

# Extreme Weather and Corporate Financing Management: Cash-Flow Channel Evidence from Chinese Listed Firms

Jiawei Ma

p2626244@mpu.edu.mo

MPI GTR Center: Macao Polytechnic University Gaming Teaching and Research Center

<https://orcid.org/0009-0000-6423-3039>

---

## Research Article

**Keywords:** extreme weather, climate risk, operating cash flow, financing constraints, leverage, cost of debt

**Posted Date:** September 21st, 2026

**DOI:** <https://doi.org/10.21203/rs.3.rs-10971926/v1>

**License:** © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

**Additional Declarations:** The authors declare no competing interests.

---

# Abstract

How does physical climate risk propagate into corporate finance, and which firms can finance their way through it? This paper traces the transmission of extreme weather into corporate cash flows and financing outcomes using a newly constructed firm-year panel that links daily weather realisations in 351 Chinese cities over 2005–2024 to the financial statements of 4,170 non-financial A-share listed firms over 2010–2024. Exposure is measured as annual counts of days exceeding local climatological thresholds for heat and rainfall, and identification relies on distributed-lag panel models with firm and province-by-year fixed effects. We first develop a stylised intertemporal financing model that delivers four testable predictions: a delayed cash-flow response, a concentration of rainfall damage among small firms, asymmetric leverage adjustment that reveals financing constraints, and price rigidity relative to quantity adjustment in bank-centred credit systems. The data confirm all four. Ten additional extreme heat days reduce the operating-cash-flow-to-assets ratio by 0.13 percentage points one year later ( $t = -3.11$ ), with no contemporaneous effect and a flat placebo lead; the estimate survives alternative exposure definitions, exclusion of the COVID-19 year, two-way and province-level clustering, and a 300-draw permutation placebo in which no reassigned exposure series reproduces the effect. The rainfall impact on cash flows is statistically zero for large firms but reaches  $-0.55$  percentage points per ten days for small firms. After heat shocks, large firms expand leverage significantly while small firms—whose cash flows are hit at least as hard—do not adjust quantities and instead tilt toward cash hoarding; effective debt costs remain unresponsive throughout. The results locate the binding margin of financing adaptation to climate extremes in ex-ante liquidity provision rather than ex-post borrowing, with direct implications for treasury management, credit allocation, and climate-related financial policy.

JEL Classification: G32; G31; Q54; C23

## 1. Introduction

The financial consequences of a warming climate are no longer a matter of projection; they are increasingly a matter of accounting. Heatwaves interrupt logistics and power supply, extreme precipitation floods premises and severs transport links, and the recurrence of such events has turned weather volatility into a standing feature of the environment in which firms produce, sell, and borrow. A substantial literature has established that natural disasters and weather extremes disrupt production and propagate through supply-chain networks (Barrot & Sauvagnat, 2016; Carvalho et al., 2021) and that temperature shocks affect earnings and asset prices at the firm level (Addoum et al., 2020, 2023; Pankratz et al., 2023). What remains considerably less understood is the pathway by which these physical shocks reach the corporate balance sheet. Do extreme weather events measurably impair the operating cash flows from which all financing decisions must ultimately be funded? If so, with what timing? And when cash flows deteriorate, which firms are able to replace the shortfall with external finance—and which are not?

These questions sit at the heart of corporate financing management. Treasury policy is, in essence, a set of arrangements for absorbing cash-flow volatility: cash buffers, committed credit lines, debt maturity ladders, and hedging programmes are all chosen before shocks arrive, under uncertainty about their frequency and severity. If weather-driven cash-flow shortfalls can be financed away ex post at stable prices, the case for costly ex-ante liquidity provision is weak. If, on the other hand, external finance is precisely least available to the firms most exposed—because the same shock that damages cash flow also damages collateral and creditworthiness—then the financing-management problem is fundamentally about preparation rather than reaction. Distinguishing between these regimes requires evidence on three margins simultaneously: the real (cash-flow) impact of weather, the quantity response of debt and liquidity, and the price response of credit.

This paper provides such evidence from China, a setting that combines near-ideal data availability with first-order economic relevance. China is simultaneously the world's largest emerging capital market, one of the countries most exposed to both heatwaves and extreme precipitation, and a bank-centred financial system in which financing frictions for smaller firms are widely documented. We construct daily weather series for 351 Chinese city centroids over 2005–2024 from the ERA5-based Open-Meteo archive and convert them into annual counts of locally extreme heat and rainfall days, defined against each city's own climatological distribution. These exposures are linked through registration cities to the annual financial statements of 4,170 non-financial A-share listed firms over 2010–2024, yielding an estimation sample of 47,870 firm-year observations. The empirical design is a distributed-lag panel model with firm fixed effects and province-by-year fixed effects, which absorbs all time-invariant firm characteristics and every province-level shock—including regional business cycles, credit policies, and disaster-relief programmes—so that identification rests on the as-good-as-random year-to-year fluctuation of local weather around firm-specific and province-specific norms.

To organise the empirics, we first develop a stylised three-period financing model in which a weather shock impairs operating cash flow with a one-period lag, after which firms choose between internal buffers and external debt subject to a borrowing constraint that tightens with the shock itself. The model generates four predictions that map directly onto our hypotheses: (i) the cash-flow response is delayed rather than contemporaneous; (ii) rainfall-type shocks, which damage lumpy and locally concentrated assets, fall disproportionately on small, undiversified firms; (iii) leverage expands after shocks only for firms whose borrowing constraint does not bind—so that the cross-sectional pattern of leverage adjustment reveals the incidence of financing frictions; and (iv) in a credit system with administered pricing elements, adjustment occurs in quantities rather than prices.

The empirical results confirm each prediction. First, ten additional extreme heat days reduce the operating-cash-flow-to-assets ratio by 0.134 percentage points in the following year ( $t = -3.11$ ), while the contemporaneous effect is precisely zero and the two-year effect reverts toward zero. The one-year lead—a placebo term—is small and insignificant, and the effect is unchanged when the COVID-19 year is excluded, when exposure is redefined as standardised anomalies, and under two-way or province-level clustering. A permutation exercise that randomly reassigns entire city exposure series across the 351

cities 300 times never produces a coefficient as large as the actual estimate, and no firm in the sample changes its registration city, eliminating selective-sorting concerns by observation rather than by assumption. Second, the rainfall effect on cash flows is entirely a small-firm phenomenon: the interaction with a small-firm indicator is  $-0.606$  percentage points per ten days ( $t = -3.31$ ), against a base effect statistically indistinguishable from zero. Third, after heat shocks, large firms raise leverage by  $0.24$  percentage points per ten days ( $t = 2.24$ ), while the small-firm interaction ( $-0.343$ ,  $t = -2.79$ ) fully offsets the base effect; small firms instead exhibit a marginally significant shift toward cash holdings. Fourth, effective debt costs show no response at any horizon or in any subsample, consistent with quantity-based adjustment in a bank-centred system with administered pricing elements.

The paper contributes to three strands of literature. To the literature on the real effects of natural disasters and weather extremes (Barrot & Sauvagnat, 2016; Carvalho et al., 2021), it adds firm-level evidence on the operating channel—cash flow—through which physical risk must pass before any financing variable can be affected, and documents its precise dynamic timing. To the climate-finance literature on risk pricing, investor attention, and managerial reaction (Bernstein et al., 2019; Dessaint & Matray, 2017; Krueger et al., 2020; Murfin & Spiegel, 2020; Sautner et al., 2023), it offers a complementary quantity-side account: on average, listed Chinese firms do not restructure liabilities after moderate weather shocks; large firms smooth through debt, small firms cannot, and prices do not move. To the financing-constraints literature (Almeida & Campello, 2007; Hadlock & Pierce, 2010; Kaplan & Zingales, 1997), it demonstrates that extreme weather can serve as a revealed-preference instrument for the incidence of constraints, because the shock is exogenous, measurable at high frequency, and asymmetric in its financial consequences. For practitioners, the findings recast climate-adaptive financing management as a problem of ex-ante liquidity architecture—committed credit lines, buffer calibration, and insurance—rather than ex-post borrowing capacity, with the caveat that this architecture is least developed exactly where it is most needed.

The remainder of the paper proceeds as follows. Section 2 reviews the literature, develops the theoretical framework, and states the hypotheses. Section 3 describes the data and variable construction. Section 4 sets out the econometric model and the identification strategy. Section 5 reports the main empirical results. Section 6 addresses endogeneity concerns and reports an extensive robustness battery. Section 7 discusses implications for financing management and concludes.

## **2. Literature, theoretical framework, and hypotheses**

### **2.1 Extreme weather and the real economy**

The aggregate and firm-level consequences of natural disasters and weather extremes are by now well documented. Barrot and Sauvagnat (2016) show that disasters striking suppliers impose substantial losses on downstream customers, which propagate along production networks; Carvalho et al. (2021) trace how the disruption from a major earthquake propagated through supply chains to the wider macroeconomy. A common feature of these estimates is that they identify relationships between

disaster realisations and real outcomes at the industry or network level; the financial margin through which firm-level effects aggregate remains comparatively opaque. Closer to the firm, Addoum et al. (2020) find limited evidence that temperature shocks are anticipated in industry-level returns, Addoum et al. (2023) show that temperature shocks affect earnings in ways only partly anticipated by markets, and Pankratz et al. (2023) show that firm-level exposure to extreme heat surprises investors and analysts. These studies establish that weather reaches corporate performance; they do not, by design, isolate the operating cash-flow margin or its financing consequences.

