Extreme Heat Inside the Firm: Production, Adaptation, and Internal Allocation in Chinese Business Groups

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Abstract

Physical climate risk does not fall evenly within an organization. We examine how extreme heat propagates across the internal layers of multi-entity business groups, linking listed-firm financials, affiliated-entity registries, and the National Tax Survey to construct a group–parent–subsidiary panel for A-share Chinese business groups over 2007–2016 that observes production and factor inputs at all three layers, matched to city-level daily meteorological data. Extreme heat significantly reduces subsidiary output but leaves parent and aggregate group output statistically unchanged. The effect operates through lower capital input and total factor productivity and concentrates among labor-intensive subsidiaries. Groups adapt along three margins at distinct horizons: short-run buffering via internal product-market reallocation, medium-run selective exit of heat-exposed subsidiaries, and long-run investment in green innovation. Aggregate firm-level evidence understates the true incidence of climate damage, identifying internal resource allocation within business groups as central to climate-adaptation policy.

1. Introduction

Extreme heat has become more frequent and more intense with global warming and is increasingly emerging as an important physical climate risk for firms and business organizations. Unlike gradual increases in average temperature, heat waves and episodes of extreme heat are typically sudden, temporally concentrated, and spatially uneven, making them especially likely to generate sharp short-run shocks to labor input, production organization, and operating cash flows. For firms, heat exposure is therefore not merely an external environmental condition. It can disrupt production, reduce operating resilience, and force organizations to adjust how labor, capital, orders, and capacity are allocated across locations. Yet the organizational consequences of such physical climate risk remain less well understood. This question is especially important for business groups. Unlike standalone firms, business groups are multi-entity organizations that operate through parent companies, subsidiaries, and internal markets for resources and products. These structures may allow groups to buffer localized shocks by reallocating resources, shifting production, or adjusting the boundaries of exposed affiliates. At the same time, they may also conceal the true incidence of climate damage when losses borne by subsidiaries are not visible in parent-company or consolidated group outcomes. The key question, therefore, is not only whether extreme heat reduces firm output, but where inside the organization climate damage appears and how business groups respond.

China provides a particularly valuable setting for for examining how physical climate risk is allocated and absorbed within business groups. First, China spans a vast territory and multiple climate zones, so exposure to heat waves and extreme heat differs markedly across provinces and cities. The National Strategy for Climate Change Adaptation 2035 explicitly notes that climate change and its adverse effects are highly heterogeneous across regions, that extreme weather events such as heat waves are becoming more frequent in many places, and that climate risks increasingly extend beyond natural ecosystems to industrial chains, infrastructure, and the broader socioeconomic system. Second, China has incorporated climate adaptation and resilience to extreme weather into the national governance agenda. Both the National Strategy for Climate Change Adaptation 2035 and the Recommendations of the CPC Central Committee on Formulating the Fifteenth Five-Year Plan emphasize improving the capacity to cope with climate change—especially extreme weather—and strengthening socioeconomic resilience. Third, listed business groups in China expanded across regions for a prolonged period, establishing subsidiaries and allocating production capacity in many cities. As extreme heat has become more

frequent in recent years, different legal entities within the same group have been exposed asymmetrically to local heat shocks. This creates a useful setting to examine how business groups internally absorb, isolate, and redistribute localized physical climate shocks.

A large climate-economy literature shows that temperature shocks reduce economic production, especially at high temperatures (Dell et al., 2012, 2014; Burke et al., 2015). More recent micro-level evidence locates these effects at the firm and plant levels. In Chinese manufacturing, high temperatures lower output—primarily through declines in total factor productivity—following a nonlinear profile that rises to a moderate range and falls sharply beyond it (Zhang et al., 2018; Chen and Yang, 2019). The pattern recurs across settings: temperature reduces supplier sales relative to suppliers serving the same client, with stronger effects among manufacturing, heat-sensitive, and financially constrained firms (Custodio et al., 2022); extreme heat lowers firm revenues and operating income worldwide, effects that investors and analysts do not fully anticipate (Pankratz et al., 2023); and heat depresses worker productivity and labor supply in Indian plants (Somanathan et al., 2021). Existing work identifies several channels: heat reduces effective labor input by lowering workers' physical capacity, effort, attendance, and hours (Graff Zivin and Neidell, 2014; Somanathan et al., 2021); it lowers total factor productivity by disrupting how labor, capital, energy, and production processes combine (Zhang et al., 2018; Chen and Yang, 2019); it leads firms to adjust capital, cut investment, or build inventory buffers, shaping current and future output (Chen and Yang, 2019; Chen et al., 2022); and it raises energy costs while reducing productivity, particularly at smaller establishments (Ponticelli et al., 2023). Taken together, extreme heat affects production through labor productivity, TFP, capital and investment, inventory adjustment, and energy costs. Yet these studies generally treat the firm or plant as a single production unit, leaving open whether climate damage is borne by production-site subsidiaries, transmitted to parent companies, or absorbed within consolidated business groups.

A related literature examines how firms adapt to climate risk, but the adaptation margins most relevant to this paper are those that involve internal reallocation, market withdrawal, and longer-run capability building. First, strategy and organizational economics research suggests that business groups and diversified firms can use internal markets to redeploy resources across affiliated units when external market adjustment is costly. Internal labor, capital, and resource markets allow group-affiliated firms to respond to shocks more flexibly than standalone firms (Acharya et al., 2023; Sohl and Folta, 2025). This logic implies that business groups may buffer localized heat shocks by reallocating orders, capacity, or resources across subsidiaries. Second, climate-economy research shows that firms may adapt to extreme temperatures through extensive-margin adjustment. Establishment-level evidence from U.S. public firms shows that persistent local temperature increases induce firms to reorganize their operating networks by cutting local employment and shutting down exposed establishments (Jin et al., 2026). Higher temperatures can also reduce entry, increase exit, and reshape the geographic distribution of firms and investment (Cascarano et al., 2025; Ma et al., 2026). These findings suggest that when heat exposure persistently lowers local productivity, firms may withdraw from exposed locations or reduce the presence of vulnerable affiliates. Third, firms may also engage in longer-run capability building, including green innovation and technological upgrading. Evidence from China suggests that climate risk can promote corporate green innovation efficiency, especially when supported by digital transformation, external supervision, green subsidies, and weaker financing constraints (Hu et al., 2022; Ren et al., 2024; He et al., 2024; Zhou and Feng, 2025). Taken together, prior research suggests several ways in which firms may respond to climate risk. Yet we know less about whether these responses occur inside business groups, where headquarters can reallocate resources, adjust subsidiary boundaries, and manage climate exposure across multiple organizational layers.

Despite this progress, an organizational dimension remains conspicuously absent from the literature. The climate-risk literature reviewed above has shown that extreme heat affects firm production and adaptation, but it generally treats the firm as a single outcome unit. At the same time, research on business groups emphasizes that group-affiliated firms are embedded in multi-entity organizations with internal capital markets, internal labor markets, and resource-redeployment channels that may help affiliated units respond to external frictions and shocks (Khanna and Yafeh, 2007; Gopalan et al., 2007; Buchuk et al., 2014; Almeida et al., 2015; Sohl and Folta, 2025). Yet this business-group literature has rarely examined physical climate risk, and the climate-risk literature has rarely opened the firm to examine how climate damage is distributed across parent companies, subsidiaries, and consolidated groups.

As a result, three questions central to corporate climate risk remain unanswered. First, when a multi-entity firm is hit by a localized heat shock, where in the organization does the damage actually land—at the production-site subsidiary, at the parent, or distributed across the group? Second, does apparent stability of firm-level output under climate shocks reflect genuine insulation, or merely the localization of losses inside subsidiaries that aggregate firm-level data cannot see? Third, when groups adapt, do short-run buffering through internal reallocation, medium-run subsidiary exit, and long-run green innovation operate jointly within the same organization, and do they map onto specific subsidiary characteristics? Answering these questions requires data that simultaneously observes the production and factor inputs of the parent, of each subsidiary, and of the consolidated group—data that, until recently, have not been available for Chinese listed business groups. The existing literature also carries an identification limitation that has received insufficient attention. Most studies measure heat exposure as annual average temperature, a specification that attenuates the nonlinear effects concentrated in the extreme heat range and biases estimated magnitudes downward (Auffhammer et al., 2013; Schlenker and Roberts, 2009; Auffhammer, 2018). More consequentially, large business groups can proactively redistribute orders and production capacity across subsidiaries in anticipation of local climate conditions. When headquarters reallocates ex ante, the output of any individual subsidiary reflects both its own heat exposure and a headquarters-driven reallocation signal. Standard firm-year panel regressions cannot fully separate these two forces, since the subsidiary's city-level heat exposure may be correlated with the group's internal allocation decisions. Failing to isolate the localized production channel from this headquarters-demand confound risks conflating a true physical shock with an endogenous organizational response, a source of omitted-variable bias that prior work has not directly addressed. These are the two constraints this paper relaxes.

Against this background, this paper studies how extreme heat is allocated and absorbed across the internal layers of business groups, and how groups adapt. We address the data constraint by linking three sources that together permit, to our knowledge, the first systematic group–parent–subsidiary analysis of physical climate risk. Listed-firm financial information comes from CSMAR; the universe of subsidiaries belonging to each listed group is identified from CnOpenData, which extracts affiliated entities from annual reports and matches them to business-registration records; and—most importantly for our identification strategy—subsidiary-level production and factor-input data come from the National Tax Survey, a stratified-random survey covering roughly 700,000 firms per year that we match to identified subsidiaries via taxpayer identification numbers and firm names. This combination yields a matched panel of A-share listed business groups, their parent companies, and their subsidiaries from 2007 to 2016, observed simultaneously in the same framework. By overlaying city-level daily meteorological data, we identify how heat shocks propagate—or fail to propagate—across organizational layers, and how groups respond. Our main findings are as follows. First, physical climate risk is layered within business organizations: extreme heat significantly reduces subsidiary output but has no statistically detectable effect on

parent-company or aggregate group output, indicating that organizational structure localizes climate damage rather than insulating against it. Second, this stratification operates through lower capital input and lower total factor productivity at the subsidiary level, and is concentrated among labor-intensive firms. Third, business groups mitigate heat shocks on three distinct margins: short-run buffering through internal product-market reallocation, medium-run selective exit of heat-exposed subsidiaries, and long-run investment in green technological innovation. A falsification test using heat exposure at headquarters locations confirms that the negative subsidiary-level effect operates through localized production rather than through demand transmitted from parents.

