

# Burning out Profits: Wildfire Exposure and Corporate Performance

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November 18, 2025

## Abstract

Climate-driven increases in wildfire activity pose growing risks to firms. Combining high-resolution wildfire dynamics from NASA's Global Fire Atlas with geolocated headquarters and subsidiaries of Chinese listed firms, we construct a firm-level exposure index and estimate its effects using panel fixed-effects models. Wildfire exposure significantly reduces corporate performance: a one-unit increase in exposure lowers next-year ROE by 0.53%, with stronger impacts for capital- and technology-intensive and financially constrained firms. Mechanism tests show that productivity losses and supply-chain disruptions are key channels. We also document limited market reaction but sizable projected long-term losses, underscoring underestimated climate-risk vulnerabilities.

**Keywords:** Climate change, Wildfire exposure, Listed companies, Firm performance, Supply chain

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# 1 Introduction

In 2024, the global temperature rose by  $1.6^{\circ}\text{C}$  above the pre-industrial level, a milestone confirmed by the Copernicus Climate Change Service and one that surpasses the IPCC's  $1.5^{\circ}\text{C}$  threshold.<sup>1</sup> Accelerated warming has intensified the frequency and severity of wildfires worldwide, generating substantial uncertainty and economic externalities for firms (Cunningham et al., 2024; Guo et al., 2024; Li and Flammer, 2025). While a growing literature examines the impacts of climate hazards on households (An et al., 2023), labor markets (Borgschulte et al., 2024; Burke et al., 2022), and public health (Bladon et al., 2014; Zhao et al., 2025), far less is known about how climate-amplified wildfires affect corporate operations and financial performance, the foundations of economic resilience and long-term growth. Understanding how wildfire exposure translates into corporate outcomes is therefore essential for assessing the economic consequences of climate change and for guiding firms' long-term resilience and operational sustainability.

Wildfire risks are multifaceted. Beyond the direct physical damage to assets, wildfires generate indirect disruptions through reduced labor productivity, transportation delays, input shortages, supply chain disruptions, and heightened investment uncertainty (Borgschulte et al., 2024; Dell et al., 2014; Pankratz et al., 2023; Sun et al., 2024a; Zivin et al., 2020). Moreover, firms differ markedly in the spatial dispersion of their operations, particularly those with extensive networks of suppliers or subsidiaries (Pankratz and Schiller, 2024). As climate risks increasingly propagate through production networks, exposure at geographically distributed operational nodes may matter as much as, or even more important than, exposure at corporate headquarters. These considerations underscore the need for firm-level, spatially precise measurements of wildfire exposure and its financial implications.

We construct a firm-level wildfire exposure by combining high-resolution wildfire dynamics from NASA's CMS Global Fire Atlas with the geolocated positions of both headquarters and subsidiaries. Using burn areas, fire-spread direction, and distance

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<sup>1</sup>Copernicus Climate Change Service (3CS), Global Climate Highlights 2024, <https://climate.copernicus.eu/copernicus-2024-first-year-exceed-15degc-above-pre-industrial-level>, accessed on 16 December, 2025.

from ignition points, we compute an annual wildfire exposure index weighted by the registered capital across headquarters and subsidiaries. This firm-level wildfire exposure index thus captures exposure across the firm's full organizational footprint.

This paper then examines whether wildfire exposure affects corporate performance for listed companies in China. By combining high-resolution wildfire information with detailed geolocation data for firms and their subsidiaries, we capture exposure across the entire company's footprint and provide a more comprehensive assessment of its impact on financial performance. Using a panel fixed-effects model, we find that greater wildfire exposure significantly reduces firm performance: a one-unit increase in wildfire exposure corresponds to a 0.53% decrease in annual Return on Equity (ROE), and subsidiary-level exposure has an even stronger effect, highlighting the importance of accounting for decentralized operational risk in corporate climate vulnerability assessments. The results remain robust to alternative measures of wildfire exposures, performance metrics, and model specifications.

To explore the mechanisms underlying the negative effects of wildfire exposures, we examine several potential transmission channels. First, wildfire exposure may reduce firm performance by lowering labor productivity. Wildfires release large amounts of fine particulates and toxic compounds that harm respiratory and cardiovascular function (Pakhtigian, 2022; Wettstein et al., 2018), and contribute to psychological distress and cognitive decline (Borgschulte et al., 2024; Johnston et al., 2021). These physical and mental health impacts can reduce employees' ability to work efficiently, thereby weakening firms' operational efficiency and overall performance. Consistent with this prediction, we find that greater wildfire exposure is associated with a larger reduction in annual profit per employee, supporting the hypothesis that reduced labor productivity is a key channel through which wildfire exposure lowers firm profitability.

A second potential channel is supply chain disruption. Natural disasters have been shown to interrupt supplier networks, reduce supply availability, and weaken firms' operational continuity (Castro-Vincenzi, 2022; Ersahin et al., 2024; Pankratz and Schiller, 2024). Because the headquarters of listed companies primarily serve managerial functions while subsidiaries often interface with local suppliers and customers, our com-

prehensive wildfire exposure index enables us to evaluate how wildfire risk propagates through firms' supply chain structures. On the one hand, wildfires may reduce the number and diversity of available suppliers, increase dependence on remaining partners, and weaken firms' bargaining power. On the other hand, population displacement from high-risk areas may also reduce local demand, destabilizing customer relationships and amplifying operational uncertainty (An et al., 2023). Taken together, these factors suggest the hypothesis that wildfire exposure may harm firm performance through disruptions to supply chain networks.

Consistent with the hypothesis, we find that wildfire exposure has a stronger negative effect on firms with greater supply chain power or higher vertical integration. Such firms typically occupy central positions in production networks and rely more heavily on stable suppliers and customer relationships, making them more vulnerable to wildfire-induced disruptions. Additional tests show that firms with a higher degree of supply-demand matching experience smaller performance declines, indicating that stronger supply chain resilience—through better coordination, inventory management, or production flexibility—can mitigate the adverse effect of wildfire exposure.

Confronted with the increasing wildfire incidents, companies may adopt various proactive adaptation strategies to mitigate the uncertainty about future operations. Prior research shows that firms tend to reduce investment in highly uncertain environments (Dixit and Pindyck, 1994), or diversify risks by increasing cross-regional investments (Sun et al., 2024b). Wildfire exposure may therefore reduce investment if firms adopt a precautionary stance in response to elevated climate risk. This leads to the hypothesis that wildfire exposure decreases investment activity as firms attempt to manage heightened uncertainty. Our results are consistent with the hypothesis that greater wildfire exposure is associated with lower investment at both the firm and the headquarters levels, suggesting a risk-averse adjustment to climate-related uncertainty. However, at the subsidiary level, we observe the opposite pattern: wildfire exposures are positively associated with subsidiary-level investment. This finding does not reflect geographic relocation, as wildfire exposure has no significant effect on subsidiary entry or exit. Although our data do not allow us to directly verify the underlying mech-

anism, this pattern is consistent with firms reallocating resources toward subsidiaries that remain operationally viable or strategically important when facing elevated wildfire risk.

An additional question is whether the market responds to wildfire exposure faced by firms and whether such reactions anticipate future performance changes. We argue that frequent wildfire incidents may weaken investor confidence in a firm's productivity and supply chain stability (Huynh and Xia, 2023), leading to a more cautious assessment of its long-term development. Consistent with this view, we find a negative stock market reaction to wildfire incidents in the month of exposure. However, this negative reaction is short-lived and does not persist in subsequent months, suggesting that investors react to immediate disruptions but do not revise expectations for the firm's long-term profitability.

Given this limited forward-looking response in the stock market, it is important to quantify the long-term implications of escalating wildfire activity directly (Cunningham et al., 2024). To further assess these implications, we project future wildfire-induced profit losses to the year 2100 under different Representative Concentration Pathways (RCP). The results show that wildfire exposure is projected to cause total profit losses for Chinese listed companies of approximately USD 31.45 million, USD 44.07 million, and USD 49.26 million under the RCP 2.6, RCP 6.0, and RCP 8.5 scenarios,<sup>2</sup> simulated by the ISIMIP2b model,<sup>3</sup> respectively (Zhao et al., 2025). Taken together, the short-lived market reaction and sizable projected long-term profit loss suggest that investors are underweighting the enduring financial risks posed by escalating wildfire activities. This implies that firms and investors need to strengthen climate-risk assessment and adaptation strategies to address these underestimated risks.

Our study contributes to the literature in three main ways. First, it advances the understanding of the firm-level economic consequences of wildfires. While prior research focuses on household finance (An et al., 2023), and labor markets (Borgschulte

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<sup>2</sup>RCP 2.6 presents strong mitigation with low emissions scenario, implied  $\sim 1.5 - 2.0^\circ C$  warming by 2100; RCP 6.0 presents a intermediate stabilization scenario, implied  $\sim 3.0^\circ C$  warming; and RCP 8.5 presents a high-emissions scenario, implied  $\sim 4.3 - 5.0^\circ C$  warming by 2100, respectively.

<sup>3</sup>The ISIMIP2b scenarios are designed to elicit the contribution of climate change to impacts arising from low-emissions climate-change scenarios, see <https://www.isimip.org/protocol/2b/>.

et al., 2024), and public health (Kozlov, 2021), evidence on corporate impacts remains limited (Xue et al., 2021; Addoum et al., 2023). As firms play a central role in economic activity, documenting how wildfires affect their performance is critical for assessing the broader economic implications of climate change. We show that wildfire exposure significantly reduces firm performance and that this effect is systematically heterogeneous: it is more pronounced in capital- and technology-intensive industries, where fixed assets, skilled labor, and innovation activities are particularly vulnerable. And the effect is also stronger among financially constrained firms, which have fewer resources to absorb the wildfire shocks. These findings demonstrate that wildfire risks are both economically meaningful and unevenly distributed, highlighting the importance of firms' structural characteristics in shaping climate-related vulnerabilities.

Second, we refine the assessment of climate risk by adopting a more granular geographical lens that captures the full operational footprint of firms. Previous studies typically rely on city-level climate variables or headquarters locations to approximate corporate exposure (Addoum et al., 2023; Javadi and Masum, 2021; Li and Flammer, 2025), which overlooks substantial micro-geographic variation in risk. Moreover, since Chinese listed companies are concentrated in first-tier cities<sup>4</sup> which face low wildfire threat due to high urbanization and robust infrastructure, conventional methods likely underestimate firms' true exposure. By integrating high-resolution wildfire data with the precise locations of both headquarters and subsidiaries, we construct a firm-level exposure measure that more accurately captures climate risk. The results show that subsidiary-level exposure, rather than headquarters exposure, drives the corporate profitability losses, implying that traditional headquarters-based measures may underestimate firms' true climate vulnerability.

In addition, this firm-level, precise exposure index allows us to examine how wildfires propagate through firms' supply chains, as subsidiaries often interface with local suppliers and customers. Our analysis shows that wildfire events weaken firms' bargaining power, exacerbate supply-demand mismatches, and disrupt production continuity, underscoring the importance of supply chain management in response to climate

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<sup>4</sup>China's first-tier cities, including Beijing, Shanghai, Guangzhou, and Shenzhen, are the most developed and influential metropolises in the country.

risks (Carvalho et al., 2020; Inoue and Todo, 2019; Pankratz and Schiller, 2024).