Within this literature, the operating channel occupies a distinctive place in the causal chain. Physical shocks must first impair operations—production, logistics, sales, or the collection of receivables—before any financing variable can be affected, because financing policy responds to the liquidity that operations generate rather than to weather per se. Studies that regress financing outcomes directly on weather therefore estimate a composite of two links—weather-to-operations and operations-to-financing—whose separate identification matters for both theory and practice. If the first link is weak or absent, null financing results are uninformative about frictions; if the first link is strong, the pattern of financing responses across firms becomes a revealed-preference test of credit access. Our design separates the links explicitly: we first establish the timing and magnitude of the cash-flow response, and only then examine which firms finance the shortfall.

## **2.2 Climate risk and corporate finance**

A growing finance literature examines how climate risk is priced, perceived, and managed. On the pricing side, physical and transition risks are reflected in housing and mortgage markets (Baldauf et al., 2020; Bernstein et al., 2019; Murfin & Spiegel, 2020), in equity returns and carbon premia (Bolton & Kacperczyk, 2021; Ilhan et al., 2021), and in the climate information investors extract from corporate disclosures (Sautner et al., 2023); Engle et al. (2020) show how portfolios can hedge climate news, and Flammer (2021) documents the financing and signalling role of green bonds. Attention is a precondition for pricing: Choi et al. (2020) show that abnormal local warmth shifts investor attention toward climate change, and Krueger et al. (2020) show that institutional investors view climate risk as financially material and engage with firms on risk management. On the credit side, banks reallocate lending across regions in response to natural disasters (Cortés & Strahan, 2017), echoing the broader evidence that shocks to bank balance sheets transmit to credit supply (Ivashina & Scharfstein, 2010). On the behavioural side, Dessaint and Matray (2017) document that managers overreact to nearby hurricane strikes that do not damage their own firms, suggesting that salience rather than fundamentals drives some financing responses. The financing-constraints and corporate-liquidity literature provides the conceptual apparatus for our heterogeneity analysis: the measurement of constraints (Hadlock & Pierce, 2010; Kaplan & Zingales, 1997), the cash-flow sensitivity of cash (Almeida et al., 2004), the secular rise of corporate cash buffers (Bates et al., 2009), the special role of cash and credit lines when capital-market access is impaired (Acharya et al., 2012; Campello et al., 2011), and the asset-tangibility channel of constraint (Almeida & Campello, 2007). If external finance is costly or rationed for some firms, identical cash-flow shocks will elicit different financing responses across the constraint distribution, and

the pattern of responses becomes informative about the constraints themselves. Our contribution is to bring these strands together: an exogenous, high-frequency physical shock; a clearly measured operating channel; and a cross-section of firms spanning the financing-friction spectrum in a bank-centred emerging market.

Two features of the Chinese setting make it particularly informative for these questions. The first is exposure. China's industrial heartlands are concentrated in regions that have experienced pronounced increases in both heatwave frequency and extreme precipitation over the past two decades, and its manufacturing supply chains are geographically dense, so that a single city's extreme season can propagate through tightly coupled production networks. The second is the financial system. Credit allocation remains bank-centred, with administered elements in loan pricing, relationship-based lending to large and state-connected firms, and chronically tighter access for small private firms despite a decade of inclusive-finance policy initiatives. This institutional configuration maps directly onto the model's parameters: credit access  $\theta$  is highly unequal across firms, and the lending rate  $R(B)$  is comparatively sticky for inframarginal borrowers. China is therefore a setting in which the quantity-price asymmetry and the size-graded constraint asymmetry should be particularly visible—and in which documenting them is particularly policy-relevant.

Relative to the existing evidence, three gaps motivate our design. First, most firm-level climate-finance studies examine prices—loan spreads, bond yields, equity returns—rather than quantities, yet in a quantity-rationed credit system prices are exactly where the signal is weakest. Second, studies of extreme weather often rely on rare catastrophic events, whose rarity limits statistical power and whose salience activates managerial overreaction channels (Dessaint & Matray, 2017) that confound the operating channel; recurrent day-count extremes identify the operating channel cleanly precisely because they are too frequent to be salient events. Third, the dynamic timing of transmission—contemporaneous versus delayed—has rarely been estimated with explicit lag structures, yet it is the timing that determines whether financing adaptation must be ex-ante or can be ex-post. Our design addresses all three gaps directly.

## 2.3 A stylised model of weather shocks and financing adjustment

To fix ideas and derive testable predictions, consider a firm that operates over three periods,  $t = 0, 1, 2$ . In period 0, nature draws a weather shock  $\omega \geq 0$  (the annual count of locally extreme days). The firm's production technology converts capital and working inputs into output, but extreme weather disrupts logistics, labour supply, and inventory turnover with a lag: operating cash flow in period 1 is

$$CF_1 = CF - \lambda\omega, \lambda > 0, (1)$$

where  $CF$  is normal operating cash flow and  $\lambda$  captures the firm's exposure sensitivity, which decreases with diversification, supply-chain redundancy, and the adaptability of local infrastructure—all correlated with firm size. The lag embodied in Eq. (1) reflects the institutional reality that weather realisations in

period 0 affect receivables collection, inventory cycles, and insurance settlement over the subsequent operating cycle, rather than instantaneously.

In period 1, having observed  $CF_1$ , the firm must fund a fixed operating programme  $I$  (essential investment, payroll, and debt service). It can draw on internal liquidity  $L$  (cash holdings) or raise external debt  $B$  at gross cost  $R(B)$ , choosing the mix to minimise the total cost of funds subject to a borrowing constraint:

$$\min_{\{B \geq 0\}} R(B) \cdot B + \rho \cdot (L_{\text{used}}) \text{ s.t. } B \leq \bar{B}(\omega, \theta), I = B + L_{\text{used}} - (CF_1 \text{ shortfall}), (2)$$

where  $\rho$  is the shadow cost of depleting liquidity (precautionary value forgone) and  $\bar{B}(\omega, \theta)$  is the maximum the firm can borrow, which depends on the shock  $\omega$ —because the same event that damages cash flow also damages collateral, order books, and lender sentiment—and on a firm-specific credit-access parameter  $\theta$  (scale, state connections, banking relationships). Two regimes emerge. For unconstrained firms ( $\theta$  high,  $\bar{B}$  non-binding), the optimal response to a cash-flow shortfall is to expand  $B$  until the marginal cost of debt equals the shadow cost of liquidity depletion: leverage rises with  $\omega$ , and cash holdings adjust smoothly at the margin. For constrained firms ( $\theta$  low,  $\bar{B}$  binding at or below current levels),  $B$  cannot rise; the entire shortfall falls on internal liquidity, and if  $L$  is insufficient the firm must compress the operating programme itself. The constraint binds exactly where the shock is most damaging, because  $\bar{B}(\omega, \theta)$  is decreasing in  $\omega$ .

Three further considerations complete the framework. First, price rigidity: in a bank-centred system with administered elements in loan pricing,  $R(B)$  is sticky for inframarginal borrowers, so adjustment occurs through quantities ( $B$  and  $L$ ) rather than prices—effective debt costs move little even when quantities do. Second, shock composition: heat-type shocks are spatially broad and affect all firms in a region through energy, labour, and logistics, whereas rainfall-type shocks are locally concentrated and lumpy (flooded premises, severed links); diversified firms can re-route activity across sites, but small, single-site firms cannot, so the exposure sensitivity  $\lambda$  for rainfall declines steeply with firm size. Third, buffer behaviour: a constrained firm that anticipates further shocks has an incentive to hoard rather than deploy cash, so its observed cash ratio may rise even as its cash flow deteriorates.

## 2.4 Hypotheses

The framework yields four testable predictions, which we take to the data in sequence.

H1 (Delayed cash-flow transmission). Extreme weather reduces operating cash flow with a lag rather than contemporaneously: the effect of period- $t$  exposure materialises in period  $t + 1$  cash flow, and period  $t + 1$  outcomes are orthogonal to period  $t + 2$  exposure (no anticipation).

H2 (Size-graded rainfall damage). The adverse cash-flow effect of extreme rainfall is concentrated in small firms, whose operations are geographically undiversified and whose infrastructure redundancy is limited.

H3 (Asymmetric financing adjustment). After extreme weather, large (plausibly unconstrained) firms expand leverage to smooth the cash-flow shortfall, whereas small (plausibly constrained) firms do not; the cross-sectional asymmetry reveals the incidence of binding financing constraints.

H4 (Quantity-price asymmetry). Effective debt costs respond weakly or not at all to extreme weather, even where quantities adjust, reflecting administered elements and relationship pricing in the bank-centred credit system.

