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ORIGINAL RESEARCH ARTICLE

The impact of extreme temperature shocks on enterprise digital transformation: Evidence from Chinese listed manufacturing companies

Huan Wang[1,2], Ying Ren[2], Dashuai Gao[1], Juping Wu[1]*, and Ruiling Ma[3]

[1]Faculty of Geography, Yunnan Normal University, Kunming, Yunnan, China
[2]School of Economics and Management, Yunnan Minzu University, Kunming, Yunnan, China
[3]Hongta Group Yuxi Cigarette Factory, Yuxi, Yunnan, China
***Corresponding author:** Juping Wu (wujuping@ynnu.edu.cn)

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Abstract: Global warming and extreme temperature shocks pose significant challenges to human societies. While much research focuses on the economic hazards of extreme temperatures, exploring proactive countermeasures holds greater research value. Utilizing daily meteorological data from prefecture-level cities in China and panel data from listed manufacturing companies (2011 – 2022), we constructed a city-level extreme temperature index in this study and employed a two-way fixed-effects model to empirically examine the impact of extreme temperatures on the digital transformation of manufacturing enterprises. The results revealed that extreme temperatures significantly predict digital transformation, a finding robust to various tests. Mechanism analysis indicated that extreme temperatures increase production costs and reduce efficiency, thereby accelerating digital transformation. Heterogeneity analysis further demonstrated that the effect is more pronounced in private enterprises, high-tech firms, and non-high-pollution industries, with a stronger impact observed in the eastern region of China. In addition, corporate environmental, social, and governance disclosure, executive rejuvenation, and digital infrastructure construction positively moderated this relationship, whereas the implementation of carbon trading policies partially weakened the effect. This study not only underscores the micro-level impacts of climate change but also provides valuable insights for enterprises seeking to mitigate the effects of extreme temperature events through digital transformation.

Keywords: Climate change; Extreme temperatures; Digital transformation; Manufacturing companies

1. Introduction

Continuous global warming and the frequent occurrence of extreme temperature events have caused irreversible catastrophic consequences for the Earth, substantially threatening human survival and development.[1,2] These phenomena have emerged as a shared developmental challenge for all nations worldwide. The Task Force on Climate-related Financial Disclosures highlighted that, in addition to global warming and natural disasters, extreme weather events and other climatic factors exert chronic impacts on production, economic activities, and social sectors, particularly extreme high and low temperatures.[3,4] The Blue Book on Climate Change in China (2022) reveals that the global average temperature from 2002 to 2021 was 1.01°C higher than that of the pre-industrialization period, indicating a persistent warming trend. Over the past two decades, the probability of temperatures dropping to −5°C or below in China's prefecture-level cities has remained relatively stable, while the probability of temperatures reaching 35°C or above has shown an upward trend (Figure 1). Notably, the warming trend of extreme high temperatures during the 1986 – 2020 period has intensified, with an increase of approximately 0.23°C per decade – nearly twice the global temperature rise during the same period. The National Strategy for Adaptation to Climate Change 2035 emphasizes that the long-term adverse impacts and sudden extreme events caused by climate change have become significant risks in China's pursuit of socialist modernization. Therefore, in-depth exploration of the economic impacts of extreme weather events will inform China's policies and actions to address climate change.

Extreme temperatures exert significant adverse effects on economic, social, business, and public health outcomes. The economic impacts of climate warming and extreme temperatures have extensively evaluated on the global scale through construction of various temperature-related indicators. For instance, Schlenker and Roberts[5] and Chen *et al.*[6] quantified the effects of extreme temperatures on agricultural productivity, demonstrating substantial negative impacts. Similarly, Hsiang[7] analyzed industry output data from 28 Caribbean countries spanning 1970 – 2006, revealing that rising temperatures significantly reduced output in both agricultural and industrial sectors, with a more pronounced effect observed in the industrial sector. Further evidence from China highlights the nonlinear relationship between temperature and industrial output. Zhang *et al.*[8] utilized data from Chinese industrial and commercial enterprises between 1998 and 2007, showing that industrial output initially increases with temperature until reaching an optimal threshold, beyond which further temperature rises lead to a sharp decline in output. Notably, extreme high temperatures were found to significantly reduce the productivity of industrial enterprises. Building on this, Yang *et al.*[9] investigated the underlying mechanisms through which temperature changes affect industrial output. Their findings indicated that temperature fluctuations indirectly influence industrial productivity by impacting gross fixed assets, investment levels, and the ratio of new product development.