This paper makes four contributions. First, it builds and analyzes, to our knowledge, a panel structure that has not previously been assembled for Chinese listed business groups of climate exposure and production , by combining listed-firm financials (CSMAR), annual-report-based affiliated-entity registries (CnOpenData), and the National Tax Survey of subsidiary production and factor inputs. This linkage allows us to observe simultaneously the production of the parent firm, of each of its subsidiaries, and of the consolidated group—an organizational triplet that is not observable in the Annual Survey of Industrial Firms used by Chen and Yang (2019) and Zhang et al. (2018), or in the Firm Registration Database used by Ma et al. (2026). Our sample also extends to 2016, beyond the 2007 endpoint of the ASIF. Because subsidiary-level output and inputs are not separately observable in standard listed-firm databases, prior firm-level work has been forced to treat firms as monolithic units; our linkage relaxes this constraint and makes the within-group allocation of climate damage directly measurable.

Second, it shifts the unit of analysis in climate economics from the standalone firm to the internal organizational hierarchy of business groups, and shows that this distinction is empirically consequential. Where Chen and Yang (2019) document that heat reduces value-added at the registered industrial firm, we show that within multi-entity organizations the same external shock is concentrated at subsidiaries while leaving parent and aggregate group output statistically unchanged. The implication is that aggregate firm-level evidence understates the true incidence of physical climate risk, because losses are partially absorbed inside organizational layers that consolidated reporting hides. This goes beyond confirming an established temperature–output relationship in a new sample; it identifies a previously unmeasured organizational margin along which climate damage is allocated.

Third, the paper places production shocks and adaptive behavior within a single empirical framework rather than studying them in isolation. We document three distinct adaptation margins operating at different horizons—short-run reallocation through internal product markets, medium-run selective subsidiary exit, and long-run green technological innovation and link each to the production channels uncovered in the same data. Ma et al. (2026) document that firms respond to extreme heat at the extensive margin by redirecting equity investment in newly established firms toward cooler regions. This paper complements their finding by identifying an analogous reallocation mechanism operating within the boundaries of existing groups, rather than building new affiliates elsewhere, heat-exposed business groups selectively exit high-temperature cities and redistribute capacity across already-owned subsidiaries. We further show that groups simultaneously invest in green technological innovation as a long-run capability-building response, a channel that operates at a different time horizon from the spatial reallocation Ma et al. (2026) document and that has not been examined in prior firm-level climate work.

Fourth, the Chinese setting has substantive external relevance. Cross-region business groups are an organizational form prevalent across emerging and many advanced economies, and the combination of pronounced regional climate heterogeneity and an intensifying climate-adaptation policy environment in China allows us to identify organizational responses to localized shocks more sharply than would be possible elsewhere.

The mechanisms we document, shock localization at frontline production units and multi-margin internal adaptation, travel naturally to other settings in which large multi-entity firms span heterogeneous climate environments.

The remainder of the paper is organized as follows. Section 2 presents the Theoretical Analysis and Research Hypotheses. Section 3 presents the sample, data sources, variable definitions, and empirical specification. Section 4 reports the baseline results and robustness checks on the effects of extreme heat on output at the group, parent-company, and subsidiary levels. Section 5 examines the mechanisms through which extreme heat affects subsidiary production and evaluates alternative explanations. Section 6 analyzes the adaptive responses of business groups to heat shocks. Section 7 concludes and discusses policy implications.

2. Theoretical Analysis and Research Hypotheses

2.1. Production Shocks from Extreme Heat

Extreme heat is first and foremost a localized physical shock that directly strikes production sites. Compared with gradual changes in average temperature, heat waves and extreme heat are more sudden and concentrated, and can compress firm output through multiple short-run channels. On the one hand, high temperatures reduce workers' physical endurance, attention, and attendance stability, thereby lowering labor productivity. On the other hand, heat can impair equipment performance, increase cooling and maintenance costs, and reduce factor coordination efficiency by disrupting production rhythms. Existing studies show that rising temperature and extreme heat significantly reduce industrial output and firm TFP, and that these effects become markedly stronger in the high-temperature range; using the Annual Survey of Industrial Firms in China, Zhang et al. (2018) and Chen and Yang (2019) document a sharp output decline above roughly 24°C–32°C, alongside reductions in firm investment and increases in inventory.

Relative to standalone firms, business groups are organized around parent-subsidiary boundaries and contain multiple internal markets for capital, products, and other resources. As a result, the impact of external shocks may be reallocated and thus mitigated within the group. First, internal capital markets and resource-integration capabilities allow groups to reallocate funds, debt, and profits across legal entities, providing liquidity support and output smoothing against local heat shocks and reducing the risk that a single subsidiary is forced to contract or exit because of temporary declines in cash flow and productivity (Grover and Kahn, 2024). Second, internal adjustment is often selective: parent firms can allocate resources differentially across affiliates according to efficiency, financing constraints, and governance characteristics, and when shocks intensify they may achieve structural clearing and risk isolation through mergers, divestitures, or shutdowns (Cascarano et al., 2025). In addition, because physical climate risk threatens future cash flows and long-run competitiveness, groups may improve medium- and long-run resilience through spatial reorganization of production and business activities, reconfiguration of internal supply networks, and green technological innovation, thereby easing the persistent effects of heat shocks (Li et al., 2025). Within this framework, subsidiaries are usually closer to actual production sites and directly exposed to local heat conditions, making them more likely to bear the initial production shock. Parent firms and group headquarters, by contrast, primarily perform control, financing, coordination, and reallocation functions; their operating outcomes are less directly affected by local heat and can be smoothed or insulated through internal markets.

Based on the above, we propose the following hypotheses:

H1. Extreme heat reduces output at the subsidiary level, and this effect attenuates at the parent and consolidated group levels.

2.2. Mechanisms

From the perspective of input decisions, extreme heat compresses subsidiaries' capital input. On the one hand, heat shocks raise current production uncertainty and marginal operating costs, weakening the incentive to expand or maintain capital utilization. On the other hand, when heat puts pressure on operating cash flow and raises financing costs, firms are more likely to postpone equipment renewal, reduce fixed-asset investment, and even suspend or cut production to limit short-run losses. Existing studies find that climate-risk exposure is associated with a higher cost of capital, lower investment efficiency, and slower investment adjustment (Acharya et al., 2022; Ginglinger and Moreau, 2023; Agoraki et al., 2024). Evidence from Chinese listed firms shows that days above 30°C significantly increase firms' debt financing costs, while broader climate-risk exposure is associated with higher cost of capital, lower investment efficiency, and slower investment adjustment (Zhao et al., 2024). Although physical capital is generally costly to adjust, subsidiaries can respond to persistent heat shocks by delaying equipment renewal, reducing fixed-asset investment, suspending capacity expansion, or disposing of underutilized assets. Therefore, extreme heat may be reflected not only in lower contemporaneous production efficiency, but also in a contraction of fixed-asset input and investment-related capital adjustment.

From the perspective of production efficiency, extreme heat also lowers subsidiaries' total factor productivity. High temperatures not only reduce worker efficiency, but also lower the operating efficiency of machinery and disrupt the optimal matching among labor, capital, and energy. As a result, even if the number of workers does not change immediately because of contractual rigidity, effective output per unit of input can still decline. Zhang et al. (2018) and Chen and Yang (2019), using the Annual Survey of Industrial Firms, document that high temperatures sharply reduce firm-level TFP and depress investment, with output losses concentrated above roughly 24°C–32°C; complementary evidence from Indian manufacturing further shows that heat mainly harms output through labor-productivity and attendance channels (Somanathan et al., 2021). Bringing this evidence into the group–parent–subsidiary framework, the suppressing effect of extreme heat on subsidiary output should manifest both as input contraction—particularly capital input, which is more flexibly adjusted than labor in the short run—and as efficiency decline.

Based on the above, we propose the following hypothesis:

H2. Extreme heat reduces subsidiary fixed-asset investment, capital stock, and total factor productivity.

2.3. Adaptive Behavior of Business Groups

Unlike standalone firms, business groups can respond to localized heat shocks through internal rather than purely market-based adjustment. According to transaction-cost theory and theories of firm boundaries, when external transactions become costly or slow, firms rely more heavily on internal organization to allocate resources (Coase, 1937). At the level of the firm population, Ma et al. (2026) show that incumbent firms respond to extreme temperatures by redirecting equity investments in newly-established firms toward milder-climate regions, and that firm entry contracts in regions with greater heat exposure. A parallel logic may operate inside the boundaries of an existing business group, where capacity, orders, and capital can be reallocated across already-owned subsidiaries without the transaction costs of new market entry. This logic is particularly relevant for business groups, whose subsidiaries are linked by ownership, control, financing, and trading relationships. Evidence on intra-group loans shows that internal capital markets can support affiliated firms' financing and investment

(Buchuk et al., 2014), while recent strategy research similarly shows that firms may proactively build internal markets for redeployment, allowing them to reconfigure assets and activities more effectively under external shocks (Sohl and Folta, 2025). Related evidence from ownership networks also suggests that commonly controlled firms can shift production activities across affiliated entities when regulatory or environmental pressures are uneven across locations (Cui et al., 2023). This implies that when some subsidiaries are exposed to extreme heat, the group may smooth local production shocks through short-run internal order adjustment, capacity reallocation, and resource redeployment, so that output at the parent-company and consolidated group levels need not decline in tandem with that of exposed subsidiaries. Based on the above, we propose the following hypothesis:

H3a. Faced with extreme-heat shocks, business groups smooth localized production losses in the short run through internal product-market and resource reallocation across subsidiaries.