Third, we contribute new insights into firms' adaptation response and the long-term implications of wildfire risk. Prior research shows firms adapt to climate risk by diversifying cross-regional investments and supply chains (Pankratz and Schiller, 2024; Pelli et al., 2023; Sun et al., 2024b), investing in innovation (Sautner et al., 2023), increasing their holdings of liquid assets (Heo, 2021a; Huang et al., 2018), physically relocating (Khanna et al., 2025; Linnenluecke et al., 2011), strengthening insurance or financial hedging (Flammer, 2021; Huang et al., 2022a,b; Li et al., 2024), and lowering leverage (Ginglinger and Moreau, 2023). Li (2025) and Li and Flammer (2025) also show that firms' adaptation is stronger for those with longer time horizons. We show that wildfire exposure reduces investment at the firm and headquarters levels but increases investment at the subsidiary level, consistent with the selective relocation of resources toward operationally viable nodes when climate risk rises (Pankratz and Schiller, 2024; Sun et al., 2024b). We distinguish between short-run market reactions and longer-run profitability consequences, showing that financial markets respond only briefly to wildfire shocks and fail to incorporate long-term climate risks. Combining empirical estimates with climate-model projections, we quantify substantial future profit losses under multiple emissions scenarios, underscoring the need for improved climate-risk assessment and adaptation strategies by firms and investors.

We organize the remainder of this paper as follows. Section 2 summarizes the data and key variable measurements. Section 3 describes the methodology. Section 4 reports our main empirical results on firm profitability and the economic mechanisms driving the results, before summarizing various robustness tests and heterogeneous analysis. Section 5 reports corporate adaptation and market reaction to wildfire exposure. In section 6 we project the corporate profitability loss caused by simulated wildfire risks under different climatic scenarios. Section 7 concludes the paper.

## 2 Data and Variable Measurement

### 2.1 Main Data Sources and Sample Constructions

To evaluate the impact of wildfires on Chinese listed companies, we construct a firm-level panel dataset by integrating multiple data sources, including data on satellite-based wildfire distribution, data on the locations of headquarters and their subsidiaries, and their financial performance, as well as other climate data, including precipitation and temperature.

**Data on the wildfire distributions.** The wildfire data are sourced from *the Global Fire Atlas*, which documents daily dynamics of individual fires between 2003 and 2016 (Andela et al., 2019). It includes the day-to-day dynamics of individual fires to determine the timing and location of ignitions, fire size, duration, daily expansion, fire line length, speed, and direction of spread, which were derived based on the Global Fire Atlas algorithm and estimated day of burn information at 500-m resolution from the Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 6 MCD64A1 burned area product.<sup>5</sup> Due to missing records in 2016, we restrict our analysis to the period from 2003 to 2015 to avoid measurement error, resulting in an initial sample of 168,251 wildfires in China. We exclude single-day fires, as these short-lived events typically have negligible effects. The final wildfire sample consists of 79,761 events, spanning between 2003 and 2015 in China.

**Data on locations of list firms.** We collect the geolocations for listed companies and their subsidiaries from the CSMAR Database for 2003–2015. Because subsidiary address information in CSMAR is often incomplete or inaccurate, we supplement it by matching historical subsidiary names through business information platforms such as *Qichacha* and *Tianyancha*,<sup>6</sup> followed by manual verification when needed. Ambiguous cases are resolved through additional manual searches to ensure accuracy. In total, we collect 25,490 headquarters addresses and 313,112 subsidiary addresses. Following Fisman et al. (2023), we focus on A-share listed firms and exclude financial companies

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<sup>5</sup>MCD64A1 burned area: <https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/MCD64A1>.

<sup>6</sup>*Qichacha* and *Tianyancha* are leading Chinese platforms that provide comprehensive business information and data verification services.

as well as financially distressed firms (that is ST and PT-labeled firms). Subsidiary data also excludes financial entities, non-A-share firms, and overseas subsidiaries. After screening, the final sample includes 23,308 listed company locations and 290,029 subsidiary locations.

**Data on financial performance.** Firm-level financial data are also obtained from CSMAR. Corporate profitability is measured using return on assets (ROA), return on equity (ROE), and return on sales (ROS). Investment behavior is proxied by the capital expenditure-to-total assets ratio. Labor productivity is measured as net profit per employee. For supply chain dimensions, we include three indicators: supply chain bargaining power, vertical integration, and supply-demand matching (detailed in Appendix A.1).

**Other Supporting Data** City-level drought data is obtained from the SPEI\_RF gridded dataset hosted in the National Ecosystem Data Bank (EcoDB) (Xia et al., 2024). This dataset provides high-spatial-resolution (1 km) Standardized Precipitation Evapotranspiration Index (SPEI) values across multiple time scales (1, 3, 6, 12, and 24 months) over mainland China from 2001 to 2021.

Temperature data are obtained from the National Centers for Environmental Information (NCEI), a division of the National Oceanic and Atmospheric Administration (NOAA). As a leading global repository of meteorological data, NCEI provides daily updated records from worldwide weather stations, ensuring both timeliness and accuracy.

## 2.2 The Measurement of Wildfire exposure

Using geographic coordinates, burn area, duration, and spread direction from *Global Fire Atlas*, we constructed a geometric model that links firm locations with wildfire pathways. Prior research shows the direction of fire spread is critical for determining which areas are affected (Du et al., 2024; He et al., 2020). We therefore incorporate both the Euclidean distance between a wildfire and a firm, and the relative angle between the firm's location and the fire's spread direction.

Figure 1 illustrates the identification strategy. Point  $j$  denotes the wildfire ignition

point, Point  $i$  the firm location. The shaded 90-degree fan-shaped area denotes the effective impact zone. The angle  $\theta$  measures the deviation between the fire's spread direction and the line from  $j$  to  $i$ . Firms with  $\cos(\theta) > 0$  lie within the wildfire-affected zone, and larger cosine values indicate closer alignment with the primary direction of fire movement, implying higher exposure. The distance between  $i$  and  $j$   $E_{ij}$  captures how close the firm is to the fire source.

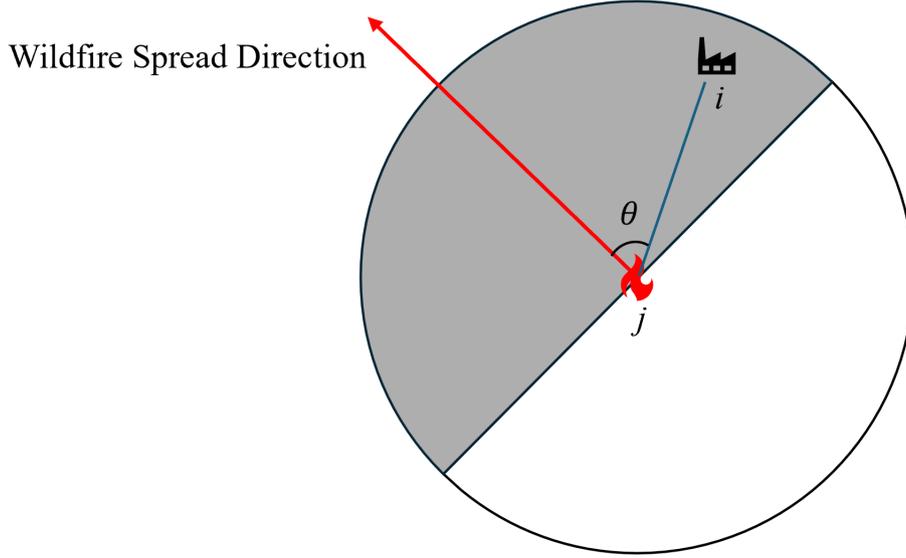


Figure 1: Wildfire Exposure Identification

for a firm  $i$  located in the fire  $j$ 's affected areas in year  $t$ , we have:

$$Wildfire\_Index_{i,t} = \sum_{j \in fire_t} \mathbf{I}_j(\cdot) \times [Distance\_Index_{i,j} * Angle\_Index_{i,j}] \quad (1)$$

$$Distance\_Index_{i,j} = 1 - \min(Radii, Distance_{i,j}) / Radii$$

$$Angle\_Index_{i,j} = \max[0, \cos(\theta)]$$

where  $Wildfire\_Index_{i,t}$  is the wildfire exposure index of firm  $i$  in year  $t$ .  $\mathbf{I}_j(\cdot)$  is an indicator function that equals 1 if wildfire  $j$  is within the impact radius and 0 otherwise.  $Radii$  is the impact radius, set to be 30 km or 50 km in the analysis.<sup>7</sup> Then we aggregate wildfire exposure across the entire organizational structure, that is, headquarters and

<sup>7</sup>As the average county area of 3,363 km<sup>2</sup> in China, equivalent to a circular radius of approximately 33 km, we use a radius of 30 km as the core impact radius in our primary analysis. To ensure the robustness of our findings, we also conduct a supplementary analysis using an impact radius of 50 km, thereby verifying the consistency of results across multiple spatial scales.

all subsidiaries, using a unified capital-based weighting scheme:

$$CWEI_{i,t} = \sum_{u \in U_i} (W_{i,u} \cdot Wildfire\_Index_{u,t}), \text{ where: } W_{i,u} = \frac{Capital_u}{\sum_{u \in U_i} Capital_u} \quad (2)$$

where  $CWEI_{i,t}$  is the aggregated wildfire exposure index of firm  $i$  (aggregating exposure from its headquarters and all subsidiaries), in year  $t$ . The set  $U_i = \{h, s_1, s_2, \dots, s_n\}$  represents the headquarters and all subsidiaries of firm  $i$ , and  $Capital_u$  is the capital stock for headquarters or the registered capital for subsidiary  $u$ . Using the same weighting scheme, we also compute exposure measures separately for the headquarters and for the set of subsidiaries.

### 2.3 Summary Statistics

Table 1 presents the summary statistics of the variables used in our analysis, including additional wildfire exposure measured by headquarters and for the set of subsidiaries with different radii, separately. All the variables, except for dummy and whether variables (SPEI and temperature), are winsorized at the first and 99th percentiles to alleviate the potential impact of outliers. The weighted wildfire exposure index is 0.154 within a 30 km radii, which increase to 0.518 if the impact radius is extended to 50 km. Moreover, the wildfire exposure index of all subsidiaries is generally larger than that of the headquarters, as the widespread distribution of subsidiaries across different geographic locations increases the exposure probability. At the firm-year level, very few subsidiaries relocate across counties. On average, each firm adds about two subsidiaries and exits another two within a country. On average, the ROE is 6.7% per firm, and 3.8% for ROA, 7.3% for ROS.