### **3. Data and variable construction**

#### **3.1 Firm financial data**

Firm financial statements are drawn from Eastmoney's annual-report cross-section services, which provide the complete balance sheet, income statement, and cash-flow statement of every A-share listed firm for each fiscal year from 2010 to 2024. We impose the standard screens: financial-industry firms (banks, insurers, securities companies, and diversified financials) are excluded because their balance sheets are not comparable to those of non-financial corporations; firms under special treatment (ST or \*ST designation, indicating financial distress or delisting risk) are excluded because their financing behaviour is dominated by workout dynamics; and firm-years with missing total assets, total liabilities, or registration information are dropped. Registration city, province, CSRC industry classification, and listing date are obtained from Eastmoney's F10 company-profile database and matched by stock code. The resulting unbalanced panel comprises 4,170 non-financial firms and 51,986 firm-year observations; requiring a complete lag structure for the exposure variables yields an estimation sample of 47,870 observations. All outcome and control variables are winsorised at the 1st and 99th percentiles to limit the influence of reporting errors.

#### **3.2 Weather data and exposure measurement**

Daily maximum temperature and daily precipitation are obtained from the Open-Meteo historical archive, an ERA5-based reanalysis product with complete coverage over China, for the centroids of 351 cities in which sample firms are registered, over the twenty-year window 2005–2024. The use of a two-decade climatological reference period is deliberate: exposure is defined relative to what local infrastructure, contracts, and supply chains are adapted to, rather than to an absolute physical threshold. Specifically, for each city we compute the 90th percentile of the daily maximum-temperature distribution and the 95th percentile of the distribution of wet days (precipitation  $\geq 1$  mm) over 2005–2024. `heat_days` then counts, for each city and year, the number of days on which maximum temperature exceeds the local 90th percentile, and `rain_days` counts days on which precipitation exceeds the local 95th percentile of wet days. Because the thresholds are local, a heat day in Harbin and a heat day in Guangzhou represent equally abnormal events relative to local norms, which is the variation relevant for economic disruption. For robustness we construct an absolute-threshold measure (days with  $T_{\max} \geq 35^{\circ}\text{C}$ ) and within-city standardised (z-score) anomalies of the day counts. All exposure variables enter the regressions scaled per ten days. Figure 1 maps the geographic distribution of average exposures across registration cities;

Fig. 2 plots the national time series, which exhibits the warming trend and episodic rainfall extremes familiar from the climate record.

Two features of the weather data deserve emphasis. First, reanalysis products such as ERA5 blend station observations with a physical model of the atmosphere, avoiding the coverage gaps and station-relocation inhomogeneities that affect raw station records in China over long horizons; the trade-off is some smoothing of extreme tails, which works against finding effects and thus renders our estimates conservative. Second, because the same gridded product is used for every city and every year, measurement error is not differential across firms, cities, or time—ruling out the correlated-measurement-error structures that most threaten panel designs of this kind. As a validation exercise, our reconstructed city-year exposure counts match an independently assembled version of the same measures with correlations above 0.999 for all three exposure variables, indicating that the exposure construction is stable and reproducible end to end.

### 3.3 Outcome and control variables

The primary real-side outcome is the operating-cash-flow-to-assets ratio ( $ocf_r$ ), the most direct accounting measure of the liquidity that operations generate and the primitive to which all financing policy responds; return on assets ( $roa$ ) serves as the corresponding profitability measure and allows us to distinguish cash-flow effects from valuation effects. On the financing side, we examine three complementary margins: the leverage ratio (total liabilities over total assets), the quantity margin of debt finance; the cash-holdings ratio (cash and equivalents over total assets), the internal-liquidity margin; and the effective cost of debt (financial expenses over total liabilities), the price margin. Controls comprise firm size (the natural logarithm of total assets), return on assets, revenue growth, and operating cash flow, with the outcome variable itself excluded from its own control set. Firm size enters the heterogeneity analysis through a time-invariant small-firm indicator equal to one if a firm's time-averaged total assets fall below the sample median; using time-averaged rather than year-by-year size preserves panel continuity of group membership. Table 1 reports summary statistics. The average firm-year exhibits 37 extreme heat days and 6.4 extreme rainfall days against local norms, with substantial dispersion across cities and years—the identifying variation of the study.

Table 1  
Summary statistics

| Variable                                                                                                                                                                                                                                                                                                      | N      | Mean  | SD    | Min    | Median | Max    |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------|-------|-------|--------|--------|--------|
| Operating CF / assets (%)                                                                                                                                                                                                                                                                                     | 51,985 | 6.00  | 8.23  | -18.18 | 5.56   | 31.39  |
| Return on assets (%)                                                                                                                                                                                                                                                                                          | 51,986 | 5.28  | 7.23  | -21.34 | 4.60   | 28.44  |
| Leverage (%)                                                                                                                                                                                                                                                                                                  | 51,986 | 42.19 | 20.22 | 5.40   | 41.52  | 88.99  |
| Cash / assets (%)                                                                                                                                                                                                                                                                                             | 51,986 | 19.41 | 14.02 | 1.53   | 15.52  | 68.55  |
| Effective debt cost (%)                                                                                                                                                                                                                                                                                       | 51,984 | 0.43  | 3.51  | -17.52 | 0.90   | 6.67   |
| Size (log assets)                                                                                                                                                                                                                                                                                             | 51,986 | 21.79 | 1.56  | 13.24  | 21.67  | 28.79  |
| Listing age (years)                                                                                                                                                                                                                                                                                           | 51,986 | 7.84  | 9.26  | -15.00 | 6.00   | 35.00  |
| Revenue growth (%)                                                                                                                                                                                                                                                                                            | 47,870 | 16.99 | 38.27 | -52.38 | 10.82  | 234.14 |
| Extreme heat days (per year)                                                                                                                                                                                                                                                                                  | 51,986 | 37.14 | 14.94 | 3.00   | 37.00  | 109.00 |
| Extreme rainfall days (per year)                                                                                                                                                                                                                                                                              | 51,986 | 6.41  | 3.59  | 0.00   | 6.00   | 26.00  |
| Days with Tmax $\geq 35^{\circ}\text{C}$                                                                                                                                                                                                                                                                      | 51,986 | 10.87 | 12.45 | 0.00   | 6.00   | 80.00  |
| Notes: Statistics for the full firm-year panel, 2010–2024 (51,986 observations, 4,170 firms). Exposure variables are city-year counts relative to local 2005–2024 climatological norms. Financial variables are in percent or as indicated and are winsorised at the 1st/99th percentiles in the regressions. |        |       |       |        |        |        |

### 3.4 Identifying variation

The identifying variation can be summarised concretely. Within a city, the annual count of extreme heat days fluctuates substantially around its climatological mean of roughly 36–37 days: the within-city standard deviation exceeds 12 days, and runs of two to three consecutive high-exposure years alternate with low-exposure years in a pattern that is essentially serially unstructured once province-by-year shocks are removed. Because firms do not switch cities, the firm fixed effect absorbs each firm's average exposure level, and because province-by-year fixed effects absorb regional co-movement—including the broad warming trend visible in Fig. 2—the coefficients are identified from the deviation of a firm's local weather in a given year from what that firm's location and that year's provincial conditions would predict. The distributed-lag structure then traces how each outcome responds to these deviations over the shock year and the two subsequent years, with the lead term providing the corresponding falsification margin. It is worth emphasising what is not part of the identification: cross-sectional differences in average exposure between, say, hotter southern and cooler northern cities play no role, nor do nationwide hot years, both of which are absorbed by the fixed-effect structure.

## 4. Econometric framework and identification

## 4.1 Specification

For each outcome  $y$  of firm  $i$  in year  $t$ , we estimate the distributed-lag panel model

$$y_{it} = \alpha + \sum_{h=0}^2 \beta_h \text{Heat}_{\{c(i), t-h\}} + \sum_{h=0}^2 \gamma_h \text{Rain}_{\{c(i), t-h\}} + X_{it}'\delta + \mu_i + \theta_{\{p(i), t\}} + \varepsilon_{it}, \quad (3)$$

where Heat and Rain are the exposure measures (in tens of days) of firm  $i$ 's registration city  $c(i)$ ;  $X_{it}$  is the vector of time-varying controls described above;  $\mu_i$  denotes firm fixed effects, which absorb all time-invariant determinants of financing policy such as business model, ownership structure, and latent managerial quality; and  $\theta_{\{p(i), t\}}$  denotes province-by-year fixed effects, which absorb every shock common to firms in a province in a given year—regional business cycles, provincial credit and industrial policies, and disaster-relief programmes among them. The lag structure traces the dynamic response over the year of the shock and the two subsequent years, allowing the data to reveal the timing predicted by hypothesis H1 rather than imposing it. Standard errors are clustered at the city level, the level at which treatment is assigned and at which spatial correlation in both exposure and outcomes is expected; Section 6 reports more conservative alternatives.