Beyond short-run internal reallocation, business groups may also adapt to persistent heat exposure in the medium run by reducing their exposure to vulnerable subsidiaries and high-temperature locations. According to theories of firm dynamics and industrial evolution, external shocks alter firms' survival thresholds and induce low-efficiency or highly vulnerable firms to exit the market (Jovanovic, 1982; Hopenhayn, 1992). In the context of climate change, existing research also finds that high temperatures significantly affect firm entry, exit, and market-structure dynamics, and that less efficient firms are more likely to exit under heat shocks (Shi and Zhang, 2023). Consistent with this selection logic, Cascarano et al. (2025) show that increases in very hot days reduce the medium-run growth of active firms through lower entry and higher exit. Ma et al. (2026) similarly find that, in the long run, regions with greater extreme-temperature exposure see contracting firm entry and incoming investment, with effects concentrated in labor-intensive tradable sectors; the analogous within-group prediction is that headquarters may selectively reduce exposure to heat-exposed subsidiaries when continued support becomes costly. Establishment-level evidence further shows that persistent local temperature increases lead firms to cut employment and shut down exposed establishments, indicating that operational networks can be adjusted on the extensive margin when heat exposure becomes recurrent (Jin et al., 2025). Based on the above, we propose the following hypothesis:

H3b. Extreme heat exposure increases the probability of selective exit or net withdrawal among heat-exposed subsidiaries in the medium run.

Beyond short-run reallocation and medium-run withdrawal, business groups may also engage in longer-term capability-based adaptation through green technological innovation. The natural-resource-based view argues that the relationship between firms and the natural environment can itself be an important source of competitive advantage, and that pollution prevention, product stewardship, and sustainable development capabilities have strategic value (Hart, 1995). The Porter hypothesis further suggests that appropriate environmental constraints can induce innovation offsets, allowing firms to reduce long-run costs and enhance competitiveness through technological progress (Porter and van der Linde, 1995). Recent evidence suggests that climate risk can promote corporate green innovation by strengthening environmental supervision and managerial attention to long-run transformation (Zhou and Feng, 2025). However, the effect of temperature exposure is not mechanically positive: rising or abnormal temperatures may crowd out R&D resources, drain labor, and reduce green innovation in the short run (Li and Lu, 2023; Hu et al., 2022; He et al., 2024). Because green technological innovation is costly, uncertain, and financing-intensive, its long-run adaptive role also depends on whether firms can obtain stable financial support for green R&D (Xiang et al., 2022; Chi et al., 2023). For business groups, internal financing and

coordination capacity may therefore make green technological innovation a long-run capability-building response rather than an immediate output-smoothing mechanism.

Based on the above, we propose the following hypothesis:

H3c. When facing extreme-heat shocks, business groups are more likely to strengthen green technological innovation as a long-run capability-based adaptation response.

3. Research Design

3.1. Sample Selection and Data Sources

Because listed business groups disclose relatively complete information on financial performance and operating locations and are broadly representative, we focus on A-share listed business groups. Because subsidiary financial information is drawn from the National Tax Survey and is available only for 2007–2016, the final sample period is 2007–2016.

Our data come from multiple sources and are matched across databases. First, financial data and basic information for listed business groups and their parent firms come mainly from the CSMAR database and include financial statements, operating addresses, registration dates, and industry classifications. Second, the list of subsidiaries and their basic information comes mainly from the CnOpenData database. This database systematically extracts affiliated firms from listed companies' annual reports and identifies their relationship to the listed company (e.g., subsidiary, associate, joint venture, or parent company), then matches these entities to business-registration records to obtain company names, unified social credit codes, taxpayer identification numbers, registered capital, paid-in capital, registered addresses, and industry classifications. Third, subsidiary financial information comes mainly from the National Tax Survey, which is jointly administered by the Ministry of Finance and the State Taxation Administration using stratified random sampling and covers roughly 700,000 firms per year across regions and industries in China. We match subsidiaries of listed companies to the survey using taxpayer identification numbers and firm names. Fourth, climate data are obtained from two sources: raw city-level daily maximum temperature data come from the National Centers for Environmental Information under the U.S. National Oceanic and Atmospheric Administration, while the remaining climate variables come from the China National Meteorological Data Service Centre. Fifth, city-level economic data come mainly from city statistical yearbooks and include GDP per capita, the balance of loans issued by financial institutions, and the number of registered urban unemployed persons.

After excluding firms in the financial sector, ST and PT firms, and firms with missing key variables, the final sample contains 43,111 subsidiary-year observations, 17,055 parent-company-year observations, and 19,193 business-group-year observations. All continuous variables are winsorized at the 1st and 99th percentiles.

3.2. Variable Definitions

Dependent variable. Firm output (*lnY*) is typically measured by gross industrial output or industrial value added. Because industrial value added contains many missing values in the National Tax Survey data, we construct *lnY* for subsidiaries using the log of gross output. For parent companies and business groups, for which gross industrial output or value added is unavailable, we measure *lnY* as the log of operating revenue.

Key explanatory variable. Extreme heat (*Temp32*). Existing studies commonly use either 90 degrees Fahrenheit or 32 degrees Celsius as the threshold for extreme heat. A day is classified as extreme heat when the daily maximum temperature in a region exceeds that threshold. We therefore use 32°C as the cutoff and calculate

the annual number of extreme-heat days in each city. Because China spans frigid, temperate, and tropical climate zones, the number of extreme-heat days in our sample ranges from 0 to 148 and is highly skewed. We therefore take the log of one plus this count.

Control variables. We consider both firm-level and city-level controls. At the firm level, given data availability for subsidiaries and the main determinants of production, we include firm size (*Size*), leverage (*Lev*), return on assets (*ROA*), and firm age (*Age*). At the city level, we include standard indicators of economic development, such as economic development (*PGDP*), financial development (*Finance*), and unemployment (*UnEmploy*). We also control for local climatic conditions, including PM2.5 air pollution (*PM2.5*), annual mean temperature (*Ytemp*), annual mean wind speed (*Ywind*), and annual cumulative precipitation (*Yrain*).

Table 1. Definition of Main Variables

Variable	Definition	Construction
lnY	Firm output	For subsidiaries, measured as the log of gross industrial output; for parent companies and business groups, measured as the log of operating revenue.
Temp32	Extreme heat	Log of one plus the number of days in a year when the daily maximum temperature in the city where the firm is located exceeds 32°C.
Size	Firm size	Log of total assets at year-end
Lev	Leverage	Ratio of total liabilities to total assets at year-end
ROA	Return on assets	Ratio of net profit to total assets at year-end
Age	Firm age	Years since listing (for listed firms) or registration (for subsidiaries)
PGDP	Economic development	Log of GDP per capita
Finance	Financial development	Log of the year-end balance of loans outstanding at financial institutions
UnEmploy	Unemployment	Log of the number of registered urban unemployed at year-end
PM2.5	Air pollution	Annual average of daily PM2.5 concentration
Ytemp	Annual mean temperature	Annual average of daily mean temperature
Ywind	Annual mean wind speed	Annual average of daily mean wind speed
Yrain	Annual cumulative precipitation	Log of annual cumulative daily precipitation

3.3. Econometric Specification

To examine the effect of extreme heat on firm production, we estimate the following regression model and run it separately for the samples of subsidiaries, parent companies, and business groups:

$$lnY_{i,t}=\alpha+\beta Temp32_{j,t}+\gamma FirmCtr_{i,t}+\theta CityCtr_{j,t}+FE+\varepsilon_{i,t} \quad (1)$$

where *i*, *j*, *t* denote firm, city, and year, respectively; $lnY_{i,t}$ is firm *i*'s output in year *t*; $Temp32_{j,t}$ measures the extreme-heat shock in city *j*, where firm *i* is located, in year *t*; $FirmCtr_{i,t}$ is the vector of firm-level control variables; $CityCtr_{j,t}$ is the vector of city-level control variables; and *FE* denotes fixed effects. To alleviate omitted-variable concerns, we alternatively include city fixed effects together with industry-by-year fixed effects, or firm fixed effects together with year fixed effects. Because daily extreme-heat realizations at the city level are determined by weather rather than by individual-firm decisions, reverse causality from firm output to local heat exposure is implausible in this setting; we therefore focus on omitted-variable bias and address it through this combination of rich controls and high-dimensional fixed effects. A significantly negative coefficient indicates that more extreme-heat days are associated with lower firm output, conditional on this set of controls. Industry classifications follow the sector categories in the 2012 CSRC Industry Classification Guidelines for Listed Companies, with manufacturing classified at the major-industry level.

3.4. Descriptive Statistics

Table 2 shows that the mean value of Size is 19.300 for subsidiaries, 21.619 for parent companies, and 21.930 for business groups. Subsidiaries are therefore substantially smaller than parent companies and business groups, while the latter two are similar in size. Correspondingly, subsidiaries' total output is also significantly lower than that of parent companies and business groups. In terms of extreme-heat shocks, the mean value of *Temp32* ranges from 3.301 to 3.438, and the standard deviation ranges from 1.023 to 1.089, indicating that different types of firms face broadly comparable heat exposure. Subsidiaries experience slightly lower extreme-heat exposure than parent companies and business groups, possibly because subsidiaries can more readily adjust operating locations. Finally, the levels of economic development and the influence of other climate factors are broadly similar across the locations where the three types of firms operate.