## 3 Empirical Strategy

To estimate the impact of wildfires on firms, we employ an ordinary least squares (OLS) regression model as specified in Equation (3):

Table 1: Summary Statistics

Variable	N	Mean	SD	P1	P99
Wildfires in 30 km	18524	0.154	0.498	0	2.411
Wildfires: Head in 30 km	18524	0.149	0.522	0	2.491
Wildfires: Subsidiaries in 30 km	18524	0.183	0.452	0	2.282
Wildfires in 50 km	18524	0.518	1.426	0	6.522
Wildfires: Head in 50 km	18524	0.507	1.488	0	6.757
Wildfires: Subsidiaries in 50 km	18524	0.581	1.236	0	5.962
ROE <sub>t+1</sub>	18524	0.067	0.097	-0.321	0.294
ROA <sub>t+1</sub>	18470	0.038	0.047	-0.104	0.175
ROS <sub>t+1</sub>	18269	0.073	0.112	-0.318	0.391
Monthly Excess Return	235417	-0.004	0.0948	-0.202	0.291
Net profit per capita <sub>t+1</sub>	18213	9.113	6.001	-12.18	13.89
Capexrate <sub>t+1</sub>	18167	0.054	0.0492	0.0005	0.217
Subsidiary Relocate	17693	0.009	0.129	0	0
Subsidiary Entrance	17693	2.012	5.852	0	21
Subsidiary Exit	17693	0.627	2.622	0	8
P/B Ratio	18524	3.510	2.560	0.850	13.51
Log(size+1)	18524	21.81	1.223	19.68	25.59
Log(age+1)	18524	1.960	0.837	0	3.091
Debt2Asset	18524	0.448	0.204	0.049	0.856
Cash2Asset	18524	0.186	0.604	0.011	0.682
Average SPEI in Subsidiaries' cities	18524	-0.021	0.224	-0.853	0.698
Average temperature in Subsidiaries' cities	18524	3.257	3.861	0.172	18.25

*Note:* This table reports the summary statistics of all variables in our main empirical analysis. The sample consists of a list of firms from 2003 to 2015 in China. Wildfire refers to the wildfire exposure index defined by Equation (2), calculated by combining the geolocations of listed firms (headquarters and subsidiaries) with wildfire records from the *Global Fire Atlas*. ROE refers to return on equity, ROA is return on assets, and ROS is return on sales. *Subsidiary relocation* is defined when a subsidiary's name reappears in a different county, or when a new subsidiary appears in a county already occupied by an existing one. *Subsidiary entry* is defined when a subsidiary name appears for the first time in a county where the parent firm has no existing subsidiaries. *Subsidiary exit* is defined when a subsidiary name disappears and no new subsidiary appears in the same county for the same parent firm.

$$Y_{i,t+1} = \beta_1 CW EI_{i,t} + \beta_0 + \beta \mathbf{Control} + \xi_{i,t} + \psi_{i,t} + \varepsilon_{i,t} \quad (3)$$

where  $Y_{i,t+1}$  denotes the performance measures of listed company  $i$  in year  $t + 1$ , including profitability (ROA, ROE, ROS), investment intensity (Capex/Assets), and labor productivity (profit per employee).  $CW EI_{i,t}$  represents the aggregated wildfire exposure risk index of firm  $i$  in year  $t$ , constructed as in Equation (2). The model also includes a vector of control variables ( $\mathbf{Control}$ ) comprising firm size, listing age, leverage, price-to-book ratio (PB), and the ratio of cash to total assets, all measured in year  $t$ .

Given the strong association between wildfire frequency and regional weather conditions, we further control for two meteorological variables: the city-level drought index (Subspei) and average annual temperature (Subavetemp), aggregated using subsidiary registered capital weights. Note that city-specific drought and high-temperature conditions affecting the headquarters location are already absorbed by city-by-year fixed effects; hence, these are not included as separate controls. The analysis covers the sample period from 2003 to 2015.

## 4 Results

### 4.1 Wildfire Exposure Risk and Corporate Performance

We begin by examining the impact of wildfire exposure risk on firm performance, as measured by return on equity (ROE), using the OLS model specified in Equation (3). The results are reported in Table 2. Columns (1) and (2) present estimates of wildfire impacts within a 30 km radius of firms, approximately corresponding to the average county area of 3,363 km<sup>2</sup> in China. Columns (3) and (4) report the effects of wildfires within a 50 km radius for robustness. The explanatory variables in columns (1) and (3) are the Corporate Wildfire Exposure Index (CWEI), while columns (2) and (4) separately include the Headquarters-level Wildfire Exposure Index (HWEI)

and the Subsidiary-level Wildfire Exposure Index (SWEI). All specifications control for a set of firm-level characteristics, including the price-to-book ratio, the logarithm of firm size, the logarithm of firm age, the debt-to-assets ratio, and the cash-to-assets ratio. We also control for weather conditions, specifically the capital-weighted average precipitation and temperature in the cities where subsidiaries are located. City-by-year and industry-by-year fixed effects are included throughout to account for time-varying geographic and sectoral heterogeneity.

The results in columns (1) and (3) indicate that heightened wildfire exposure is associated with a decline in firm performance across both distance thresholds. A one-unit increase in the wildfire exposure index (CWEI) within a 30 km radius lowers a firm's ROE by 0.53%, equivalent to 0.055 standard deviations given an ROE standard deviation of 0.097 from the CSMAR database. Based on the market value of medium-sized listed companies in China (10 billion CNY), a back-of-the-envelope calculation indicates that such an increase in CWEI would lead to an annual profit reduction of approximately 50 million CNY (about USD 8 million).

To further investigate the source of this effect, we decompose the aggregated wildfire exposure index into headquarters- and subsidiary-level exposure indices. As shown in columns (2) and (4), subsidiary-level wildfire exposure exerts a statistically significant negative effect on performance, even after controlling for headquarters-level exposure and other firm-level factors. This finding underscores the importance of incorporating subsidiary-level risk exposure in corporate climate vulnerability assessments. The Shapley decomposition results reveal that the negative impact of wildfire exposure on listed companies' performance primarily stems from subsidiary locations. Specifically, subsidiary exposure accounts for 79.0% of the total negative impact. In contrast, parent company exposure contributes only 21.0% of the total effect, underscoring the significant impacts through subsidiary networks.

## 4.2 Robustness Checks

To ensure the robustness of our results, we conduct a series of robustness checks including: alternative wildfire exposure measures, alternative firm performance mea-

Table 2: Baseline Effects of Wildfire Exposure on Firm Performance

Dept. Vars.	$ROE_{t+1}$			
	(1)	(2)	(3)	(4)
Wildfires in 30 km	-0.005** (0.002)			
Wildfires: Head in 30 km		-0.002 (0.002)		
Wildfires: Subsidiaries in 30 km		-0.006** (0.002)		
Wildfires in 50 km			-0.002** (0.001)	
Wildfires: Head in 50 km				-0.001 (0.001)
Wildfires: Subsidiaries in 50 km				-0.002*** (0.001)
Observations	18,524	18,524	18,524	18,524
Adjusted R-squared	0.144	0.144	0.144	0.144
Controls	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

*Notes:* This table reports the baseline results of wildfire exposures on firm performance, measured by ROE in year  $t+1$ . Wildfires in K km is the firm's exposure to wildfire in the fireline direction of zone K in year  $t$ , which is the capital-weighted average of the headquarters' wildfire exposure in K km and the subsidiaries' wildfire exposure in K km in year  $t$ . We control a series of firm's characteristics, including P/B Ratio, the logarithmic of firm's size, the logarithmic of firm's age, debt-to-assets, cash-to-assets. We also control for the weather conditions, including the capital-weighted average of precipitation and the capital-weighted average of temperature in subsidiaries' cities. City-by-year fixed effects and industry-by-year fixed effects are included in all columns. Robust standard errors (in parentheses) are clustered at the firm level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

asures, and alternative model specification. Regression results are reported in Table 3, Table 4 and Table 5, all of which support the robustness of our conclusions.

**Alternative Wildfire Exposure Measures.** Given the spatial nature of wildfire exposure, we construct a binary indicator that equals 1 if a firm is located within a potential wildfire impact zone (as depicted by the shaded area in Figure 3), and 0 otherwise. Using this classification, we define six dummy variables based on the 30 km and 50 km thresholds for the Corporate, Headquarters-level, and Subsidiary-level Wildfire Exposure Indices (CWEL, HWEL, and SWEI), and incorporate them into Equation (3). The results, presented in Table 3, confirm that wildfire exposure significantly reduces firm performance across these alternative risk measurement approaches.

Table 3: Robustness I: Different Measurements of Wildfire Exposure

Dept. Vars.	$ROE_{t+1}$			
	(1)	(2)	(3)	(4)
Dummy of wildfire in 30 km	-0.004** (0.002)			
Dummy of wildfire: Head in 30 km		-0.005** (0.003)		
Dummy of wildfire: Subsidiaries in 30 km		-0.003* (0.002)		
Dummy of wildfire in 50 km			-0.002 (0.002)	
Dummy of wildfire: Head in 50 km				-0.004* (0.003)
Dummy of wildfire: Subsidiaries in 50 km				-0.002 (0.002)
Observations	18,524	18,524	18,524	18,524
Adjusted R-squared	0.144	0.144	0.144	0.144
Controls	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

*Notes:* This table reports the robustness of wildfire exposures on firm performance, measured by ROE in year  $t+1$ . Dummy of wildfire in  $K$  km takes a value of one if firm  $i$  is located in the fireline direction of wildfires in year  $t$ . We control a series of a firm's characteristics, including P/B Ratio, the logarithm of the firm's size, the logarithm of the firm's age, debt-to-assets, and cash-to-assets. We also control the weather conditions, including the capital-weighted average of precipitation and the capital-weighted average of temperature in subsidiaries' cities. City-by-year fixed effects and industry-by-year fixed effects are included in all columns. Robust standard errors (in parentheses) are clustered at the firm level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Alternative Firm Performance Measures** To address potential measurement bias from relying on a single performance metric, we replace return on equity (ROE) with alternative profitability measures—return on assets (ROA) and return on sales (ROS)—to verify the consistency of our findings. As shown in Table 4, the negative effect of wildfires on firm performance remains statistically significant and highly robust within the 30 km radius under these alternative profitability measures.

Table 4: Robustness II: Different Measurements of Firm Performance

Dept. Vars.	$ROA_{t+1}$		$ROS_{t+1}$	
	(1)	(2)	(3)	(4)
Wildfires in 30 km	-0.002*		-0.005*	
	(0.001)		(0.003)	
Wildfires in 50 km		-0.001		-0.001
		(0.000)		(0.002)
Observations	18,599	18,599	18,459	18,459
Adjusted R-squared	0.235	0.235	0.232	0.232
Controls	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

*Notes:* This table reports the robustness of wildfire exposures on firm performance, measured by ROA and ROS in year  $t+1$ . Wildfires in  $K$  km is firm's exposure to wildfire in the fireline direction of zone  $K$  in year  $t$ , which is the capital-weighted average of the headquarter's wildfire exposure in  $K$  km and the subsidiaries' wildfire exposure in  $K$  km in year  $t$ . We control a series of firm's characteristics, including P/B Ratio, the logarithmic of firm's size, the logarithmic of firm's age, debt-to-assets, cash-to-assets. We also control the weather conditions, including the capital-weighted average of precipitation and the capital-weighted average of temperature in subsidiaries' cities. City-by-year fixed effects and industry-by-year fixed effects are included in all columns. Robust standard errors (in parentheses) are clustered at the firm level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Alternative Model Specification** To control for potential estimation bias due to unobserved time-invariant heterogeneity, such as management quality or corporate culture (Martínez-Caro et al., 2020), we incorporate firm fixed effects. This approach accounts for inherent firm-level characteristics and mitigates omitted variable bias. As shown in Table 5, after controlling for firm fixed effects, the negative impact of wildfire exposure risk on firm performance remains statistically significant.