## 4.2 Identification assumptions

The identifying assumption is that, conditional on firm fixed effects and province-by-year fixed effects, the sequence of local weather realisations is as good as randomly assigned with respect to firm outcomes. Several features of the design make this assumption credible, and Section 6 subjects each to explicit empirical scrutiny. First, reverse causality is physically impossible: no firm's financing decision affects the weather of its registration city. Second, anticipation is testable rather than assumed away: if firms adjusted financing in advance of extreme seasons, lead terms would enter significantly, so we augment Eq. (3) with a one-year lead of exposure as a placebo. Third, selective migration is checked by observation: firms could in principle sort across exposure zones by relocating their registration, but as documented below, not a single firm in the sample changes its registration city during 2010–2024. Fourth, measurement error in the reanalysis-based exposure is plausibly classical at the city-year level and therefore attenuates coefficients toward zero, rendering our significant estimates conservative; we nonetheless verify robustness to alternative threshold and standardisation choices. Fifth, because exposure varies at the city-year level, spatial correlation is the relevant inferential concern; we address it with city-level clustering in the baseline and with two-way and province-level clustering in robustness. Finally, we implement a permutation placebo that reassigns entire city exposure time series—preserving their autocorrelation, distributional shape, and cross-sectional dispersion—across the 351 cities three hundred times, thereby generating the exact distribution of coefficients that the panel structure would produce under the null of no true geographic assignment.

## 5. Empirical results

### 5.1 The cash-flow channel

Table 2 reports estimates of Eq. (3) for the two real-side outcomes. The pattern is a precise empirical counterpart of the model's first prediction. Extreme heat has no contemporaneous effect on operating cash flow (0.000,  $t = 0.00$ ), a large and highly significant effect one year later ( $-0.134$  percentage points per ten days,  $t = -3.11$ ), and a smaller, statistically insignificant effect at the two-year horizon ( $-0.052$ ,  $t = -1.22$ ). The response is thus delayed and transitory: extreme heat in year  $t$  damages the cash conversion cycle of year  $t + 1$ —through disrupted collections, inventory accumulation, and settlement delays—and then dissipates, exactly as working-capital transmission implies. In economic magnitude, the one-year effect corresponds to about 1.6% of the sample standard deviation of operating cash flow per ten additional heat days; for a city-year at the 90th percentile of the exposure distribution (roughly 20 days above the median), the implied drag approaches 0.3 percentage points of assets, a first-order liquidity event for firms near covenant or payroll margins. Rainfall coefficients are negative but imprecisely estimated in the pooled sample, a pattern that Section 5.3 shows to conceal strong heterogeneity by firm size. Return on assets responds positively, if modestly, at the one-year horizon (0.085,  $t = 2.01$ ), indicating that the cash-flow effect is not a mechanical reflection of accounting profitability: heat impairs the timing of collections and payments—the margin that matters for liquidity management—more than it impairs booked margins.

Table 2  
Extreme weather and the cash-flow channel: distributed-lag estimates

| Heat days (t)      | (1) Operating CF/assets (%) | (2) ROA (%)    |
|--------------------|-----------------------------|----------------|
|                    | <b>0.0002</b>               | <b>-0.0378</b> |
|                    | (0.00)                      | (-0.74)        |
| Heat days (t - 1)  | -0.1336***                  | 0.0846**       |
|                    | (-3.11)                     | (2.01)         |
| Heat days (t - 2)  | -0.0517                     | 0.0005         |
|                    | (-1.22)                     | (0.01)         |
| Rain days (t)      | 0.0441                      | 0.0491         |
|                    | (0.29)                      | (0.35)         |
| Rain days (t - 1)  | -0.2192                     | 0.3282**       |
|                    | (-1.30)                     | (2.00)         |
| Rain days (t - 2)  | -0.1488                     | 0.1948         |
|                    | (-0.80)                     | (1.25)         |
| Controls           | Yes                         | Yes            |
| Firm FE            | Yes                         | Yes            |
| Province × year FE | Yes                         | Yes            |
| Observations       | 47,870                      | 47,870         |
| Firms              | 4,170                       | 4,170          |

Notes: Estimates of Eq. (3) with firm and province-by-year fixed effects. Exposures are in tens of days per year relative to local climatology. Controls are firm size, return on assets, revenue growth, and operating cash flow, excluding the outcome. t-statistics based on city-clustered standard errors in parentheses. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels.

## 5.2 Financing adjustment: quantities, buffers, and prices

Table 3 turns to the financing side. In the pooled sample, none of the three margins responds significantly to either exposure at any horizon: leverage moves by less than a tenth of a percentage point per ten heat days at every lag; cash holdings are flat; and effective debt costs are statistically indistinguishable from zero throughout. Two readings are possible, and they are not mutually exclusive. The first is that the median listed firm is sufficiently liquid to absorb a moderate, transitory cash-flow shock without restructuring its liabilities—the buffer does its job silently, so nothing appears in the quantity margins. The second is that the pooled estimate averages over firms in opposite regimes of the model of Section 2.3: unconstrained firms, which expand debt, and constrained firms, which cannot. The

heterogeneity analysis below shows that the second reading is the operative one. For financing-management purposes, the pooled null is itself an important benchmark: ex-post liability restructuring is not the average margin of adaptation to extreme weather among Chinese listed firms.

Table 3  
Extreme weather and financing outcomes: pooled estimates

| Heat days (t)                                                                                                                                     | (1) Leverage (%) | (2) Cash/assets (%) | (3) Debt cost (%) |
|---------------------------------------------------------------------------------------------------------------------------------------------------|------------------|---------------------|-------------------|
|                                                                                                                                                   | <b>0.1309</b>    | <b>-0.0557</b>      | <b>0.0297</b>     |
|                                                                                                                                                   | (0.79)           | (-0.63)             | (0.83)            |
| Heat days (t - 1)                                                                                                                                 | 0.0873           | 0.0415              | 0.0025            |
|                                                                                                                                                   | (0.89)           | (0.51)              | (0.07)            |
| Heat days (t - 2)                                                                                                                                 | 0.0967           | -0.0063             | -0.0129           |
|                                                                                                                                                   | (0.98)           | (-0.06)             | (-0.43)           |
| Rain days (t)                                                                                                                                     | -0.1316          | 0.1310              | 0.0429            |
|                                                                                                                                                   | (-0.39)          | (0.44)              | (0.41)            |
| Rain days (t - 1)                                                                                                                                 | -0.0383          | -0.1315             | 0.1293            |
|                                                                                                                                                   | (-0.10)          | (-0.39)             | (1.37)            |
| Rain days (t - 2)                                                                                                                                 | -0.4453          | 0.1600              | 0.0828            |
|                                                                                                                                                   | (-1.09)          | (0.56)              | (0.90)            |
| Controls                                                                                                                                          | Yes              | Yes                 | Yes               |
| Firm FE                                                                                                                                           | Yes              | Yes                 | Yes               |
| Province × year FE                                                                                                                                | Yes              | Yes                 | Yes               |
| Observations                                                                                                                                      | 47,870           | 47,870              | 47,869            |
| Firms                                                                                                                                             | 4,170            | 4,170               | 4,170             |
| Notes: Same specification as Table 2. t-statistics (city-clustered) in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels. |                  |                     |                   |

## 5.3 Heterogeneity by firm size: revealed financing frictions

Table 4 interacts the one-year-lagged exposures—the horizon at which the cash-flow effect materialises—with the time-invariant small-firm indicator, estimating base effects for large firms and differential effects for small firms within a single regression per outcome. The results decompose the pooled null into an economically coherent asymmetry. First, confirming H2, the rainfall effect on operating cash flow is entirely a small-firm phenomenon: the base effect for large firms is + 0.061 (t = 0.31), while the small-firm interaction is - 0.606 (t = - 3.31), implying a small-firm effect of roughly - 0.55 percentage points per

ten days—more than four times the pooled heat effect. Flooding damages premises, inventory, and local transport links in a lumpy fashion that diversified firms can re-route around and single-site firms cannot. Second, confirming H3, the leverage response to heat is mirror-imaged across the size distribution: large firms expand leverage by 0.244 percentage points per ten days ( $t = 2.24$ ), but the small-firm interaction ( $-0.343$ ,  $t = -2.79$ ) fully offsets the base effect. The firms with the least cash-flow damage obtain the external funds; the firms with the most damage do not. This is precisely the cross-sectional signature of a binding borrowing constraint in the model—the constraint binds exactly where the shock bites hardest, because the shock simultaneously erodes cash flow and creditworthiness. Third, small firms tilt toward internal buffers instead: the small-firm interaction for cash holdings after heat is positive and marginally significant ( $0.173$ ,  $t = 2.05$ ), consistent with the precautionary accumulation of internal liquidity by firms whose access to external funds is impaired—the same cash-flow-sensitivity-of-cash logic formalised by Almeida et al. (2004) and documented for crisis periods by Bates et al. (2009) and Campello et al. (2011). Finally, confirming H4, effective debt costs respond to nothing, anywhere: neither in the pooled sample, nor in interactions, nor at any horizon. Adjustment in China's bank-centred credit system occurs in quantities and in access, not in inframarginal prices—a pattern reminiscent of the quantity-first credit contraction documented by Ivashina and Scharfstein (2010). Figure 4 displays the interaction estimates graphically.