Table 2. Descriptive Statistics

Panel A : Descriptive Statistics for Subsidiaries

Variables	N	Mean	Min	p25	Median	p75	Max	SD
lnY	43111	18.806	12.359	17.712	18.918	20.054	22.986	1.903
Temp32	43111	3.301	0.000	2.996	3.638	4.025	4.625	1.089
Size	43111	19.300	15.152	18.188	19.283	20.425	23.289	1.691
Lev	43111	0.547	0.001	0.320	0.546	0.741	1.709	0.309
ROA	43111	0.050	-0.420	0.001	0.036	0.097	0.512	0.125
Age	43111	10.572	2.000	6.000	9.000	14.000	30.000	6.016
PGDP	43111	11.043	9.412	10.663	11.154	11.496	12.130	0.592
Finance	43111	17.663	14.556	16.467	17.847	18.873	20.096	1.437
UnEmploy	43111	10.672	8.576	10.026	10.589	11.257	12.553	0.972
PM2.5	43111	36.235	14.413	30.953	35.741	42.414	54.441	8.342
Ytemp	43111	16.270	4.104	13.582	16.740	18.378	23.965	4.603
Ywind	43111	2.226	1.215	1.963	2.199	2.526	3.321	0.428
Yrain	43111	6.929	5.505	6.499	7.027	7.351	7.845	0.531

Panel B: Descriptive statistics of the parent company

Variables	N	Mean	Min	p25	Median	p75	Max	SD
lnY	17055	20.266	14.201	19.422	20.357	21.317	24.489	1.795
Temp32	17055	3.438	0.000	3.178	3.738	4.127	4.644	1.023
Size	17055	21.619	19.421	20.808	21.475	22.225	25.247	1.142
Lev	17055	0.371	0.021	0.202	0.358	0.522	0.865	0.208
ROA	17055	0.040	-0.153	0.011	0.035	0.066	0.220	0.055
Age	17055	15.425	4.000	12.000	15.000	19.000	29.000	5.157
PGDP	17055	11.106	9.450	10.742	11.200	11.550	12.456	0.598
Finance	17055	17.913	14.556	16.892	18.088	19.073	20.154	1.427
UnEmploy	17055	10.757	8.670	10.192	10.638	11.306	12.553	0.923
PM2.5	17055	36.202	14.987	31.568	35.255	41.866	54.687	8.054
Ytemp	17055	16.694	4.907	13.653	16.903	20.278	23.965	4.666
Ywind	17055	2.224	1.186	1.977	2.182	2.503	3.431	0.426
Yrain	17055	6.955	5.548	6.506	7.073	7.398	7.847	0.535

Panel C: Descriptive statistics of the group company

Variables	N	Mean	Min	p25	Median	p75	Max	SD
lnY	19193	21.273	18.078	20.283	21.144	22.114	25.258	1.437
Temp32	19193	3.425	0.000	3.135	3.714	4.111	4.644	1.029
Size	19193	21.930	19.549	21.012	21.760	22.641	25.830	1.263
Lev	19193	0.441	0.048	0.273	0.440	0.608	0.893	0.211
ROA	19193	0.041	-0.160	0.014	0.038	0.067	0.193	0.052
Age	19193	15.814	4.000	12.000	16.000	19.000	29.000	5.278
PGDP	19193	11.115	9.462	10.776	11.216	11.550	12.281	0.590
Finance	19193	17.949	14.563	16.929	18.138	19.103	20.154	1.432

UnEmploy	19193	10.784	8.666	10.201	10.659	11.315	12.553	0.936
PM2.5	19193	36.023	14.789	31.378	34.980	41.591	54.595	8.075
Ytemp	19193	16.668	4.524	13.580	16.916	20.338	23.965	4.718
Ywind	19193	2.228	1.185	1.977	2.187	2.523	3.357	0.426
Yrain	19193	6.955	5.550	6.504	7.073	7.398	7.847	0.535

4. Empirical Results: Effects of Extreme Heat on Firm Output

4.1. Baseline Results

We first examine the effect of extreme heat on subsidiary gross output. Table 3 reports the results. Columns (1) and (2) exclude control variables, while columns (3) and (4) add firm-level and city-level controls. Columns (1) and (3) include city fixed effects and industry-by-year fixed effects, whereas columns (2) and (4) include firm fixed effects and year fixed effects. Across all four specifications, the coefficient on *Temp32* is negative and statistically significant, indicating that extreme heat robustly suppresses subsidiary gross output. In the most restrictive specification in column (4), which includes both controls and firm and year fixed effects, a 1% increase in the number of extreme-heat days is associated with a 0.034% reduction in subsidiary gross output. The estimated coefficients on the firm-level and city-level controls are largely consistent with standard production-side predictions. Among the additional climate variables, PM2.5 concentration is negatively associated with subsidiary gross output, whereas annual mean temperature, annual mean wind speed, and annual cumulative precipitation are not statistically significant.

Table 3. Effects of Extreme Heat on Subsidiary Output

	(1)	(2)	(3)	(4)
Variables	*lnY*	*lnY*	*lnY*	*lnY*
Temp32	-0.078***	-0.050***	-0.053***	-0.034*
	(0.024)	(0.017)	(0.019)	(0.018)
Size			0.786***	0.687***
			(0.006)	(0.026)
Lev			0.523***	0.101**
			(0.033)	(0.048)
ROA			2.398***	1.610***
			(0.070)	(0.095)
Age			0.006***	-0.053**
			(0.002)	(0.024)
PGDP			0.180***	0.113**
			(0.064)	(0.056)
Finance			0.073*	0.061
			(0.042)	(0.038)
UnEmploy			-0.047	-0.036
			(0.029)	(0.029)
PM2.5			-0.027***	-0.015***
			(0.005)	(0.005)
Ytemp			-0.009	-0.009
			(0.006)	(0.007)
Ywind			0.027	-0.028
			(0.062)	(0.062)
Yrain			-0.011	-0.022

			(0.045)	(0.042)
Constant	19.064***	19.083***	1.694	5.110***
	(0.080)	(0.056)	(1.061)	(1.135)
Observations	43,088	36,503	43,088	36,503
R-squared	0.139	0.781	0.563	0.801
Fixed Effects	City&Ind#Year	Firm&Year	City&Ind#Year	Firm&Year
F test	10.76	8.596	1600	93.10
R2_Adj	0.124	0.709	0.555	0.735

*Note: Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The same applies below.*

We next examine the effect of extreme heat on output at the parent-company and business-group levels. Table 4 reports the results, with Panel A and Panel B presenting the regressions for parent companies and business groups, respectively. For brevity, Table 4 and the subsequent tables omit the coefficients on control variables. Table 4 shows that, across all specifications, the coefficients on *Temp32* in the *lnY* regressions for parent companies and business groups are statistically insignificant. That is, extreme heat does not significantly affect production at the parent-company or group level. The descriptive statistics in Table 2 further show that parent companies and business groups are similar in size and are substantially larger than subsidiaries; even the smallest parent company is larger than the average subsidiary. Once firms reach a sufficiently large scale, they are more likely to mobilize various resources to respond to extreme climate shocks, for example by reallocating production and business models or innovating heat-adaptation technologies. Taken together with Table 3, these results indicate that extreme heat significantly depresses output only at the subsidiary level, while the effects on parent companies and business groups are not statistically significant.

Table 4. Effects of Extreme Heat on Parent-Company and Business-Group Output

Panel A. Effects of Extreme Heat on Parent-Company Output				
	(1)	(2)	(3)	(4)
Variables	*lnY*	*lnY*	*lnY*	*lnY*
Temp32	-0.006	-0.018	-0.002	-0.029
	(0.024)	(0.021)	(0.024)	(0.024)
Constant	20.289***	20.339***	4.235***	10.836***
	(0.089)	(0.072)	(1.613)	(1.696)
Observations	17,038	16,766	17,038	16,766
R-squared	0.276	0.892	0.591	0.903
Control	No	No	Yes	Yes
Fixed Effects	City&Ind#Year	Firm&Year	City&Ind#Year	Firm&Year
F test	0.0656	0.731	206.8	36.69
R2_Adj	0.247	0.874	0.574	0.886
Panel B. Effects of Extreme Heat on Business-Group Output				
	(1)	(2)	(3)	(4)
Variables	*lnY*	*lnY*	*lnY*	*lnY*
Temp32	0.012	0.004	-0.007	-0.006
	(0.017)	(0.015)	(0.010)	(0.010)
Constant	21.232***	21.273***	-0.230	3.542***

	(0.063)	(0.051)	(0.705)	(0.739)
Observations	19,177	18,931	19,177	18,931
R-squared	0.259	0.916	0.867	0.963
Control	No	No	Yes	Yes
Fixed Effects	City&Ind#Year	Firm&Year	City&Ind#Year	Firm&Year
F test	0.523	0.0562	1446	241.6
R2_Adj	0.232	0.903	0.862	0.957

4.2. Robustness Checks

We first verify robustness by changing the measure of extreme heat. International studies commonly use 90 degrees Fahrenheit as the threshold for high temperature, which is approximately 32.2 degrees Celsius. To demonstrate the stability of our results, we construct six alternative measures, *Temp32.1* through *Temp32.6*, analogous to *Temp32*. We also use percentiles to define extreme heat. Specifically, during the 2007–2016 sample period, a day is classified as extreme heat if the daily maximum temperature in a region falls within the top 10% of its historical maximum-temperature distribution, from which we construct *Temp90*. Table 5 reports the results. For brevity, we show only the results for *Temp32.2* and *Temp90*; the results for *Temp32.1* and the other alternative measures are similar. Consistent with the baseline findings, extreme heat significantly reduces output only for subsidiaries, while the effects on parent companies and business groups remain statistically insignificant.

Table 5. Robustness Test: Alternative Measures of Extreme Heat

	(1)	(2)	(3)	(4)	(5)	(6)
	Subsidiaries	Parent companies	Business groups	Subsidiaries	Parent companies	Business groups
Variables	*lnY*	*lnY*	*lnY*	*lnY*	*lnY*	*lnY*
Temp32.2	-0.041**	-0.024	-0.001			
	(0.017)	(0.023)	(0.010)			
Temp90				-0.051*	-0.019	-0.001
				(0.026)	(0.026)	(0.011)
Constant	5.162***	10.800***	3.518***	5.253***	10.826***	3.517***
	(1.134)	(1.695)	(0.740)	(1.147)	(1.727)	(0.753)
Observations	36,503	16,766	18,931	36,503	16,766	18,931
R-squared	0.801	0.903	0.963	0.801	0.903	0.963
Control	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Firm&Year	Firm&Year	Firm&Year	Firm&Year	Firm&Year	Firm&Year
F test	93.22	36.62	241.7	93.02	36.50	242.2
R2_Adj	0.735	0.886	0.957	0.735	0.886	0.957

We also examine the nonlinear features of extreme-heat shocks using temperature bins. Specifically, we divide each city's daily maximum temperature during the sample period into several intervals and construct a set of temperature-bin variables, including $HTbox_{high}$, *HTbox26*, and *HTbox20*, to capture exposure at different temperature ranges. The temperature-bin variables measure the number of days falling into each maximum-temperature interval, with one intermediate temperature range omitted as the reference category. After controlling for firm characteristics, city-level macro variables, and fixed effects, Table 6 reports the effects of the temperature bins on output. Columns (1) and (2) show that for subsidiaries, the coefficients on the low- and medium-temperature bins are generally insignificant, with only modest positive coefficients in some intermediate ranges, whereas the coefficient on the highest-temperature bin, $HTbox_{high}$, is significantly negative under both fixed-effect

specifications. This indicates that what truly suppresses subsidiary output is greater exposure to extreme heat. Columns (3)–(6) show that for parent-company and business-group samples, most temperature-bin coefficients are insignificant, with only weak positive or negative effects in a few intermediate temperature ranges, and the effect of the highest-temperature bin is much weaker than at the subsidiary level. Overall, the temperature-bin results show that the effect of temperature shocks is concentrated in the highest temperature range and robustly reduces subsidiary production, whereas the direct effects on parent-company and business-group output are comparatively limited. This further supports the robustness of the baseline results.