The detrimental effects of extreme temperatures have been extensively validated through empirical research, which expands from macroeconomic analyses to sector-specific impacts in agriculture and industry. However, research on the micro-level implications and mechanisms of extreme temperatures remains relatively scarce, particularly regarding coping strategies. Most existing studies predominantly focus on carbon emissions.[10,11] Developed countries struggle to implement effective measures to mitigate the adverse effects of extreme heat,[12] whereas in developing economies, domestic scholars offer limited guidance for enterprises to address extreme temperatures, primarily emphasizing site selection strategies[13] and tax planning.[14] Nonetheless, emerging evidence suggests that long-term innovation acceleration can partially counteract the threats posed by extreme temperatures. For instance, technological innovation has been demonstrated to mitigate the impacts of climate change,[15] with digital technology development emerging as a pivotal driver for fostering a new paradigm of digitalized enterprises. Digital transformation can effectively reduce enterprises' reliance on traditional labor-intensive production processes and enhance operational efficiency, thereby providing a viable strategy to cope with extreme temperature shocks. Whether extreme temperature

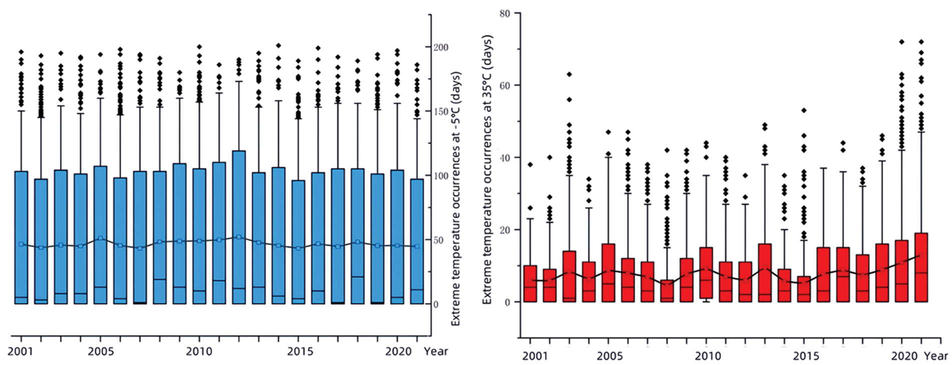

Figure 1. Incidence rate of extreme temperature occurrence at −5°C and 35°C at prefecture-level cities in China

shocks will accelerate the digital transformation of manufacturing companies needs to be further examined.

To address the gap in literature, we constructed and measured the extreme temperature index of prefecture-level cities based on the data of China's A-share-listed manufacturing enterprises from 2011 to 2022; empirically examined the impact of extreme temperature on the digital transformation of listed manufacturing enterprises; and validated and analyzed the mechanism and moderating effect. Possible contributions of the research in this paper include the following: first, it complements the relevant research on the micro impact of extreme temperature. Existing literature related to extreme temperatures mostly focuses on the industry level and lacks research on micro groups. Second, it provides lessons and sheds light on effective measures for companies to cope with extreme temperature events to minimize economic hazards, addressing the lack of research on related countermeasures.

2. Research hypothesis

Extreme temperatures pose significant risks to health and safety of workers employed by businesses, increasing the likelihood of heat-related illnesses and accidents.[16] These conditions lead to reduced productivity, higher absenteeism rates, and ultimately diminished business performance.[17-19] To counteract these effects, labor inputs may be increased to meet production targets, but such strategy could incur higher costs. Furthermore, health-related concerns and abnormal temperature fluctuations can trigger labor migration, altering inter-regional labor supply dynamics. Regions frequently experiencing extreme temperatures often face a decline in both the quantity and quality of labor supply, driving up wages and employment costs.[20-24] Digital transformation offers a solution by automating routine and repetitive tasks, reducing reliance on traditional labor, and enabling dynamic optimization of the workforce through a "survival of the fittest" approach.

Unlike the direct impact of extreme temperatures on agriculture, which is often described as "dependent on the weather,"[25-27] the effects on industrial enterprises are more nuanced. Beyond increased production costs, extreme temperatures also reduce operational efficiency. High temperatures impair workers' attention and decision-making abilities, thereby lowering productivity.[28-30] In addition, industrial output exhibits an optimal temperature range; deviations above or below this range result in significant declines in output.[8] Rising temperatures exacerbate energy consumption, particularly for electricity[31,32] and cooling systems,[33] leading to higher energy costs,[34] and reduced total factor productivity (TFP) and fixed asset turnover efficiency.[9]

Digital transformation can mitigate these challenges by enhancing productivity through cost reduction, innovation, and optimized production processes. By minimizing downtime, conserving resources,[35] and improving TFP,[36] enterprises can better withstand the adverse impacts of extreme temperatures. Therefore, this paper argues that extreme shocks accelerate the digital transformation of enterprises. The research framework is illustrated in Figure 2, whereas the research hypotheses are given below:

H_1: Extreme temperatures positively impact enterprise digital transformation.

H_2: Extreme temperatures increase enterprise cost pressure, reduce enterprise productivity, and thus accelerate enterprise digital transformation.