Table 4  
Heterogeneity by firm size: interaction estimates at the one-year horizon

| Outcome                                                                                                                                                                                                                                                                                                                                                                                                                                                                 | Heat (t – 1)<br>base | Heat × small          | Rain (t – 1)<br>base | Rain × small          |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------|-----------------------|----------------------|-----------------------|
| Operating CF/assets (%)                                                                                                                                                                                                                                                                                                                                                                                                                                                 | -0.1252**<br>(-2.49) | -0.0159 (-0.30)       | 0.0606 (0.31)        | -0.6063***<br>(-3.31) |
| Leverage (%)                                                                                                                                                                                                                                                                                                                                                                                                                                                            | 0.2445** (2.24)      | -0.3429***<br>(-2.79) | 0.7748 (1.64)        | -1.8246***<br>(-3.51) |
| Cash/assets (%)                                                                                                                                                                                                                                                                                                                                                                                                                                                         | -0.0411 (-0.51)      | 0.1734** (2.05)       | -0.2713<br>(-0.66)   | 0.2952 (0.60)         |
| Debt cost (%)                                                                                                                                                                                                                                                                                                                                                                                                                                                           | 0.0157 (0.44)        | -0.0333 (-1.39)       | 0.1021 (0.91)        | 0.0286 (0.21)         |
| Notes: Each cell reports the base coefficient (large firms) or the interaction with the small-firm indicator from a single regression per outcome that interacts the full lag structure with the indicator and includes firm and province-by-year fixed effects and standard controls. Small firms have time-averaged total assets below the sample median. t-statistics (city-clustered) in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels. |                      |                       |                      |                       |

## 5.4 Economic magnitudes and interpretation

How large are these effects in terms that a treasurer would recognise? Consider a firm in a city that experiences an unusually hot year—twenty additional extreme heat days, roughly the gap between a median and a 90th-percentile exposure year. The point estimates imply a shortfall of about 0.27 percentage points of assets in next year's operating cash flow, or roughly CNY 60 million for the median

sample firm with assets near CNY 22 billion in logarithmic terms. For a large firm, the implied response—an increase in leverage of about half a percentage point—comfortably covers the shortfall at prevailing debt costs of around 0.4–0.9 percent of liabilities. For a small firm facing an equivalently abnormal rainfall season, the implied cash-flow shortfall exceeds one percentage point of assets, and the estimated financing response is nil; the shortfall must therefore be absorbed by compressing investment, delaying payments to suppliers, or drawing down the very buffers that precautionary logic would seek to preserve. The asymmetry is not a statistical curiosity; it is a quantified statement about which firms will enter the next extreme season with depleted defences.

It is also instructive to consider what the data rule out. The flat contemporaneous response and the flat lead exclude stories based on immediate salience or anticipation—managers are neither overreacting to the current season nor pre-positioning for the next one, in contrast to the behavioural pattern documented by Dessaint and Matray (2017) for hurricane strikes near headquarters. The transitory two-year reversion excludes permanent productivity destruction of the kind that would warrant structural recapitalisation. And the absence of any debt-cost response excludes the pricing channel through which forward-looking physical risk operates in the mortgage-market evidence of Murfin and Spiegel (2020) and the disaster-driven credit reallocation of Cortés and Strahan (2017): recurrent extremes, unlike secular sea-level rise, are apparently not priced into inframarginal loan rates in this system. What remains—delayed cash-flow damage, quantity-based smoothing by the unconstrained, and quiet absorption by the constrained—is a narrower and, for financing management, a more actionable characterisation of the problem.

## 5.5 Why does rainfall not move large firms at all?

The complete absence of a rainfall effect among large firms—against a strongly negative small-firm effect—merits interpretation. Large firms typically operate multiple establishments across cities and provinces, so that a flood in one locality interrupts a fraction of their logistics network while leaving the remainder intact; they carry commercial property and business-interruption insurance at materially higher rates; and their supplier contracts more often contain force-majeure and re-routing provisions. Small firms, by contrast, are commonly single-establishment operations embedded in one local economy: the same flood reaches their premises, their workforce, their customers, and their suppliers simultaneously. The estimated asymmetry is thus not merely a financing-friction gradient but a real-side diversification gradient, and its magnitude provides a rare market-based estimate of the value of operational diversification against climate extremes.

## 6. Endogeneity concerns and robustness

This section confronts the threats to identification catalogued in Section 4.2, taking the one-year lagged heat effect on operating cash flow ( $-0.134$ ,  $t = -3.11$ ) as the benchmark. Table 5 assembles the battery; Fig. 3 plots the full dynamic path and Fig. 5 the permutation placebo distribution.

Omitted variables. The province-by-year fixed effects absorb any shock shared by firms in a province, but one might worry about omitted determinants that vary at the city-year level and correlate with local weather—for instance, city-specific industrial policies or infrastructure investments timed after extreme seasons. Such confounders would need to satisfy a demanding set of requirements: they must respond to weather with the same one-year lag as our estimated cash-flow effect, they must not respond contemporaneously (since the contemporaneous coefficient is precisely zero), and they must operate through working capital rather than profitability (since the ROA response differs in sign and timing). Policy responses to disasters typically arrive quickly and visibly; a confounder with this exact delayed, narrow signature is difficult to construct. The permutation placebo provides the corresponding non-parametric check: any city-year omitted structure that is independent of the true geographic assignment of weather is destroyed by reassignment, and no reassigned series reproduces the estimate.

Anticipation and pretrends. If firms adjusted financing or operations in advance of extreme seasons, future exposure would predict current outcomes. It does not: the one-year lead of heat exposure enters at  $-0.069$  ( $t = -1.30$ ), and the dynamic path in Fig. 3 is flat before the shock, drops sharply at  $t + 1$ , and reverts toward zero at  $t + 2$ . The absence of pretrends is what one would expect if weather realisations are unforecastable at annual horizons, and the shape of the response—delayed, then transitory—is what the working-capital mechanism predicts.

Measurement. Replacing the local percentile threshold with the absolute  $35^{\circ}\text{C}$  threshold leaves the coefficient negative but renders it insignificant ( $-0.066$ ,  $t = -0.96$ ). This contrast is itself informative: it is locally abnormal heat—deviations from what regional infrastructure, contracts, and labour arrangements are built around—that disrupts cash conversion, rather than crossing an absolute physical threshold that many southern cities cross routinely. Redefining exposure as within-city standardised anomalies preserves the effect ( $-0.172$ ,  $t = -2.58$ ), so the result does not hinge on the day-count scaling.

Sample composition and specification. Excluding 2020, the COVID-19 year, leaves the estimate unchanged ( $-0.135$ ,  $t = -3.03$ ), establishing that pandemic-era disruptions—which were themselves spatially correlated—do not drive the result. A parsimonious specification retaining only the one-year lag yields  $-0.137$  ( $t = -3.23$ ), confirming that the estimate is not an artefact of the joint lag structure.

Inference. Two-way clustering by firm and year yields  $t = -2.76$ , and clustering at the province level—only 31 clusters, a deliberately conservative choice—yields  $t = -3.38$ . The effect survives both, so spatial or serial correlation in the errors does not account for its precision.

Sorting. Exposure is assigned by registration city, so endogenous relocation would invalidate the design: firms disproportionately harmed by weather might re-register elsewhere, contaminating the assignment. We verify directly that no firm changes its registration city during the sample period—zero of 4,170. Sorting is thus excluded observationally, not merely by assumption.

Permutation placebo. As a final omnibus check, we reassign each city's entire exposure time series to a randomly drawn city, preserving the autocorrelation, distributional shape, and cross-sectional dispersion

of weather while destroying its true geographic assignment, and re-estimate the benchmark specification 300 times. The resulting placebo distribution is centred at zero with a standard deviation of 0.031, and not a single draw produces a coefficient as large in magnitude as the actual – 0.134 (permutation  $p < 0.01$ ; Fig. 5). The panel structure alone, in other words, essentially never generates effects of the size we estimate; the cash-flow response is attached to the true geography of the shocks.

