Extreme Heat, Supply Chain Risks and Enterprise Performance

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Abstract: This paper examines the impact of exposure to high temperatures on the performance of downstream enterprises. By constructing “supplier-customer” pairs during 2010-2019, we explore exogenous variation in temperature and find that high temperatures in suppliers' regions significantly reduce the performance of downstream enterprises. The effects are more pronounced for non-state-owned, smaller, less digitalized, more supply-chain-concentrated, and less monopolistic enterprises. The possible channel is that upstream suppliers pass on the increased costs and risks due to high temperatures to downstream customers, leading to adverse impacts on their performance. Furthermore, downstream enterprises also conduct adaptive behaviors. This study enriches the research on the impact of extreme weather on business activities and provides insights for business managers on how to sustainably adapt to supply chain risks in a warming world.

Keywords: Extreme high temperatures; Supply chain risks; Enterprise performance; Climate adaptation; Sustainable development

1. Introduction

Global warming makes extreme heat becoming more frequent and severe, causing huge socio-economic losses (Newman and Noy, 2023). The Sixth Assessment Report of the Intergovernmental Panel on Climate Change highlights that unsustainable energy and land use have raised global average surface temperature by 1.1℃ since pre-industrial (IPCC, 2021). High temperatures might not only cause socio-economic losses in local areas but also spread across regions through the supply chain. According to the *Blue Book on Climate Change of China in 2022*, China saw a record of 3,501 station-days of extreme heat and the heatwave dried up major rivers, even impacting Yangtze River. Water scarcity raises power generation and use costs in Chongqing and Sichuan (Hoekstra, 2014). Government had to conduct forced power rationing policy, leading to shutdowns and production halts in many local businesses. This action also resulted in crises for enterprises in other regions due to delayed deliveries from suppliers in Chongqing and Sichuan (China Meteorological Administration, 2022). In such circumstances, many enterprises disclose the impact of weather events on their revenue in annual reports and take high temperature risks into consideration on their supply chain strategic planning (Carbon Disclosure Project, 2021). However, little research has been conducted yet to explore the effect of high temperature shocks on enterprise's performance through the supply chain.

In this paper, we investigate the impact of exposure to high temperatures on the performance of downstream enterprises in China. To accomplish this, we construct a novel dataset with "supplier-customer" pairs from 2010 to 2019 in China. Specifically, we leverage the CSMAR database which provides listed enterprises' top five suppliers and match these suppliers with the weather data based on their geographical information. Our final panel dataset comprises annual "supplier-customer" upstream-downstream enterprise pairs, with over 15,000 observations. This unique dataset enables us to connect weather conditions in suppliers' regions with customers' performance and exploit their causal relationship via the supply chain.

Our empirical method is a two-way fixed effect model which takes advantage of the exogenous variation of weather variables. Specifically, we use the return on assets (ROA) to measure enterprise performance in our baseline regression, and use the degree-days of high temperatures in the locations of upstream suppliers as the key independent variable. Moreover, the model controls for the heating degree days and meteorological factors in the locations of the upstream suppliers, as well as downstream enterprise fixed effects and year fixed effects. We cluster the standard errors at the "supplier- customer" pair level to address serial correlation issues. The results reveal that for every 100·℃ day increase in high temperature days in the locations of upstream suppliers, the asset return rate of downstream enterprises will decrease by 0.24 percentage points. The estimates are robust across several different specifications. The findings suggest that the adverse impact of high temperatures on local enterprises exhibits a spillover effect along the supply chain, leading to deteriorated performance in downstream enterprises.

In addition, the effects are heterogeneous in terms of ownership structure, enterprise size, digitalization level, supply chain concentration, and market concentration. We find that the effects are more pronounced for non-state-owned enterprises, smaller enterprises, enterprises with lower digitalization levels, enterprises with concentrated supply chains, and monopolistic enterprises. In contrast, other types of enterprises experience relatively small impacts. These findings reflect the influence of factors such as ownership structure, enterprise size, digitalization level, supply chain concentration, and market concentration on an enterprise's ability to cope with high-temperature shocks from upstream suppliers.

To understand the possible reasons underlying the adverse impacts of high-temperature shocks from upstream suppliers, we explore three potential channels: the cost pass-through effect, the production impediment effect, and the climate adaptation effect. First, suppliers have incentives to raise product prices to compensate for losses caused by high-temperature shocks. Downstream enterprises are forced to bear these pass-through costs, threatening their performance. Second, high-temperature shocks lead to insufficient supplies, quality deterioration, and delivery delays from suppliers. This may make downstream enterprise unable to obtain raw materials or intermediate goods as per original contractual terms, thus disrupting production and adversely affecting their performance. Third, it is costly for downstream enterprises to adapt to the high-temperature shocks from their suppliers. Transaction costs associated with renegotiating with existing suppliers or contracting with new suppliers further lead to performance declines. Our analysis indicates that all the three channels play important roles in explaining the adverse impacts of high-temperature shocks from upstream suppliers. Furthermore, we find that downstream customer enterprises tend to conduct adaptive behaviors in response to upstream high-temperature shocks.

This paper contributes to the literature in several aspects. First, it builds on studies that examine socio-economic impacts of high temperatures and climate change. These studies have shown that high temperatures significantly affect human capital (Zivin et al., 2018), physiological health (Deschenes and Greenstone, 2011), psychological well-being (Thompson et al., 2018), and cognitive abilities (Gaoua et al., 2012). This could further decrease working hours (Zivin and Neidell, 2014), leading to a decline in labor productivity (Kjellstrom et al., 2009; Somanathan et al., 2021). Moreover, high temperatures can affect capital productivity by increasing friction and wear in machinery (Fox M. F. et al., 2010). Given the labor costs and equipment maintenance costs, high temperature shocks could cause a decline in total factor productivity (Zhang et al., 2018; Chen and Yang, 2019; Yang et al., 2020) and enterprises' profitability performance (Pankratz et al., 2023). However, external shocks (e.g. high temperatures) often disrupt individual enterprises and hence the entire supply chain operations (Carvalho et al., 2014). Enterprises within these chains may face indirect risks due to the impacts on their suppliers or customers. Therefore, it is reasonable to consider the entire supply network, not just individual enterprises or regions, for research on the effects of high temperatures. This paper complements the literature by exploring the impact of high temperatures in upstream suppliers' regions on downstream enterprises' performance from the supply chain viewpoint, enhancing understanding of the high temperatures' effects on socio-economic outcomes.

Second, this paper is relevant to studies on the spillover effects within the supply chain. In upstream-and-downstream relationships, enterprises can have spillover impact on productivity of their partner enterprises (Serpa and Krishnan, 2018). Pfeffer and Salancik's (2003) posits that due to a lack of independent resources and capabilities to complete production, enterprises must cooperate with other enterprises. Enterprises specialize in their respective roles, interconnecting and interdepending to form a vast supply network. While this enhances economic efficiency, it also causes uncertainty and unpredictability (Bak and Chen, 1991). A decline in one enterprise's output not only affects its own performance but also impacts its business partners within the supply network, exhibiting a risk spillover effect (Javorcik, 2004). The adverse impacts intended for a single enterprise to propagate across multiple nodes in the supply chain, with the shock cascading like a "waterfall" through the production network (Acemoglu et al., 2012), potentially triggering disturbances in the entire economic system (Bak et al., 1993). In the capital market, the co-movement tendencies between customer and supplier stock prices (Cohen and Frazzini, 2008; Hertzel et al., 2008; Menzly and Ozbas, 2010), also implying a risk-binding relationship of "sharing prosperity and adversity" between upstream and downstream enterprises. In this paper, we contribute to this strand of literature by investigating the spillover effect through the supply chain caused by a particularly important shock--high temperatures.

Third, this paper is closely related to research exploring how the effects of climate change and natural disasters spread through the supply chain (Barrot and Sauvagnat, 2016; Seetharam, 2018; Cláudia et al., 2022; Pankratz and Schiller, 2024). Most existing studies focus on developed countries. However, climate change might exert disproportionate risks to developing countries. Due to their lower levels of economic development, developing countries are more vulnerable to extreme weather events such as high temperatures (Letta & Tol, 2019; Jones and Olken, 2010). Moreover, developed nations would also experience losses from high temperatures in developing countries arising from the global supply chain (Sun et al., 2024). Consequently, it is necessary for both themselves and developed countries to understand the risks associated with high temperatures via the supply chain in developing countries. To the best of our knowledge, this paper provides the first detailed investigation, using the Chinese enterprises microdata, to understand the impacts of high temperatures through the supply chain as well as the underlying mechanisms and downstream enterprises' adaptive behaviors. By revealing the extensive adverse effects of high temperatures, we highlight the necessity for regional and global collaborative efforts to combat climate change, like fulfilling the Nationally Determined Contributions under the Paris Agreement and strengthening National Adaptation Plans. Simultaneously, by elucidating the role of supply chains in transmitting heat shocks, we offer insights to guide enterprises in flexibly formulating coping methods and adaptation strategies.