3. Data, variables, and methods

3.1. Study area and data sources

3.1.1. Study area and research subjects

This study covers 287 prefecture-level cities in China's major climatic zones – tropical/subtropical

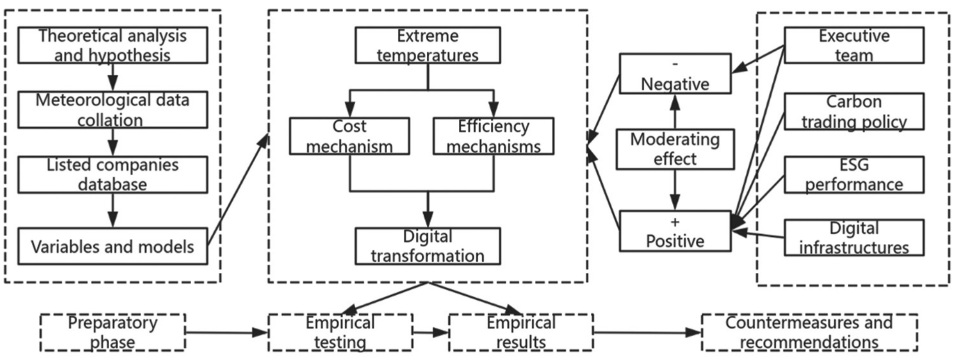

Figure 2. Research framework

(eastern/southern), temperate (northern), and arid (northwestern) – which represent the wide spectrum of climatic zones emblematic of the different characteristics of extreme temperature exposure. We analyzed 12,908 firm-year observations (2011 – 2022) from 1824 A-share manufacturing firms, whose spatial distribution reveals high-density clustering in the Yangtze River Delta (28.7% of firms) and Pearl River Delta (22.1% of firms). The western region, although covering a relatively lower density, all have enterprises included in the study sample.

3.1.2. Company data

Shanghai and Shenzhen A-share listed companies from 2011 to 2022 were taken as the research subjects, and their company-level data were obtained from the China Stock Market and Accounting Research (CSMAR) database (https://data.csmar.com/) with the following processing: first, retaining the data of manufacturing companies; second, excluding samples such as special treatment; and third, shrinking the tail at 1% level for continuous type variables. Municipal-level control variables were obtained from the City Statistical Yearbook (https://www.stats.gov.cn/).

3.1.3. Weather data

Weather data were obtained from China Meteorological Administration (CMA), which contains daily observations of meteorological indicators such as average temperature, maximum temperature, minimum temperature, precipitation, barometric pressure, relative humidity, sunshine hours, and average wind speed, and provides detailed geographic coordinate information for each weather station. The latitude and longitude of the weather stations were matched with the cities in the provinces to confirm the geographical zones before retrieving the daily observation data compiled by the domestic weather stations, and Python was used to process the cleaned data, which were compiled into a CSV file on a daily basis, with the latitude and longitude and the values of the daily average temperature and extreme temperature retained as needed. The daily CSV files were spread and then projected, and the daily data were interpolated using the inverse distance weighting method. The data are partitioned and counted and spliced by administrative divisions, and finally, the day-by-day meteorological data such as temperature and humidity were obtained for each prefecture-level city in the country. For a city containing only one station, the maximum and minimum temperatures observed at the station were taken as the extreme temperatures of the day; if there were multiple stations within the city, the maximum and minimum values were calculated for all stations.

3.2. Mold

In this study, we constructed an ordinary least squares (OLS) model to analyze the impact of extreme temperatures on the digital transformation of enterprises.

$$\mathrm{Digital}_{i,j,t} = \alpha_0 \mathrm{Exrteme}_{j,t} + \alpha_1 \mathrm{Extreme}_{j,t-1} + \beta_1 X_{i,t} + \beta_2 X'_{j,t} + \theta_0 W_{j,t} + \theta_1 W_{j,t-1} + \varepsilon_{i,j,t} \quad \text{(I)}$$

Where i refers to enterprises, t is time, and j denotes prefecture-level cities. The explanatory variable is the extreme temperature ($\mathrm{Extreme}_{j,t}$); the explanatory variable is the degree of enterprise digital transformation ($\mathrm{Digital}_{i,j,t}$); and $X_{i,t}$ and and $X'_{j,t}$ are a series of control variables at the enterprise level and macroeconomic level, respectively, which are the other climate variables (including average wind speed, average humidity, and hours of light) at the prefecture level. In the actual regressions, industry-fixed effects as well as time-fixed effects were controlled for, and all standard errors were clustered at the city×year level. Given the possible lags in the effects of weather variables on various economic variables, we also included the lagged term sums of these weather variables in the model.

3.3. Variables

3.3.1. Explanatory variables

This study measured corporate digital transformation through text analysis[37] of annual reports using keyword frequency metrics ($\mathrm{Digital}_1$: absolute count; $\mathrm{Digital}_2$: frequency ratio). We identified five keyword dimensions (artificial intelligence, blockchain, cloud computing, big data, and digital technology applications), collected all A-share listed firms' annual reports from CSMAR through Python, and extracted text using Java PDFBox. To ensure accuracy, we rigorously excluded: (i) keywords preceded by negations (*e.g.*, "not," "non-," "un-," "lack," "without," and "failed to") within a ±5-word window through dependency parsing and a predefined negation lexicon, and (ii) contexts referencing external entities (*e.g.*, shareholders/suppliers' activities) or executive backgrounds, retaining only firm-owned digital initiatives. $\mathrm{Digital}_1$ aggregates validated keyword counts; $\mathrm{Digital}_2$ computes their proportion to total words, thereby eliminating false positives (*e.g.*, "no AI deployment") while capturing genuine transformation actions (*e.g.*, "launched our blockchain system").