Table 5: Robustness III: Higher-dimensional fixed effects

Dept. Vars.	ROE <sub>t+1</sub>	ROA <sub>t+1</sub>	ROS <sub>t+1</sub>	ROE <sub>t+1</sub>	ROA <sub>t+1</sub>	ROS <sub>t+1</sub>
	(1)	(2)	(3)	(4)	(5)	(6)
Wildfires in 30 km	-0.002 (0.002)	-0.002** (0.001)	-0.003* (0.002)			
Wildfires in 50 km				-0.001** (0.001)	-0.001** (0.000)	-0.001** (0.001)
Observations	20,040	20,121	19,950	20,040	20,121	19,950
Adjusted R-squared	0.314	0.465	0.423	0.314	0.465	0.423
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* This table reports the robustness of wildfire exposures on firm performance. Wildfires in K km is the firm's exposure to wildfire in the fireline direction of zone K in year t, which is the capital-weighted average of the headquarter's wildfire exposure in K km and the subsidiaries' wildfire exposure in K km in year t. Higher-dimension fixed effects, including firm fixed effects and industry-by-year fixed effects, are included in all columns. We control a series of firm's characteristics, including P/B Ratio, the logarithmic of firm's size, the logarithmic of firm's age, debt-to-assets, cash-to-assets. We also control the weather conditions, including the capital-weighted average of precipitation and the capital-weighted average of temperature in subsidiaries' cities. Robust standard errors (in parentheses) are clustered at the firm level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

### 4.3 Heterogeneity

#### 4.3.1 Heterogeneity by Industry

Given the substantial impacts of wildfires on both labor and physical capital (McWethy et al., 2019), their effects on firm performance are likely to vary with industry characteristics. Industries can be classified into three categories based on their primary factor inputs: labor-intensive, capital-intensive, and technology-intensive. Capital-intensive industries, which rely heavily on fixed assets, tend to locate production facilities in resource-rich areas such as forests and mineral reserves. This spatial pattern leads to significant overlap with high wildfire-risk zones, exposing firms to considerable risks of asset damage and sunk costs. In technology-intensive industries, competitiveness depends critically on the retention of high-skilled talent and continuous investment in R&D. Wildfire exposure may accelerate the out-migration of technical workers and divert post-disaster resources away from innovation, thereby crowding out R&D expenditures. In contrast, firms in labor-intensive industries may be less affected, as low-

skilled labor is relatively substitutable, and their asset-light strategies and geographically dispersed capacity reduce vulnerability to localized disasters.

Based on the factor intensity of each listed firm’s primary industry, we classify the sample into the three aforementioned categories to analyze how wildfire impacts vary by factor allocation mode. The results, reported in Table 6, reveal significant industrial heterogeneity in the effect of wildfire exposure on firm performance, as measured by ROE. The adverse impact is most pronounced in capital- and technology-intensive industries, whereas the coefficient for labor-intensive industries is statistically insignificant.

Table 6: Heterogeneous effects of wildfires across industries

	Labor intensive	Capital intensive	Technology intensive	Labor intensive	Capital intensive	Technology intensive
	(1)	(2)	(3)	(4)	(5)	(6)
Wildfires in 30 km	0.008 (0.012)	-0.008*** (0.002)	-0.019** (0.008)			
Wildfires in 50 km				0.003 (0.004)	-0.003*** (0.001)	-0.016*** (0.005)
Observations	2,430	13,929	1,293	2,430	13,929	1,293
Adjusted R-squared	0.142	0.153	0.148	0.142	0.153	0.152
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry by Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*Notes:* This table reports the heterogeneous effects of wildfires across industries. The listed companies are separated into three groups, based on the factor intensity characteristics of the industries in which the list firm operated, including labor intensive, capital intensive, and technology intensive. The dependent variables are ROE in year  $t+1$ . Wildfires in  $K$  km is the firm’s exposure to wildfire in the fireline direction of zone  $K$  in year  $t$ , which is the capital-weighted average of the headquarter’s wildfire exposure in  $K$  km and the subsidiaries’ wildfire exposure in  $K$  km in year  $t$ . We control a series of firm’s characteristics, including P/B Ratio, the logarithmic of firm’s size, the logarithmic of firm’s age, debt-to-assets, cash-to-assets. We also control the weather conditions, including the capital-weighted average of precipitation and the capital-weighted average of temperature in subsidiaries’ cities. City-by-year fixed effects and industry-by-year fixed effects are included in all columns. Robust standard errors (in parentheses) are clustered at the firm level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

To further investigate cross-industry heterogeneity, we reclassify the sample into 10 sectors following the Guidelines for Industry Classification of Listed Companies (China Securities Regulatory Commission, 2012). As shown in Figure 2, wildfire exposure significantly reduces firm performance in most industries. Notably, manufacturing and technology & information exhibit particularly strong negative effects—consistent with their characterization as capital-intensive<sup>8</sup> and technology-intensive

<sup>8</sup>In China, a significant proportion of listed manufacturing firms—such as those in semiconductor

sectors, respectively. Although the estimated coefficient for manufacturing is numerically small, its economic significance is substantial: given the sector’s large asset base and high operating revenues, a marginal decline of 0.01 percentage points may translate into economic losses on the order of hundreds of millions of CNY. These findings underscore the need for manufacturing firms to proactively address the financial risks posed by wildfires.

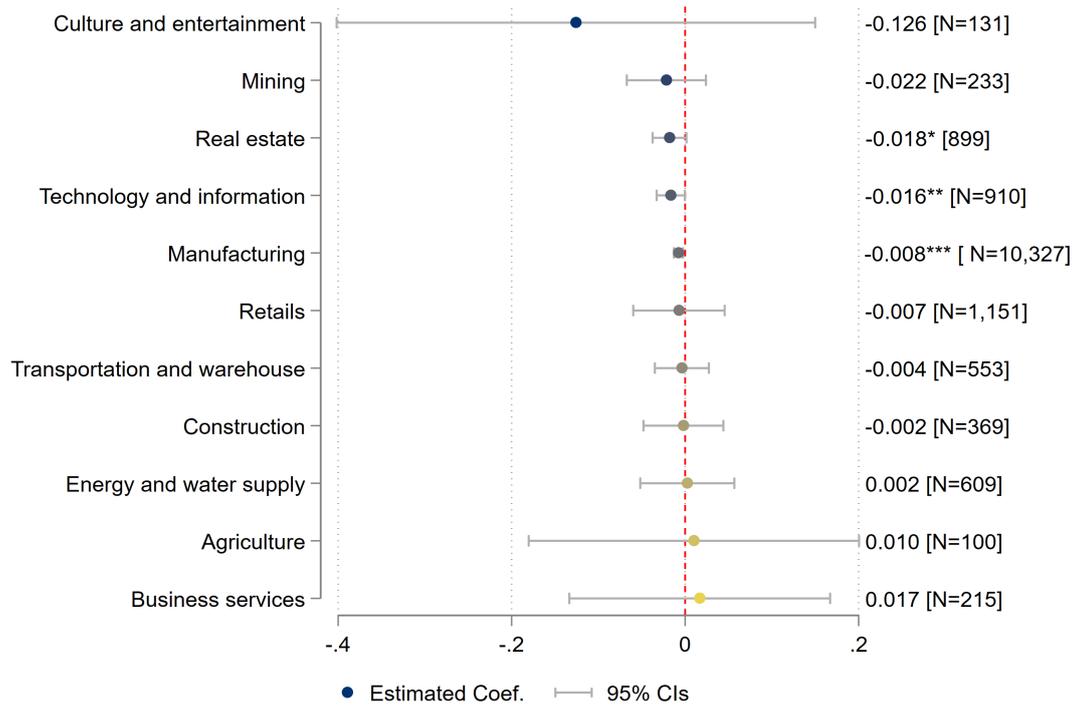


Figure 2: Heterogeneous Effects of Wildfires across Industries

#### 4.3.2 Heterogeneity by Financial Positions and Financial Constraints

Wildfires not only damage business assets but also increase operating costs during post-disaster recovery (Lopes and Póvoa, 2022; Javadi and Masum, 2021). Consequently, a firm’s financial health plays a critical role in moderating the impact of wildfire exposure on profitability. Financially vulnerable firms are more severely affected by natural disasters, as direct asset destruction and indirect operational disruptions compound existing financial strains. Moreover, firms facing liquidity shortages

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and automotive production—are capital-intensive.

or financing constraints often lack the resources to support timely recovery, potentially prolonging operational downtime and leading to sustained performance deterioration.

To systematically examine the moderating roles of financial condition and financing constraints, we employ three established measures: the Z-score (Altman, 1968) to capture financial soundness, and the Kaplan-Zingales (KZ) index (Kaplan and Zingales, 1997) and the Size-Age (SA) index (Hadlock and Pierce, 2010) to measure financing constraints.

The Z-score provides a comprehensive indicator of financial health, with higher values indicating greater stability and lower bankruptcy risk. We split the sample at the median Z-score to compare the effects of wildfire exposure across firms with differing financial conditions. Regression results in Panel A of Figure 3 show that firms with weaker financial positions experience significantly larger declines in performance following wildfire events.

The KZ and SA indices are widely used proxies for financing constraints, with higher values reflecting more limited access to external capital. Such constraints can restrict both investment capacity and operational flexibility, thereby amplifying the negative impact of wildfire exposure on firm performance. Using median splits based on the KZ and SA indices, we classify firms into high- and low-constraint subgroups. Results in Panels B and C of Figure 3 confirm that firms subject to greater financing constraints suffer more pronounced performance losses after wildfire events.

## 4.4 Mechanism Analysis

### 4.4.1 Labor Productivity

A substantial body of literature demonstrates that exposure to wildfires can adversely affect both physical and mental health (Reid et al., 2016). Therefore, one potential channel through which wildfires may negatively influence firm performance is by reducing employees' labor productivity. On the one hand, wildfire smoke and hazardous particulate matter (e.g., PM2.5) can cause respiratory and cardiovascular issues or trigger allergic reactions among employees (Wettstein et al., 2018; Pakhtigian, 2022). Prolonged exposure may lead to chronic health conditions (Kozlov, 2021), fur-

