating that our findings are robust to this alternative sample definition.

Insert Tables 3 about here

4.3.2. Propensity score matching (PSM) tests

To address potential self-selection concerns—namely, that firms located in the neighborhood area may systematically differ from those in the control group in ways that also influence disclosure behavior—we conduct a robustness test using propensity score matching (PSM). We construct a matched sample of treatment and control firms based on their likelihood of being exposed to typhoon events.

Specifically, we estimate the propensity score using a logit model where the treatment variable is *Neighbor*, and covariates include all control variables used in model (1): *Size*, *BM*, *LEV*, *ROA*, *InsInvestorProp*, *AnaNum*, *Volatility*, and *DisAcc*, along with year and industry fixed effects. Matching is performed using the kernel matching algorithm.

Table 4 reports the regression results based on the matched sample. Across all specifications, the coefficient on *Neighbor* remains statistically significant and consistent in both sign and magnitude with the baseline results. These findings provide additional support for the robustness of our main conclusions.

Insert Tables 4 about here

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5. Further tests

5.1. Influencing mechanism analysis

In the hypothesis development section, we propose that extreme weather influences management earnings forecasts through a mechanism whereby managers increase disclosure to mitigate heightened information asymmetry caused by such events. However, we also acknowledge that extreme weather may affect the characteristics of management earnings forecasts due to strategic disclosure incentives or behavioral biases among managers. In this section, we first test the information asymmetry mechanism, followed by an examination of these alternative explanations.

5.1.1. Information asymmetry

To assess whether a reduction in information asymmetry serves as a mechanism linking typhoon exposure to forecasting behavior, we adopt a three-step empirical strategy. First, we estimate the effect of typhoon exposure on the likelihood and quality of management earnings forecasts, as presented in our baseline analyses. Second, we examine whether typhoon exposure affects stock market illiquidity, which we use as a proxy for information asymmetry. Third, we include the illiquidity measure in the baseline regression models to jointly assess the effects of typhoon exposure and market illiquidity on management earnings forecast behavior.

In the second step, we estimate the following model using monthly data:

$$Illiquidity_{im} = \alpha + \beta \cdot Neighbor_{im} + \gamma \cdot Z_{im} + \mu_i + \tau_m + \theta_{j \times t} + \varepsilon_{im} \quad (3)$$

Here, $Illiquidity_{it}$ serves as the indicator of information asymmetry among investors. Following prior studies (Nagar et al., 2019), *Illiquidity* is measured using the bid-ask spread (*Spread*) and the Amihud liquidity metric (*Amihud*) (Amihud, 2002). *Spread* is calculated as the difference between the bid and ask prices divided by the mid-price squared, while *Amihud* is calculated as the absolute value of daily returns divided by daily trading volume, averaged monthly. Control variables Z_{it} include the monthly price-to-earnings ratio (*PE*), market capitalization (*StockMV*), and lagged market-wide illiquidity (*ALLIQ*). This regression includes firm, month, and industry-year fixed effects to absorb unobserved heterogeneity.

In the third step, we first re-estimate the forecast issuance model by incorporating the average illiquidity (from May to September of year t) into the Probit specification:

$$\Pr(Forecast_{it} = 1) = \Phi(\alpha + \beta_1 \cdot Neighbor_{it} + \beta_1 \cdot Illiquidity_{it} + \gamma \cdot X_{it} + \lambda_t + \theta_j + \delta_p + \varepsilon_{it}) \quad (4)$$

Second, we re-estimate the forecast quality model by including the same illiquidity measure:

$$MEF_{it} = \alpha + \beta_1 \cdot Neighbor_{it} + \beta_2 \cdot Illiquidity_{it} + \gamma \cdot X_{it} + \mu_i + \lambda_t + \delta_p + \varepsilon_{it} \quad (5)$$

Table 5 reports the empirical results of the mechanism analysis. In Panel A, we find that the coefficient on *Neighbor* is significantly positive across both specifications, indicating that typhoon exposure increases stock illiquidity—whether measured by the bid-ask spread (*Spread*) or the Amihud illiquidity ratio (*Amihud*). These results support the view that typhoon events exacerbate information asymmetry in the capital market.

In Panel B, we incorporate these illiquidity measures into the baseline models. The coefficient on *Neighbor* remains statistically significant and comparable in magnitude after controlling for illiquidity. At the same time, *Spread* and *Amihud* are significantly associated with the likelihood of forecast issuance but show no significant relationship with forecast precision or accuracy.

These findings suggest that a deteriorating information environment contributes to managers' increased willingness to disclose forecasts. However, the observed improvements in forecast quality are less likely to be explained solely by reduced information asymmetry. Thus, we conclude that information asymmetry serves as a partial, but not exclusive, mechanism through which extreme weather influences managerial disclosure behavior.

Insert Table 5 about here

5.1.2. Alternative explanations

To validate the interpretation of our baseline findings, we examine two alternative explanations. First, we consider whether managers affected by extreme weather exhibit heuristic-driven pessimism, issuing negatively biased forecasts due to the salience and emotional impact of the event. Prior studies suggest that natural disasters can influence managerial decision-making through heuristic biases rather than rational expectation updating (Kong et al., 2021; Dessaint and Matray, 2017). According to salience theory (Tversky and Kahneman, 1973; Bordalo et al., 2012, 2013), highly visible and emotionally charged events—such as typhoons—may lead individuals to overweight the probability of extreme negative outcomes. In the corporate context, this suggests that managers may overestimate the earnings impact of extreme weather and issue pessimistically biased forecasts, even if actual fundamentals are not severely impaired.