Table 6. Robustness Test Using Temperature Bins

	(1)	(2)	(3)	(4)	(5)	(6)
	Subsidiaries		Parent companies		Business groups	
Variables	*lnY*	*lnY*	*lnY*	*lnY*	*lnY*	*lnY*
$HTbox_{high}$	-0.055**	-0.052**	0.007	-0.036	-0.022*	-0.018
	(0.024)	(0.023)	(0.030)	(0.030)	(0.012)	(0.013)
HTbox26	0.025	-0.085	0.086	-0.067	-0.035	-0.041
	(0.077)	(0.071)	(0.093)	(0.074)	(0.037)	(0.038)
HTbox20	-0.018	-0.135*	0.045	-0.003	-0.073*	-0.035
	(0.076)	(0.071)	(0.093)	(0.076)	(0.039)	(0.035)
HTbox14	0.063	0.025	0.055	0.040	0.017	0.021
	(0.050)	(0.047)	(0.058)	(0.043)	(0.023)	(0.021)
HTbox8	-0.004	-0.009	0.042	0.023	-0.007	-0.007
	(0.026)	(0.024)	(0.032)	(0.027)	(0.012)	(0.011)
HTbox2	0.031	-0.012	0.058**	0.038*	0.015	0.015*
	(0.022)	(0.020)	(0.026)	(0.022)	(0.010)	(0.009)
HTbox_4	0.029	-0.005	0.031	0.036*	-0.005	0.000
	(0.019)	(0.017)	(0.023)	(0.021)	(0.009)	(0.009)
HTbox_10	0.034	0.007	0.026	0.018	0.004	0.004
	(0.022)	(0.020)	(0.028)	(0.026)	(0.011)	(0.010)
HTbox_16	0.058**	0.011	0.013	0.021	-0.018	-0.012
	(0.028)	(0.027)	(0.027)	(0.024)	(0.013)	(0.010)
$HTbox_{low}$	-0.063	-0.008	0.025	0.020	-0.003	-0.002
	(0.046)	(0.044)	(0.048)	(0.038)	(0.021)	(0.016)
Constant	1.258	5.872***	3.137*	10.546***	0.160	3.699***
	(1.353)	(1.401)	(1.875)	(1.837)	(0.804)	(0.844)
Observations	43,088	36,503	17,038	16,766	19,177	18,931
R-squared	0.563	0.801	0.591	0.903	0.867	0.963
Control	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	City&Ind#Year	Firm&Year	City&Ind#Year	Firm&Year	City&Ind#Year	Firm&Year
F test	918.1	53.94	120.0	21.89	828.8	141.9
R2_Adj	0.555	0.735	0.574	0.886	0.862	0.957

Table 7 examines the robustness of the baseline findings along two dimensions: excluding firms in the real estate sector and using alternative office-city definitions. Columns (1)–(6) all exclude firms in the real estate sector. Columns (1), (3), and (5) use the baseline location definition, whereas columns (2), (4), and (6) use the alternative office-city definition to assign heat exposure. Columns (1)–(2) correspond to subsidiaries, columns

(3)–(4) to parent companies, and columns (5)–(6) to business groups. The coefficient on *Temp32* remains significantly negative in the subsidiary sample under both location definitions, whereas the coefficients for parent companies and business groups remain statistically insignificant and close to zero. These results indicate that the baseline pattern is not driven by the special features of the real estate sector or by the specific definition of the firm's office city. After excluding the real estate sector and alternatively assigning heat exposure based on the office-city definition, extreme heat continues to be associated with lower subsidiary-level activity, while no systematic temperature effect is detected at the parent-company or business-group level.

Table 7. Robustness Test Excluding the Real Estate Sector and Using Alternative Office-City Definitions

	(1)	(2)	(3)	(4)	(5)	(6)
	Subsidiaries		Parent companies		Business groups	
Variables	*lnY*	*lnY*	*lnY*	*lnY*	*lnY*	*lnY*
Temp32	-0.049***	-0.041**	-0.015	-0.027	-0.006	-0.007
	(0.019)	(0.018)	(0.024)	(0.023)	(0.010)	(0.010)
Constant	1.521	5.424***	4.388***	9.990***	-0.047	3.807***
	(1.057)	(1.140)	(1.617)	(1.675)	(0.712)	(0.733)
Observations	41,359	35,340	16,350	16,078	18,111	17,855
R-squared	0.581	0.806	0.592	0.910	0.868	0.968
Control	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	City&Ind#Year	Firm&Year	City&Ind#Year	Firm&Year	City&Ind#Year	Firm&Year
F test	1603	87.22	200.5	39.29	1310	236.6
R2_Adj	0.573	0.743	0.574	0.893	0.863	0.962

5. Mechanisms Through Which Extreme Heat Affects Subsidiary Production

5.1. Production Mechanisms

We next investigate the channels through which extreme heat affects subsidiary production from the perspectives of factor input and production efficiency. Specifically, we measure fixed-asset input, denoted by *lnK*, as the log of net fixed assets at year-end; labor input, denoted by *lnL*, as the log of the number of employees at year-end; and total factor productivity using the LP and OP methods, denoted by TFP_{LP} and TFP_{OP}, respectively. We also examine *lnE*, an emissions or energy-use indicator, to assess whether heat exposure is associated with changes in energy-related production conditions.

Table 8 shows that the coefficients on *Temp32* are significantly negative for *lnK*, TFP_{LP}, and TFP_{OP}; the coefficient for *lnL* is positive but statistically insignificant; and the coefficient for *lnE* is significantly positive. These results indicate that extreme heat is associated with lower fixed-asset input and lower total factor productivity at the subsidiary level, while it has no statistically detectable effect on employment. The positive coefficient on *lnE* suggests that heat exposure may increase energy-related operating needs, possibly through cooling, ventilation, equipment protection, or other heat-mitigation activities. One possible interpretation is that extreme heat affects subsidiary production through both input adjustment and efficiency loss. On the input side, subsidiaries may delay fixed-asset investment, reduce equipment renewal, suspend capacity expansion, or dispose of underutilized assets when repeated heat shocks raise operating uncertainty and production costs. On the efficiency side, high temperatures can reduce workers' effective productivity, impair machinery performance, and disrupt coordination among labor, capital, and energy inputs, thereby lowering total factor productivity. By contrast, employment may not respond immediately because labor contracts and staffing arrangements are

relatively sticky in the short run. Overall, the results support the mechanism that extreme heat suppresses subsidiary gross output through a combination of fixed-asset adjustment and productivity decline, rather than through immediate employment contraction.

Table 8. Mechanisms: How Extreme Heat Affects Subsidiary Output

	(1)	(2)	(3)	(4)	(5)
Variables	*lnK*	*lnL*	TFP_{LP}	TFP_{OP}	*LnE*
Temp32	-0.069***	0.009	-0.033*	-0.037**	0.068*
	(0.014)	(0.009)	(0.018)	(0.018)	(0.039)
Constant	3.611***	-2.275***	4.876***	5.697***	-17.536***
	(0.994)	(0.614)	(1.113)	(1.128)	(3.182)
Observations	36,503	36,503	36,503	32,865	24,291
R-squared	0.940	0.935	0.736	0.694	0.752
Control	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Firm&Year	Firm&Year	Firm&Year	Firm&Year	Firm&Year
F test	52.41	52.83	73.13	48.71	20.03
R2_Adj	0.921	0.913	0.648	0.605	0.648

5.2. Heterogeneous Effects

Table 8 indicates that when subsidiaries are exposed to extreme heat, they are more likely to respond by reducing capital input rather than labor input. At the same time, employees have a lower tolerance for extreme heat than production equipment, and heat may cause heatstroke, dehydration, or even fatal accidents. The negative impact of extreme heat should therefore be stronger for labor-intensive subsidiaries. To examine this possibility, we measure labor intensity using *lnL/lnY*, *lnL/Size*, and *lnL*, and divide the sample at the median into labor-intensive and non-labor-intensive subsidiaries. Table 9 shows that *Temp32* has a significantly negative effect on *lnY* only for labor-intensive subsidiaries. Holding other conditions constant, a 1% increase in extreme-heat days significantly reduces gross output by 0.049%–0.062%, roughly twice the baseline estimate. Notably, extreme heat and air pollution appear to affect firm production differently. PM2.5 is negatively associated with gross output in both subsamples, but this pattern is not central to our proposed heat-related labor-intensity mechanism and should therefore be interpreted with caution.