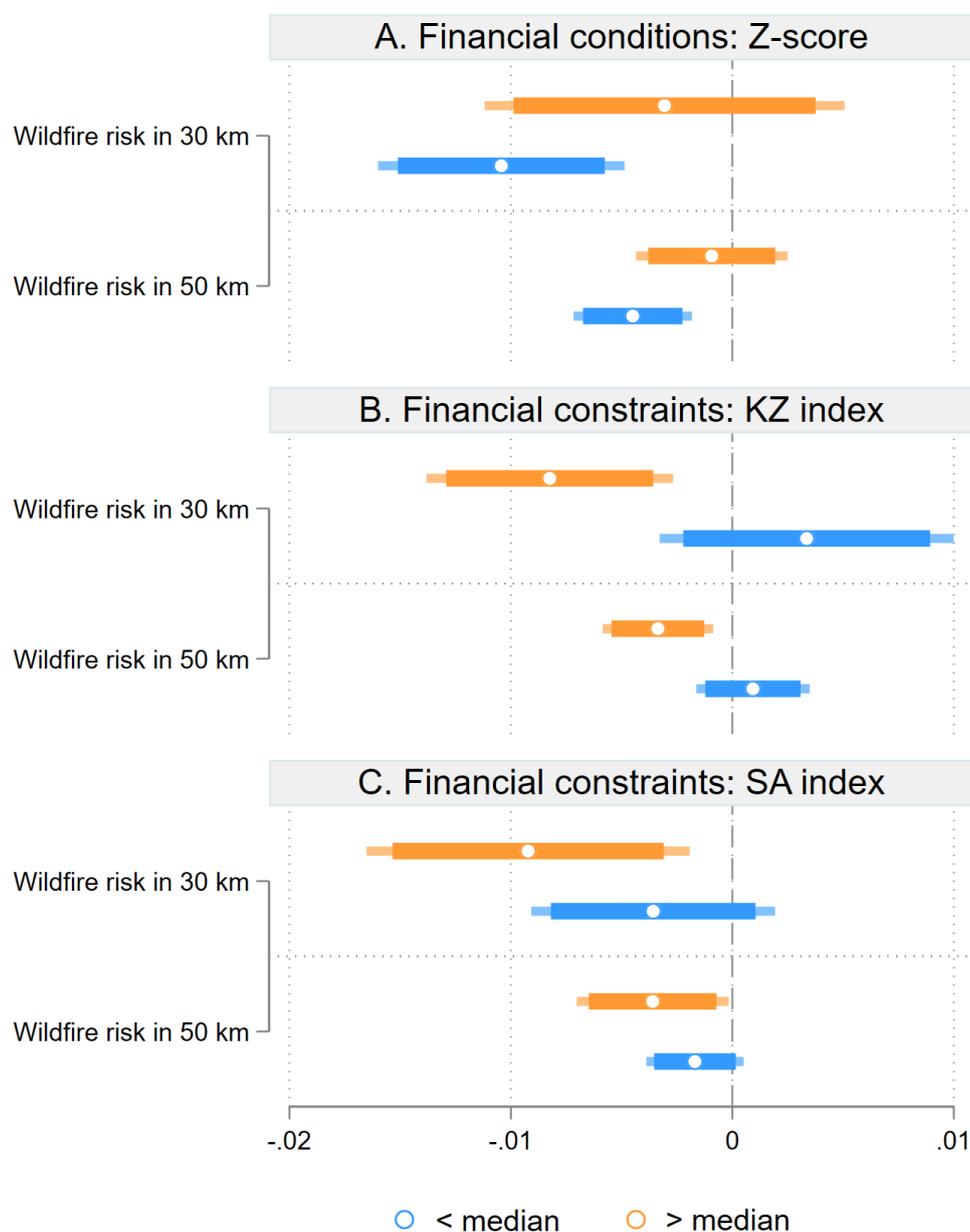


Figure 3: Heterogeneous Effects of Wildfires on Firms with Different Financial Conditions and Constraints

*Notes:* This figure reports the heterogeneous effects of wildfire exposure by financial positions and financial constraints. We separate the sample based on the median value of Z-score, KZ-index and SA-index. The full tables are reported in Extended Table A1 of Appendix A.2. All models include city-by-year fixed effects and industry-by-year fixed effects, with robust standard errors. Each dot represents a separate estimation; the thick line indicates the 90% CIs and the thin line is the 95% CI accordingly.

ther diminishing workers' capacity. Moreover, such extreme environmental conditions can impair both attendance and on-the-job efficiency (Burke et al., 2022). On the other hand, safety threats and evacuation pressures related to wildfires can elevate anxiety and stress levels among employees, thereby undermining concentration and productivity. In addition, post-disaster trauma may exert lasting effects on workforce productivity (Johnston et al., 2021).

To examine whether declines in labor productivity serve as a transmission mechanism through which wildfires affect firm performance, we replace the dependent variable in Model (6) with annual profit per employee. This allows us to directly test the relationship between wildfire exposure risk and workforce productivity. The empirical results presented in Table 7 reveal a significant negative correlation between wildfire exposure and employee productivity. Specifically, the regression results in column (1) indicate that increased wildfire exposure within a 30km radius significantly reduces profit per employee. Furthermore, the significantly negative coefficients on subsidiaries' wildfire exposure in columns (3) and (4) suggest that this adverse effect is not confined to headquarters but permeates the entire corporate network.

#### 4.4.2 Supply Chain

Wildfire-induced damages can disrupt supply chains (Bladon et al., 2014), directly causing production delays and increased costs, which subsequently reduce corporate revenue and profit margins (Parast and Subramanian, 2021). Sun et al. (2024a) emphasize that the globalization of supply chains allows losses from extreme heat risks to transcend geographic boundaries and amplify economic impacts. In particular, Wang et al. (2021) estimate that 59% of the economic losses from the 2018 California wildfires were indirect, transmitted through supply chains. Moreover, wildfires can heighten environmental uncertainty and propagate such risks along supply networks. Research by Singh (2020) indicates that natural disasters significantly undermines corporate financial performance, particularly when firms lack effective supply chain risk management practices. Therefore, the supply chain may constitute a central transmission mechanism through which wildfire exposure affects the performance of listed companies. In

Table 7: Mechanism analysis I: Effects of Wildfire Exposure on Labor Productivity

Dept. Vars.	Annual Profit per Employee			
	(1)	(2)	(3)	(4)
Wildfire in 30 km	-0.382** (0.173)			
Wildfire in 50 km		-0.117 (0.087)		
Wildfire: Head in 30 km			-0.172 (0.168)	
Wildfire: Subsidiaries in 30 km			-0.342*** (0.126)	
Wildfire: Head in 50 km				-0.045 (0.082)
Wildfire: Subsidiaries in 50 km				-0.128*** (0.047)
Observations	18,424	18,424	18,424	18,424
Adjusted R-squared	0.110	0.109	0.110	0.110
Controls	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

*Notes:* This table represents the mechanism analysis that wildfires negatively affect firms' performance through hurting labor productivity. The dependent variables are net profit per employee in firm  $i$ . Wildfire in  $K$  km is the firm's exposure to wildfire in the fireline direction of zone  $K$  in year  $t$ , which is the capital-weighted average of the head quarter's wildfire exposure in  $K$  km and the subsidiaries' wildfire exposure in  $K$  km in year  $t$ . We control a series of firm's characteristics, including P/B Ratio, the logarithmic of firm's size, the logarithmic of firm's age, debt-to-assets, cash-to-assets. We also control the weather conditions, including the capital-weighted average of and the capital-weighted average of temperature in subsidiaries' cities. City-by-year fixed effects and industry-by-year fixed effects are included in all columns. Robust standard errors (in parentheses) are clustered at the firm level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

what follows, we systematically investigate the channels through which wildfire exposure influence firm performance from a supply chain perspective.

In modern supply chain management, supply-demand matching, supply chain power, and vertical integration are recognized as critical determinants of efficiency and competitiveness (Porter, 2008; Fisher et al., 1997). Supply chain power, denoting a firm's influence over other chain members, is often derived from factors such as market share, brand value, and technological advantage, which are key sources of power in a supply network (Cox, 2004). Vertical integration, which reflects a firm's control over upstream and downstream activities, enhances competitiveness primarily by reducing transaction costs and improving supply chain stability, as posited by Transaction Cost Economics (Williamson, 1985). Finally, supply-demand matching, which measures the alignment between production and market needs, is crucial for mitigating operational uncertainties and optimizing resource allocation. Inefficient matching can lead to the detrimental 'bullwhip effect', thereby underscoring the importance of coordination and information sharing (Lee et al., 1997).

Based on this framework, we partition the sample according to different dimensions of firms' supply chain characteristics, including supply chain power, degree of vertical integration, supply-demand matching level, and supply-demand deviations. Details on the construction of these variables are provided in Appendix A.1. The results are reported in Figure 4.

Panel A of Figure 4 shows that supply chain power significantly moderates the impact of wildfire exposure on firm performance. Among firms with greater supply chain power, wildfire exposure exerts a stronger and more statistically significant negative effect on performance. By contrast, the effect is statistically insignificant for firms with low supply chain power. One possible explanation is that powerful firms often occupy central positions in supply chain networks, which tend to be more complex and extensive. As a result, if a critical node within such a network is disrupted by wildfires, the resulting ripple effects and aggregate damages are likely to be more severe.

Regarding the moderating effect of vertical integration (Panel B), the results indicate that the negative impact of wildfire exposure risk on corporate performance is

primarily concentrated in firms with a higher degree of vertical integration, while it is statistically insignificant in those with lower integration. This finding is closely tied to the inherent characteristics of vertical integration. While it helps reduce external transaction costs and enhances resource coordination, it also entails significant internal coordination costs (?) may lead to over-reliance on specific regions or supply chain segments. When these areas or links are affected by natural disasters such as wildfires, multiple business units of a vertically integrated firm can be disrupted simultaneously, substantially amplifying operational risks. Furthermore, vertical integration increases the complexity of risk management, requiring firms to address not only core operational risks but also coordinate mitigation efforts across the entire supply chain—a particularly challenging task in disaster scenarios.

The results in Panel C and Panel D highlight the moderating role of supply-demand matching in the relationship between wildfire exposure and firm performance. They show that firms with a lower degree of supply-demand matching experience a more pronounced negative effect from wildfire exposure, regardless of whether the mismatch is measured by inventory fluctuations or deviations in supply and demand. This pattern can be explained by the fact that firms with poor supply-demand alignment often operate under inherent imbalances, which wildfires further exacerbate. In contrast, a high level of supply-demand matching generally indicates stronger supply chain resilience. Such firms are better able to respond swiftly to external shocks through flexible inventory management, efficient production scheduling, and close collaboration with upstream and downstream partners. Firms with weaker matching capabilities, however, often lack this adaptive capacity, making their supply chains more vulnerable to paralysis and operational disruption when disasters strike.

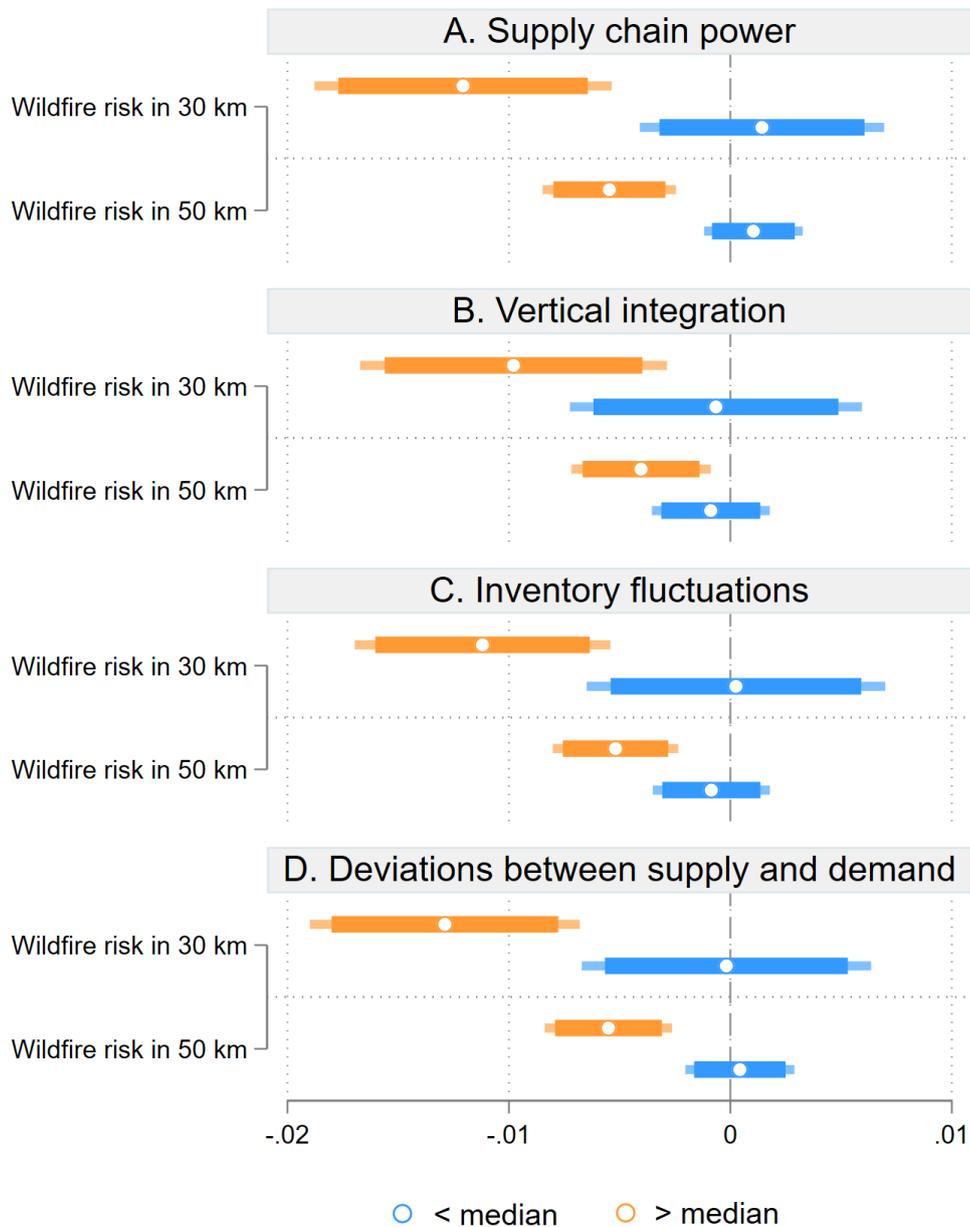


Figure 4: Mechanism analysis II: Effects of Wildfire Exposure on Supply Chain

*Notes:* This figure reports the mechanism of the negative effects of wildfire exposure on supply chain. We separate the sample based on the median value of supply chain power, degree of vertical integration, inventory fluctuations, and supply-demand deviations constructed in Appendix A.1. The full tables are reported in Extended Table A2 of Appendix A.3. All models include city-by-year fixed effects and industry-by-year fixed effects, with robust standard errors. Each dot represents a separate estimation; the thick line indicates the 90% CIs and the thin line is the 95% CI accordingly.