Finally, this paper adds to the literature regarding enterprises' adaptive behaviors in response to high temperature shocks. On one hand, by improving working environments, for example, increasing consumption of electricity (Deschênes, 2011), air conditioning (Abel et al., 2018), and other measures to regulate workshop temperatures to comfortable levels, enterprises can effectively mitigate the adverse impacts of high temperatures on labor productivity and avoid the economic losses (Somanathan et al., 2021). On the other hand, enterprises can allocate more production tasks to factories located in areas less affected by high temperatures or break up with the original suppliers and try to turn to new suppliers with suitable climate (Pankratz and Schiller, 2024), including imports from overseas enterprises less impacted by high temperatures (Zhang et al., 2024) In this paper, we attempt to examine whether downstream enterprises adapt to risks associated with high-temperatures in their suppliers' regions, and confirm the existence of adaptive behaviors from an ex-post perspective.

The subsequent sections of this paper are organized as follows: Section 2 describes data and introduces our empirical strategy; Section 3 presents results, including baseline results, robustness checks, and heterogeneity analyses; Section 4 discusses mechanisms; Section 5 includes extensions; and Section 6 concludes.

2. Research Design

2.1. Data

The enterprise-level data utilized in this study are primarily sourced from the China Stock Market & Accounting Research Database (CSMAR), China Industry Business Performance Data and National Enterprise Tax Survey Database, focusing on Chinese A-share listed enterprises from 2010 to 2019.

The sample is refined through the following steps: (i) excluding observations with missing values for key variables; (ii) eliminating observations that violate fundamental accounting principles, such as those with current assets, fixed assets, or net fixed assets exceeding total assets; (iii) removing financial enterprises.

The weather data are obtained from the National Meteorological Information Center, including daily average temperature, average wind speed, average relative humidity, average atmospheric pressure, precipitation, and sunshine duration across meteorological stations. Building upon the observed information, this study employs the Inverse Distance Weighting (IDW) spatial interpolation technique to transform the raw data into gridded datasets with a $0.1° \times 0.1°$ resolution. By integrating with China's administrative division codes, the data are classified and aggregated to derive daily meteorological data for each prefecture-level city and county from 2010 to 2019. For stations with missing data, linear interpolation is adopted to impute the missing values.

The construction of the top five suppliers and customers for listed enterprises follows this procedure: 1) leveraging the CSMAR database's provision of listed enterprises' top five suppliers, a match is conducted with business registration information to obtain the registered addresses and other messages of these suppliers. 2) enterprise data are matched one-to-one with the weather data for each county in China through the county codes of the listed enterprises' top five suppliers' locations. 3) matching China Industry Business Performance Data and National Enterprise Tax Survey Database with the top five suppliers of listed enterprises based on enterprise names and organizational codes, the financial data of these suppliers is acquired. 4) dropping singleton observations. This process results in a panel dataset with 15,626 observations, comprising the "supplier-customer" upstream-downstream enterprise pairs at the yearly level.

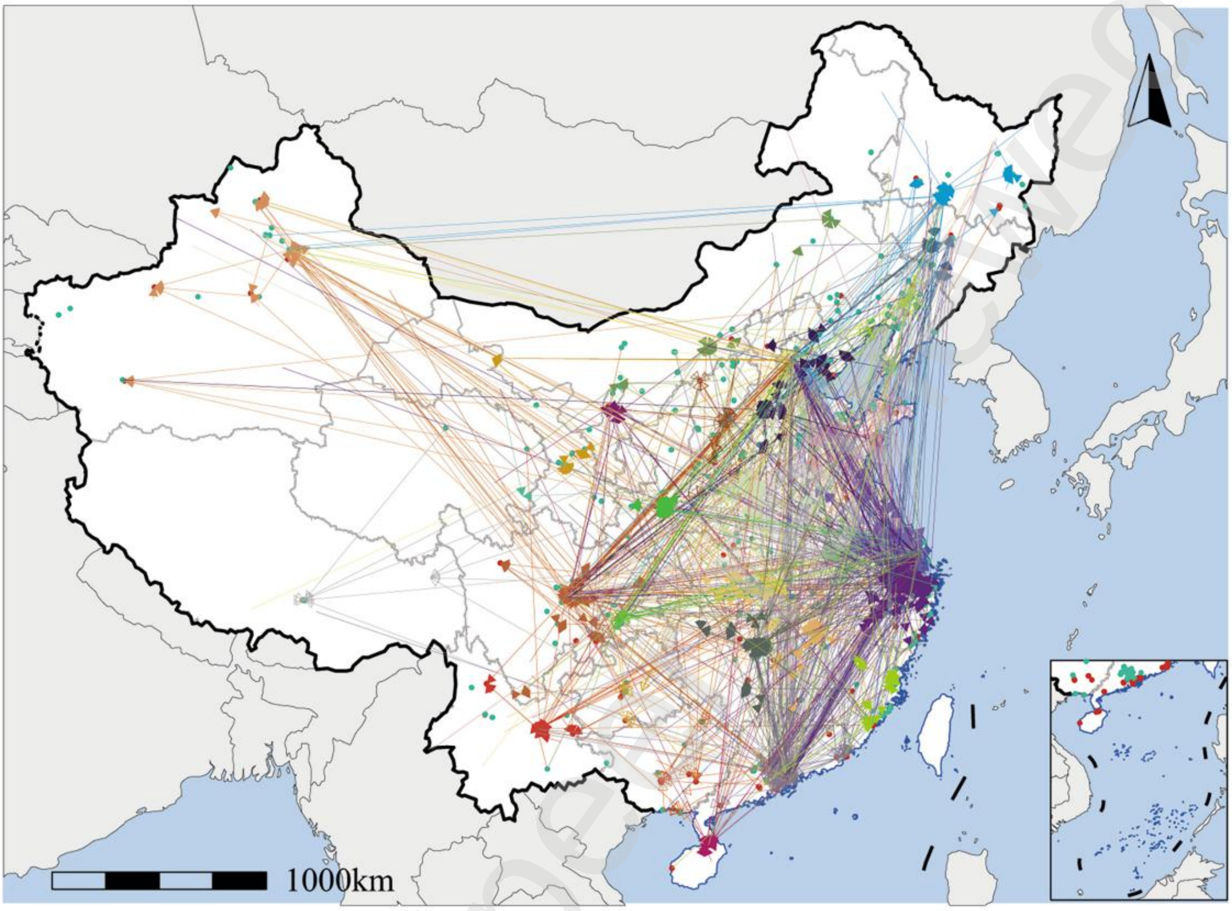

Figure 1: Distribution of "Supplier-Customer" of listed enterprises in China.

2.2. Main variables

The dependent variable, representing enterprise performance, is measured by the return on assets (ROA). ROA is calculated as the ratio of net profit to average total assets, enabling comparisons across enterprises of different asset scales. To avoid the influence of outliers, we will winsorize the dependent variable in robustness checks.

The key independent variable is the degree-days of high temperatures (CDD) in the locations of upstream suppliers. Through an empirical study of 500,000 Chinese manufacturing plants, Zhang et al. (2018) found that enterprise productivity exhibits a noticeable decline once temperatures exceed 80°F (26.7°C). Consequently, this study sets the high-temperature threshold at 26°C in the baseline regressions, with CDD computed as the cumulative sum of daily average temperatures exceeding 26°C within a year. In robustness checks, we will vary the high-temperature threshold.

The control variables include heating degree-days (HDD10), and several meteorological characteristics of upstream suppliers' locations. To avoid the "bad control" problem (Dell et al., 2012), enterprise-level characteristics are not included as controls in the baseline model. HDD10 is calculated as the cumulative sum of daily average temperatures below 10°C within a year, controlling for the impact of low temperatures in upstream suppliers' locations on downstream enterprise performance. Following Zhang et al. (2018) and Chen and Yang (2019), the meteorological controls include annual average wind speed (WDSP), annual average relative humidity (HUMID), annual average atmospheric pressure (PRESSURE), annual sunshine duration (SUNSHINE), and annual precipitation (PRCP). Furthermore, downstream enterprise fixed effects and year fixed effects are included to account for unobservable enterprise-level and year-level factors. Table 1 and Table 2 present the detailed descriptions and summary statistics for each variable.

Table 1: Descriptions of the main variables.