Table 9. Heterogeneous Effects of Extreme Heat on Subsidiary Output

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*lnY*	*lnY*	*lnY*	*lnY*	*lnY*	*lnY*
	Labor-intensive			Non-labor-intensive		
Temp32	-0.054**	-0.050**	-0.062***	-0.004	-0.011	0.013
	(0.022)	(0.022)	(0.022)	(0.025)	(0.031)	(0.030)
PM2.5	-0.011*	-0.015**	-0.012*	-0.020***	-0.016**	-0.018**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)
Constant	4.369***	6.782***	6.404***	10.069***	8.570***	9.724***
	(1.437)	(1.364)	(1.379)	(1.681)	(2.092)	(2.058)
Observations	18,469	18,778	19,004	16,432	16,436	16,368
R-squared	0.787	0.778	0.748	0.853	0.794	0.769
Control	Yes	Yes	Yes	Yes	Yes	Yes

Fixed Effects	Firm&Year	Firm&Year	Firm&Year	Firm&Year	Firm&Year	Firm&Year
F test	47.02	46.86	42.22	42.47	42.80	42.45
R2_Adj	0.720	0.709	0.672	0.790	0.705	0.670

5.3. Identification Test: Production-Site Shock or Headquarters-Demand Shock?

We construct a heat variable for the city where the parent company is located, $Temp32_p$, together with a high-heat exposure dummy, $Temp32_{ph}$, which equals one if the heat variable for the parent company's city is above the median and zero otherwise. We include these variables together with the subsidiary-city heat variable *Temp32* and a full set of controls in the regression framework to examine whether heat at the parent-company location affects subsidiary output. The results in Table 10 show that regardless of whether the parent-city heat variable is included, the coefficient on *Temp32* remains significantly negative in all four regressions, indicating that local heat shocks robustly suppress subsidiary output. By contrast, the coefficient on the parent-city extreme-heat variable $Temp32_p$ is insignificant in columns (1) and (2), and the high-exposure dummy $Temp32_{ph}$ is likewise insignificant in columns (3) and (4). This implies that extreme heat in the city where the parent company is located does not have a significant effect on the output of geographically separate subsidiaries. The evidence suggests that the negative effect of extreme heat on subsidiary production mainly comes from the subsidiary's own local heat environment, rather than operating indirectly through internal product-market channels. Overall, the evidence in Table 10 supports the view that subsidiary output losses are not primarily driven by headquarters-location heat shocks or by demand shocks transmitted from the parent company. Instead, the negative effect of extreme heat is better understood as a localized production shock that directly hits the subsidiary's own production environment. This finding does not rule out internal reallocation within the group as an adaptive response after the shock occurs; rather, it rules out the interpretation that the baseline subsidiary-level output decline is mechanically caused by heat-induced demand or order contractions originating from the headquarters city.

Table 10. Internal Transmission Test of Headquarters-Demand Shocks

	(1)	(2)	(3)	(4)
Variables	*lnY*	*lnY*	*lnY*	*lnY*
Temp32	-0.062***	-0.041**	-0.062***	-0.046**
	(0.021)	(0.020)	(0.020)	(0.019)
Temp32_p	0.005	-0.008		
	(0.015)	(0.020)		
$Temp32_{ph}$			0.015	0.006
			(0.023)	(0.023)
Constant	2.014*	5.053***	2.013*	5.010***
	(1.102)	(1.197)	(1.102)	(1.197)
Observations	40,730	34,437	40,730	34,437
R-squared	0.561	0.799	0.561	0.799
Control	Yes	Yes	Yes	Yes
Fixed Effects	City&Ind#Year	Firm&Year	City&Ind#Year	Firm&Year
F test	1051	62.64	1051	63.07
R2_Adj	0.552	0.731	0.552	0.731

To further examine whether this conclusion is robust to exposure-location mismatch, we conduct a falsification test based on exposure at the headquarters office location. Specifically, in the baseline framework we

replace the subsidiary-city exposure measure with the extreme-heat indicator corresponding to the parent company's headquarters office location, while keeping the control variables and fixed-effect structure unchanged. If the decline in subsidiary output were mainly driven by demand or order shocks transmitted from headquarters, extreme heat at headquarters should significantly affect the output of geographically separate subsidiaries. By contrast, if the shock is primarily a localized production shock operating at frontline production sites, then once exposure is incorrectly assigned to the headquarters location, the estimated coefficient should attenuate substantially and become insignificant. Table 11 reports the results under different fixed-effect combinations and sample settings. Overall, the coefficient on the headquarters-office extreme-heat indicator is insignificant in every column. This falsification result strengthens the interpretation that heat affects subsidiaries through localized production conditions. It also provides a basis for distinguishing the source of the initial shock from the group's subsequent adaptive response: the shock originates locally at the subsidiary site, while the group may still respond by reallocating production or orders across affiliates.

Table 11. Falsification Test Based on Exposure at Headquarters Office Locations

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*lnY*	*lnY*	*lnY*	*lnY*	*lnY*	*lnY*
Temp32	-0.011	0.004	0.004	-0.013	-0.002	0.007
	(0.023)	(0.021)	(0.023)	(0.027)	(0.011)	(0.011)
Constant	2.409*	2.464***	3.690**	12.141***	-0.117	3.404***
	(1.365)	(0.765)	(1.629)	(1.446)	(0.761)	(0.570)
Observations	41,415	41,167	16,341	16,061	18,472	18,220
R-squared	0.554	0.590	0.582	0.904	0.865	0.963
Control	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	City&Ind#Year	Firm&Year	City&Ind#Year	Firm&Year	City&Ind#Year	Firm&Year
F test	996.5	739.3	199.8	36.89	1356	249.2
R2_Adj	0.547	0.568	0.565	0.887	0.860	0.957

6. Adaptive Responses of Business Groups to Extreme Heat

6.1. Adaptation Through Internal Product Markets

The previous subsection shows that the baseline output loss is not driven by heat exposure at the parent-company location, supporting the interpretation of extreme heat as a localized production shock at the subsidiary site. We now examine whether business groups respond to such localized shocks by reallocating production or orders across subsidiaries through internal product markets. This analysis focuses not on whether headquarters heat transmits demand shocks to subsidiaries, but on whether the heat exposure of other subsidiaries within the same group is associated with compensating output adjustments by the focal subsidiary. Compared with $Temp32_{ss}$, which captures the absolute number of heat-exposed affiliates and may partly reflect group size, $Temp_{share}$ and $Temp32_{pm}$ are less mechanically tied to the total number of subsidiaries and therefore provide complementary evidence on the internal distribution and average intensity of same-group heat exposure.

Specifically, based on the baseline heat measure *Temp32*, we construct three same-group heat variables. First, $Temp32_{ss}$ is the number of subsidiaries within the same group that are in an extreme-heat state, measuring the scale of heat-exposed subsidiaries within the group. Second, $Temp_{share}$ is the share of all subsidiaries that are in an extreme-heat state, capturing the distribution of heat exposure intensity within the group. Third, $Temp32_{pm}$ is the average level of heat exposure among other subsidiaries in the same group, excluding the focal firm, capturing

the average extent of internal heat exposure. Including these variables together with *Temp32* in the regression allows us to test whether, after controlling for firm and city characteristics and fixed effects, heat exposure of other subsidiaries in the group changes the output response of a given subsidiary to extreme-heat shocks. Table 12 shows that the coefficient on *Temp32* is significantly negative in all columns and close in magnitude to the baseline estimates, indicating that the direct suppressing effect of extreme heat on subsidiary output remains robust even after controlling for the internal heat structure of the group. More importantly, under specifications with city fixed effects and industry-by-year fixed effects, the coefficients on $Temp32_{ss}$, $Temp_{share}$, and $Temp32_{pm}$ are all significantly positive. These results indicate that, after controlling for the focal subsidiary's own heat exposure, the output of a subsidiary is higher when other subsidiaries within the same group face greater heat exposure. This pattern is consistent with internal reallocation: when some affiliates are exposed to heat shocks, the group may shift orders, production tasks, or capacity utilization toward other subsidiaries that are less constrained or better able to absorb additional production. Because these variables capture the heat exposure of other group affiliates rather than direct transaction flows, we interpret the evidence as suggestive of internal product-market reallocation rather than as definitive proof of a specific order-transfer channel. In other words, internal product markets play a partial buffering role, offsetting some of the local heat shock at the subsidiary level, with the ultimate objective of maintaining aggregate group output as much as possible.

Table 12. Tests of the Internal Product-Market Channel

	(1)	(2)	(3)
Variables	*lnY*	*lnY*	*lnY*
Temp32	-0.059***	-0.068***	-0.065***
	(0.019)	(0.019)	(0.019)
$Temp32_{ss}$	0.006***		
	(0.001)		
$Temp_{share}$		0.158***	
		(0.029)	
$Temp32_{pm}$			0.053***
			(0.008)
Constant	1.603	1.632	1.751
	(1.067)	(1.067)	(1.066)
Observations	42,749	42,749	42,749
R-squared	0.563	0.563	0.564
Control	Yes	Yes	Yes
Fixed Effects	City&Ind#Year	City&Ind#Year	City&Ind#Year
F test	1473	1473	1482
R2_Adj	0.555	0.555	0.556

Note: The internal product-market variables vary mainly at the "group × city" level, and city × year fixed effects absorb the effect of *Temp32*. We therefore treat the specification with city fixed effects plus industry × year fixed effects as our main specification.

6.2. Adaptation Through Market Exit

When extreme heat exerts a significant negative impact on subsidiary production, business groups may close, relocate, or transfer affected subsidiaries in response to the prospect that the impact of extreme heat will intensify as global warming continues. To test this adaptation channel, we use business group–city–year observations and construct $exSub_{num}$, the net number of subsidiary exits from city *j* by group *i* in year *t*, measured as the number of

subsidiaries in the previous year minus the number in the current year. When $exSub_{num}$ is greater than zero, exits exceed entries; when it is below zero, entries exceed exits. The mean of $exSub_{num}$ is -0.185, indicating that, on average, business groups were still establishing new subsidiaries during the sample period. The minimum is -5 and the maximum is 2, implying that a business group could have up to five net subsidiary entries or two net subsidiary exits in a city in a given year. We estimate the following model:

$$exSub_{num_{i,j,t}} = \alpha + \beta Temp32_{j,t} + \gamma FirmCtr_{i,t} + \theta CityCtr_{j,t} + FE + \varepsilon_{i,j,t} \quad (2)$$

where i, j, and t denote business group, city, and year, respectively; $exSub_{num_{i,j,t}}$ is the net number of subsidiary exits from city j by group i in year t; $Temp32_{j,t}$ is the extreme-heat shock in city j in year t; $FirmCtr_{i,t}$ is the vector of firm-level controls; $CityCtr_{j,t}$ is the vector of city-level controls; and FE denotes fixed effects. To mitigate omitted-variable bias, we include either city fixed effects plus year fixed effects, or city fixed effects, firm fixed effects, and year fixed effects.