To test this, we construct a binary variable *Negative* that equals 1 if the forecasted earnings are lower than realized net income, and 0 otherwise. Columns (1) and (2) of Table 6 show that the coefficients on *Neighbor* are positive but statistically insignificant, suggesting no systematic increase in downward bias following disaster exposure. This result does not support the pessimism-based heuristic explanation.

Second, we examine whether the increased disclosure observed in our baseline results is instead driven by a greater likelihood of selectively disclosing good news. Research indicates that natural disasters increase managerial incentives to manipulate earnings or misrepresent performance to mask operational challenges and sustain investor confidence (Chen et al., 2024; Ding et al., 2021; Huynh and Xia, 2023). Building on this, managers may selectively disclose good news to elevate investors' expectations of the firm. Following Chen et al. (2022), we define a dummy variable *Goodnews* that equals 1 if the forecasted net income is greater than the previous year's actual net income, and zero otherwise.

Columns (3) and (4) of Table 6 present the results. Once again, the coefficients on *Neighbor* are positive but not statistically significant, providing no evidence to support the presence of selective good-news disclosure. Overall, the findings do not support the hypothesis that our results are driven by forecast bias or strategic selective disclosure incentives.

Insert Table 6 about here

5.2. Heterogeneity analyses

This study further investigates how the impact of extreme weather on management earnings forecasts varies across different corporate characteristics. We examine three heterogeneity factors: executive career concern, corporate climate risk exposure, and corporate external financing pressure.

5.2.1. Effect of executive career concern

We first examine whether the impact of extreme weather on management earnings forecasts varies with the intensity of executive career concerns, proxied by the age of top executives. According to career concern theory, younger executives—facing longer future career horizons—are more sensitive to market perceptions of their competence and, therefore, have stronger incentives to proactively disclose information in response to external shocks (Andreou et al., 2017; Belenzon et al., 2019). In contrast, older executives may be less motivated to engage in active disclosure due to diminished reputational and advancement concerns at later stages of their careers (James, 2020).

In the context of Chinese listed firms, the chairman typically plays a more prominent role in strategic decision-making and external communication than the CEO—a structure that aligns more closely with the CEO role in developed markets. Accordingly, we use chairman age as our measure of executive age. To test for heterogeneity, we split the sample into two subgroups—firms with younger chairmen and those with older chairmen—based on the annual median age of chairmen.

We then re-estimate the baseline regressions for each subgroup and present the results in Panels A and B of Table 7. For firms with younger chairmen, the coefficients on *Neighbor* are statistically significant across all three columns in Panel A. In contrast, for firms with older chairmen, the coefficients on *Neighbor* are not statistically significant in any specification, as shown in Panel B. These findings support the view that younger executives, driven by stronger career concerns, are more responsive to external uncertainty in their disclosure behavior, whereas older executives are less likely to adjust their disclosure strategies in response to climate-related shocks.

Insert Table 7 about here

5.2.2. Effect of corporate climate risk exposure

Next, we examine whether the impact of extreme weather on management earnings forecasts is more pronounced for firms with greater exposure to such events. Following Ai and Gao (2023), we use the scale of a firm's fixed assets as a proxy for climate risk exposure, as firms with larger fixed asset holdings are more susceptible to operational and financial disruptions caused by extreme weather.

To test this heterogeneity, we divide the sample into two groups based on the annual median of fixed asset holdings: a large fixed asset group and a small fixed asset group. We then re-estimate the baseline regressions separately for each subgroup and report the results in Panels A and B of Table 8.

The results show that for firms with larger fixed assets, the coefficients on *Neighbor* are significantly positive in the *Forecast* model and significantly negative in both the *Precision* and *Accuracy* models, suggesting that extreme weather increases the likelihood of forecast issuance and improves forecast quality for firms with greater physical exposure. In contrast, for firms with smaller fixed assets, the coefficients on *Neighbor* are statistically insignificant across all three specifications.

Overall, these results support the view that the effect of extreme weather on managerial disclosure decisions is more pronounced for firms with greater exposure to physical climate risks.

Insert Table 8 about here

5.2.3. Effect of corporate external financing pressure

Finally, we examine whether the relationship between extreme weather and management earnings forecasts differs by the degree of corporate external financing pressure. Firms facing greater financing constraints are more motivated to reduce information asymmetry and cater to stakeholder expectations, especially in response to external shocks. In the context of the Chinese capital market, non-state-owned enterprises (non-SOEs) generally encounter greater financing pressures than state-owned enterprises (SOEs) due to weaker political connections and limited access to preferential financing channels (Zhang and Zheng, 2020). We therefore expect the baseline relationship to be more pronounced for non-SOEs.

To test this heterogeneity, we split the sample into SOEs and non-SOEs based on ownership type and re-estimate the baseline regressions for each group. The results are reported in Panels A and B of Table 9. For non-SOEs, the coefficients on *Neighbor* are significantly negative in both the *Precision* and *Accuracy* models, indicating that climate disaster exposure is associated with improved forecast quality. However, the coefficient is not significant in the *Forecast* model. In contrast, for SOEs, the coefficients on *Neighbor* are not significant across all three models. These findings suggest that non-SOEs respond more actively to climate-related uncertainty by enhancing the quality of their forecasts, consistent with their stronger financing motivations and greater sensitivity to market expectations.

Insert Table 9 about here

5.3. Analysis of firms in disaster zones

In our baseline analysis, firms located in the disaster zone were excluded to isolate the impact of extreme weather on firms in the neighborhood area. However, extreme weather events may affect disclosure behavior through different channels depending on geographic proximity. Firms located within the disaster zone—defined as within 200 kilometers of the typhoon landing site—are more likely to experience direct physical disruptions (e.g., infrastructure damage, power outages), which may constrain managerial information processing and limit their ability to issue forward-looking disclosures.