Type	Symbol	Name	Measurement
Dependent Variable	ROA	Return on Total Assets	Net profit total/average total assets balance Average Total Assets Balance = (Ending Total Assets Balance + Beginning Total Assets Balance) / 2
Independent Variable	CDD26	Cooling Degree Days	Sum of degree days with daily average temperature exceeding 26°C per year
Control Variable	HDD10	Heating Degree Days	Sum of degree days with daily average temperature below 10°C per year
	WDSP	Annual average wind speed	Average daily wind speed over the course of the year
	HUMIDITY	Annual average relative humidity	Average daily relative humidity over the course of the year
	PRESSURE	Annual average pressure	Average daily atmospheric pressure over the course of the year
	SUNSHINE	Annual sunshine hours	Average daily sunshine hours over the course of the year
	PRCP	Annual precipitation	Average daily precipitation over the course of the year

Table 2: Summary Statistics.

Variable	N	Mean	p50	SD	Max	Min
ROA	15626	3.168	3.376	8.139	23.97	-55.20
CDD26	15626	159.8	139.4	117.3	552.5	0
HDD10	15626	828.7	525.3	780.6	5471	0.00708
WDSP	15626	2.246	2.209	0.481	6.016	0.671
HUMIDITY	15626	68.54	71.51	9.624	90.12	35.02
PRESSURE	15626	987.2	1006	47.38	1017	597.8
SUNSHINE	15626	1981	1902	466.6	3362	688.6
PRCP	15626	1086	1048	499.7	2881	0

2.3. Empirical model

To examine the impact of high temperatures in the locations of upstream suppliers on the performance of downstream enterprises, we establish the following benchmark model:

$$Y_{it} = \beta_0 + \beta_1 CDD_{ct} + \beta_2 HDD_{ct} + \beta_3 W_{ct} + \delta_i + \delta_t + \varepsilon_{(i\sim c)t} \#(1)$$

The dependent variable Y_{it} represents the performance of downstream enterprise i in year t, namely the ROA. The independent variable is the cumulative cooling degree days (CDD_{ct}) in year t in the location c of the upstream supplier. HDD_{ct} represents the heating degree days in year t in the location c of the upstream supplier. W_{ct} represents a series of meteorological characteristics control variables for the location c of the upstream supplier in year t. δ_i and δ_t respectively represent the downstream enterprise fixed effects and the year fixed effects. $\varepsilon_{(i\sim c)t}$ represents the random disturbance term. To control for within-group correlation, we cluster the standard errors at the "supplier-enterprise" matching pair level to address the risk of excessive rejection of the null hypothesis caused by serial correlation. The coefficient β_1 is the coefficient of interest. A negative β_1 indicates that high temperatures in the locations of upstream suppliers indeed have a negative impact on the performance of downstream enterprises.

3. Results

3.1. Benchmark

Table 3 reports the baseline regression results. Column (1) presents the estimates without control variables, column (2) includes heating degree-days, and column (3) further includes meteorological control variables. All three regressions show statistically significant coefficients at the 1% level. In economic terms, a 100°C·day increase in the degree-days of high temperatures in upstream suppliers' locations is associated with a 0.24 percentage point decline in the return on assets (ROA) of downstream enterprises. This finding indicates that the adverse impact of high temperatures on local enterprises exhibits a spillover effect along the supply chain. Consequently, it provides evidence that high temperatures in suppliers' locations lead to deteriorated performance in downstream enterprises.

Furthermore, we find that the magnitude of the regression coefficients is relatively small, suggesting that the impact of high temperatures on enterprises is not as prominent as other climate-related natural disasters (Pankratz and Schiller, 2024). Unlike powerful natural forces that directly inflict large-scale destruction on enterprises' production facilities, the effects of high temperatures are more indirect and prolonged, affording enterprises more time to adapt to heat shocks. The coefficient of HDD10 is close to zero, implying that low temperatures in suppliers' locations have a negligible impact on downstream enterprise performance.

Table 3: Baseline Regression.

	(1) ROA	(2) ROA	(3) ROA
CDD26	-0.0016***	-0.0026***	-0.0024***
	(0.0005)	(0.0008)	(0.0008)
HDD10			0.0001
			(0.0001)
_cons	3.4257***	5.0795***	5.0305***
	(0.0946)	(1.7974)	(1.7981)
Weather CV	NO	YES	YES
Enterprise FE	YES	YES	YES
Year FE	YES	YES	YES
N	15626	15626	15626
R^2	0.52	0.52	0.52

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the “supplier-enterprise” matching level are reported in parentheses.

3.2. Robustness checks

To address potential concerns, we conduct a comprehensive array of robustness checks and report the results in the appendix. First, since there is no consensus on the definition of “high temperature”, we vary the high-temperature threshold and the measures of high temperatures to test the consistency of conclusions. Table A1 and Table A2 report the results. Second, to flexibly capture the marginal effects of temperature variations on downstream enterprise performance, we take the binned temperature approach, further checking the effects of temperature variations. Table A3 reports the results. Third, considering the enterprises' production and operations are susceptible to the impact of high temperatures in adjacent counties, we construct a degree-days measure at the city level for suppliers' locations and re-estimates the model. Table A4 reports the results. Fourth, if downstream enterprises and upstream suppliers are located closely, it is challenging to disentangle whether the deterioration in downstream enterprise is direct impact of local temperature or indirect transmission through the supply chain. To rule out the differential impacts of temperatures in other regions, we exclude "supplier-customer" pairs that located close to each other and control for downstream temperature, weather and enterprise characteristics. Table A5 and Table A6 report the results. Fifth, larger supplier enterprises are likely to operate factories across multiple locations, making it difficult to attribute the impact to high temperatures at their headquarters' location. Therefore, we exclude such enterprises with geographically dispersed assets. Table A7 reports the results. Sixth, a policy aimed to encourage enterprises to apply modern information technologies in supply chain construction and innovate supply chain technologies has been introduced from 2018.[1] In order to rule out the policy impacts, we either exclude the pilot enterprises or only use data prior to the policy. Table A8 reports the results. Finally, we also vary the measures of the dependent variable, apply alternative fixed effects and standard errors, making sure the conclusion withstands different model settings. Table A9 and Table A10 report the results.

All the results consistently demonstrate that high temperatures in upstream suppliers' locations exert a negative impact on the performance of downstream enterprises, significant at least at the 10% level. The magnitude of the regression coefficients also remains consistent with the baseline results. Full discussions are presented in the appendix.

3.3. Heterogeneity analysis

Facing high-temperature risks, enterprises with different characteristic may suffer from unequal losses. To further explore the differences in the impact of high-temperature shocks on supply chains among different enterprises, we conduct the following heterogeneity analysis.

3.3.1. Ownership Structure:

We categorize the full sample into state-owned enterprises (SOEs) and non-SOEs based on the proportion of state capital in equity ownership, and conduct separate regressions for each subsample. The results in columns (1) and (2) of Table 4 indicate that the impact of high temperatures in suppliers' locations on the performance of SOEs is small and insignificant. However, non-SOEs experience a significant negative effect at the 5% significance level. This finding suggests that SOEs, benefiting from state credit and various favorable policy, enjoy inherent advantages in resource acquisition and

[1] The policy details are introduced in the Appendix.

market competition. As a result, they face less pressure from supply chain disruptions. In the event of supply shortages, SOEs can leverage government influence to swiftly transition to new suppliers, securing stable sources of supply. In contrast, non-SOEs lack state credit guarantees and cannot access government channels and resources, making it challenging for them to establish collaborative relationships with suitable new suppliers in the short term. Consequently, as high temperatures in suppliers' locations increase, non-SOEs experience a notable decline in performance.

3.3.2. Enterprise Size:

Based on the natural logarithm of total assets, we divide the full sample into four quartiles. Separate regressions are conducted for the first quartile (small enterprises) and the fourth quartile (large enterprises) subsamples. The results in columns (3) and (4) of Table 4 reveal that high temperatures in suppliers' locations do not significantly impact the performance of large enterprises, but small enterprises experience a significant negative effect at the 5% significance level. This finding highlights large enterprises have stronger risk-bearing capabilities than small enterprises. When there are supply disruptions from upstream suppliers, they can mitigate supply chain pressures through internal resource reallocation and external financing, thereby maintaining normal production and smoothing out performance fluctuations. In contrast, small enterprises with limited funds and inventory lack supply chain resilience, rendering them vulnerable to such shocks. Consequently, when upstream suppliers are impacted by high temperatures, small enterprises experience a noticeable decline in performance.

3.3.3. Digitalization Level:

Drawing upon Yuan et al. (2021), we construct an enterprise digitalization index and split the full sample into high and low digitalization subsamples based on the median. The results in columns (5) and (6) of Table 4 demonstrate that when enterprises have a lower digitalization level, high temperatures in suppliers' locations exert a negative impact on downstream enterprise performance at the 1% significance level. However, when enterprises have a higher digitalization level, the impact of high temperatures in suppliers' locations on downstream enterprise performance is insignificant. This finding suggests that digital transformation not only effectively enhances supply chain efficiency but also significantly strengthens supply chain resilience. By integrating technologies such as big data and AI throughout the supply chain process, enterprises can effectively elevate the intelligence level of their supply chain management, enabling real-time detection of potential production risks, and multi-channel optimization of supplier structures and inventory management. This ensures business stability and maintains normal production and operations. In contrast, enterprises with low digitalization levels lack effective supply chain shock warning and response mechanisms, rendering them vulnerable to supply chain risks.