Table 5  
Endogeneity and robustness battery for the cash-flow effect of extreme heat

| Robustness check (outcome: operating CF/assets)                                                                                                                                                                                                                                        | Coefficient | t-statistic | N      |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------|-------------|--------|
| (1) Lead placebo: heat days ( $t + 1$ )                                                                                                                                                                                                                                                | -0.0690     | (-1.30)     | 43,709 |
| (2) Absolute threshold: days $\geq 35^{\circ}\text{C}$ ( $t - 1$ )                                                                                                                                                                                                                     | -0.0663     | (-0.96)     | 47,870 |
| (3) Standardised heat anomaly (z-score, $t - 1$ )                                                                                                                                                                                                                                      | -0.1722***  | (-2.58)     | 47,870 |
| (4) Excluding year 2020: heat days ( $t - 1$ )                                                                                                                                                                                                                                         | -0.1354***  | (-3.03)     | 43,795 |
| (5) One-year lag only: heat days ( $t - 1$ )                                                                                                                                                                                                                                           | -0.1370***  | (-3.23)     | 47,870 |
| (6) Two-way clustering (firm and year)                                                                                                                                                                                                                                                 | -0.1336***  | (-2.76)     | 47,870 |
| (7) Province-level clustering                                                                                                                                                                                                                                                          | -0.1336***  | (-3.38)     | 47,870 |
| (8) Permutation placebo (300 draws): share $ b  \geq  actual $                                                                                                                                                                                                                         | 0.0%        | –           | –      |
| (9) Firms changing registration city, 2010–2024                                                                                                                                                                                                                                        | 0 of 4,170  | –           | –      |
| Notes: The benchmark is the coefficient on heat days ( $t - 1$ ) in column (1) of Table 2 (– 0.1336, $t = -3.11$ ). Each row modifies one element of the design. Rows 8–9 report design checks rather than coefficients. ***, **, * denote significance at the 1%, 5%, and 10% levels. |             |             |        |

## 7. Discussion and conclusion

This paper set out to trace how physical climate risk propagates into corporate finance, and which firms can finance their way through it. The answer, in a comprehensive panel of Chinese listed firms, is threefold. First, the transmission runs through operating cash flow and runs on a delay: extreme heat reduces the operating-cash-flow-to-assets ratio one year after the shock, with no contemporaneous effect, no persistence beyond the second year, and no anticipation—a timing signature that points squarely at the cash conversion cycle rather than at valuation, salience, or attention channels. Second, the damage is distributed unequally in a way that theory predicts: spatially broad heat affects firms across the size distribution, while locally lumpy rainfall concentrates its cash-flow damage on small, undiversified firms. Third, and most consequentially for financing management, the adjustment to the shock is asymmetric in the direction that reveals financing frictions: large firms expand leverage precisely when cash flow deteriorates, small firms—hit at least as hard—do not adjust debt quantities and instead tilt toward cash hoarding, and effective debt costs move nowhere at all. Credit, in other

words, flows toward the firms that need it least after extreme weather, which is exactly what a borrowing-constraint model with shock-sensitive credit limits implies.

A second implication concerns the pricing of climate exposure in credit markets. The absence of any effective debt-cost response—even for small firms whose cash-flow damage is large and measurable—suggests that recurrent weather extremes are not being priced into loan contracts in this system. Whether this reflects implicit guarantees, relationship-based cross-subsidisation, or simple inattention is beyond the present data, but each interpretation carries the same warning: if quantities are rationed and prices do not adjust, credit misallocation after extreme seasons is likely, and the wedge between privately incurred damage and contractually recognised risk will widen as extremes become more frequent. Lenders that learn to read exposure-adjusted cash-flow forecasts—of the kind our estimates make computable—would hold an informational edge over competitors who price on collateral and history alone.

For corporate financing management, these findings reorganise the climate-adaptation problem around ex-ante architecture. Because the cash-flow impact arrives with a predictable one-year lag and because ex-post borrowing is unavailable to the firms that need it most, the effective margins of adaptation are those established before the shock: committed credit lines whose availability does not condition on the borrower's post-shock state; liquidity buffers calibrated to location-specific exposure rather than to industry norms; maturity ladders that avoid concentrating refinancing needs in high-exposure seasons; and insurance or parametric hedges for the rainfall risk that bank credit manifestly does not replace. The heterogeneity results carry a distributional warning for practice and policy alike: the market failure we document—credit allocated against, rather than toward, post-shock need—is precisely the failure that guarantee schemes, targeted refinancing facilities, or lender-of-resort windows are designed to correct, and our estimates provide the magnitudes against which such interventions can be sized.

For the academic literature, the paper demonstrates that extreme weather offers a class of well-measured, plausibly exogenous, and recurring shocks with which the incidence of financing constraints can be identified in the cross-section, complementing instrument-based and index-based approaches (Hadlock & Pierce, 2010; Kaplan & Zingales, 1997). It also offers a methodological template—local climatological thresholds, distributed-lag designs, lead placebos, and permutation inference on geographic assignment—that travels to other settings in which treatment varies spatially at high frequency.

Several qualifications bound the claims. The sample comprises listed firms, which are larger and better financed than the corporate population at large; the constraint asymmetry we document is therefore likely to be a lower bound for the economy. Exposure is assigned at registration-city centroids, abstracting from within-city variation and from the spatial dispersion of firms' plants and suppliers, which classical measurement-error logic suggests attenuates our estimates. The shocks we study are moderate and recurrent; the financing dynamics of catastrophic, tail events may differ in kind, not merely in degree. And while the permutation placebo and lead tests make spurious-assignment explanations

implausible, the design cannot speak to channels operating through province-level policy responses, which are absorbed by the fixed effects. Extending the analysis to unlisted firms, to bank-firm matched credit registers that would open the black box of credit allocation after shocks, and to the adaptation investments that might attenuate the cash-flow sensitivity itself, are natural and valuable next steps.

## Declarations

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRedit authorship contribution statement: Jiawei Ma – Conceptualization, Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest: The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability: The analysis dataset (Stata .dta and .csv) and the Stata replication script that reproduce all tables and figures are submitted as supplementary files with this manuscript. Firm financial statement data are from Eastmoney (via the AkShare interface); firm registration information is from the Eastmoney F10 database; daily weather data are from the Open-Meteo archive (open-meteo.com).

## References

1. Acharya VV, Davydenko SA, Strebulaev IA (2012) Cash holdings and credit risk. *Rev Financial Stud* 25(12):3572–3609
2. Addoum JM, Ng DT, Ortiz-Bobea A (2020) Temperature shocks and establishment sales. *Rev Financial Stud* 33(3):1331–1366
3. Addoum JM, Ng DT, Ortiz-Bobea A (2023) Temperature shocks and industry earnings news. *J Financ Econ* 150(1):1–45
4. Almeida H, Campello M (2007) Financial constraints, asset tangibility, and corporate investment. *Rev Financial Stud* 20(5):1429–1460
5. Almeida H, Campello M, Weisbach MS (2004) The cash flow sensitivity of cash. *J Finance* 59(4):1777–1804
6. Baldauf M, Garlappi L, Yannelis C (2020) Does climate change affect real estate prices? Only if you believe in it. *Rev Financial Stud* 33(3):1256–1295
7. Barrot J-N, Sauvagnat J (2016) Input specificity and the propagation of idiosyncratic shocks in production networks. *Quart J Econ* 131(3):1543–1592
8. Bates TW, Kahle KM, Stulz RM (2009) Why do U.S. firms hold so much more cash than they used to? *J Finance* 64(5):1985–2021

9. Bernstein A, Gustafson MT, Lewis R (2019) Disaster on the horizon: The price effect of sea level rise. *J Financ Econ* 134(2):253–272
10. Bolton P, Kacperczyk M (2021) Do investors care about carbon risk? *J Financ Econ* 142(2):517–549
11. Campello M, Giambona E, Graham JR, Harvey CR (2011) Liquidity management and corporate investment during a financial crisis. *Rev Financial Stud* 24(6):1944–1979
12. Carvalho VM, Nirei M, Saito YU, Tahbaz-Salehi A (2021) Supply chain disruptions: Evidence from the Great East Japan Earthquake. *Quart J Econ* 136(2):1255–1321
13. Choi D, Gao Z, Jiang W (2020) Attention to global warming. *Rev Financial Stud* 33(3):1112–1145
14. Cortés KR, Strahan PE (2017) Tracing out capital flows: How financially integrated banks respond to natural disasters. *J Financ Econ* 125(1):182–199
15. Dessaint O, Matray A (2017) Do managers overreact to salient risks? Evidence from hurricane strikes. *J Financ Econ* 126(1):97–121
16. Engle RF, Giglio S, Kelly B, Lee H, Stroebel J (2020) Hedging climate change news. *Rev Financial Stud* 33(3):1184–1216
17. Flammer C (2021) Corporate green bonds. *J Financ Econ* 142(2):499–516
18. Hadlock CJ, Pierce JR (2010) New evidence on measuring financial constraints: Moving beyond the KZ index. *Rev Financial Stud* 23(5):1909–1940
19. Ilhan E, Sautner Z, Vilkov G (2021) Carbon tail risk. *Rev Financial Stud* 34(3):1540–1571
20. Ivashina V, Scharfstein D (2010) Bank lending during the financial crisis of 2008. *J Financ Econ* 97(3):319–338
21. Kaplan SN, Zingales L (1997) Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quart J Econ* 112(1):169–215
22. Krueger P, Sautner Z, Starks LT (2020) The importance of climate risks for institutional investors. *Rev Financial Stud* 33(3):1067–1111
23. Murfin J, Spiegel M (2020) Is the risk of sea level rise capitalized in residential real estate? *Rev Financial Stud* 33(3):1217–1255
24. Pankratz NMC, Bauer R, Derwall J (2023) Climate change, firm performance, and investor surprises. *Manage Sci* 69(12):7352–7398
25. Sautner Z, van Lent L, Vilkov G, Zhang R (2023) Firm-level climate change exposure. *J Finance* 78(3):1449–1498