To account for this, we extend the baseline model by reintroducing disaster-zone firms and include a binary indicator, *Disaster*, which equals 1 if a firm is located in the disaster zone during a typhoon year. Table 10 presents the estimation results. The coefficient on *Disaster* is negative and statistically significant in the *Forecast* model, suggesting that firms directly affected by typhoons are less likely to issue earnings forecasts. Moreover, the coefficients on *Disaster* are significantly positive in the *Precision* and *Accuracy* models, indicating that even when forecasts are issued, they are of lower quality—characterized by wider forecast ranges and greater deviation from realized earnings. These findings support the hypothesis that extreme weather increase managerial information acquisition costs and reduce disclosure capacity (Gao et al., 2022).

In contrast, the coefficients on *Disaster* are statistically insignificant in both the *Negative* and *Goodnews* models, suggesting that the observed patterns are unlikely driven by managerial pessimism or selective disclosure of favorable news. Importantly, the results for the *Neighbor* variable remain consistent with our previous analyses.

Overall, this analysis highlights the nuanced effects of extreme weather on corporate disclosure decisions. The differential findings between disaster-zone and neighborhood firms suggest that the impact of extreme weather events is shaped by firms' physical proximity to the disaster, underscoring the importance of geographically disaggregated approaches in studying disclosure responses to environmental shocks.

Insert Table 10 about here

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6. Conclusions

This study investigates how extreme weather events influence managerial earnings forecasts disclosure decisions. We posit that both the direct impacts of extreme weather and managers' responses to such events jointly contribute to increased investor uncertainty regarding firms' future performance, thereby heightening information asymmetry and deteriorating the overall information environment. Based on the theory of voluntary disclosure, we expect that managers will respond to this increased opacity by providing more firm-specific information, particularly forward-looking disclosures related to future earnings.

However, alternative mechanisms may complicate this relationship. Specifically, heightened disclosure costs, strategic disclosure incentives, and psychological biases triggered by extreme weather events may discourage information disclosure, increase the likelihood of selectively disclosing favorable information, or lead to a greater tendency to issue pessimistic forecasts. These alternative channels present competing or confounding hypotheses relative to the voluntary disclosure perspective.

We exploit typhoon events in China to examine the relationship between extreme weather and managerial disclosure behavior. Based on the geographical proximity of firm headquarters to typhoon landfall sites, we categorize firms into three groups: those located in disaster zones, neighborhood areas, and other areas. Using a dataset of Chinese A-share listed firms from 2010 to

2021, we find that firms located in neighborhood areas are more likely to issue management earnings forecasts, and their forecasts exhibit greater precision and accuracy compared to those of unaffected firms. Importantly, we find no evidence that these forecasts are more likely to be negatively biased or selectively disclose good news.

Mechanism analysis indicates that these effects are primarily driven by managerial incentives to mitigate the heightened information asymmetry caused by extreme weather events. Heterogeneity analyses further reveal that the effects are more pronounced among firms with younger executives, higher fixed asset intensity, and non-state ownership.

We also examine the impact of extreme weather on firms located in disaster zones. The results show that these firms are less likely to issue earnings forecasts, and their forecasts tend to be less precise and less accurate than those of unaffected peers. These findings underscore the importance of considering geographic proximity when evaluating the economic consequences of extreme weather.

This study contributes to the literature on extreme weather and managerial disclosure by identifying the conditions under which climate shocks influence forecast behavior. It advances our understanding of the determinants of management earnings forecasts and provides new evidence on how firms' information environments evolve in response to natural disasters. The findings offer practical implications for regulators and investors seeking to foster a more transparent disclosure environment in the face of growing climate-related uncertainty.

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Table 1. Descriptive statistics

Variables	N	Mean	SD	p25	p50	p75
Forecast	17,535	0.487	0.500	0	0	1
Precision	6,712	0.266	0.300	0.120	0.192	0.299
Accuracy	6,712	0.115	0.352	0.0190	0.0520	0.124
Neighbor	6,712	0.209	0.406	0	0	0
Size	6,712	21.98	1.095	21.20	21.84	22.59
BM	6,712	0.479	0.244	0.285	0.442	0.639
LEV	6,712	0.371	0.191	0.214	0.357	0.510
ROA	6,712	0.0540	0.0470	0.0260	0.0480	0.0760
InsInvestorProp	6,712	40.40	25.54	16.47	40.86	61.82
AnaNum	6,712	10.08	9.658	3	7	14
Volatility	6,712	0.135	0.0660	0.0920	0.120	0.157
DisAcc	6,712	0.0720	0.0740	0.0240	0.0490	0.0940
Horizon	6,712	119.4	47.13	80	112	166

Note: This table reports the descriptive statistics for the key variables in our sample with the period between 2010 and 2021. All values are winsorized at the 1% and 99% percentiles.