3.3.4. Supply Chain Concentration:

Following Wu and Yao (2023), we measure an enterprise's supply chain concentration as the ratio of the procurement value from its top five suppliers to the total annual procurement value. Using the median as the threshold, the full sample is divided into subsamples of enterprises with dispersed and concentrated supply chains. The results in columns (7) and (8) of Table 4 reveal that when enterprises have a lower supply chain concentration, high temperatures in suppliers' locations do not significantly impact downstream enterprise performance. However, when enterprises have a higher supply chain concentration, high temperatures in suppliers' locations exert a significant negative impact on downstream enterprise performance at the 5% significance level. Ge et al. (2022) finds that while supply chain concentration significantly enhances enterprise performance, it also increases performance volatility, exposing enterprises to greater uncontrollable operational risks. Enterprises with highly concentrated supply chains have fewer alternative suppliers and rely more heavily on key suppliers. Once a key supplier is impacted by high temperatures and fails to fulfill contractual obligations, a cascading "butterfly effect" ensues, leading to a serious supply shortage. Consequently, enterprises are forced to bear more severe economic losses. In contrast, enterprises with dispersed supply chains can distribute their total procurement across multiple suppliers, effectively maintaining supply chain stability and mitigating weather risks.

3.3.5. Market Concentration:

Following Zhu et al. (2024), we measure an enterprise's bargaining power as the ratio of the procurement value from its top five customers to the total annual procurement value. Using the median as the threshold, the full sample is divided into subsamples of enterprises with weak and strong bargaining power. The results in columns (9) and (10) of Table 4 indicate that high temperatures in suppliers' locations do not significantly impact the performance when enterprises have strong bargaining power. However, enterprises with weak bargaining power experience a significant negative effect at the 5% significance level. This finding suggests enterprises with greater bargaining power can pass on the economic losses to other market participants, thereby shielding themselves from the adverse impacts of weather risks. In contrast, enterprises with limited bargaining power have to face price competition from industry peers and bear a greater portion of the cost burden. Consequently, when upstream suppliers are impacted by high temperatures, enterprises with weak bargaining power experience a noticeable decline in performance.

DV: ROA	(1) SOE	(2) Non SOE	(3) Small scale	(4) Large scale	(5) Low digital level	(6) High digital level	(7) Decentra-lized SC	(8) Centra-lized SC	(9) Strong bargaining power	(10) Weak bargaining power
CDD26	-0.0006	-0.0024**	-0.0052**	0.0001	-0.0042***	0.0002	-0.0002	-0.0032**	-0.0011	-0.0023**
	(0.0010)	(0.0011)	(0.0025)	(0.0008)	(0.0012)	(0.0009)	(0.0009)	(0.0013)	(0.0011)	(0.0011)
HDD10	-0.0001	0.0005**	0.0003	0.0002	-0.0002	0.0004*	0.0003**	-0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
_cons	5.2567***	3.7367	0.4628	5.2015***	2.5843	5.5201**	3.8294**	5.0235*	2.2153	6.0875**
	(2.0390)	(2.5592)	(5.7877)	(1.6309)	(2.5097)	(2.2042)	(1.7222)	(2.8106)	(1.6547)	(2.7864)
Weather CV	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	5977	9461	3753	3939	7681	7916	7802	7786	7592	7996
R^2	0.50	0.56	0.62	0.67	0.59	0.61	0.65	0.56	0.64	0.56

Table 4: Heterogeneity Test.

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the "supplier-enterprise" matching level are reported in parentheses.

4. Mechanisms

We have shown that high temperatures in suppliers' regions lead to poor performance in downstream enterprises. In this section, we propose three potential channels to explain the effect: cost pass-through effect, production impediment effect and climate adaptation effect, and test whether they are the key mechanisms through which high temperatures in upstream suppliers' locations impact the performance of downstream enterprises.

6.1 The Cost Pass-Through Effect

High temperatures significantly increase enterprises' energy consumption (Deschênes, 2011), diminish their employee productivity and operational efficiency of production equipment (Kjellstrom et al., 2009). Therefore, local enterprises' labor and production costs increase. Confronted with these additional costs, supplier enterprises may pass through a portion of these costs to downstream customers by raising product prices or adjusting transaction terms. As a result, it exposes downstream enterprises additional costs resulted from high temperatures in suppliers' regions, impairing their performance.

To test this channel, we replace the dependent variable with several measures of suppliers' costs, including supplier operating costs, supplier labor costs, supplier sales costs, supplier management costs, and customer cost-profit ratio. Specifically, supplier operating costs are measured by the logarithm of operating costs (Cost_Supplier), supplier labor costs are measured by the logarithm of wage payable (Salary_Supplier), supplier sales costs are measured by the logarithm of selling expenses (Selling expense_Supplier), supplier management costs are measured by the logarithm of administrative expenses (Administ expense_Supplier), and the customer cost-profit ratio is measured by operating profit/operating cost (CPR_Customr).

Columns (1)–(5) in Table 5 report the results for the cost pass-through effect. The results in columns (1)–(4) respectively demonstrate that high temperatures in upstream suppliers' locations significantly increase the operating costs, labor costs, sales costs, and administrative costs of supplier enterprises. Facing additional cost pressures, suppliers exhibit a greater propensity to pass these costs downstream to their customer enterprises. The result in column (5) demonstrates that high temperatures in upstream suppliers' locations significantly reduce the cost-profit ratio of downstream customer enterprises, indicating that customer enterprises are indeed compelled to bear the costs passed through by suppliers. These additional costs augment enterprises' operating burdens, consequently reducing the performance of downstream enterprises.

6.2 The Production Impediment Effect

When upstream suppliers experience unanticipated high-temperature shocks, leading to declines in productivity and output contraction (Zhang et al., 2018), they may fail to fulfill contractual obligations due to insufficient supply quantities and deteriorated quality. Downstream enterprises have difficulty securing sufficient and stable factor supplies at reasonable prices. According to Cannikin Law, lack of a certain factor causes the whole production impediments, consequently reducing downstream enterprises' total factor productivity. It leads to declines in output and revenue under the same cost, ultimately undermining enterprise performance.

We consider two variables to test the production impediment effect. Drawing upon Zhang (2023), supply chain efficiency is measured by inventory turnover ratio (ITR, the ratio of operating income to inventory), and customer productivity is measured by the TFP calculated using the LP method. The result in column (6) shows that high temperatures in upstream suppliers' locations significantly diminish supply chain efficiency between upstream and downstream enterprises. It suggests that suppliers cannot fulfill original contract requirements due to high temperatures, leading to declines in supply quality, reductions in supply quantity, or delays in delivery times. Consequently, downstream enterprises experience disruptions in production. The result in column (7) indicates that high temperatures in upstream suppliers' locations significantly reduce the total factor productivity of downstream enterprises. Decreases in production efficiency typically imply a waste of economic resources, ultimately leading to a decline in enterprise performance.

6.3 The Climate Adaptation Effect

Downstream enterprises can adapt to upstream high-temperature shocks by attempting to establish contractual relationships with suitable new suppliers. The transaction costs incurred during this process significantly impact enterprise performance (Bernard et al., 2014; Antras et al., 2014). In order to cover the transaction costs and build new relationship with suitable suppliers, enterprises have to divert financial resources, causing a decline in enterprises' performance.

Since transaction costs involve inventory management, search, negotiation, and other direct and indirect expenses, we use the fee-asset ratio (Fee, the sum of financial expenses and administrative expenses divided by total assets) as a measure. The regression in column (8) of Table 5 shows that high temperatures in upstream suppliers' locations significantly increase the transaction costs of downstream enterprises. As upstream suppliers struggle to fulfill their contractual obligations, downstream enterprises must try to locate new suppliers. The search costs and switching costs exacerbate the burden on enterprises and subsequently reduce their performance.

Table 5: Mechanism Test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Supplier_Cost	Supplier_Salary	Supplier_Selling	Supplier_Administ	Customer_CPR	Customer_ITR	Customer_TFP	Customer_Fee

			expense	expense				
CDD26	0.0007	0.0009**	0.0015***	0.0011**	-0.0009**	-0.5243***	-0.0001**	0.0012**
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.2005)	(0.0000)	(0.0006)
HDD10	0.0001	0.0002**	0.0002*	0.0003**	0.0001**	0.0659	-0.0000	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0489)	(0.0000)	(0.0001)
_cons	5.4634***	10.3627***	9.6908***	9.8760***	-1.4255	1.0e+03	8.3209***	6.8805***
	(1.3679)	(1.3583)	(1.5456)	(1.4086)	(1.7918)	(1.2e+03)	(0.1208)	(1.7820)
Weather CV	YES	YES	YES	YES	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
N	2468	3193	2987	3261	15626	15528	14178	15615
R^2	0.73	0.64	0.63	0.60	0.41	0.49	0.91	0.42

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the "supplier-enterprise" matching level are reported in parentheses.