## 5 Corporate Adaptation and Strategic Responses to Wildfire Exposure

### 5.1 Corporate Adaptation

**Investment Decision** To mitigate growing climate risks, firms may adopt various proactive adaptation strategies. Prior research indicates that firms can diversify risk through cross-regional investments (Sun et al., 2024a) or by increasing liquid asset holdings (Huang et al., 2022a; Heo, 2021b), thereby enhancing resilience to climate-related threats. In China, however, corporate awareness of wildfire risks remains underdeveloped, the market for related insurance products is lagging, and compensation mechanisms do not fully cover all types of wildfire-induced losses. These institutional constraints leave firms with limited external tools for risk diversification or transfer, exposing them to a highly uncertain environment. Classical studies suggest that high uncertainty often leads to reduced investment (Pindyck, 1990; Dixit and Pindyck, 1994). When firms face elevated uncertainty, they tend to delay or cancel investment plans, as uncertainty increases the volatility of a project's net present value and raises investment risks. Consequently, Chinese listed companies are likely to respond to heightened wildfire exposure risk by cutting investments.

To test whether listed companies reduce investment expenditures when faced with increased wildfire exposure risk, we estimate the regression model specified in Equation (3), using the ratio of capital expenditure to total assets as the dependent variable. The results are presented in Table 8. Regression results in columns (1) and (2) show that the coefficients of the wildfire exposure risk index are significantly negative within the 30 km and 50 km radii, suggesting that Chinese listed companies tend to reduce investment in response to heightened uncertainty caused by increased wildfire activity. Columns (3) and (4) further examine the effects of wildfire exposure risk at headquarters and subsidiary locations on corporate investment. The results indicate that the coefficient on headquarters' wildfire exposure is significantly negative, implying a strong association between wildfire exposure at the headquarters and subsequent reductions in firm-level investment. This finding suggests that firms adopt more conser-

vative investment strategies at the headquarters level to protect core assets and mitigate potential financial losses in the face of natural disaster risks. In contrast, the coefficient on subsidiary wildfire exposure is significantly positive, indicating that wildfire exposure at subsidiaries may prompt firms to take proactive adaptation measures. These could include additional investment in subsidiaries to enhance operational resilience and ensure business continuity, or the adoption of advanced technologies and facilities to mitigate environmental impact and improve sustainability performance.

Table 8: Corporate Adaptation to Wildfire Exposure I: Reducing Investments

Dept. Vars.	Capital Expenditure/Total Assets			
	(1)	(2)	(3)	(4)
Wildfire in 30 km	-0.003** (0.001)			
Wildfire in 50 km		-0.001* (0.001)		
Wildfire: Head in 30 km			-0.005*** (0.001)	
Wildfire: Subsidiaries in 30 km			0.004*** (0.001)	
Wildfire: Head in 50 km				-0.002*** (0.001)
Wildfire: Subsidiaries in 50 km				0.001*** (0.000)
Observations	18,444	18,444	18,444	18,444
Adjusted R-squared	0.185	0.185	0.186	0.186
Controls	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

*Notes:* This table reports firm's response to wildfires by reducing investments. The department variables are the ratio of capital expenditure over assets. Wildfire in K km is the firm's exposure to wildfire in the fireline direction of zone K in year t, which is the capital-weighted average of the head quarter's wildfire exposure in K km and the subsidiaries' wildfire exposure in K km in year t. The specifications are the same as in baseline model. Robust standard errors (in parentheses) are clustered at the firm level. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Subsidiary Entry and Exit** To further investigate the seemingly counterintuitive finding that wildfire exposure at the subsidiary level is associated with increased investment, we examine subsidiary entry and exit following wildfire exposure. The results are presented in Table A3, where Panels A and B report regression estimates using

the number of subsidiaries entering and exiting, respectively, as the dependent variables.

The results indicate no statistically significant relationship between the degree of wildfire exposure and changes in the number of subsidiaries. This suggests that firms do not respond to climate risks through simple geographic relocation. Instead, they may increase adaptive investment in existing subsidiaries—for instance, by allocating special budgets for fire protection equipment in high-risk areas, or by retrofitting production facilities with disaster-resilient technologies. The presence of such defensive investment behavior offers a plausible micro-level explanation for the positive association between subsidiary-level wildfire exposure and corporate investment.

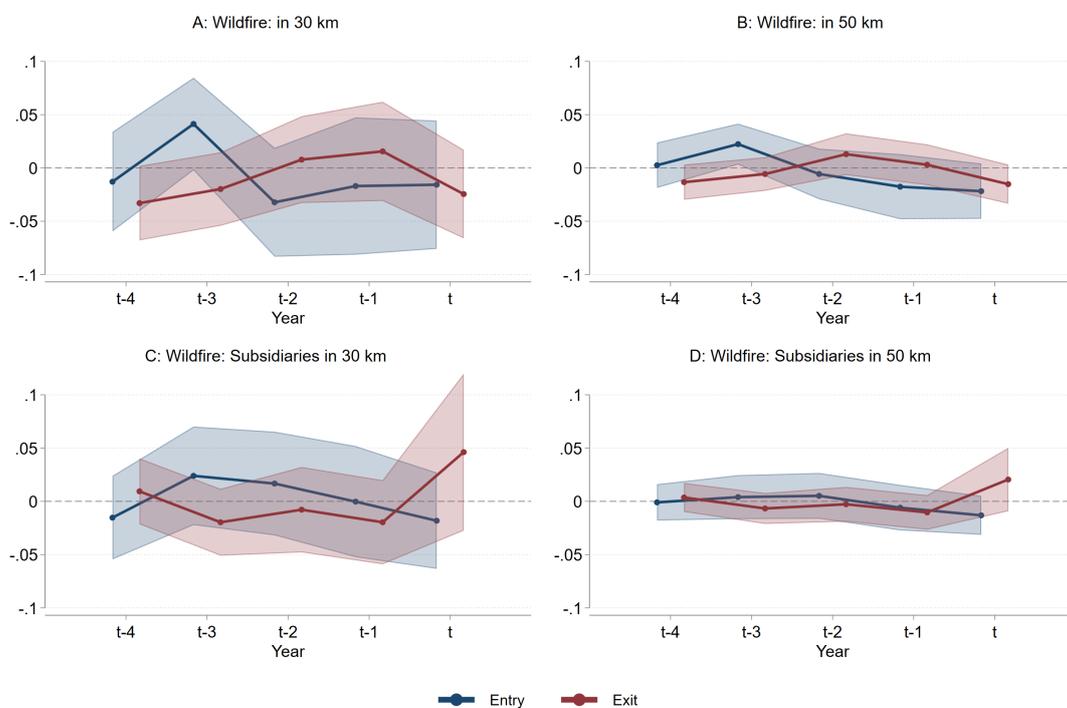


Figure 5: Corporate Adaptation to Wildfire Exposure II: Subsidiary Entry and Exit

*Notes:* This figure reports firm's response to wildfires through enters or exits the risky areas. The dependent variables are the number of subsidiaries entry and exits after wildfire exposure in year t-4 to year t. The full tables are reported in Extended Table A3 of Appendix A.4. Figures display coefficient estimates with 95% confidence intervals. All models include city-by-year fixed effects and industry-by-year fixed effects, with robust standard errors clustered at the city level.

## 5.2 Market Reactions

Our empirical findings demonstrate a significant adverse effect of wildfires on the financial performance of Chinese listed firms. This result naturally leads to a further question: whether such negative performance effects transmit to the capital market. To address this, we next examine the relationship between wildfire exposure risk and the excess returns of publicly traded stocks.

Given the financial market's ability to react swiftly to new information and the high volatility of stock prices in response to natural disasters, we employ monthly—rather than annual—data for analysis<sup>9</sup>. Following the approach of Thanh (2023) and accounting for overall market movements, we measure returns using monthly excess stock returns, defined as a firm's monthly stock return minus the market's monthly return.

Table 9 reports the results from re-estimating the model using monthly frequency data for the wildfire exposure index and monthly excess returns (AR) as the dependent variable. Columns(1) and (2) show that an increase in wildfire exposure significantly reduces a firm's excess stock return in the same month, suggesting a negative immediate market reaction to wildfire exposure. However, column (3) and (4) indicates that wildfire exposure has no significant effect on excess returns in the subsequent month. This pattern is consistent with investors incorporating wildfire exposure into stock prices within the first month of exposure, after which the market has largely absorbed this information.

Overall, the results in Table 9 confirm that the adverse effect of wildfires on firm performance transmits to financial markets, though the transmission is short-lived. The market reacts promptly to wildfire exposure and incorporates it into stock prices within a relatively short period.

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<sup>9</sup>Monthly returns capture market dynamics more precisely, allowing us to better isolate the immediate market response to wildfire events, while annual data may obscure short-term fluctuations due to temporal aggregation, making it difficult to accurately gauge the near-term impact of wildfires on stock returns.

Table 9: Market's Response to Wildfire Exposure

Dept. Vars.	AR <sub>ym</sub>		AR <sub>ym+1</sub>	
	(1)	(2)	(3)	(4)
Wildfire in 30 km <sub>ym</sub>	-0.003** (0.001)		-0.001 (0.002)	
Wildfire: Head in 30 km <sub>ym</sub>		-0.001 (0.002)		-0.001 (0.002)
Wildfire: Subsidiaries in 30 km <sub>ym</sub>		-0.004** (0.002)		-0.001 (0.002)
Observations	235,417	235,417	236,864	236,864
Adjusted R-squared	0.009	0.009	0.008	0.008
Controls	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes
Month-by-Year FE	Yes	Yes	Yes	Yes

*Notes:* This table reports the market response to wildfire exposure, measured by firm's monthly excess return. All wildfire exposure are measured by monthly basic at year y and month m. We control a series of firm's characteristics, including P/B Ratio, the logarithmic of firm's size, the logarithmic of firm's age, debt-to-assets, cash-to-assets. We also control the weather conditions, including the capital-weighted average of precipitation in subsidiaries' city, and the capital-weighted average of temperature in subsidiaries' city at a month-of-year scale. City-by-year fixed effects, industry-by-year fixed effects, and month-of-year fixed effects are included in all columns. Robust standard errors (in parentheses) are clustered at the firm level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## 6 Projections of Corporate Profitability Loss under Intensifying Wildfire Scenarios

To further examine the impact of escalating wildfires driven by intensifying climate change after 2015 (Cunningham et al., 2024) on corporate performance, we project future wildfire-induced profit losses for firms using wildfire data from 2016 to 2100 under Representative Concentration Pathways (RCP)<sup>10</sup>, including the RCP-2.6, RCP-6.0, and RCP-8.5 scenarios (Zhao et al., 2025) simulated by the ISIMIP2b model (Reyer et al., 2024).