Table 2. Baseline regression results

Variables	(1) *Forecast*	(2) *Forecast*	(3) *Precision*	(4) *Precision*	(5) *Accuracy*	(6) *Accuracy*
Neighbor	0.176***	0.068*	-0.039***	-0.039***	-0.058***	-0.056***
	(5.757)	(1.933)	(-3.242)	(-3.206)	(-3.715)	(-3.636)
Size	-0.185***	-0.176***	-0.014	-0.014	0.038*	0.038*
	(-11.439)	(-10.614)	(-0.870)	(-0.863)	(1.888)	(1.865)
BM	0.247***	0.231***	0.266***	0.266***	0.289***	0.287***
	(3.331)	(3.053)	(5.188)	(5.167)	(4.493)	(4.457)
LEV	-0.229***	-0.215***	0.065	0.067	0.075	0.077
	(-3.122)	(-2.890)	(1.252)	(1.278)	(1.092)	(1.111)
ROA	3.264***	3.350***	-1.374***	-1.380***	1.402***	1.381***
	(13.625)	(13.917)	(-6.376)	(-6.359)	(5.394)	(5.267)
InsInvestorProp	-0.008***	-0.007***	-0.001***	-0.001***	-0.001*	-0.001**
	(-15.766)	(-14.810)	(-2.637)	(-2.774)	(-1.744)	(-1.963)
AnaNum	0.008***	0.006***	0.000	0.000	-0.001	-0.001
	(5.965)	(4.577)	(0.183)	(0.167)	(-1.642)	(-1.637)
Volatility	1.685***	1.630***	0.001	-0.004	0.152	0.145
	(6.907)	(6.662)	(0.010)	(-0.042)	(1.404)	(1.329)
DisAcc	0.506***	0.498***	-0.319***	-0.316***	-0.375***	-0.371***
	(3.459)	(3.387)	(-4.914)	(-4.860)	(-4.413)	(-4.351)
Horizon			0.001***	0.001***	0.001***	0.001***
			(3.677)	(3.728)	(3.794)	(3.834)
Constant	-2.500***	-2.798***	0.490	0.492	-0.986**	-0.979**
	(-7.960)	(-9.158)	(1.456)	(1.445)	(-2.353)	(-2.311)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	No	No
Province FE	No	Yes	No	Yes	No	Yes
Observations	17,535	17,535	6,712	6,712	6,712	6,712
R-squared	0.187	0.196	0.339	0.340	0.271	0.274

Note: This table presents the regression results examining the effects of typhoon events on the likelihood, precision, and accuracy of management earnings forecasts. *Neighbor* equals 1 if the firm is located within 200–500 km of the typhoon landfall site in the event year. All models include year fixed effects; other fixed effects are specified in the table. Robust t-statistics are in parentheses and based on firm-clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Robustness test: Controlling for other climate risks

Variables	(1) *Forecast*	(2) *Forecast*	(3) *Precision*	(4) *Precision*	(5) *Accuracy*	(6) *Accuracy*
Neighbor	0.166***	0.068*	-0.037***	-0.036***	-0.058***	-0.056***
	(4.946)	(1.742)	(-2.706)	(-2.659)	(-3.244)	(-3.147)
Size	-0.190***	-0.180***	-0.014	-0.015	0.038*	0.037*
	(-10.650)	(-9.833)	(-0.809)	(-0.864)	(1.797)	(1.711)
BM	0.270***	0.249***	0.243***	0.242***	0.298***	0.295***
	(3.283)	(2.954)	(4.328)	(4.297)	(4.090)	(4.041)
LEV	-0.268***	-0.260***	0.103*	0.105*	0.112	0.114
	(-3.266)	(-3.128)	(1.785)	(1.820)	(1.436)	(1.463)
ROA	3.151***	3.205***	-1.323***	-1.335***	1.450***	1.417***
	(11.458)	(11.619)	(-5.773)	(-5.775)	(5.088)	(4.922)
InsInvestorProp	-0.008***	-0.007***	-0.001**	-0.001**	-0.001	-0.001*
	(-14.605)	(-13.747)	(-2.276)	(-2.400)	(-1.578)	(-1.826)
AnaNum	0.009***	0.007***	-0.000	-0.000	-0.001	-0.001
	(5.855)	(4.761)	(-0.348)	(-0.364)	(-1.412)	(-1.403)
Volatility	1.568***	1.520***	0.037	0.036	0.222*	0.215*
	(5.845)	(5.649)	(0.379)	(0.365)	(1.764)	(1.703)
DisAcc	0.544***	0.530***	-0.346***	-0.343***	-0.453***	-0.447***
	(3.345)	(3.249)	(-4.831)	(-4.781)	(-4.869)	(-4.799)
Horizon			0.001***	0.001***	0.001***	0.001***
			(3.186)	(3.192)	(3.366)	(3.371)
Constant	-2.337***	-2.654***	0.480	0.507	-1.031**	-0.987**
	(-6.608)	(-7.270)	(1.336)	(1.394)	(-2.328)	(-2.217)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	No	No
Province FE	No	Yes	No	Yes	No	Yes
Observations	14,258	14,258	5,377	5,377	5,377	5,377
R-squared	0.188	0.196	0.358	0.359	0.303	0.306

Note: This table reports robustness test results after excluding firm-year observations in the control group that are located in provinces facing extreme climate risks. Extreme climate risk is identified using the Chinese Climate Physical Risk Index (CCPRI), which aggregates annual province-level data on extreme low temperature days, high temperature days, rainfall days, and drought days. Observations with total extreme weather days above the 75th percentile are removed. This procedure ensures that control firms are not themselves significantly affected by non-typhoon climate shocks. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Robustness test: Propensity score matching