5. Extension Discussion

5.1. Enterprises' Adaptive Behaviors

When high temperatures in upstream suppliers' locations severely disrupt the normal production of downstream enterprises, the latter are likely to adopt corresponding adaptive measures. Pankratz and Schiller (2024) indicate that high temperatures in suppliers' locations increase the risk of supply chain disruptions between upstream and downstream enterprises. If the actual number of heat waves exceeds customer enterprises' prior expectations, the likelihood of supply chain relationships terminating increases by 7.4%. Additionally, by identifying the entry of new suppliers for customer enterprises, Pankratz and Schiller (2024) find that the high temperature shocks in the locations of new suppliers are significantly less than those of old suppliers. It means that enterprises prefer to establish cooperative relationships with suppliers from more climate-pleasant regions. Even if supply chain relationships are not entirely severed, downstream enterprises may adjust their supplier distributions, reserving suppliers from various regions within their supply systems to better adapt to high temperatures (Juanma, 2024). While these studies provide evidence of enterprises' adaptive behaviors in response to high-temperature shocks from upstream enterprises, they have not evaluate the improvement effects after enterprises adopt such adaptive measures.

We attempt to identify the effects of adaptive behaviors from an ex-post perspective. Specifically, we examine whether the negative effects diminish for longer time periods. We re-estimate the model using the cumulative degree-days of high temperatures (CDD26) over the past two, three, four, and five years as the key independent variable. Table 6 reports the results. The findings reveal that the impact of high temperatures in upstream suppliers' locations on downstream enterprise performance becomes smaller and less significant as the time period becomes longer. This suggests that enterprises are gradually adapting to high temperatures in suppliers' locations in terms of ex-post performance.

Table 6: Adaptive Behavior Test.

	(1) ROA	(2) ROA	(3) ROA	(4) ROA
CDD26_2	-0.0014***			
	(0.0004)			
CDD26_3		-0.0010***		
		(0.0003)		
CDD26_4			-0.0007***	
			(0.0003)	
CDD26_5				-0.0006***
				(0.0002)
_cons	5.1295***	5.1516***	5.2143***	5.2399***
	(1.7919)	(1.7961)	(1.8023)	(1.8082)
Weather CV	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	15626	15626	15626	15626
R^2	0.52	0.52	0.52	0.52

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the "supplier-enterprise" matching level are reported in parentheses.

5.2. Future Impact of Climate Change on Supply Chains

Under the assumption that downstream enterprises adopt adaptive measures, we employ future climate data to predict the impact of climate change on supply chain risks. The future climate data used in this study is derived from the Sixth Coupled Model Intercomparison Project (CMIP6) initiated by the World Climate Research Programme (WCRP). General Circulation Models (GCMs) are tools used to predict global climate change, taking into account complex interactions between the atmosphere, oceans, and Earth systems. They are the most authoritative tools for forecasting future temperature trajectories under different scenarios. We select seven representative GCMs: CNRM-CM6-1, CNRM-ESM2-1, CanESM5, IPSL-CM6A-LR, MIROC-ES2I, MIROC6, and MRI-ESM2-0, and obtain gridded data with a 2.5° spatial resolution (approximately 4.5 kilometers near the equator) for the period 2041-2060 under the SSP1-2.6 (low emission) and SSP5-8.5 (high emission) pathways. The SSP1-2.6 scenario assumes an increase in the sustainability of global economic development, with countries implementing strong climate change mitigation policies, achieving net-zero emissions after 2050. The SSP5-8.5 scenario assumes an intensified development of fossil fuel resources in the future, with a lack of international governance on climate issues, leading to an uncontrolled growth of greenhouse gas emissions.

We first calculate the changes in cooling degree days and heating degree days for each county in China based on the aforementioned future climate data and the climate data from 2010 to 2019. Since the estimated coefficient from the above past-five-years-CDD26 regression can reflect the impact of high temperatures in the supplier's location after adopting adaptive behaviors, we combine the estimated coefficient with these changes to predict the impact of future temperature changes in China. The results in Table 7 show that during the period 2041-2060, high temperatures in upstream suppliers' locations will lead to an additional decline of 0.04-0.15 percentage points in downstream enterprises' performance compared to current averages.

Table 7: Assessing the Future Impact of Climate Change on Supply Chain Risks Using GCMs.

RCP-SSP Pathways	**SSP126**		**SSP585**	
GCMs	**CDD26**	**ROA**	**CDD26**	**ROA**
CNRM-CM6-1	69.94	-0.04	1120.50	-0.67
CNRM-ESM2-1	58.67	-0.04	89.19	-0.05
CanESM5	90.09	-0.05	186.31	-0.11
IPSL-CM6A-LR	54.08	-0.03	119.00	-0.07
MIROC-ES2I	39.96	-0.02	73.65	-0.04
MIROC6	40.98	-0.02	71.86	-0.04
MRI-ESM2-0	54.87	-0.03	102.96	-0.06
Median	54.87	-0.03	102.96	-0.06
Mean	58.37	-0.04	251.92	-0.15

Note: Detailed descriptions of the specific models including CNRM-CM6-1, CNRM-ESM2-1, CanESM5, IPSL-CM6A-LR, MIROC-ES2I, MIROC6, MRI-ESM2-0 can be found on the official website of the World Climate Research Programme (https://www.wcrp-climate.org/).

6. Conclusion

This paper investigates the effects of high temperature shocks in suppliers' locations on the performance of their downstream enterprises. By constructing "supplier-customer" pairs in conjunction with daily meteorological data from 2010 to 2019, we reveal that high temperatures in upstream suppliers' locations significantly reduce the performance of downstream enterprises. In non-state-owned, smaller, less digitalized, more supply-chain-concentrated, and less monopolistic enterprises, the effects are more pronounced. The possible mechanism includes the cost pass-through effect, production impediment effect, and climate adaptation effect. Furthermore, we explore the adaptive behaviors of downstream enterprises and the future impact of high temperature shocks on supply chains.

This paper makes three key contributions. First, we highlight that the impact of high temperatures in upstream suppliers' regions on downstream enterprises' performance from the supply chain viewpoint. We address limitations in existing literature focusing on local impacts. This explains the cross-regional transmission mechanisms, enhancing understanding of the high temperatures' effect on economic activities. Second, by identifying the top five suppliers for each listed enterprise and constructing supplier-customer pairs, we provide empirical evidence from a developing country on the economic consequences of high temperature shocks. We reveal that the adverse effect of high temperature shocks can be propagated widespread, highlighting the necessity for regional and global collaborative efforts to combat climate change. Third, from a novel ex-post perspective, we empirically explore the existence and effect of downstream enterprises' adaptive behaviors in response to high temperature shocks in their suppliers' regions.

This paper has some limitations and prospects for future research. First, the measurements of the suppliers' locations are inaccurate. Considering that many upstream enterprises have several factories located in different areas, our rough identification of the high-temperature shocks from suppliers may lack persuasiveness. Future research could try to find new identification strategy to solve the issue. Second, due to data limitations, we do not directly observe the actual behaviors adopted by enterprises in response to high temperatures, such as product price adjustments or order delivery delays. Thus, all the potential transmission mechanisms are inferred indirectly and we lack direct evidences. Third, given the complexity and long-term nature of climate change, there are some uncertainties and simplifying assumptions in measuring the impact of high temperatures on future supply chain risks. Future research could use more comprehensive assessment models, coupled with more granular scenario analyses, to improve the accuracy of future impact assessments.

References

[1] Abel, D. W., et al. (2018). Air-quality-related health impacts from climate change and from adaptation of cooling demand for buildings in the eastern United States: An interdisciplinary modeling study. PLOS Medicine, 15(7), e1002599.

[2] Acemoglu, D., et al. (2012). The network origins of aggregate fluctuations. Econometrica, 80(5), 1977-2016.

[3] Agarwal, S., Qin, Y., Shi, L., Wei, G., & Zhu, H. (2021). Impact of Temperature on Morbidity: New Evidence from China. Journal of Environmental Economics and Management, 109(5), 102495.

[4] Antras, P., Fort, T. C., & Tintelnot, F. (2014). The Margins of Global Sourcing: Theory and Evidence from US enterprises. Working Paper.

[5] Bak, P., & Chen, K. (1991). Self-Organized Criticality. Scientific American, 264, 46.