First, we exclude 337 firms that were delisted or designated as ST/PT between 2015 and 2024, under the assumption that the remaining firms continue operating with their existing subsidiary structures under prevailing conditions through 2100. To account for heterogeneity across subsectors, we disaggregate the manufacturing sector into 10 distinct industries.

Second, we estimate the return on equity (ROE) under different scenarios. In the baseline scenario, ROE is set to the industry median for the period 2011-2015 and is held constant thereafter. Using projected wildfire data under the three RCP scenarios, we compute a wildfire exposure index for each firm in each scenario based on Equation (1 and 2). We then apply OLS regression to estimate the ROE of firms exposed to wildfire under each scenario.

Third, to calculate net profits under the baseline and RCP scenarios, we assume that the ratio of net assets to total assets remains constant, while the growth rate of total assets follows the industry's average growth rate over the past five years. We derive the total asset growth rate for each firm between 2011 and 2015 and use the median value across all firms in each industry as the baseline growth rate. Net profit is calculated as ROE multiplied by the product of total assets and the net assets ratio. Risk-free discount factors are set to 1.4% (Stern, 2006) and 2% (Nordhaus, 2007). The profit difference is defined as the net profit under the baseline scenario minus that

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<sup>10</sup>RCPs refer to a set of pathways developed for the climate modeling community to serve as a basis for long-term and near-term modeling experiments. These pathways span a range of radiative forcing values found in the literature, from 2.6 to 8.5 W/m<sup>2</sup> in the year 2100. (Van Vuuren et al., 2011)

under each RCP scenario.

Finally, we use bootstrap sampling to estimate the mean profit difference and its confidence interval. All monetary values are converted into million U.S. dollars using an exchange rate of 6.2284.

As illustrated in Figure 6, profit losses attributable to wildfires generally escalate over time as climate change intensifies, increasing with the severity of greenhouse gas concentrations and projected temperature rises (RCP8.5 > RCP6.0 > RCP2.6). Specifically, under a discount rate of 1.4%, wildfire exposure within a 30 km radius is projected to cause total profit losses for Chinese listed companies of approximately USD 31.45 million, USD 44.07 million, and USD 49.26 million under the RCP2.6, RCP6.0, and RCP8.5 scenarios, respectively. We also project the profit losses attributable to wildfire exposure within a 50 km radius in Figure A.1 in the Appendix A.5.

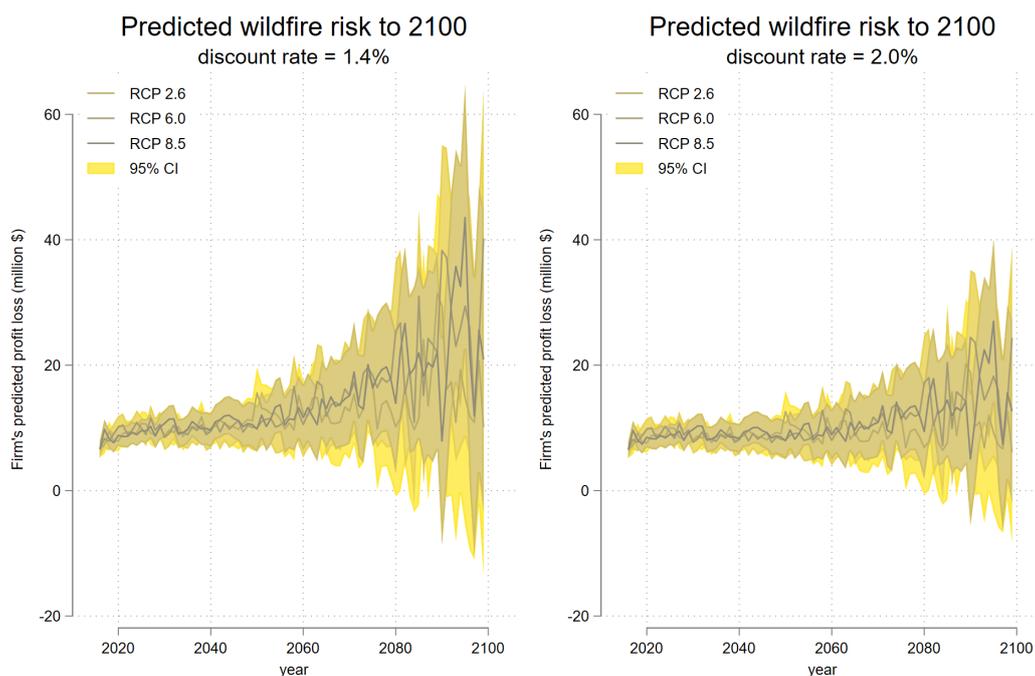


Figure 6: Projected firm-level profit loss by 2100: Wildfires within 30 km

## 7 Conclusion

This study examines the impact of wildfires on the operation performance of listed companies in China, introducing a new perspective on measuring wildfire exposure.

Unlike prior studies that predominantly rely on wildfire smoke concentration as a proxy, we construct a more accurate wildfire exposure index by integrating multi-dimensional data—including wildfire locations, spread trajectories, corporate geographic coordinates, and so on—to assess wildfire exposure more accurately.

We find that overall wildfire exposure significantly impairs the performance of Chinese listed firms, and this effect may transmit to capital markets, affecting short-term stock returns. Furthermore, by incorporating subsidiary-level analysis, our study uncovers a previously overlooked channel of climate risk transmission within corporate structures, confirming that subsidiary exposure to wildfires substantially affects parent companies' economic outcomes. Our analysis also reveals considerable heterogeneity in the wildfire's impacts, driven by industries, financial conditions, and financial constraints.

Although limited by data availability and reliability, our analysis focuses exclusively on listed companies, which may restrict the generality of the findings. Listed firms typically possess more developed risk management systems and greater resources to respond to disruptions, making them likely more resilient to wildfire exposure than micro, small, and medium-sized enterprises (MSMEs). Nevertheless, by integrating subsidiary-level wildfire exposure into our framework, we partially extend the relevance of our conclusions. Since subsidiaries often resemble MSMEs in terms of scale, risk tolerance, and managerial maturity, this approach enhances the applicability of our findings to a broader set of enterprises and offers valuable insights into the climate risks faced by the wider business sector.

Mechanism analysis identifies a significant negative correlation between wildfire exposure risk and employee productivity, suggesting that reduced labor productivity may be a key channel through which wildfires adversely affect firm performance. Further analysis indicates that the supply chain serves as a potentially important mechanism by which wildfires influence corporate profitability. Specifically, the negative effect on firm performance is more pronounced for companies with greater supply chain power, a higher degree of vertical integration, or lower supply-demand matching when exposed to wildfires. These findings underscore the critical role of supply

chain management in corporate risk management strategies, particularly in mitigating disruptions caused by climate-related events.

We also examine the firm's responses to wildfire exposure risk. Results show that Chinese listed companies tend to adopt more conservative investment strategies in the face of wildfire exposure risks at the headquarters level. In contrast, wildfire exposure at subsidiaries may prompt firms to take proactive adaptation measures and increase investment. This offers a new perspective on corporate responses to climate change and supports the development of more effective risk management measures.

The findings of this study carry important practical implications for understanding and mitigating wildfire exposure and for improving business management practices. First, they reveal the significant adverse effects of wildfires on the performance of listed companies in China and emphasize the need for careful assessment and management of risks at the subsidiary level. Against the backdrop of increasing global climate change, corporate management should enhance awareness of wildfires as an emerging climate risk and adopt comprehensive measures to evaluate and address associated threats. Furthermore, the results suggest that wildfire smoke not only poses health hazards but can also indirectly disrupt business operations by impairing employee productivity. Therefore, when formulating risk response strategies, companies should consider not only measures to protect physical assets but also initiatives to mitigate the costs of employee exposure to climate-related risks.

From a supply chain perspective, this study highlights the importance of supply chain management in corporate risk mitigation. Enterprises characterized by supply-demand imbalances should strengthen their supply chain management, while firms with substantial influence within their supply chains should also develop effective risk response strategies to prevent operational disruptions. Our analysis also reveals that as firms enhance internal resource integration and increase vertical integration, they should remain vigilant against the potential for accelerated risk propagation and reduced flexibility in risk response.

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# A Appendix

## A.1 Supply Chain Metrics Calculation

### A.1.1 Supply Chain Power

Supply chain power is a key indicator of a firm's influence within its supply chain, reflecting the extent to which it can dominate commercial credit terms and bargaining power. Specifically, firms with greater supply chain power are typically able to establish business terms that work in their favor (Huo et al., 2017). This advantage manifests in their credit purchase arrangements with upstream suppliers as well as in their advance collection strategies toward downstream customers.

Based on this theoretical framework, we employ balance sheet items—accounts payable, notes payable, and advances from customers—to measure a firm's bargaining power and credit conditions relative to upstream suppliers. These items effectively capture the firm's procurement-side influence. At the same time, its influence over downstream customers is assessed using accounts receivable, notes receivable, and prepayments to suppliers, which reflect the firm's control and collection capacity in the sales process.

Drawing on the methodologies of Benton and Maloni (2005), we construct a supply chain power index (SSR), calculated as in Equation (A.1). This index serves as a positive measure: a higher value indicates stronger supply chain power.

$$SSR = \frac{AP + UR + NP - AR - PE - NR}{TA} \quad (\text{A.1})$$

where AP denotes accounts payable; UR represents unearned revenue; NP denotes notes payable; AR represents accounts receivable; PE denotes prepaid expenses; NR denotes notes receivable; and TA represents total assets.

### A.1.2 Vertical Integration

Vertical integration refers to the internalization of supply chain activities that were previously conducted through market transactions, integrating upstream and down-

stream operations to enhance control over the supply chain (Perry, 1989). This strategy increases interdependency among business units within the firm, thereby improving efficiency while also raising operational complexity. A higher degree of vertical integration generally corresponds to a lower degree of firm specialization, and vice versa.

Among the various methods for measuring vertical integration, the value-added-to-sales (VAS) ratio is widely adopted due to its theoretical soundness and operational feasibility. Initially proposed by Adelman (1955), this approach assesses the extent of vertical integration by calculating the ratio of a firm's value added to its sales revenue. A higher ratio indicates a greater level of vertical integration. We employ a refined version of the VAS method to measure vertical integration. The specific calculation is given by Equation (A.2).

$$\begin{aligned}
 VAS &= \frac{AV - \pi + \pi_{normal}}{S - \pi + \pi_{normal}} \\
 &= \frac{AV - \pi + NA \times ROAE}{S - \pi + NA \times ROAE} \tag{A.2}
 \end{aligned}$$

where  $AV$  denotes value added;  $\pi$  represents after-tax profit;  $\pi_{normal}$  represents normal profit;  $S$  represents sales (operating revenue);  $NA$  represents net assets; and  $ROAE$  denotes return on average equity.