Variables	(1) *Forecast*	(2) *Forecast*	(3) *Precision*	(4) *Precision*	(5) *Accuracy*	(6) *Accuracy*
Neighbor	0.184***	0.082**	-0.038***	-0.038***	-0.055***	-0.053***
	(5.466)	(2.102)	(-2.874)	(-2.833)	(-3.192)	(-3.096)
Size	-0.195***	-0.186***	-0.017	-0.017	0.035	0.034
	(-11.149)	(-10.353)	(-0.970)	(-0.968)	(1.618)	(1.573)
BM	0.266***	0.254***	0.268***	0.268***	0.321***	0.318***
	(3.281)	(3.063)	(4.875)	(4.850)	(4.509)	(4.462)
LEV	-0.241***	-0.232***	0.096	0.098*	0.077	0.079
	(-3.019)	(-2.868)	(1.617)	(1.649)	(1.016)	(1.037)
ROA	3.362***	3.425***	-1.340***	-1.348***	1.491***	1.464***
	(12.830)	(13.021)	(-5.947)	(-5.931)	(5.333)	(5.182)
InsInvestorProp	-0.008***	-0.008***	-0.001***	-0.001***	-0.001*	-0.001**
	(-15.455)	(-14.625)	(-2.669)	(-2.818)	(-1.771)	(-2.029)
AnaNum	0.009***	0.007***	0.000	0.000	-0.001	-0.001
	(5.950)	(4.881)	(0.205)	(0.190)	(-1.201)	(-1.189)
Volatility	1.552***	1.498***	0.024	0.019	0.191	0.181
	(5.928)	(5.711)	(0.255)	(0.199)	(1.588)	(1.498)
DisAcc	0.596***	0.586***	-0.373***	-0.370***	-0.446***	-0.440***
	(3.751)	(3.675)	(-5.357)	(-5.295)	(-5.091)	(-5.012)
Horizon			0.001***	0.001***	0.001***	0.001***
			(3.804)	(3.860)	(3.364)	(3.399)
Constant	3.957***	3.806***	0.544	0.550	-0.946**	-0.925**
	(11.326)	(10.467)	(1.463)	(1.457)	(-2.105)	(-2.037)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	No	No
Province FE	No	Yes	No	Yes	No	Yes
Observations	14,012	14,012	5,721	5,721	5,721	5,721
R-squared	0.130	0.139	0.359	0.359	0.294	0.296

Note: This table reports the regression results based on a propensity score matched sample to address potential self-selection bias. The propensity scores are estimated using a logit model with *Neighbor* as the treatment variable and covariates including *Size*, *BM*, *LEV*, *ROA*, *InsInvestorProp*, *AnaNum*, *Volatility*, and *DisAcc*, along with year and industry fixed effects. Matching is performed using kernel matching under the common support condition. The regressions are then re-estimated using the matched sample. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, based on two-tailed tests.

Table 5. Mechanisms analysis

Panel A: Regression of illiquidity on climate disasters

Variables	(1) *Spread*	(3) *Amihud*
Neighbor	0.002***	0.006***
	(13.467)	(8.478)
PE	0.000***	0.000**
	(3.496)	(2.405)
StockMV	-0.006***	-0.006***
	(-143.097)	(-28.191)
ALLIQ	0.112***	0.428***
	(185.308)	(143.909)
Constant	-0.075***	0.714***
	(-89.399)	(171.981)
Firm FE	Yes	Yes
Month FE	Yes	Yes
Industry-year FE	Yes	Yes
Observations	415,375	415,375
R-squared	0.625	0.535

Panel B: Regression of management earnings forecasts on illiquidity and climate disasters

Variables	(1) *Forecast*	(2) *Precision*	(3) *Accuracy*	(4) *Forecast*	(5) *Precision*	(6) *Accuracy*
Neighbor	0.073**	-0.040***	-0.054***	0.074**	-0.040***	-0.054***
	(2.043)	(-3.286)	(-3.517)	(2.050)	(-3.281)	(-3.524)
Spread	18.327***	-0.892	-0.898			
	(10.815)	(-1.334)	(-1.168)			
Amihud				1.781***	-0.046	0.020
				(6.433)	(-0.538)	(0.228)
Size	-0.155***	-0.015	0.036*	-0.140***	-0.016	0.036*
	(-9.105)	(-0.905)	(1.865)	(-7.756)	(-0.994)	(1.864)
BM	0.392***	0.236***	0.263***	0.123	0.254***	0.274***
	(4.924)	(4.383)	(3.957)	(1.539)	(4.810)	(4.203)
LEV	-0.301***	0.100*	0.121*	-0.186**	0.100*	0.120*
	(-3.849)	(1.824)	(1.750)	(-2.410)	(1.822)	(1.739)
ROA	3.453***	-1.628***	0.966***	3.293***	-1.623***	0.971***
	(13.319)	(-6.642)	(3.293)	(12.836)	(-6.620)	(3.317)
InsInvestorProp	-0.007***	-0.001**	-0.001*	-0.008***	-0.001**	-0.001*
	(-14.209)	(-2.417)	(-1.820)	(-14.931)	(-2.427)	(-1.890)

AnaNum	0.005***	0.000	-0.001	0.007***	0.000	-0.001
	(3.828)	(0.573)	(-1.201)	(4.852)	(0.386)	(-1.319)
Volatility	0.392	0.032	0.195*	1.720***	-0.015	0.143
	(1.417)	(0.336)	(1.795)	(6.614)	(-0.167)	(1.346)
DisAcc	0.415***	-0.280***	-0.328***	0.489***	-0.284***	-0.331***
	(2.714)	(-4.179)	(-3.847)	(3.209)	(-4.247)	(-3.883)
Horizon		0.001***	0.001***		0.001***	0.001***
		(4.052)	(4.720)		(4.031)	(4.735)
Constant	-3.902***	0.539	-0.920**	-3.620***	0.539	-0.962**
	(-11.494)	(1.558)	(-2.290)	(-9.654)	(1.549)	(-2.369)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes
Industry FE	Yes	No	No	Yes	No	No
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,818	6,457	6,457	16,818	6,457	6,457
R-squared	0.201	0.343	0.270	0.198	0.342	0.270