## Figures

Figure 1. Geographic Distribution of Extreme Weather Exposure

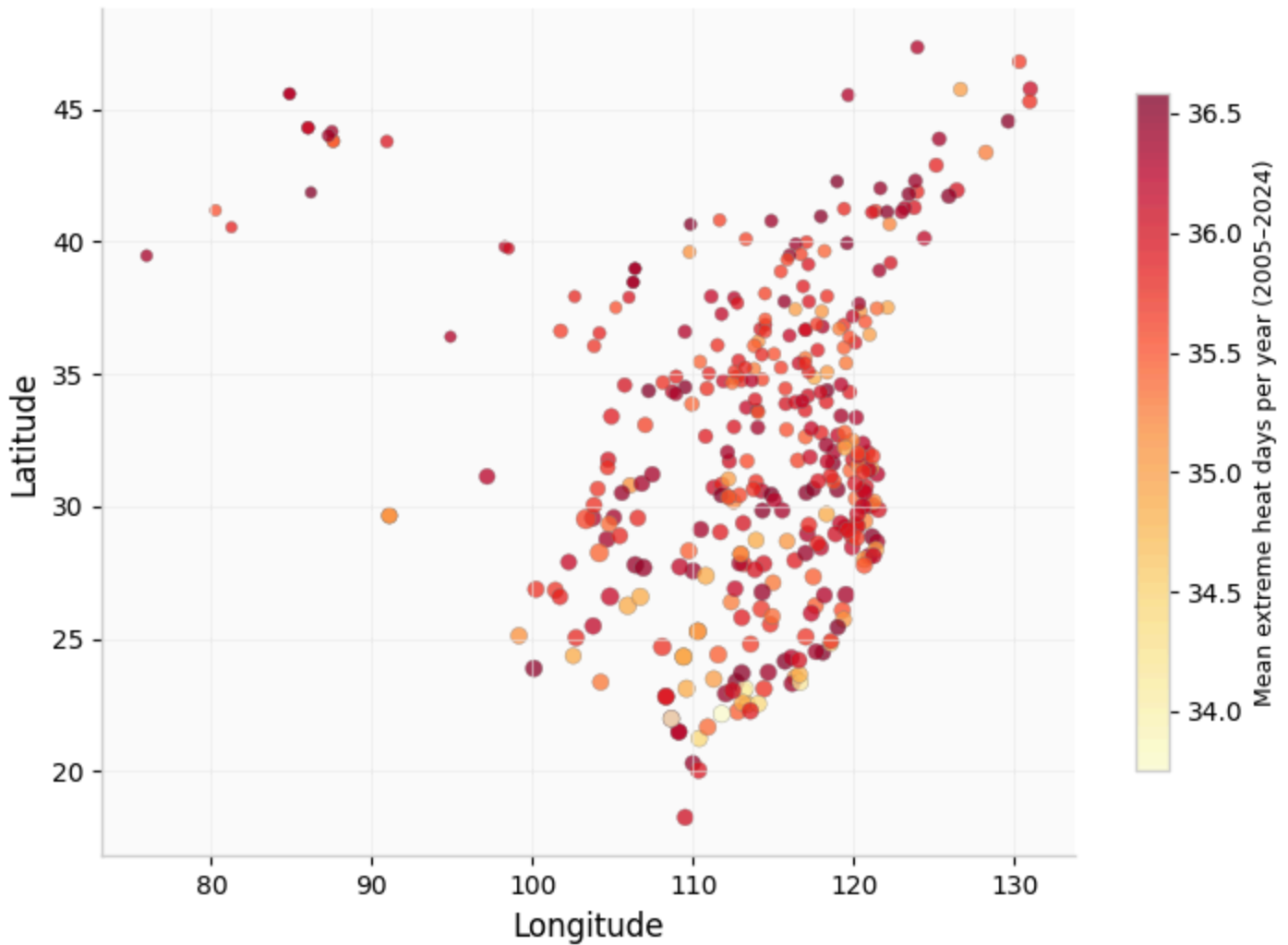


Figure 1

*Geographic distribution of extreme weather exposure. Each point is a sample firm's registration city; colour intensity shows the average annual number of extreme heat days (maximum temperature above the local 2005–2024 90th percentile); point size is proportional to the average annual number of extreme rainfall days (precipitation above the local 95th percentile of wet days).*

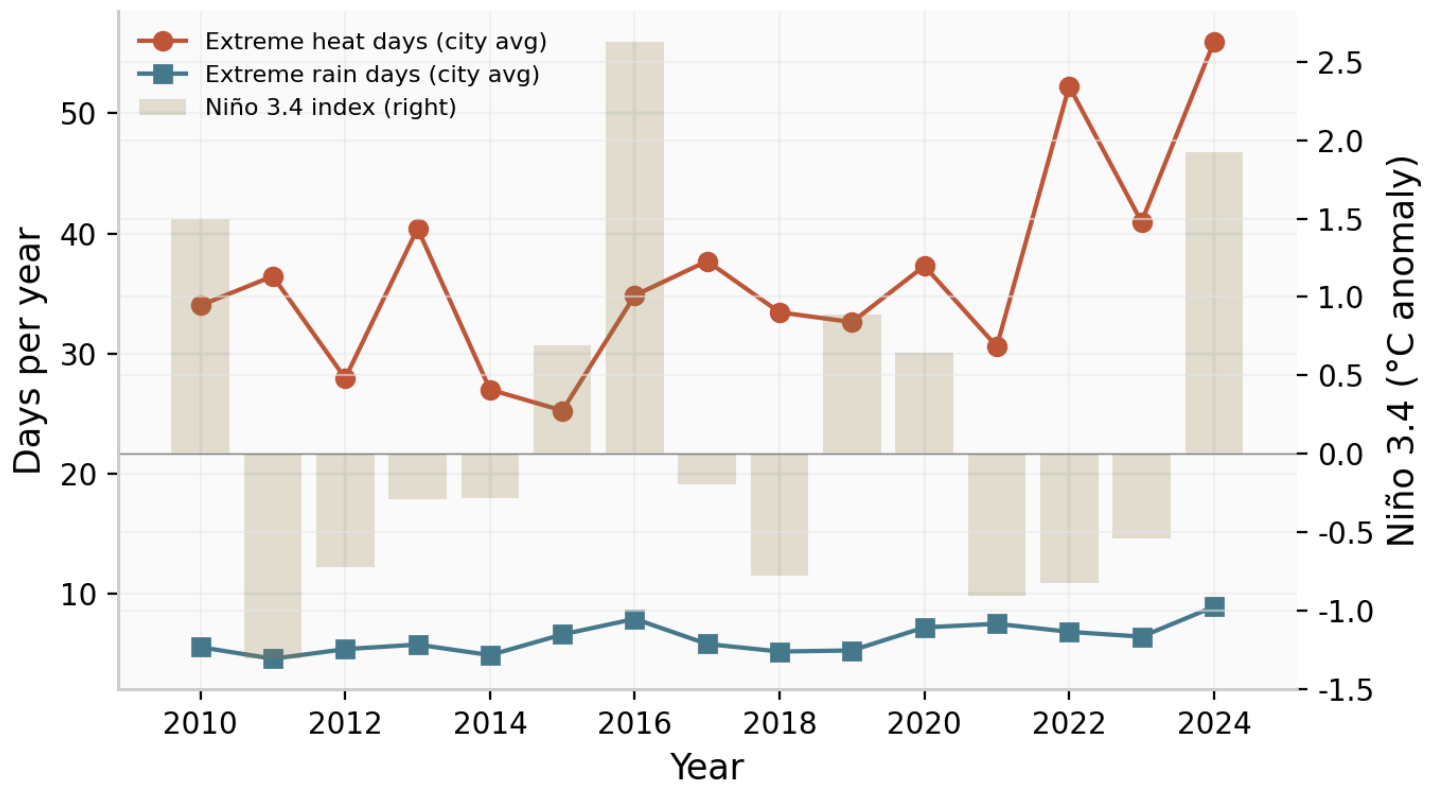


**Figure 2**

*National average extreme heat days and extreme rainfall days per city-year, 2005–2024, relative to local climatological norms.*

Dynamic response to extreme heat exposure (per ten days)