[6] Bak, P., Chen, K., Scheinkman, J. A., & Woodford, M. (1993). Aggregate Fluctuations from Independent Sectoral Shocks: Self-Organized Criticality in a Model of Production and Inventory Dynamics. Ricerche Economiche, 47(3), 3-30.

[7] Barrot, J. N., & Sauvagnat, J. (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. The Quarterly Journal of Economics, 131(3), 1543-1592.

[8] Bernard, A. B., Moxnes, A., & Saito, Y. U. (2014). Production Networks, Geography and enterprise Performance. CEPR Working Paper.

[9] Boute, R., et al. (2007). An analysis of inventory turnover in the Belgian manufacturing industry, wholesale and retail and the financial impact on inventory reduction. Wholesale and Retail and the Financial Impact on Inventory Reduction.

[10] Carvalho, V., Nirei, M., & Saito, Y. U. (2014). Supply chain disruptions: evidence from the great east-Japan earthquake. RIETI Discussion Paper Series, 14-E-035.

[11] Castro-Vincenzi, J. (2022). Climate hazards and resilience in the global car industry. Job Market Paper.

[12] Chen, X., & Yang, L. (2019). Temperature and Industrial Output: enterprise-level Evidence from China. Journal of Environmental Economics and Management, 95, 257-274.

[13] Cláudia Custódio, M. A. Ferreira, E. Garcia-Appendini, & A. Lam (2022). How Does Climate Change Affect enterprise Sales? Identifying Supply Effects.

[14] Cohen, L., & Frazzini, A. (2008). Economic Links and Predictable Returns. Journal of Finance, 62, 1977–2011.

[15] Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: evidence from the last half century. American Economic Journal: Macroeconomics, 4(3), 66-95.

[16] Deschenes, O., & Greenstone, M. (2011). Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US. American Economic Journal: Applied Economics, 3(4), 152-185.

[17] Deschenes, O., & Greenstone, M. (2019). Extreme weather events, mortality, and migration. Rev. Econ. Stat., 91(4), 659-81.

[18] Fox, Malcolm F., Eds. Roy M. Mortier, & Stefan T. Orszulik. (2010). Chemistry and technology of lubricants. Dordrecht: Springer, Vol. 107115.

[19] Gaoua, N. J., Grantham, J., Racinais, S., & EI Massioui, F. (2012). Sensory Displeasure Reduces Complex Cognitive Performance in the Heat. Journal of Environmental Psychology, 32(2), 158-163.

[20] Ge, S., Guan, Q., & Luo, W. (2022). Supply Chain Configuration and enterprise Performance:

Efficiency and Stability. World Economy Studies, (04), 32-46+135-136.
[21]Graff-Zivin, J., Neidell, M. (2010). Temperature and the allocation of time: Implications for climate change. Journal of Labor Economics, 104, 32(1), 1-26.
[22]Graff-Zivin, J., Hsiang, S. M., Neidell, M. (2018). Temperature and human capital in the short and long run. Journal of the Association of Environmental and Resource Economists, 5(1), 77-105.
[23]Hertzel, M. G., Li, Z., Officer, M. S., & Rodgers, K. J. (2008). Inter-enterprise Linkages and the Wealth Effects of Financial Distress along the Supply Chain. Journal of Financial Economics, 87(4), 374-387.
[24]Hoekstra, A. Y. (2014). Water scarcity challenges to business. Nature Climate Change, 4(5), 318-320.
[25]Javorcik, B. S. (2004). Does foreign direct investment increase the productivity of domestic enterprises? In search of spillovers through backward linkages. American Economic Review, 94(3), 605-627.
[26]Jones, B. F., & Olken, B. A. (2010). Climate Shocks and Exports. American Economic Review, 100(2), 454-59.
[27]Juanma Castro-Vincenzi, Gaurav Khanna, Nicolas Morales, & Nitya Pandalai-Nayar. (2024). Weathering The Storm: Supply Chains And Climate Risk. NBER Working Paper, 32218.
[28]Kjellstrom, T. R., Kovats, S. J., Lloyd, S. J., Holt, R. S., & Tol, R. S. J. (2009). The Direct Impact of Climate Change on Regional Labor Productivity. Archives of Environmental & Occupational Health, 64(4), 217-227.
[29]Koumanakos, D. P. (2008). The effect of inventory management on enterprise performance. International Journal of Productivity and Performance Management, 57(5), 355-369.
[30]Letta, M., & Tol, R. S. J. (2019). Weather, climate and total factor productivity. Environmental and Resource Economics, 73(1), 283-305.
[31]Li, H., Wang, Y., & Wu, D. (2021). Research on Patent Quality's lmpact Mechanism on the Competitiveness of Enterprises for Export:The Exploration from the Perspective of Knowledge Width. World Economy Studies, 2021(01), 32-46+134.
[32]Menzly, L., & Ozbas, O. (2010). Market segmentation and cross-predictability of returns. The Journal of Finance, 65(4), 1555-1580.
[33]Newman, R., & Noy, I. (2023). The global costs of extreme weather that are attributable to climate change. Nature Communications, 14(1), 1045.
[34]Pankratz, N., Bauer, R., & Derwall, J. (2023). Climate change, enterprise performance, and investor surprises. Management Science, 69(3), 1234-1256.
[35]Pankratz, N., & Schiller, C. M. (2024). Climate Change and Adaptation in Global Supply-Chain Networks. The Review of Financial Studies, 36(9), 987-1011.
[36]Pfeffer, J., & Salancik, G. R. (2003). The External Control of Organizations: A Resource Dependence Perspective. Stanford University Press.
[37]Rupa, B., & Brian, M. (2011). High Ambient Temperature and Mortality in California: Exploring the Roles of Age, Disease, and Mortality Displacement. Environmental Research, 111(8), 1286-1292.
[38]Sachin, M., & Mabert, V. (2010). Exploring the Relationship Between Efficient Supply Chain Management and enterprise Innovation: An Archival Search and Analysis. Journal of Supply Chain Management, 46(4), 81-94.
[39]Seetharam, I. (2018). The indirect effects of hurricanes: Evidence from enterprise internal networks. Working Paper.

[40] Serpa, J. C., & Krishnan, H. (2018). The impact of supply chains on enterprise-level productivity. Management Science, 64(2), 511-532.
[41] Shah, R., & Shin, H. (2007). Relationships among information technology, inventory, and profitability: An investigation of level invariance using sector level data. Journal of Operations Management, 25(4), 768-784.
[42] Shin, H., & Soenen, L. (1998). Efficiency of working capital and corporate profitability. Financial Practice and Education, 8(2), 37-45.
[43] Somanathan, E., Somanathan, R., Sudarshan, A., et al. (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. Journal of Political Economy, 129(6), 1797-1827.
[44] Thompson, R. R., Hornigold, L., Page, T., & Waite, T. (2018). Associations between High Ambient Temperatures and Heat Waves with Mental Health Outcomes: A Systematic Review. Public Health, 161, 171-191.
[45] Williamson, O. E. (1981). The economics of organization: the transaction cost approach. American Journal of Sociology, 87(3), 548-577.
[46] Wu, Q., & Yao, X. (2023). enterprise Digital Transformation and Supply Chain Configuration: Centralization or Diversification. China Industry Economy, 2023(08), 99-117.
[47] Sun, Y., et al. (2024). Global supply chains amplify economic costs of future extreme heat risk. Nature, 609, 654-661.
[48] Yang, L., Shi, J., & Chen, X. (2020). The Effect of Temperature Changes on China's Industrial Production and Mechanism Analysis. China Economic Quarterly, 20(05), 299-320.
[49] Yuan, C., Xiao, T., Geng, C., & Sheng, Y. (2021). Digital Transformation and Division of Labor between Enterprises: Vertical Specialization or Vertical Integration. China Industry Economy, 2021(09), 137-155.
[50] Zhang, P., Deschenes, O., Meng, K., & Zhang, J. (2018). Temperature Effects on Productivity and Factor Reallocation: Evidence from a Half Million Chinese Manufacturing Plants. Journal of Environmental Economics and Management, 88, 1-17.
[51] Zhang, Z., Zhang, W., Wu, Q., Liu, J., & Jiang, L. (2024). Climate Adaptation through Trade: Evidence and Mechanism from Heatwaves on Firms' Imports. China Economic Review, 56, 123-135.
[52] Zhang, Q., & Duan, Y. (2023). Digital Empowerment, Industrial Chain Integration, and Total Factor Productivity. Business Management Journal, 45(04), 5-21.
[53] Zhu, Y., Yu, D. (2024). Digital transformation and firms' bargaining power: Evidence from China. Journal of Business Research, 183, 114851.