Note: This table presents the results of a three-step mechanism analysis testing whether information asymmetry mediates the effect of typhoon exposure on management earnings forecasts. Panel A reports the effect of *Neighbor* on investor information asymmetry, proxied by bid-ask spread (*Spread*) and the Amihud illiquidity ratio (*Amihud*), using monthly data. Panel B re-estimates the baseline forecast issuance and quality models by incorporating average illiquidity (May–September) into the regressions. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Testing alternative explanations

Variables	(1) *Negative*	(2) *Negative*	(3) *Goodnews*	(4) *Goodnews*
Neighbor	0.058	0.044	0.068	0.091
	(1.334)	(0.867)	(1.343)	(1.538)
Size	-0.058**	-0.067**	0.087**	0.084**
	(-2.232)	(-2.496)	(2.451)	(2.301)
BM	0.416***	0.465***	-0.586***	-0.596***
	(3.449)	(3.775)	(-3.691)	(-3.676)
LEV	0.322***	0.293**	1.217***	1.266***
	(2.781)	(2.501)	(7.711)	(7.805)
ROA	5.072***	5.346***	12.671***	12.753***
	(11.425)	(11.788)	(10.677)	(10.529)
InsInvestorProp	0.001*	0.001**	-0.001	-0.001
	(1.685)	(2.094)	(-1.097)	(-0.913)
AnaNum	-0.003	-0.004*	0.004	0.004
	(-1.627)	(-1.826)	(1.445)	(1.322)
Volatility	0.979***	0.951***	0.562	0.553
	(2.988)	(2.874)	(1.300)	(1.271)
DisAcc	0.383*	0.358	1.225***	1.235***
	(1.733)	(1.610)	(3.586)	(3.557)
Horizon	-0.001***	-0.001***	0.002***	0.002***
	(-3.376)	(-3.367)	(3.654)	(3.832)
Constant	0.280	0.485	-1.832**	-1.635**
	(0.378)	(0.641)	(-2.526)	(-2.167)
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes
Province FE	No	Yes	No	Yes
Observations	7,670	7,670	5,689	5,689
Pseudo R^2	0.053	0.061	0.156	0.162

Note: This table presents regression results testing two alternative explanations for the baseline findings. Columns (1)–(2) use the binary variable *Negative*, which equals 1 if the forecasted earnings are lower than realized earnings, to examine whether managers exhibit pessimism-driven forecast bias after typhoon exposure. Columns (3)–(4) use the dummy variable *Goodnews*, equal to 1 if the forecasted earnings exceed the previous year's actual earnings, to test for selective disclosure of favorable news. Robust t-statistics are reported in parentheses and are based on standard errors clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Heterogeneity analysis: Effect of executive career concern intensity

Panel A: Test results for younger chairmen			
Variables	(1) *Forecast*	(2) *Precision*	(3) *Accuracy*
Neighbor	0.102*	-0.053***	-0.066***
	(1.923)	(-3.150)	(-2.891)
Size	-0.102***	-0.019	0.004
	(-3.807)	(-0.753)	(0.136)
BM	0.115	0.292***	0.342***
	(0.951)	(3.599)	(3.096)
LEV	-0.459***	0.139	0.215*
	(-4.105)	(1.568)	(1.926)
ROA	4.322***	-0.998***	1.812***
	(11.732)	(-3.442)	(4.826)
InsInvestorProp	-0.009***	-0.001*	-0.001
	(-11.557)	(-1.877)	(-1.387)
AnaNum	0.005**	-0.000	-0.001
	(2.075)	(-0.194)	(-0.897)
Volatility	1.584***	-0.101	0.138
	(4.367)	(-0.814)	(0.814)
DisAcc	0.498**	-0.182**	-0.307**
	(2.272)	(-1.983)	(-2.388)
Horizon		0.001**	0.001**
		(2.352)	(2.386)
Constant	-4.087***	0.549	-0.346
	(-7.633)	(1.006)	(-0.532)
Year FE	Yes	Yes	Yes
Firm FE	No	Yes	Yes
Industry FE	Yes	No	No
Province FE	Yes	Yes	Yes
Observations	7,573	2,907	2,907
R-squared	0.220	0.399	0.308
Panel B: Test results for older chairmen			
Neighbor	0.034	-0.019	-0.036
	(0.727)	(-1.067)	(-1.583)
Size	-0.230***	-0.056**	0.016
	(-10.654)	(-2.134)	(0.521)
BM	0.298***	0.293***	0.276***

	(2.985)	(3.785)	(3.033)
LEV	-0.063	0.082	0.056
	(-0.616)	(1.105)	(0.599)
ROA	2.437***	-1.719***	1.121***
	(7.216)	(-4.643)	(2.671)
InsInvestorProp	-0.006***	-0.001	-0.001
	(-9.596)	(-1.539)	(-0.939)
AnaNum	0.008***	0.001	-0.001
	(4.593)	(0.608)	(-0.879)
Volatility	1.501***	0.143	0.212
	(4.489)	(1.036)	(1.355)
DisAcc	0.508**	-0.435***	-0.463***
	(2.505)	(-4.470)	(-3.544)
Horizon		0.001***	0.001***
		(3.350)	(3.879)
Constant	-1.749***	1.382**	-0.532
	(-4.529)	(2.480)	(-0.796)
Year FE	Yes	Yes	Yes
Firm FE	No	Yes	Yes
Industry FE	Yes	No	No
Province FE	Yes	Yes	Yes
Observations	9,878	3,429	3,429
R-squared	0.189	0.363	0.312