3.3.2. Core explanatory variable

The incidence rate of extreme temperatures, including extreme high and extreme low temperatures, was measured in terms of the duration of extreme weather in the city, which was determined in accordance to published methods.[20,34] A fixed threshold method was used, with 35°C and −5°C as the criteria: if the daily maximum temperature exceeded 35°C, it was included in the number of extreme-high-temperature days, while below −5°C, it was included in the number of extreme-low-temperature days, which was eventually summed up to obtain the specific value of the number of days of extreme temperatures (Figure 3).

With reference to Wang *et al.*'s study[38] on the influencing factors of digital transformation, we adopted four categories of control variables for this study: enterprise characteristics, financial characteristics, governance structure, and macroeconomic factors, and added climate control variables at the city level to exclude interference from other climate factors. Specifically, the enterprise characteristics control variables include firm size (Size, measured by the natural logarithm of total assets), firm age (FirmAge, measured by the number of years since establishment), and firm nature (SOE, or state-owned enterprises, assigned a value of 1, otherwise 0); the financial characteristics control variables include asset-liability ratio (Lev, measured by the ratio of total liabilities to total assets), profitability (ROA, measured by the ratio of net profit to total assets), and book-to-market ratio (BM, measured by the ratio of book value to market value); the governance structure control variables include board size (Board, measured by the number of board members), CEO duality (Dual, assigned a value of 1 if the chairman and CEO are the same person, otherwise 0), ownership concentration (Top1, measured by the shareholding ratio of the largest shareholder), independent director size (Indep, measured by the number of independent directors), Big Four audit (Big4, assigned a value of 1 if audited by one of the Big Four accounting firms, otherwise 0), audit opinion (Opinion, assigned a value of 1 if the opinion is standard unqualified, otherwise 0), and internal control index (IC, measured by the firm's internal control index); the macroeconomic control variables include economic development level (GDP, measured by the natural logarithm of city GDP), education level (EDU, measured by the proportion of the population with higher education in the city), and environmental regulation (EVN, measured by the natural logarithm of urban environmental pollution control investment); and the climate control variables include average city humidity (Wet, measured by annual average humidity), average wind speed (Wind, measured by annual average wind speed), and sunshine duration (Sun, measured by annual sunshine hours).

4. Results

4.1. Descriptive statistics

Table 1 shows the results of descriptive statistics for each variable in the model. Digital transformation $Digital_1$ variable has a mean value of 47.16, a maximum value of 1264, and a minimum value of 0. The $Digital_1$ variable has a mean value of 1.051, a maximum value of 6.139, and a minimum value of 0, indicating that there is a large difference in the digital transformation between enterprises. Extreme temperature has a mean value of 35.52 days, of which the minimum value is 0, the maximum value is 172, and the standard deviation is 39.64, indicating that there is a significant difference in the degree of exposure to extreme temperatures between firms. The distribution of all other variables is within reasonable limits.

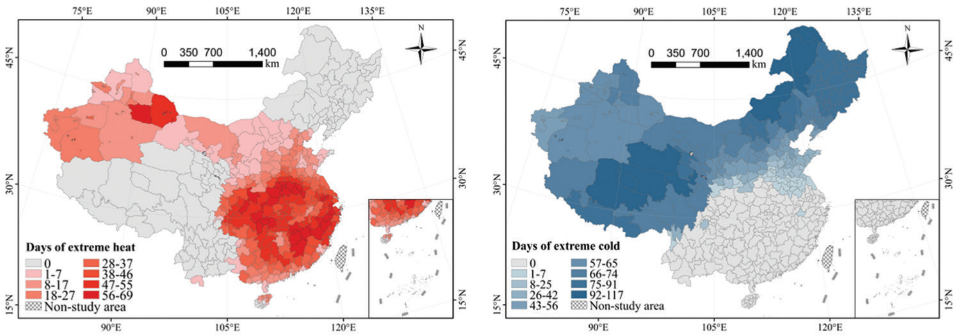

Figure 3. Distribution of extreme-high (top) and extreme-low temperatures (bottom) in prefecture-level cities in China in 2022