Table 13 reports the regression results. Across alternative fixed-effect structures and control sets, the coefficient on *Temp32* is significantly positive. This indicates that greater extreme-heat exposure is associated with a higher net number of subsidiary exits from a city. Equivalently, business groups either close or relocate more subsidiaries away from heat-exposed cities, or reduce the establishment of new subsidiaries in those cities. Since $exSub_{num}$ is a net exit measure, the result should be interpreted as evidence of net subsidiary withdrawal from heat-exposed local markets rather than as a pure measure of physical closure.

Table 13. Adaptive Behavior: Subsidiary Exit

	(1)	(2)	(3)	(4)
Variables	$exSub_{num}$	$exSub_{num}$	$exSub_{num}$	$exSub_{num}$
Temp32	0.031***	0.026***	0.021**	0.016*
	(0.007)	(0.007)	(0.008)	(0.008)
Constant	-0.286***	-0.270***	-1.785***	-1.007
	(0.025)	(0.024)	(0.483)	(0.642)
Observations	119,190	119,093	112,651	112,547
R-squared	0.026	0.095	0.031	0.097
Control	No	No	Yes	Yes
Fixed Effects	City&Year	City&Firm&Year	City&Year	City&Firm&Year
F test	18.24	13.03	15.14	11.13
R2_Adj	0.0228	0.0691	0.0282	0.0706

Furthermore, the heterogeneity results above show that the negative effect of extreme heat is significant mainly for labor-intensive subsidiaries. Business-group adaptation should therefore also be concentrated on labor-intensive subsidiaries. We measure labor intensity using the ratio of social-security employment to registered capital (*LY1*) and the ratio of social-security employment to paid-in capital (*LY2*), and then construct the net number of exits for high- and low-labor-intensity subsidiaries. The results in Table 14 show that for both *LY1* and *LY2*, the coefficient on *Temp32* is significantly positive only for the high-labor-intensity subgroup and is insignificant for the low-labor-intensity subgroup. This suggests that business groups respond to extreme-heat shocks mainly by selectively withdrawing labor-intensive subsidiaries from heat-exposed local markets.

Table 14. Adaptive Behavior: Subsidiary Exit in Labor-Intensive Firms

	(1)	(2)	(3)	(4)
Variables	$exHigh1_{num}$	$exLow1_{num}$	$exHigh2_{num}$	$exLow2_{num}$

	LY1		*LY2*	
Temp32	0.015**	0.008	0.013*	0.010
	(0.007)	(0.010)	(0.007)	(0.010)
Constant	-0.588	-0.151	-0.546	-0.256
	(0.521)	(0.718)	(0.521)	(0.727)
Observations	74,670	61,182	74,500	61,299
R-squared	0.100	0.106	0.098	0.106
Control	Yes	Yes	Yes	Yes
Fixed Effects	City&Firm&Year	City&Firm&Year	City&Firm&Year	City&Firm&Year
F test	7.074	7.289	6.907	7.568
R2_Adj	0.0603	0.0609	0.0587	0.0610

Note: These exit results also imply that our baseline production estimates are conservative. Because extreme heat may induce the most vulnerable subsidiaries to exit, the surviving sample is positively selected. As a result, the estimated output losses among remaining subsidiaries should be interpreted as a lower bound of the true production effects of extreme heat.

6.3. Adaptation Through Green Technological Innovation

In addition to passively adapting through market exit, business groups may also actively develop green technologies to cope with increasingly frequent heat shocks. To examine this channel, we use business group–year observations and measure green technological innovation as the log of one plus the total number of green invention and utility-model patents applied for by the business group in a given year. We estimate:

$$GrePat_{i,t}=\alpha+\beta Temp32_{Sub_{i,t}}+\gamma FirmCtr_{i,t}+\theta CityCtr_{j,t}+FE+\varepsilon_{i,t} \quad (3)$$

where i, j, and t denote business group, city, and year, respectively; $GrePat_{i,t}$ is the level of green technological innovation of business group i in year t; $Temp32_{Subi,t}$ is the sum of extreme-heat shocks across the cities where all subsidiaries of group i are located in year t; $FirmCtr_{i,t}$ is the vector of firm-level controls; $CityCtr_{j,t}$ is the vector of city-level controls; and *FE* denotes fixed effects.

Table 15 reports the results. Across alternative fixed-effects structures and control sets, the coefficient on $Temp32_{Sub}$ is significantly positive, indicating that the greater the aggregate extreme-heat exposure faced by a group's subsidiaries, the more likely the group is to develop new green technologies, such as energy-saving and environmental technologies or heat-adaptation technologies. In untabulated results, we also construct alternative measures of green innovation based on green invention patents and utility-model patents separately, on granted rather than applied green patents, and on next-period patent applications or grants. The results remain similar.

Table 15. Adaptive Behavior: Green Technological Innovation

	(1)	(2)	(3)	(4)
Variables	*GrePat*	*GrePat*	*GrePat*	*GrePat*
$Temp32_{Sub}$	0.203***	0.091***	0.097***	0.051***
	(0.011)	(0.011)	(0.011)	(0.012)
Constant	-0.566***	0.060	-6.023***	-4.299***
	(0.058)	(0.060)	(0.901)	(0.659)
Observations	19,900	19,691	18,996	18,778
R-squared	0.282	0.705	0.339	0.712
Control	No	No	Yes	Yes
Fixed Effects	City&Ind#Year	Firm&Year	City&Ind#Year	Firm&Year
F test	323.5	73.06	38.34	13.59

R2_Adj	0.253	0.657	0.312	0.663

Further, consistent with Table 14, we test whether extreme heat shocks to labor-intensive subsidiaries are more likely to stimulate green technological innovation at the group level. Specifically, we separately calculate the total extreme-heat exposure faced by labor-intensive and non-labor-intensive subsidiaries, as defined by LY1 and LY2, and regress group-level green innovation on these exposure measures. Table 16 shows that the greater the extreme-heat exposure of labor-intensive subsidiaries, the more likely the business group is to undertake green technological innovation.

Table 16. Adaptive Behavior: Green Technological Innovation in Labor-Intensive Firms

	(1)	(2)	(3)	(4)
Variables	*GrePat*	*GrePat*	*GrePat*	*GrePat*
	LY1		*LY2*	
$Temp32_{Sub}$	0.025***	0.015**	0.025***	0.014**
	(0.007)	(0.006)	(0.007)	(0.006)
Constant	-4.388***	-4.458***	-4.387***	-4.472***
	(0.660)	(0.663)	(0.659)	(0.663)
Observations	18,778	18,778	18,778	18,778
R-squared	0.712	0.712	0.712	0.711
Control	Yes	Yes	Yes	Yes
Fixed Effects	Firm&Year	Firm&Year	Firm&Year	Firm&Year
F test	13.23	11.97	13.18	11.90
R2_Adj	0.663	0.663	0.663	0.663

6.4. City-Level Long-Run Effects of Extreme-Heat Shocks

The analysis above focuses mainly on the effects of extreme heat on current subsidiary production, exit, and innovation within business groups, and thus primarily captures firms' short-run micro-level responses. Extreme heat, however, is not a one-time accidental shock. Under global warming it is a systemic risk characterized by rising frequency, intensifying severity, and pronounced regional heterogeneity. Firms' production decisions, subsidiary location choices, and green-innovation activities ultimately accumulate over space and time into long-run changes in a city's industrial structure, number of firms, and innovation performance. Against this background, we further examine the long-run effects of extreme-heat shocks on total output generated by group subsidiaries, the number of subsidiaries, and green technological innovation, in order to reveal how climate shocks reshape China's industrial geography and green transformation over space.

To examine the long-run production effects of extreme heat at the city level, we further analyze changes over time at the city scale. Taking city *j* as the unit of observation, we first aggregate subsidiary output, parent-company output, and business-group output to the city-year level, obtaining total subsidiary output $Y_{sub,jt}$, total parent-company output $Y_{par,jt}$, and total business-group output $Y_{gro,jt}$. We then construct output growth between 2007 and 2016 as $DY_{sub,jt}=\frac{Y_{sub,j2016}-Y_{sub,j2007}}{Y_{sub,j2007}}$, $DY_{par,jt}=\frac{Y_{par,j2016}-Y_{par,j2007}}{Y_{sub,j2007}}$, and $DY_{gro,jt}=\frac{Y_{gro,j2016}-Y_{gro,j2007}}{Y_{gro,j2007}}$.

At the city level, we also calculate changes or differences in the extreme-heat measure *Temp32* and in control variables such as GDP per capita, industrial structure (the ratio of secondary to tertiary industry), the unemployment rate, PM2.5, mean temperature, wind speed, and precipitation, thereby constructing *DTemp32,*

Dpgdp, *Dsecond*, *Dunemploy*, *DPM2.5*, *DYtemp*, *DYwind*, and *DYrain*. In addition, we use averages over 2007–2011 and 2012–2016 to build medium- and long-run change measures such as DMY_{sub}, DMY_{par}, DMY_{gro}, and *DMTemp32*, so as to capture how a persistent increase in extreme heat affects the urban production structure. The regression model can be written as:

$$DY_{sub,j}/DY_{par,j} \mid DY_{gro,j} = \alpha + \beta DTemp32_j + \gamma DCityCtr_j + \varepsilon_j \quad (4)$$

$$DMY_{sub,j} \mid DMY_{par,j} \mid DMY_{gro,j} = \alpha + \beta DMTemp32_j + \gamma DMCityCtr_j + \varepsilon_j \quad (5)$$

where j denotes city; $DY_{sub,j}$, $DY_{par,j}$, $DY_{gro,j}$ are the long-run changes in output for subsidiaries, parent companies, and business groups in city j; $DMY_{sub,j}$, $DMY_{par,j}$, $DMY_{gro,j}$ are medium- to long-run output changes measured using five-year averages; $DTemp32_j$ and $DMTemp32_j$ are, respectively, the short-run and medium- to long-run changes in the intensity of extreme heat; and $CityCtr_j$ and $DMCityCtr_j$ are vectors of changes in city-level controls. To emphasize the before-after identification strategy, we do not include fixed effects in these city-difference regressions and instead estimate cross-sectional models with robust standard errors after differencing.