Appendix A

1. Varying the High-Temperature Threshold:
Alternative high-temperature thresholds of 25℃, 27℃, 28℃, 29℃, and 30℃ were employed to construct the degree-days of high temperatures, replacing the original key independent variable in the benchmark model. The results consistently demonstrate that high temperatures in upstream suppliers' locations exert a negative impact on the performance of downstream enterprises, significantly significant at least at the 5% level. The following table reports the robustness of the baseline conclusions.

Table A1: Robustness Test-1

	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) ROA
CDD25	-0.0019***				
	(0.0007)				
CDD27		-0.0030***			
		(0.0010)			
CDD28			-0.0036***		
			(0.0013)		
CDD29				-0.0042**	
				(0.0017)	
CDD30					-0.0051**
					(0.0024)
HDD10	0.0001	0.0001	0.0002	0.0002*	0.0003*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
_cons	4.9964***	5.1463***	5.3866***	5.6800***	5.9121***
	(1.8108)	(1.7842)	(1.7710)	(1.7586)	(1.7499)
Weather CV	YES	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	15626	15626	15626	15626	15626
R^2	0.52	0.52	0.52	0.52	0.52

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the "supplier-enterprise" matching level are reported in parentheses.

2. Varying the Measure of High Temperatures:
Instead of using degree-days, the number of days with temperatures exceeding the threshold was adopted as the key independent variable for re-estimation. With thresholds set at 25℃, 26℃, 27℃, 28℃, 29℃ and 30℃, the results consistently reveal a negative effect of high temperatures in upstream suppliers' locations on downstream enterprise performance, all significant at the 10% level. It further reinforces the robustness of the baseline conclusions. In all, the results indicate that as the temperature threshold increases, the absolute value of the regression coefficient gradually grows

larger. It suggests that more extreme heat in upstream suppliers' locations exerts more severe adverse impacts on downstream enterprises' performance.

Table A2: Robustness Test-2

	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) ROA	(6) ROA
DAY25	-0.0046* (0.0024)					
DAY26		-0.0058** (0.0025)				
DAY27			-0.0090*** (0.0029)			
DAY28				-0.0114*** (0.0034)		
DAY29					-0.0153*** (0.0044)	
DAY30						-0.0127** (0.0051)
_cons	5.6885*** (1.8196)	5.5609*** (1.8142)	5.1748*** (1.8030)	5.0648*** (1.7920)	5.1058*** (1.7851)	5.9453*** (1.7558)
Weather CV	YES	YES	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	15626	15626	15626	15626	15626	15626
R^2	0.52	0.52	0.52	0.52	0.52	0.52

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the "supplier-enterprise" matching level are reported in parentheses.

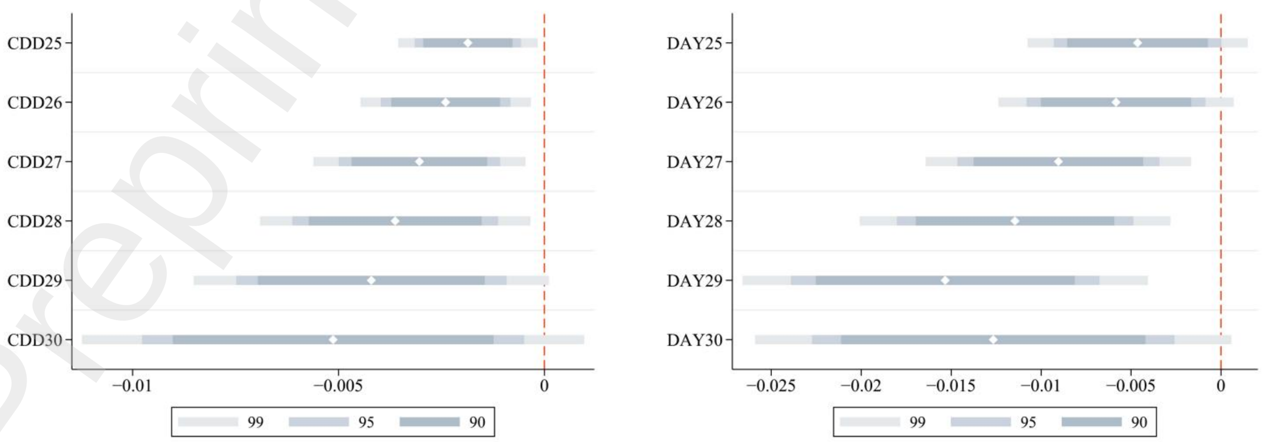

Figure : Estimation Results of Constructing Explanatory Variables with Different Threshold Temperatures.

3. Binned Temperature Approach:

To relax functional form constraints and more flexibly capture the marginal effects of temperature variations on downstream enterprise performance, this study employs a binned temperature approach for re-estimation. Ten temperature bins are constructed, each spanning a 5℃ interval. Each represents the number of days within a year where the average temperature falls in bin m, including ⩽-10℃, -10℃~-5℃, -5℃~0℃, 0℃~5℃, 5℃~10℃, 10℃~15℃, 15℃~20℃, 20℃~25℃, 25℃ ~30℃, and ⩾30℃. The baseline bin is set as 5℃~10℃. The results reveal that when the number of days with average temperatures falling in the highest (⩾30℃) bins increases, downstream enterprises' performance declines. The coefficients are significant at the 5% level.

Table A3: Robustness Test-3

	(1) ROA	(2) ROA
TEMP1	-0.0011	0.0021
	(0.0053)	(0.0060)
TEMP2	-0.0093	-0.0088
	(0.0082)	(0.0097)
TEMP3	-0.0033	0.0007
	(0.0054)	(0.0069)
TEMP4	-0.0059	-0.0021
	(0.0068)	(0.0077)
TEMP6	-0.0062	-0.0060
	(0.0072)	(0.0080)
TEMP7	-0.0025	-0.0016
	(0.0056)	(0.0063)
TEMP8	-0.0112^{*}	-0.0121^{*}
	(0.0065)	(0.0068)
TEMP9	-0.0038	-0.0059
	(0.0038)	(0.0043)
TEMP10	-0.0179^{**}	-0.0206^{**}
	(0.0073)	(0.0081)
_cons	5.2512^{***}	6.5296^{**}
	(1.4921)	(2.8435)
Weather CV	YES	YES
Enterprise FE	YES	YES
Year FE	YES	YES
N	15626	15626
R^2	0.52	0.52

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the "supplier-enterprise" matching level are reported in parentheses.

4. Varying the Geographic Scope of High-Temperature Measurement:
Considering that supplier enterprises may operate multiple factories across different counties, and some employees may commute between counties, the enterprises' production and operations are susceptible to the impact of high temperatures in nearby counties. To isolate the potential interference from adjacent counties, we construct a degree-days measure at the city level for suppliers' locations and re-estimates the model. In column (1), the key independent variable is the cumulative sum of daily average temperatures exceeding 26℃ within a year for the suppliers' city (CDD26city). In column (2), the key independent variable is the total number of days with daily average temperatures exceeding 26℃ within a year for the supplier's city (DAY26city). After considering nearby interference factors, the absolute value of the regression coefficients slightly expands compared to the baseline regression. Both are significant at the 5% level, confirming the robustness of the baseline conclusions. However, due to the large geographical range of cities, the weather conditions within counties may be very different, resulting in inaccurate high-temperature measure. Therefore, the benchmark regression still uses the cumulative cooling degree days at the county levels.

Table A4: Robustness Test-4

	(1) ROA	(2) ROA
CDD26city	-0.0024***	
	(0.0008)	
DAY26city		-0.0053**
		(0.0026)
_cons	4.8714***	5.4796***
	(1.8573)	(1.8463)
Weather CV	YES	YES
Enterprise FE	YES	YES
Year FE	YES	YES
N	15626	15626
R^2	0.52	0.52

5. Controlling for Downstream Temperature, Weather, and enterprise Characteristics:
To mitigate potential interference from enterprise characteristics and weather conditions at downstream customers' locations, we add other control variables into the model. These include the degree-days of high temperatures (CDD26_Custom), heating degree-days (HDD10_Custom), and meteorological characteristics (annual average wind speed, annual average relative humidity, annual average atmospheric pressure, annual average sunshine duration, and annual average precipitation, represented by Weather CV_Custom) at downstream customers' locations, as well as enterprise-level controls for downstream enterprises (including enterprise size, enterprise age, and leverage ratio, represented by Enterprise Control). As shown, the regression coefficients remain statistically significant at least at the 5% level, further confirming the robustness of the baseline conclusions.