Table 1. Descriptive statistics

Variable name	n	Mean	SD	Min	Max
$Digital_1$	12,908	47.16	87.83	0	1264
$Digital_2$	12,908	1.051	1.24	0	6.139
Extreme	12,908	35.52	39.64	0	173
Size	12,908	21.98	1.288	19.14	26.45
Lev	12,908	0.426	0.203	0.027	0.908
ROA	12,908	0.038	0.065	-0.373	0.257
Board	12,908	2.141	0.210	1.099	2.833
ListAge	12,908	1.947	0.925	0	3.401
Indep	12,908	35.70	8.567	0	60
Dual	12,908	0.250	0.433	0	1
TOP1	12,908	35.06	15.12	8.020	75.84
BM	12,908	0.643	0.241	0.064	1.246
SOE	12,908	0.401	0.490	0	1
Big4	12,908	0.060	0.237	0	1
Opinion	12,908	0.966	0.180	0	1
IC	12,908	648.9	127.9	0	999.8
GDP	12,908	91662	56665	2093	467749
EDU	12,908	33.23	29.02	1	93
ENV	12,908	0.262	0.089	0	0.879
Wind	12,908	5.359	1.043	2.222	8.967
Wet	12,908	70.93	9.098	35.63	84.46
Sun	12,908	1935	428.5	752.4	3386

4.2. Baseline regression results

Table 2 reports the results of multiple regressions of extreme temperatures on firms' digital transformation, where industry-fixed effects and year-fixed effects are not included in columns (1) and (3). As seen from the regression results, the coefficients of the extreme temperature variables are significantly positive under all models, indicating that the frequency of extreme temperatures promotes the digital transformation of manufacturing firms, and Hypothesis 1 is basically verified. The lagged terms of extreme temperature are all significantly positive, indicating the continuity of the effect of extreme temperature on enterprise digital transformation. Company size, shareholder size, and the number of years on the market have a facilitating effect on enterprise digital transformation, which is basically consistent with existing research. Turning to the climate variables, the coefficients of the light hours and average wind speed variables are significantly positive and have a facilitating effect on enterprise digital transformation, while average humidity has an inhibitory effect.

4.3. Robustness test

To ensure the results are robust, firstly, the measure of digital transformation was replaced, drawing on Yuan *et al.*[39] and Zhao *et al.*[40] to increase the frequency of words related to digital transformation of enterprises to 99, to re-measure the degree of digital transformation of enterprises; the results are as shown in column (1) of Table 3. The extreme temperature variable is significantly positive. Second, the extreme temperature in the benchmark regression was calculated using an absolute threshold, which is simple, but also has defects.[41] To avoid the bias generated using the fixed threshold method, this study re-measured the urban extreme temperature index using the relative threshold and expanding the fixed threshold method, respectively, and carried out the test. Column (2) of Table 3 expands the range of extreme temperatures to above 30°C and below 0°C, and the results are still significant. Column (3) of Table 3 draws on Alexander *et al.*'s percentile interpolation[42] and refers to Pan and Zhai[43] to calculate the cumulative number of days of extreme temperatures using the 95% percentile of daily high temperatures and the 5% percentile of daily low temperatures, respectively, and the results showed that the extreme temperatures still have a facilitating effect on the digital transformation of enterprises. Up to this point, possible bias due to variable measurement is ruled out.

Considering the early development of digital economy in Zhejiang Province, the national leader, as well as the persistence of the role of temperature, we deleted the samples of listed companies based in Zhejiang Province, as well as lagged one period of the enterprise digital transformation variables; the results are shown in the columns (4) and (5) of Table 3. The extreme temperature variables are significantly positive at the 1% level, which further excludes the sample bias that may be generated due to the differences in time and geography.

5. Mechanistic analysis

In light of the reliable results from the baseline regression, we further tested the mechanism. According to the previous analysis, extreme temperatures promote the digital transformation of enterprises by increasing enterprise costs and reducing enterprise efficiency. To test hypothesis 2, we measured enterprise cost pressure from the perspectives of wage structure, cost growth

Table 2. Extreme temperatures and enterprise digital transformation: baseline regression