Note: This table presents the subsample regression results examining how executive age moderates the effect of typhoon exposure on earnings forecasts. Chairman age is used as a proxy for executive career concern intensity, with firms split into two groups based on the annual median age. Panel A reports results for firms with younger chairmen, and Panel B for firms with older chairmen. Robust t-statistics are in parentheses and are based on firm-level clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Heterogeneity analysis: Effect of corporate climate risk exposure

Panel A: Test results for the large fixed assets group			
Variables	(1) *Forecast*	(2) *Precision*	(3) *Accuracy*
Neighbor	0.102**	-0.065***	-0.071***
	(2.091)	(-3.485)	(-2.983)
Size	-0.171***	-0.026	0.031
	(-7.431)	(-0.751)	(0.671)
BM	0.394***	0.178**	0.212*
	(3.808)	(2.110)	(1.953)
LEV	0.034	0.136	0.251**
	(0.321)	(1.489)	(2.253)
ROA	4.518***	-2.854***	-0.185
	(12.981)	(-7.157)	(-0.333)
InsInvestorProp	-0.005***	-0.001*	-0.000
	(-7.966)	(-1.894)	(-0.379)
AnaNum	0.004*	0.001	-0.002
	(1.808)	(0.484)	(-1.032)
Volatility	2.084***	-0.033	0.133
	(5.915)	(-0.226)	(0.728)
DisAcc	0.116	-0.141	-0.164
	(0.553)	(-1.470)	(-1.171)
Horizon		0.001**	0.001***
		(2.128)	(3.481)
Constant	-3.137***	0.854	-0.859
	(-6.751)	(1.201)	(-0.860)
Year FE	Yes	Yes	Yes
Firm FE	No	Yes	Yes
Industry FE	Yes	No	No
Province FE	Yes	Yes	Yes
Observations	9,114	2,999	2,999
R-squared	0.179	0.409	0.311
Panel B: Test results for the small fixed assets group			
Neighbor	0.024	-0.011	-0.025
	(0.461)	(-0.667)	(-1.162)
Size	-0.204***	-0.013	0.050*
	(-8.273)	(-0.611)	(1.926)
BM	0.137	0.299***	0.287***

	(1.179)	(3.794)	(2.905)
LEV	-0.410***	-0.028	-0.078
	(-3.832)	(-0.410)	(-0.833)
ROA	2.512***	-0.827***	1.915***
	(7.406)	(-3.453)	(6.468)
InsInvestorProp	-0.008***	-0.001	-0.000
	(-11.654)	(-1.181)	(-0.572)
AnaNum	0.009***	-0.000	-0.002*
	(4.637)	(-0.439)	(-1.949)
Volatility	1.123***	-0.033	0.088
	(3.251)	(-0.278)	(0.584)
DisAcc	0.834***	-0.305***	-0.376***
	(3.933)	(-3.160)	(-3.126)
Horizon		0.001***	0.000
		(2.720)	(1.347)
Constant	-5.469***	0.433	-1.189**
	(-9.928)	(0.999)	(-2.193)
Year FE	Yes	Yes	Yes
Firm FE	No	Yes	Yes
Industry FE	Yes	No	No
Province FE	Yes	Yes	Yes
Observations	8,416	3,391	3,391
R-squared	0.227	0.351	0.342

Note: This table presents the subsample regression results assessing the heterogeneity in the effect of typhoon exposure on earnings forecasts based on firms' climate risk exposure. The sample is split by the annual median value of fixed asset holdings. Panel A reports results for firms with larger fixed assets (high exposure), while Panel B presents results for firms with smaller fixed assets (low exposure). Robust t-statistics are in parentheses and are based on firm-level clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Heterogeneity analysis: Effect of corporate external financing pressure

Panel A: Test results for the state-owned enterprises (SOEs)			
Variables	(1) *Forecast*	(2) *Precision*	(3) *Accuracy*
Neighbor	0.088	-0.044	-0.057
	(1.368)	(-1.268)	(-1.498)
Size	-0.150***	0.007	-0.005
	(-6.027)	(0.159)	(-0.113)
BM	0.411***	0.049	0.060
	(3.527)	(0.434)	(0.465)
LEV	0.317***	-0.046	0.111
	(2.581)	(-0.371)	(0.770)
ROA	3.928***	-3.313***	-0.701
	(8.691)	(-6.584)	(-1.235)
InsInvestorProp	0.004***	-0.002	-0.002
	(3.156)	(-1.558)	(-1.074)
AnaNum	-0.001	0.003*	-0.000
	(-0.661)	(1.664)	(-0.094)
Volatility	2.432***	-0.226	-0.241
	(6.062)	(-0.988)	(-1.047)
DisAcc	0.439*	-0.117	0.003
	(1.850)	(-0.624)	(0.020)
Horizon		0.001	0.001
		(1.236)	(1.543)
Constant	-3.998***	0.318	0.215
	(-7.962)	(0.345)	(0.224)
Year FE	Yes	Yes	Yes
Firm FE	No	Yes	Yes
Industry FE	Yes	No	No
Province FE	Yes	Yes	Yes
Observations	7,231	1,203	1,203
R-squared	0.123	0.399	0.321
Panel B: Test results for the non-state-owned enterprises (non-SOEs)			
Neighbor	0.055	-0.031**	-0.044***
	(1.280)	(-2.443)	(-2.625)
Size	-0.157***	-0.025	0.034
	(-6.473)	(-1.429)	(1.458)
BM	0.284***	0.267***	0.304***