Table 17 reports the results. On the one hand, cities experiencing larger increases in extreme-heat intensity during the sample period exhibit significantly smaller growth in subsidiary output. The conclusion is robust whether we use annual-change indicators or five-year-average changes, indicating that extreme heat exerts a clear and persistent drag on output at the city level. On the other hand, changes in extreme heat are not systematically related to changes in output at the parent-company or business-group levels. This suggests that in the long run extreme heat affects city-level production primarily by suppressing the accumulation and expansion of subsidiary capacity in the local area, while business groups can partially offset the shock through cross-regional deployment and internal structural adjustment.

Table 17. Long-Run Effects: Output of Subsidiaries, Parent Companies, and Business Groups

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	DY_{sub}	DY_{par}	DY_{gro}	DMY_{sub}	DMY_{par}	DMY_{gro}
DTemp32	-12.993***	-1.078	0.312			
	(4.065)	(0.935)	(0.746)			
DMTemp32				-1.150*	-0.281	0.001
				(0.585)	(0.286)	(0.308)
Constant	9.426	3.145*	2.537*	1.414	1.199***	0.794*
	(8.176)	(1.677)	(1.346)	(0.880)	(0.418)	(0.404)
Observations	198	169	172	241	206	207
R-squared	0.100	0.049	0.063	0.062	0.086	0.120
Control	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	No	No	No
F test	2.609	1.301	1.854	1.879	2.837	4.362
R2_Adj	0.062	0.001	0.017	0.030	0.049	0.0846

Internal product markets and resource reallocation are more likely to serve as short- to medium-run buffering mechanisms when firms face localized heat shocks. Their core manifestation is the immediate adjustment of orders, capacity, and business activities across group affiliates, which mainly smooths current production losses and need not necessarily translate into stable, observable long-run spatial restructuring. By contrast, subsidiary exit and green innovation better capture business groups' long-run adaptation to persistent heat risk. We therefore further examine the long-run adaptive effects of extreme heat at the city level and jointly

analyze changes in subsidiary location patterns and green innovation within a unified framework. Specifically, using city *j* as the unit of observation, we construct two outcome variables: one is the net change in the number of group subsidiaries in the city, and the other is the change in the number of green patent applications in that city. Accordingly, in Table 18, columns (1) and (2) use the annual difference in the number of subsidiaries, $DSub_j$, and the five-year-average difference, $DMSub_j$, as the dependent variables, while columns (3) and (4) use the annual difference in the total number of city-level green patent applications, $DGrePat_j$, and the five-year-average difference, $DMGrePat_j$. The key explanatory variables are changes in city-level extreme-heat intensity, including the annual difference $DTemp32_j$ and the five-year-average difference $DMTemp32_j$, while controlling for corresponding changes in GDP per capita, industrial structure, employment, pollution, and meteorological conditions. This yields two representative city-level long-run models:

$$DSub_j/DGrePat_j = \alpha + \beta DTemp32_j + \gamma DCityCtr_j + \varepsilon_j \quad (6)$$

$$DMSub_j/DMGrePat_j = \alpha + \beta DMTemp32_j + \gamma DMCityCtr_j + \varepsilon_j \quad (7)$$

where $DSub_j$ denotes the net change in the number of group subsidiaries in city j over the sample period; $DGrePat_j$ denotes the change in the number of green patent applications in the same period; $DTemp32_j$ is the change in the intensity of extreme heat; $CityCtr_j$ denotes changes in city characteristics, including GDP per capita, industrial structure, unemployment, *PM2.5*, average temperature, wind speed, and precipitation; and ε_j is the error term. In columns (2) and (4), analogous long-difference models are constructed using five-year-average changes in $DMSub_j$, $DMGrePat_j$, $DMTemp32_j$ and the corresponding city controls $DMCityCtr_j$ to capture structural adjustment over the medium to long run.

Table 18 reports the results. First, from the perspective of long-run changes in subsidiary numbers, an increase in the intensity of extreme heat significantly suppresses net subsidiary entry at the city level. Using annual differences as an example, the coefficient on $DTemp32_j$ is negative and statistically significant. This indicates that, after controlling for economic growth, structural adjustment, employment, and environmental factors, cities experiencing faster increases in extreme heat are more likely to see net subsidiary exits or slower subsidiary expansion by business groups. The results based on the five-year-average changes in $DMSub_j$ and $DMTemp32_j$ also show a significant negative relationship, indicating that this effect is not a short-run fluctuation but has medium- to long-run persistence. It suggests that business groups adapt spatially by contracting or ceasing to expand their subsidiary presence in cities where heat pressure rises markedly.

Second, from the perspective of city-level responses in green technological innovation, increases in extreme-heat intensity are significantly positively associated with changes in the number of green patent applications. Whether we pair annual changes in $DGrePat_j$, $Temp32_j$ or five-year-average changes in $DMGrePat_j$ with $DMTemp32_j$, the corresponding coefficients on heat changes are positive and statistically significant. This indicates that in cities experiencing more severe and persistent extreme-heat shocks, green innovation activity is more active. At the city level, extreme heat not only induces spatial reconfiguration of firm networks, but also accelerates investment in green innovation.

Table 18. Long-Run Effects: Subsidiary Exit and Green Technological Innovation

	(1)	(2)	(3)	(4)
Variables	DSub	DMSub	DGrePat	DMGrePat

DTemp32	-1.697**		69.375**	
	(0.710)		(28.411)	
DMTemp32		-0.701***		27.579**
		(0.199)		(12.662)
Constant	5.382***	2.084***	38.315	11.465
	(1.484)	(0.272)	(46.866)	(24.298)
Observations	243	268	172	186
R-squared	0.033	0.103	0.123	0.081
Control	Yes	Yes	Yes	Yes
Fixed Effects	No	No	No	No
F test	1.621	4.076	2.971	2.511
R2_Adj	-0.001	0.075	0.080	0.039

7. Conclusion

This paper investigates how physical climate risk is allocated and absorbed within multi-layer business organizations. Where Chen and Yang (2019) and Zhang et al. (2018) establish that extreme heat reduces output and TFP at the registered industrial firm, and Ma et al. (2026) show that firms adapt by redirecting entry and equity investment toward milder-climate regions, we open the firm itself to ask where, inside the organization, climate damage actually lands and how groups adapt internally. By linking listed-firm financials (CSMAR), annual-report-based affiliated-entity registries (CnOpenData), and the National Tax Survey, we construct what is, to our knowledge, the first matched group–parent–subsidiary panel that simultaneously observes production and factor inputs at all three organizational layers, and combine it with city-level daily meteorological data over 2007–2016. Three findings stand out. First, climate damage is sharply stratified within business groups: extreme heat significantly suppresses subsidiary output while leaving parent-company and aggregate group output statistically unchanged. Aggregate firm-level evidence therefore understates the true incidence of physical climate risk, because losses are concentrated and absorbed at frontline production units. Second, the subsidiary-level effect operates through reduced capital input and lower total factor productivity rather than through labor input, and is concentrated in labor-intensive subsidiaries. A falsification test using extreme heat at headquarters locations confirms that the channel is localized production, not demand transmitted from parents. Third, business groups do not bear heat shocks passively. They adapt on three margins operating at distinct horizons: short-run buffering through internal product-market reallocation, medium-run selective exit of heat-exposed subsidiaries, and long-run investment in green technological innovation. Extreme heat therefore reshapes both organizational boundaries and technological trajectories, not only contemporaneous output.

Several limitations and avenues for future research deserve emphasis. Our identification relies on a rich set of firm-level and city-level controls together with high-dimensional fixed effects, which absorb time-invariant firm and city heterogeneity as well as industry-specific time shocks. Because daily extreme-heat realizations at the city level are unlikely to be driven by individual-firm decisions, reverse causality is a limited concern in this setting; nonetheless, the absence of a quasi-experimental shock or instrument means our estimates should be read as identifying conditional associations rather than fully exogenous treatment effects, and the magnitude in our most demanding specification is modest in size though robust to a battery of alternative measures, sample restrictions, and falsification tests. Future work using exogenous variation in heat exposure or in subsidiary location decisions would help sharpen the causal interpretation. In addition, our sample is restricted to A-share listed business groups, which are larger and more capable of cross-regional operations than typical firms; the

magnitudes we estimate may therefore represent lower bounds on the climate sensitivity of smaller and less diversified organizations. Finally, although the National Tax Survey provides unusually rich subsidiary-level information, it ends in 2016, so our analysis cannot speak directly to the most recent intensification of climate risk. Extending similar group–parent–subsidiary linkages to other emerging economies and to more recent data is a natural next step.

The findings carry several policy implications that follow directly from the within-group stratification of climate damage. First, because losses are concentrated at subsidiaries while parent and group-level performance appears stable, evaluations of corporate climate exposure based on consolidated financials understate the underlying physical risk. Climate-adaptation governance should therefore extend beyond the standalone firm and explicitly target the subsidiary level, with risk identification, early-warning, and emergency-dispatch mechanisms designed to cover parent firms, subsidiaries, and major production bases. Second, since the negative output effect is concentrated in labor-intensive subsidiaries and operates through capital input and productivity rather than labor input, targeted heat-protection investment, labor-protection arrangements, and production-contingency planning in labor-intensive sectors and high-exposure regions are likely to deliver disproportionate resilience gains. Third, our evidence that adaptation operates simultaneously through short-run reallocation, selective exit, and long-run green innovation suggests that resilience policy should be coordinated across horizons: supporting internal resource-reallocation capacity within business groups for short-run buffering, while using green finance, tax incentives, and R&D support to encourage the long-run accumulation of heat-adaptation technology. Together, these measures can strengthen the resilience of multi-layer firms—and the broader economy—to intensifying physical climate risk.

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