Explained variable	$Digital_1$		$Digital_2$	
	(1)	(2)	(3)	(4)
$Extreme_{j,t}$	0.043**	0.061***	0.001***	0.002***
	(0.019)	(0.021)	(0.000)	(0.001)
$Extreme_{j,t-1}$	0.039**	0.072***	0.003***	0.003***
	(0.019)	(0.020)	(0.001)	(0.001)
Size	7.403***	7.082***	0.370***	0.281***
	(0.430)	(0.466)	(0.017)	(0.019)
Lev	−2.105	1.954	−0.266***	−0.016
	(1.720)	(1.730)	(0.067)	(0.068)
ROA	2.097	−4.457	−0.099	−0.206
	(4.014)	(3.993)	(0.148)	(0.148)
Board	0.422	1.581	0.191***	0.274***
	(1.581)	(1.551)	(0.066)	(0.065)
ListAge	8.128***	1.704**	0.460***	0.073**
	(0.642)	(0.806)	(0.025)	(0.031)
Indep	−0.097**	−0.048	0.001	0.002
	(0.048)	(0.047)	(0.002)	(0.002)
Dual	0.373	0.378	0.002	−0.005
	(0.572)	(0.559)	(0.021)	(0.021)
TOP1	−0.036	−0.032	−0.004***	−0.002**
	(0.026)	(0.025)	(0.001)	(0.001)
BM	1.980**	−9.410***	−0.202***	−0.301***
	(0.992)	(1.369)	(0.038)	(0.051)
SOE	−1.368	−1.105	−0.103**	−0.059
	(1.134)	(1.118)	(0.048)	(0.048)
Big4	−0.423	−0.830	−0.129**	−0.145**
	(1.342)	(1.315)	(0.058)	(0.057)
Opinion	2.261*	1.971	0.047	0.019
	(1.329)	(1.300)	(0.055)	(0.053)
LnIC	−0.615	2.880**	−0.097**	0.023
	(1.258)	(1.251)	(0.046)	(0.046)
LnGDP	0.612	−0.545	0.160***	−0.032
	(0.700)	(0.967)	(0.029)	(0.037)
LnEDU	0.436	0.182	0.029	0.021
	(0.674)	(0.670)	(0.027)	(0.026)
LnENV	1.309	1.237	0.064	−0.271**
	(2.847)	(3.038)	(0.106)	(0.111)
$Wind_{j,t}$	−0.330	−1.572**	−0.091***	−0.084***
	(0.703)	(0.740)	(0.028)	(0.029)
$Wind_{j,t-1}$	−2.339***	−0.632	−0.034	−0.012
	(0.692)	(0.737)	(0.026)	(0.027)

(Cont'd...)

Table 2. *(Continued)*

Explained variable	**$Digital_1$**		**$Digital_2$**	
	(1)	**(2)**	**(3)**	**(4)**
$Wet_{j, t}$	0.674***	0.228**	0.021***	0.013***
	(0.086)	(0.101)	(0.003)	(0.004)
$Wet_{j, t-1}$	0.278***	0.071	0.015***	0.005
	(0.090)	(0.099)	(0.003)	(0.004)
$Sun_{j, t}$	17.308***	6.300**	0.536***	0.307**
	(2.781)	(3.125)	(0.110)	(0.120)
$Sun_{j, t-1}$	4.881*	1.278	0.244**	0.116
	(2.566)	(2.727)	(0.096)	(0.101)
Industry-fixed effects	No	Yes	No	Yes
Year-fixed effects	No	Yes	No	Yes
Observations	12,908	12,908	12,908	12,908
R-squared	0.179	0.223	0.165	0.340

Notes: Standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01.

Table 3. Extreme temperatures and enterprise digital transformation: robustness test

Explained variable: $Digital_2$	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	Replacing digital transformation	**Changing the measurement**	**Relative threshold**	**Delete Zhejiang**	**Variables lagged**
$Extreme_{j, t}$	0.009*	0.018***	0.006**	0.026***	0.030***
	(0.005)	(0.007)	(0.003)	(0.009)	(0.008)
$Extreme_{j, t-1}$	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Other climate variables	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.248	0.313	0.248	0.248	0.328

rate, *etc.*, constructed the logarithmic form of the Cobb–Douglas production function to estimate the TFP of the enterprise, and tested model (II) and the production function (III) as follows:

$$\mathrm{Digital}_{i,j,t} = \pm_0 \mathrm{Extreme}_{j,t} + \pm_1 \mathrm{Extreme}_{j,t-1} + \alpha_2 \mathrm{M} + \alpha_3 \mathrm{M} \times \mathrm{Extreme}_{j,t} + \beta_1 \mathrm{X}_{i,t} + \beta_2 \mathrm{X}'_{j,t} + \theta_0 \mathrm{W}_{j,t} + \theta_1 \mathrm{W}_{j,t-1} + \varepsilon_{i,j,t} \quad \text{(II)}$$

Where M is the mechanism variable, including: employee pay share ($Wage_1$), executive pay share ($Wage_2$), cost growth rate (Cost), and TFP (TPF_OLS, TPF_LP). If the hypothesis is valid, then high employee salary share and high cost growth rate will strengthen the effect of extreme temperature on digital transformation; on the contrary, high executive compensation share and higher TFP will weaken the effect of extreme temperature on digital transformation. We, therefore, focus on the interactivity coefficient.

$$lnY_{i,t} = \mu_0 + \mu_1 lnK_{i,t} + \mu_2 lnL_{i,t} + \mu_3 lnM_{i,t} + \varepsilon_{i,t} \quad \text{(III)}$$

Where Y represents the output of the enterprise, measured by the company's main business income for the year; K represents the level of input of capital factors, measured by the company's investment in fixed assets for the year; L represents the level of input of labor factors, measured by the company's cash flow statement for the year, "cash paid to and for employees;" and M represents the enterprise's intermediate products and raw material input, measured by the company's cash flow statement for the year, "cash paid for purchasing goods and receiving labor."