### A.1.3 Supply-Demand Matching

Supply-demand matching is a key indicator of the efficiency and stability of collaboration between upstream and downstream enterprises in the supply chain. A high degree of supply-demand matching can significantly reduce operational uncertainty, thereby enhancing supply chain resilience. When facing external shocks, strong matching enables firms to respond to market changes more flexibly and efficiently, improving their ability to withstand disruptions and adapt to environmental shifts (Chowdhury and Quaddus, 2017; Hosseini et al., 2019). Based on the existing literature, the following two indicators are used to capture the extent of supply-demand matching optimization. Both Matching1 and Matching2 are negative indicators, i.e. higher values reflect

a lower degree of supply-demand matching.

**Inventory Fluctuation** Low inventory levels and efficient inventory management are essential for cost reduction and operational efficiency. Smaller inventory fluctuations indicate that a firm can satisfy downstream demand with lower inventory investment (Tao et al., 2022), reflecting a higher degree of supply-demand matching. Following Tao et al. (2022), we construct the first supply-demand matching index as in Equation (A.3).

$$\text{Matching1}_{i,t} = \ln |\text{Inv}_{i,t} - \text{Inv}_{i,t-1}| \quad (\text{A.3})$$

where  $\text{Inv}_{i,t}$  is the net inventory value of the  $i$  enterprise at the end of year  $t$ .

**Deviation Between Supply and Demand Fluctuations** Drawing on Shan et al. (2014) and Yang et al. (2020), the second supply-demand matching index is defined as the deviation between fluctuations in firm production and market demand.

$$\text{Matching2}_{i,t} = \frac{\sigma(\text{Production}_{i,t})}{\sigma(\text{Demand}_{i,t})} \quad (\text{A.4})$$

Where  $\text{Production}_{i,t}$  is the production volume of the enterprise in year  $t$ ,  $\text{Demand}_{i,t}$  is the demand of the enterprise in year  $t$ , measured by sales;  $\sigma()$  represents the standard deviation of the variable.

## A.2 Heterogeneity Analysis

Table A1: Heterogeneous Effects of Wildfires on Firms with Different Financial Conditions and Constraints

Dept. Vars.	ROE <sub>t+1</sub>			
	>median (1)	<median (2)	>median (3)	<median (4)
<b>Panel A: Financial conditions, Z-score</b>				
Wildfire in 30 km	-0.003 (0.004)	-0.010*** (0.003)		
Wildfire in 50 km			-0.001 (0.002)	-0.004*** (0.001)
Chow test	1.179***		1.180***	
Observations	7,689	9,967	7,689	9,967
Adjusted R-squared	0.186	0.114	0.186	0.114
<b>Panel B: Financial constraints, KZ index</b>				
Wildfire in 30 km	-0.008*** (0.003)	0.003 (0.003)		
Wildfire in 50 km			-0.003*** (0.001)	0.001 (0.001)
Chow test	1.124***		1.124***	
Observations	11,304	6,331	11,304	6,331
Adjusted R-squared	0.118	0.210	0.118	0.210
<b>Panel C: Financial constraints, SA index</b>				
Wildfire in 30 km	-0.009** (0.004)	-0.004 (0.003)		
Wildfire in 50 km			-0.004** (0.002)	-0.002 (0.001)
Chow test	1.086***		1.086***	
Observations	7,882	9,731	7,882	9,731
Adjusted R-squared	0.166	0.129	0.166	0.129
Controls	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

Notes: This table separates the sample based on the median value of Z-score, KZ-index and SA-index. Specifically, Z-score measures the firms' financial conditions, while KZ-index and SA-index measure firms' financial constrains. The dependent variables are ROE in year t+1. Wildfire in K km is the firm's exposure to wildfire in the fireline direction of zone K in year t, which is the capital-weighted average of the head quarter's wildfire exposure in K km and the subsidiaries' wildfire exposure in K km in year t. We control a series of firm's characteristics, including P/B Ratio, the logarithmic of firm's size, the logarithmic of firm's age, debt-to-assets, cash-to-assets. We also control the weather conditions, including the capital-weighted average of precipitation and the capital-weighted average of temperature in subsidiaries' cities. City-by-year fixed effects and industry-by-year fixed effects are included in all columns. Robust standard errors (in parentheses) are clustered at the firm level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

### A.3 Mechanism Analysis

Table A2: Mechanism analysis II: Effects of Wildfire Exposure Risk on Supply Chain

Dept. Vars.	ROE <sub>t+1</sub>			
	>median (1)	<median (2)	>median (3)	<median (4)
<b>Panel A: Supply chain power</b>				
Wildfire in 30 km	-0.012*** (0.003)	0.001 (0.003)		
Wildfire in 50 km			-0.005*** (0.001)	-0.001 (0.001)
Chow test	1.196***		1.197***	
Observations	10,050	7,581	10,050	7,581
Adjusted R-squared	0.141	0.165	0.141	0.165
<b>Panel B: Degree of vertical integration</b>				
Wildfire in 30 km	-0.010*** (0.004)	-0.001 (0.003)		
Wildfire in 50 km			-0.004** (0.002)	-0.001 (0.001)
Chow test	1.226***		1.227***	
Observations	10,144	7,428	10,144	7,428
Adjusted R-squared	0.141	0.178	0.141	0.178
<b>Panel C: Inventory fluctuations</b>				
Wildfire in 30 km	-0.011*** (0.003)	0.001 (0.003)		
Wildfire in 50 km			-0.005*** (0.002)	-0.001 (0.001)
Chow test	1.313		1.131	
Observations	9,727	7,765	9,727	7,765
Adjusted R-squared	0.152	0.135	0.152	0.135
<b>Panel D: Deviations between supply and demand</b>				
Wildfire in 30 km	-0.013*** (0.003)	-0.001 (0.003)		
Wildfire in 50 km			-0.006*** (0.001)	0.001 (0.001)
Chow test	1.166		1.166	
Observations	9,624	7,914	9,624	7,914
Adjusted R-squared	0.108	0.177	0.108	0.177
Controls	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

*Notes:* This table reports the mechanism analysis that wildfires negatively affect firms' performance through destroying their supply chain. We separate the sample into two groups based on the different measurements of firm's supply chain, including their supply chain power (Panel A), verticalization of supply chain (Panel B), the inventory fluctuations (Panel C), and the deviations between supply and demand (Panel D). The dependent variables are ROE in year t+1. The specifications are the same as in baseline model. Robust standard errors (in parentheses) are clustered at the firm level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## A.4 Corporate Adaptation

Table A3: Corporate Adaptation to Wildfire Exposure II: Subsidiary Entry and Exit

VARIABLES	Wildfire Exposure in		Exposure of Subsidiary	
	30 km (1)	50 km (2)	30 km (3)	50 km (4)
<b>Panel A: Subsidiary Entry</b>				
Wildfire in year t	-0.016 (0.031)	-0.022* (0.013)	-0.018 (0.023)	-0.013 (0.009)
Wildfire in year t-1	-0.017 (0.033)	-0.018 (0.016)	-0.000 (0.027)	-0.006 (0.011)
Wildfire in year t-2	-0.032 (0.026)	-0.006 (0.012)	0.017 (0.025)	0.005 (0.011)
Wildfire in year t-3	0.041* (0.022)	0.022** (0.010)	0.024 (0.024)	0.004 (0.011)
Wildfire in year t-4	-0.013 (0.024)	0.003 (0.011)	-0.015 (0.020)	-0.001 (0.009)
Observations	9,879	9,879	9,879	9,879
Adjusted R-squared	0.187	0.188	0.187	0.187
<b>Panel B: Subsidiary Exit</b>				
Wildfire in year t	-0.025 (0.021)	-0.015 (0.009)	0.046 (0.038)	0.020 (0.015)
Wildfire in year t-1	0.016 (0.024)	0.003 (0.010)	-0.020 (0.020)	-0.010 (0.008)
Wildfire in year t-2	0.008 (0.021)	0.013 (0.010)	-0.008 (0.020)	-0.003 (0.008)
Wildfire in year t-3	-0.020 (0.018)	-0.006 (0.008)	-0.020 (0.016)	-0.007 (0.007)
Wildfire in year t-4	-0.033* (0.18)	-0.013 (0.008)	0.009 (0.016)	0.004 (0.007)
Observations	9,879	9,879	9,879	9,879
Adjusted R-squared	0.0382	0.0382	0.0384	0.0386
Controls	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes

*Notes:* This table reports firm's response to wildfires through enters or exits the risky areas. The dependent variables in Panel A are the number of subsidiaries entry after wildfires, while Panel B are the number of subsidiaries exits after wildfires. Wildfire in K km is the firm's exposure to wildfire in the fireline direction of zone K in year t-n, which is the capital-weighted average of the head quarter's wildfire exposure in K km and the subsidiaries' wildfire exposure in K km in year t-n. The specifications are the same as in baseline model. Robust standard errors (in parentheses) are clustered at the firm level. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## A.5 Projections of Corporate Profitability Loss

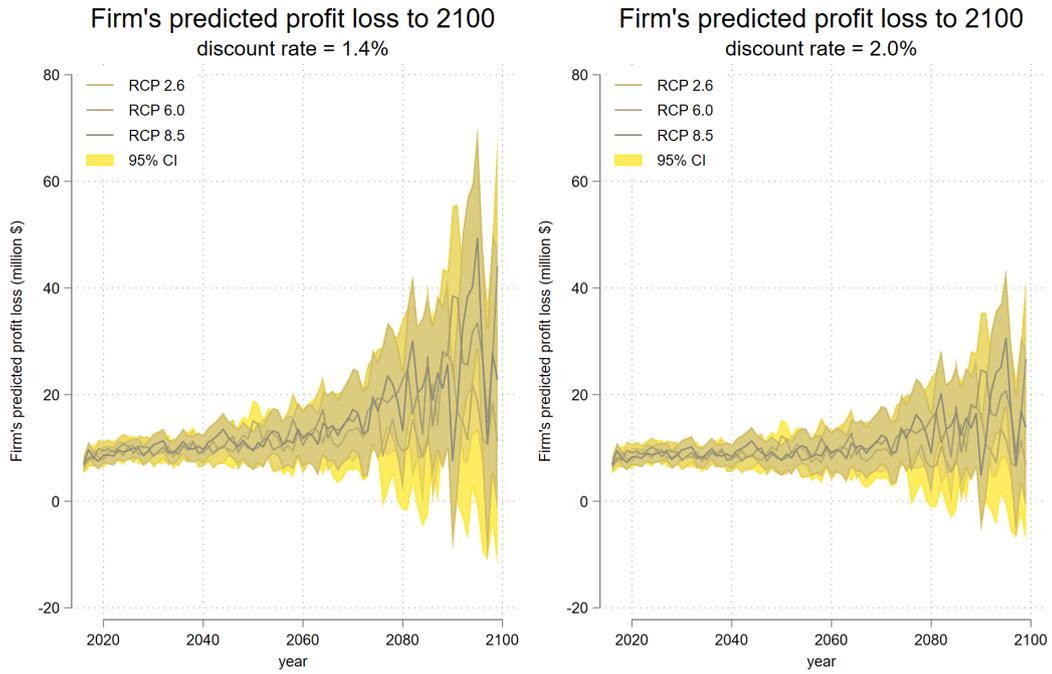


Figure A.1: Projected firm-level profit loss by 2100: Wildfires within 50 km