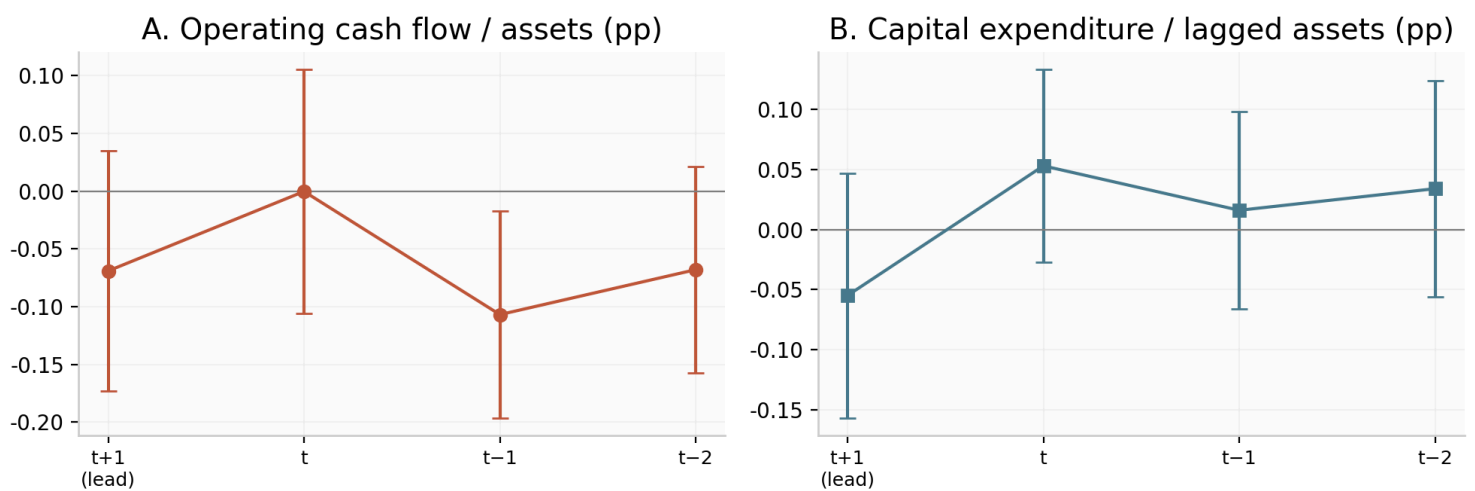


**Figure 3**

*Dynamic response of the operating-cash-flow-to-assets ratio to extreme heat exposure (per ten days), estimated with a one-year lead and contemporaneous, one-year, and two-year lags. The specification*

includes firm and province-by-year fixed effects and standard controls; whiskers show 95% confidence intervals based on city-clustered standard errors.

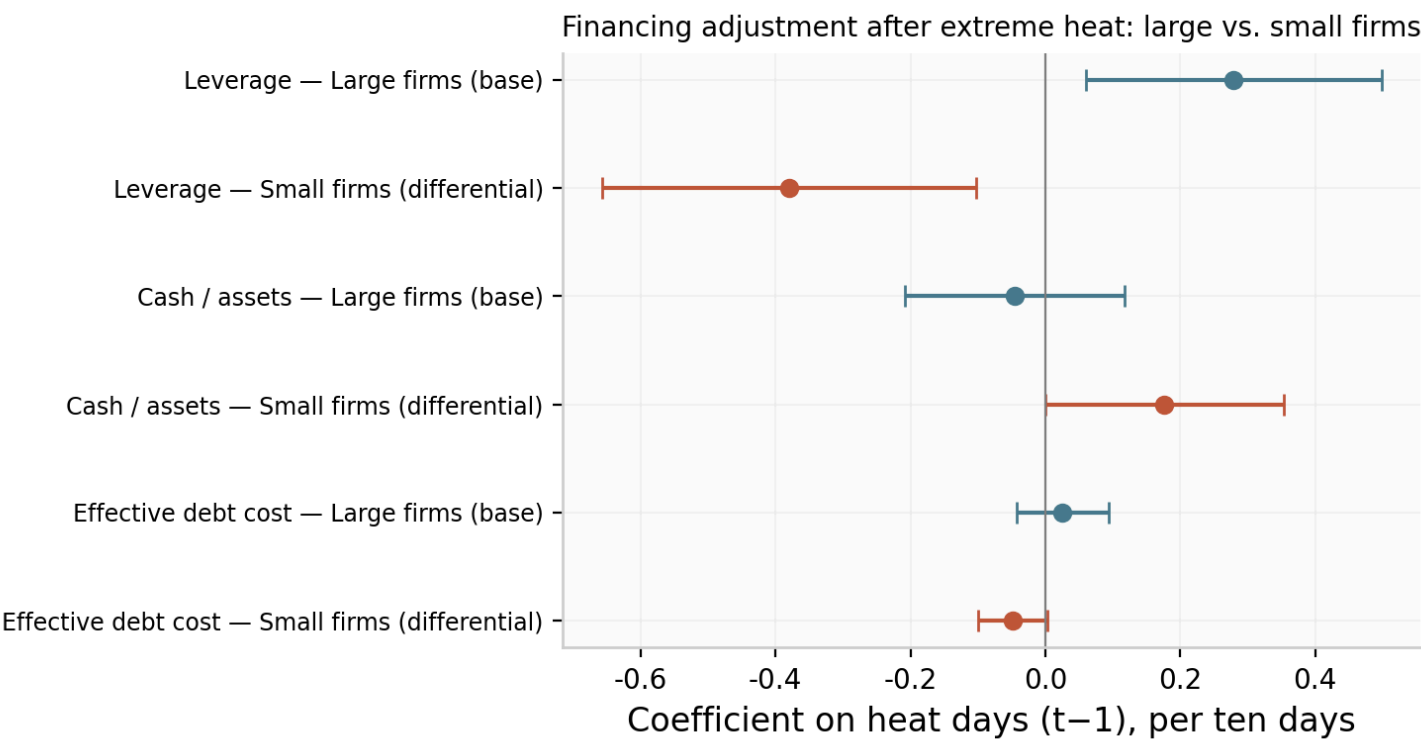


Figure 4

Heterogeneity by firm size: interaction coefficients of one-year-lagged heat and rainfall exposure with the small-firm indicator, with 95% confidence intervals (city-clustered standard errors).

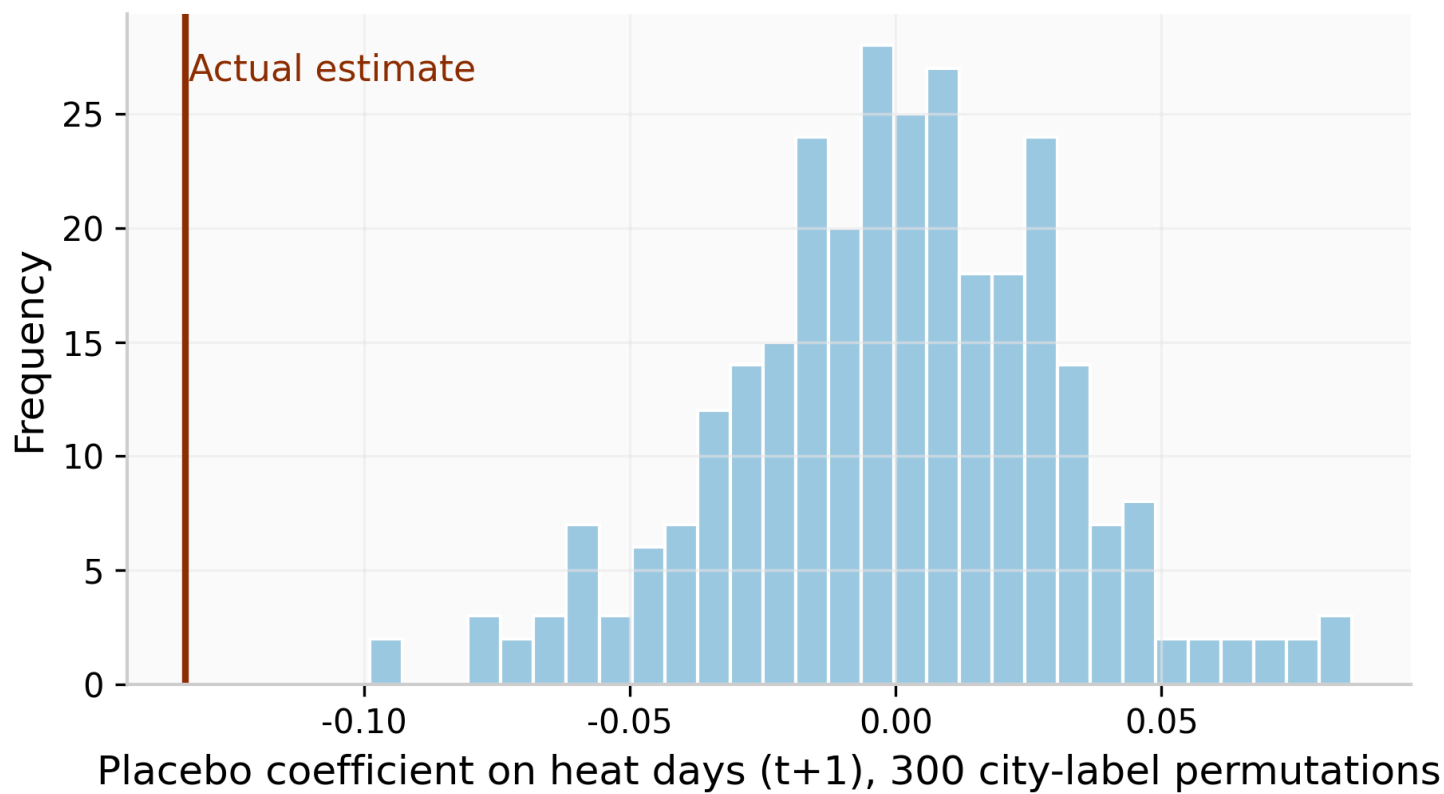


**Figure 5**

*Permutation placebo. Histogram of 300 estimates of the one-year-lagged heat coefficient obtained by randomly reassigning entire city exposure series across the 351 cities. The vertical line marks the actual estimate (-0.134).*