Table 4 reports the results of the mechanism tests. Among them, columns 1, 2, and 3 show results of the cost mechanism tests. The coefficient of the interaction term between employee wage share and extreme temperature is significantly positive, and the coefficient of the interaction term between cost growth rate and extreme temperature is also significantly positive, suggesting that the effect of extreme temperature on digital transformation diminishes as firms' production costs increase, while on the contrary, the coefficient of the interaction term between the share of executive compensation and extreme temperature is significantly negative, which proves, in the reverse direction, that there is a production cost mechanism. Subsequently, the measured TFP of enterprises was integrated into model (4), and the coefficient of the interaction term between TFP and extreme temperature under the two measures is significantly negative, indicating that the effect of extreme temperature on the digital transformation of enterprises attenuates with the enhancement of their production efficiency, and the production efficiency mechanism exists.

6. Further analysis

The distribution of extreme temperatures has geographical differences, and its effect on the digital transformation of enterprises may vary depending on the nature, capability, and geographical location of manufacturing enterprises, or whether the characteristics of company management, internal, and external policies of enterprises will have an impact on the digital transformation effect of extreme temperatures, which needs to be further tested and analyzed.

6.1. Heterogeneity analysis

According to the nature of ownership, the listed manufacturing enterprises were divided into SOE and private enterprises, and the results are shown in Figure 4. The sample of non-SOE is significant, which may be related to the greater cost pressure borne by private enterprises. Subsequently, manufacturing enterprises were divided into four groups according to whether they are high-tech industries and highly polluting enterprises, and the results showed that extreme temperatures have the most obvious effect on high-tech enterprises, which have stronger foundations, better technologies, more talents, *etc.*, and are more favorable to engage in digital transformation. To examine the geographical differences, the manufacturing enterprises will be divided into three groups according to the place of registration in the east, central and west China, and the results showed that the impact of extreme temperatures

Table 4. Extreme temperatures and enterprise digital transformation: mechanistic analysis

Explained variable: $Digital_2$	Cost mechanism			Efficiency mechanism	
	(1)	(2)	(3)	(4)	(5)
$Extreme_{j,t}$*$Wage_1$	0.007**				
	(0.003)				
$Extreme_{j,t}$*$Wage_2$		−0.007**			
		(0.003)			
$Extreme_{j,t}$*Cost			0.001*		
			(0.000)		
$Extreme_{j,t}$*TPF_OLS				−0.005*	
				(0.003)	
$Extreme_{j,t}$*TPF_LP					−0.005*
					(0.003)
$Extreme_{j,t-1}$	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Other climate variables	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	12,908	12,908	12,908	12,908	12,908
R-squared	0.248	0.323	0.323	0.366	0.319

Table 5. Extreme temperatures and enterprise digital transformation: moderating effects

Explained variable: $Digital_2$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Extreme_{j,t}$*TMTAge	−0.003***						
	(0.001)						
$Extreme_{j,t}$ *OverseaBack		−0.010**					
		(0.005)					
$Extreme_{j,t}$*FinBack			0.001				
			(0.004)				
$Extreme_{j,t}$*Female				−0.001			
				(0.002)			
$Extreme_{j,t}$*Tan					−0.018***		
					(0.006)		
$Extreme_{j,t}$*ESG						0.022*	
						(0.012)	
$Extreme_{j,t}$*DF							1.974***
							(0.414)
$Extreme_{j,t-1}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other climate variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,908	12,908	12,908	12,908	12,908	12,908	12,908
R-squared	0.248	0.313	0.313	0.323	0.318	0.323	0.193

on the digital transformation of enterprises is more obvious in the eastern region.

6.2. Executive team

Executive teams (TMTs) serve as the core decision-makers driving corporate conduct, positioning them as a pivotal force in organizational change and development. The heterogeneity within TMTs substantially shapes executive decision-making patterns.[44,45] As primary architects of strategic design, execution, and adaptation, TMTs critically influence the implementation of digital transformation initiatives. Notably, variations in TMT characteristics – including diversity in age, gender, educational attainment, and professional expertise – fundamentally alter cognitive frameworks and strategic choices.[46] This analysis selected variables such as average age of executives (TMTAge), percentage of female executives (Female), percentage of executives with overseas experience (OverseaBack), and percentage of executives with financial backgrounds (FinBack), and the results are shown in columns (1) to (4) of Table 5 and Figure 5A and 5B. The coefficients of the interaction terms of the average age of executives, the percentage of executives with overseas experience and extreme temperatures are all significantly negative, indicating that younger executive has a facilitating effect, while overseas study experience has a dampening effect. The proportion of female executives and the proportion of executives with financial background do not play a role.