Table A5: Robustness Test-5

	(1) ROA	(2) ROA	(3) ROA	(4) ROA	(5) ROA	(6) ROA	(7) ROA
CDD26_Supplier	-0.0026***	-0.0021**	-0.0021**	-0.0024***	-0.0026***	-0.0021**	-0.0021**
	(0.0008)	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
HDD10_Supplier	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
CDD26_Custom	-0.0016	-0.0003	-0.0001		-0.0016	-0.0002	-0.0002
	(0.0015)	(0.0016)	(0.0018)		(0.0015)	(0.0016)	(0.0018)
HDD10_Custom			0.0002				0.0000
			(0.0006)				(0.0006)
_cons	4.1787**	46.8615	46.7390	-51.9160***	-54.9696***	-12.3177	-12.3506
	(1.9124)	(31.3083)	(31.2582)	(8.2660)	(8.5149)	(31.6140)	(31.5663)
Weather CV_Supplier	YES	YES	YES	YES	YES	YES	YES
Weather CV_Custom	NO	YES	YES	NO	NO	YES	YES
Enterprise Control	NO	NO	NO	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
N	14943	14483	14483	15554	14873	14418	14418
R^2	0.53	0.54	0.54	0.54	0.54	0.55	0.55

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the "supplier-enterprise" matching level are reported in parentheses.

6. Excluding Close Samples:

If downstream enterprises and upstream suppliers are located closely, high temperatures in suppliers' locations would also directly impact downstream enterprises. In such cases, it becomes challenging to disentangle whether the deterioration in downstream enterprise performance is attributable to the direct impact of high temperatures or the indirect transmission through the supply chain. Consequently, we exclude observations where downstream enterprises and upstream suppliers are geographically close and re-estimates the model. Specifically, column (1) excludes samples where the distance between downstream enterprises and upstream suppliers is less than 10 km. column (2) excludes distances less than 20 km, column (3) excludes distances less than 50 km, column (4) excludes distances less than 100 km, and column (5) excludes distances less than 200 km. The regression results reveal that even after excluding observations with close supplier-customer locations, high temperatures in suppliers' locations still exert a significant negative impact on downstream enterprise performance. The regression coefficients are significant at least at the 10% level, further confirming the robustness of the baseline conclusions.

Table A6: Robustness Test-6

(1)	(2)	(3)	(4)	(5)
ROA	ROA	ROA	ROA	ROA

CDD26	-0.0021^{**}	-0.0023^{***}	-0.0021^{**}	-0.0016^{*}	-0.0017^{*}
	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0010)
HDD10	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
_cons	4.8006^{**}	5.0987^{***}	4.8196^{**}	5.5987^{***}	5.9091^{***}
	(1.8997)	(1.9551)	(2.0026)	(2.0578)	(2.1994)
Weather CV	YES	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	13625	12601	11449	10544	9127
R^2	0.53	0.53	0.52	0.51	0.51

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the "supplier-enterprise" matching level are reported in parentheses.

7. Excluding Suppliers with Geographically Dispersed Assets:

Some larger supplier enterprises may operate factories across multiple locations, making it difficult to attribute the impact to high temperatures at their headquarters' location. Therefore we exclude such enterprises with geographically dispersed assets. In column (1), samples where the supplier is a publicly listed enterprise are excluded. Column (2) further excludes samples where the supplier is a publicly listed enterprise or an affiliate. The results show that high temperatures in suppliers' locations still exert a significant negative impact on downstream enterprise performance. The regression coefficients are significant at least at the 5% level, further confirming the robustness of the baseline conclusions.

Table A7: Robustness Test-7

	(1) ROA	(2) ROA
CDD26	-0.0022^{**}	-0.0027^{***}
	(0.0009)	(0.0009)
HDD10	0.0002	0.0002
	(0.0001)	(0.0002)
_cons	5.2349^{***}	3.7985^{*}
	(1.9716)	(2.0712)
Weather CV	YES	YES
Enterprise FE	YES	YES
Year FE	YES	YES
N	14468	13685
R^2	0.53	0.52

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the "supplier-enterprise" matching level are reported in parentheses.

8. Excluding the Impact of Supply Chain Policy:

In 2018, the Ministry of Commerce, along with seven other government agencies, jointly launched a nationwide pilot program for supply chain innovation and application. For the first time, 269 enterprises were selected to implement policy supporting the development of supply chain innovation. It aimed to encourage enterprises to apply modern information technologies in supply chain construction and innovate supply chain technologies. The policies may promote enterprises to upgrade their supply chain system, making it more resistant to high temperature shocks, thereby underestimating the impact of upstream high temperatures on downstream enterprise performance. Therefore, it is necessary to exclude the impact of national supply chain policies. Specifically, column (1) of excludes pilot enterprises, column (2) excludes observations from 2018 and subsequent years. The results show that even after accounting for policy influences, high temperatures in suppliers' locations still exert a significant negative impact on downstream enterprise performance. The regression coefficients are significant at least at the 1% level, further confirming the robustness of the baseline conclusions.

Table A8: Robustness Test-8

	(1) ROA	(2) ROA
CDD26	-0.0024***	-0.0030***
	(0.0008)	(0.0008)
HDD10	0.0001	-0.0000
	(0.0001)	(0.0001)
_cons	-0.0024***	-0.0030***
	(0.0008)	(0.0008)
Weather CV	YES	YES
Enterprise FE	YES	YES
Year FE	YES	YES
N	15476	13030
R^2	0.52	0.58

9. Varying Measures of the Dependent Variable:

Column (1) uses the return on assets (ROA_2) to be the dependent variable, which is calculated as the ratio of net income to total asset balance. It allows us to measure the efficiency of capital utilization in enterprises. Column (2) uses ROA_3, calculated as the ratio of net income to average total assets (average total assets = (total assets at the end of the period + total assets at the end of the previous period)/2). It allows us to measure the efficiency of capital utilization in enterprises at the average level of this year. Column (3) uses ROA_4, calculated as the ratio of trailing twelve months (TTM) net income to average total assets. It allows us to measure the efficiency of capital utilization in enterprises after excluding seasonal fluctuations. Column (4) uses the operating profit margin (Profit), calculated as the ratio of operating profit to operating revenue. It allows us to measure the profitability efficiency of the business process in enterprises. Column (5) uses the operating profit margin before interest and taxes (Profit_2). It allows us to measure the profitability efficiency of the business process in enterprises after excluding tax incentives and other policy benefits. Column (6) uses the operating profit margin before interest, taxes, depreciation, and amortization (Profit_3). It allows us to measure the profitability efficiency of the business process in enterprises after excluding tax incentives, as well as the renewal in long-term operations. All the regression coefficients remain statistically significant at least at the 5% level, further confirming the robustness of the baseline conclusions.

Table A9: Robustness Test-9

	(1) ROA_2	(2) ROA_3	(3) ROA_4	(4) Profit	(5) Profit_2	(6) Profit_3
CDD26	-0.0186^{***}	-0.0052^{***}	-0.0052^{***}	-0.0380^{**}	-0.0573^{***}	-0.0563^{***}
	(0.0052)	(0.0015)	(0.0015)	(0.0178)	(0.0210)	(0.0210)
HDD10	0.0015^{*}	0.0001	0.0001	0.0062^{**}	0.0055	0.0056
	(0.0008)	(0.0002)	(0.0002)	(0.0029)	(0.0038)	(0.0038)
_cons	-6.5068	4.1966	4.1966	-73.8563	-72.6937	-65.4298
	(19.9429)	(2.9519)	(2.9519)	(79.3959)	(89.3423)	(88.8993)
Weather CV	YES	YES	YES	YES	YES	YES
Enterprise FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	15626	14571	14571	15626	15626	15626
R^2	0.25	0.33	0.33	0.43	0.38	0.38

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the "supplier-enterprise" matching level are reported in parentheses.

10. Varying Fixed Effects and Clustering Approaches:

Building upon the baseline regressions, we further vary the fixed effects and clustering level for standard errors to test the robustness of the results. In column (1), enterprise, year, and industry fixed effects are controlled, with the clustering level remaining consistent with the baseline regressions. Column (2) adjusts the clustering level to the county-year level while maintaining the same fixed effects as the baseline. Column (3) controls both enterprise, year, and industry fixed effects, as well as county-year clustering. The regression results reveal that the coefficients of the key independent variable remain negatively significant, significant at least at the 5% level, further confirming the robustness of the baseline conclusions.

Table A10: Robustness Test-10

	(1) ROA	(2) ROA	(3) ROA
CDD26	-0.0023^{***}	-0.0024^{***}	-0.0023^{**}
	(0.0008)	(0.0007)	(0.0007)
HDD10	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)
_cons	5.0284^{***}	5.0305^{***}	5.0284^{***}
	(1.7018)	(1.3930)	(1.3936)
Weather CV	YES	YES	YES

Enterprise FE	YES	YES	YES
Year FE	YES	YES	YES
Industry FE	YES	NO	YES
Cluster Group	YES	NO	NO
Cluster District	NO	YES	YES
Cluster Year	NO	YES	YES
N	15626	15626	15626
R^2	0.55	0.52	0.55

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. "CV" abbreviates control variables, while "FE" stands for fixed effects. Robust standard errors clustered at the "supplier-enterprise" matching level are reported in parentheses.