	(2.653)	(4.717)	(4.164)
LEV	-0.333***	0.042	0.058
	(-3.253)	(0.763)	(0.750)
ROA	3.053***	-1.257***	1.522***
	(10.130)	(-5.488)	(5.333)
InsInvestorProp	-0.006***	-0.001***	-0.001*
	(-9.727)	(-2.642)	(-1.658)
AnaNum	0.007***	0.000	-0.001
	(3.560)	(0.138)	(-1.195)
Volatility	0.870***	-0.004	0.186
	(2.789)	(-0.040)	(1.522)
DisAcc	0.325*	-0.315***	-0.392***
	(1.690)	(-4.710)	(-4.093)
Horizon		0.001***	0.001***
		(3.512)	(3.482)
Constant	-6.431***	0.744**	-0.899*
	(-12.401)	(1.997)	(-1.869)
Year FE	Yes	Yes	Yes
Firm FE	No	Yes	Yes
Industry FE	Yes	No	No
Province FE	Yes	Yes	Yes
Observations	10,299	5,466	5,466
R-squared	0.183	0.338	0.277

Note: This table presents the subsample regression results examining how external financing pressure moderates the impact of typhoon exposure on earnings forecasts. Firms are classified as state-owned enterprises (SOEs) or non-SOEs based on ownership type. Panel A reports results for SOEs, and Panel B for non-SOEs. Robust t-statistics are in parentheses and are based on firm-level clustered standard errors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Analysis of firms in disaster zones

Variables	(1) *Forecast*	(2) *Precision*	(3) *Accuracy*	(4) *Negative*	(5) *Goodnews*
Disaster	-0.050*	0.028**	0.036*	-0.012	0.007
	(-1.653)	(2.022)	(1.942)	(-0.294)	(0.135)
Neighbor	0.084**	-0.033**	-0.060***	0.040	0.068
	(2.027)	(-2.239)	(-3.009)	(0.765)	(1.105)
Size	-0.190***	-0.000	0.042	-0.079***	0.071*
	(-9.272)	(-0.019)	(1.466)	(-2.802)	(1.833)
BM	0.211**	0.270***	0.399***	0.505***	-0.572***
	(2.274)	(4.227)	(4.851)	(3.870)	(-3.347)
LEV	-0.200**	0.093	0.076	0.228*	1.180***
	(-2.231)	(1.312)	(0.808)	(1.813)	(6.975)
ROA	3.590***	-1.028***	2.105***	5.409***	11.511***
	(12.506)	(-4.218)	(6.957)	(11.349)	(10.026)
InsInvestorProp	-0.006***	-0.002***	-0.002**	0.002**	-0.000
	(-10.992)	(-3.013)	(-2.484)	(2.084)	(-0.069)
AnaNum	0.005***	-0.000	-0.001	-0.005**	0.006*
	(3.082)	(-0.464)	(-1.266)	(-2.041)	(1.747)
Volatility	1.647***	0.014	0.141	0.626*	0.095
	(5.408)	(0.122)	(0.933)	(1.780)	(0.200)
DisAcc	0.593***	-0.323***	-0.303***	0.471**	1.313***
	(3.361)	(-4.222)	(-2.961)	(2.055)	(3.519)
Constant	-5.717***	0.161	-1.146*	0.420	-0.966
	(-12.160)	(0.355)	(-1.946)	(0.704)	(-1.187)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	No
Industry FE	Yes	No	No	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Observations	11,975	4,574	4,574	6,785	5,005
R-squared	0.197	0.361	0.296	0.057	0.157

Note: This table presents regression results comparing firms located in disaster zones (within 200 km of typhoon landfall) and those in the neighborhood area (200–500 km). *Disaster* is a binary variable equal to 1 if a firm is located in the disaster zone during a typhoon year. *Neighbor* equals 1 for firms in the neighborhood area. The dependent variables include forecast issuance, forecast precision and accuracy, and the likelihood of negative or good-news forecasts. Robust t-statistics are reported in parentheses and clustered at the firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix. Variable definitions

Variable Name	Sign	Variable Definition
Forecast Issuance	*Forecast*	A dummy variable equal to 1 if a firm voluntarily issues a management earnings forecast in a given year, and 0 otherwise.
Forecast Precision	*Precision*	The precision of management's earnings forecasts, defined as the range between the highest and lowest forecasted net profits divided by the actual net profit.
Forecast Accuracy	*Accuracy*	The accuracy of management's earnings forecasts, calculated as the absolute difference between the forecasted and actual net profit, divided by the actual net profit.
Proximity to Typhoon	*Neighbor*	A dummy variable equal to 1 if a firm is located 200–500 km from a typhoon landfall site in a year with a typhoon event, and 0 otherwise.
Firm Size	*Size*	Firm size, measured by the natural logarithm of total assets at the end of the period.
Book-to-Market Ratio	*BM*	Book-to-Market Ratio, measured by the book value of equity divided by market value.
Leverage	*LEV*	Debt Ratio, measured by total liabilities at period end divided by total assets.
Return on Assets	*ROA*	Return on Assets, measured by net profit divided by total assets.
Institutional Ownership	*InsInvestorProp*	Institutional Investor Ownership Proportion, measured by the number of shares held by institutional investors divided by the number of outstanding shares.
Analyst Coverage	*AnaNum*	Number of Analysts Following the Firm, measured by the natural logarithm of the number of analysts tracking the firm.
Return Volatility	*Volatility*	Return Volatility, measured by the annual variance of the firm's monthly return rates.
Discretionary Accruals	*DisAcc*	Manipulation Accruals, calculated using the modified Jones model.
Forecast Horizon	*Horizon*	Forecast Horizon, defined as the number of days between the release date of the earnings forecast and the actual disclosure date of the annual report.