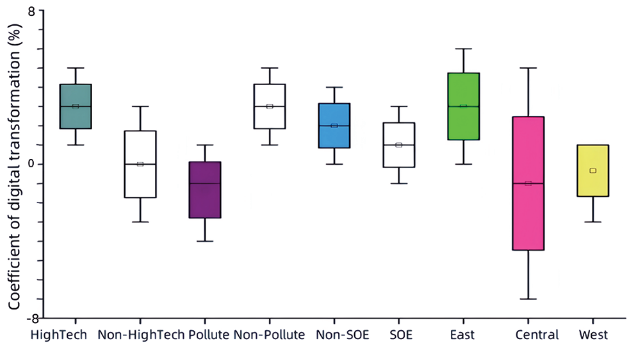

Figure 4. Heterogeneity analysis

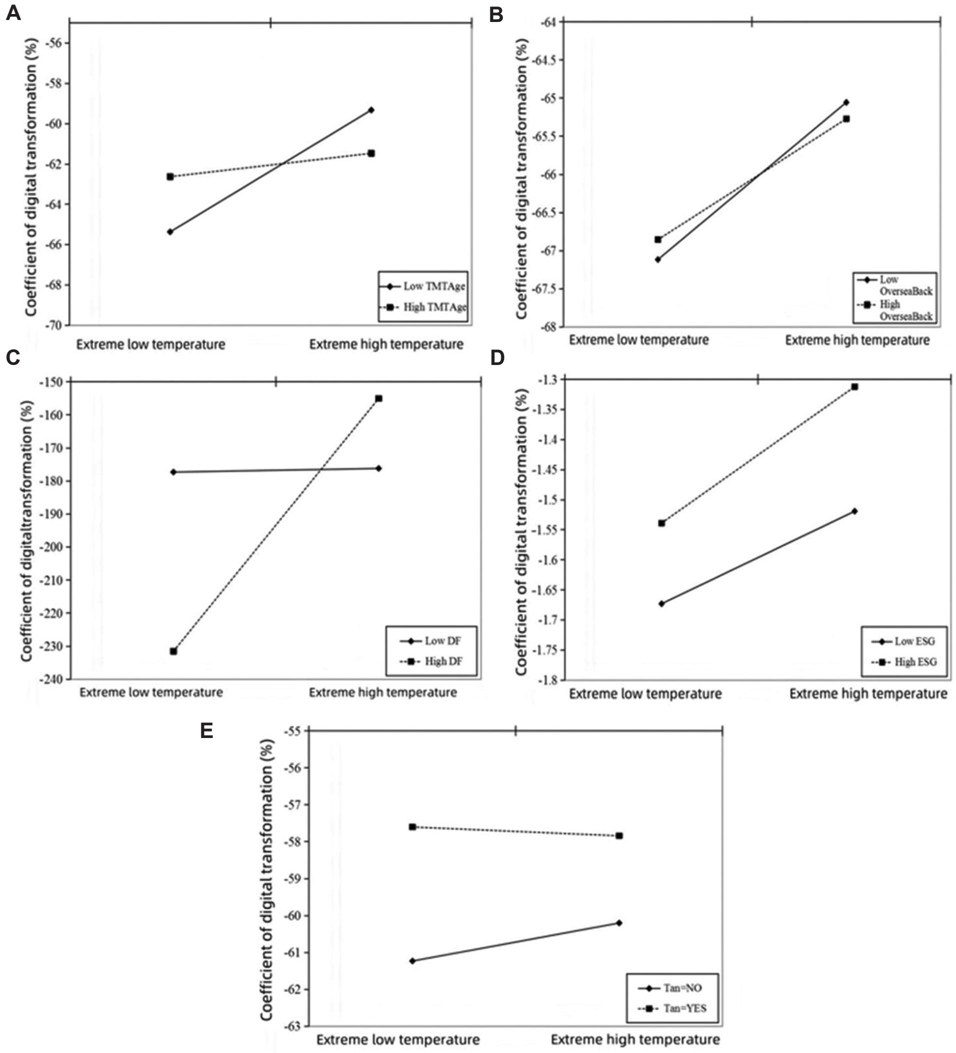

Figure 5. (A-E) Moderating effect diagram

6.3. Carbon trading policies

In the face of persistent environmental pollution and extreme weather events, carbon emissions and carbon governance have become global focal points in the environmental theme. The National Development and Reform Commission issued the implementation rules of the Notice on Carbon Emission Trading Pilot Work in October 2011, and we tested whether the implementation of this policy will, to a certain extent, slow down the pressure of carbon emissions from over-emitting manufacturing enterprises, and whether it will play a role in the digital transformation of extreme temperatures. A dummy variable is constructed to represent the carbon trading pilot (Tan), which takes the value of 1 if a province is part of the pilot region and the year is in the year of or after the launch of the pilot in that province, otherwise it takes the value of 0. The pilot consists of seven regions: Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, and Shenzhen, with Shenzhen, Shanghai, Beijing, Guangdong, and Tianjin launching in 2013, and Chongqing and Hubei launching in 2014. Column (3) of Table 5 and Figure 5E show the regression results after adding the cross-multiplier term, and the coefficient of the cross-multiplier term is significantly negative, which indicates that the carbon trading pilot policy weakens the impact of extreme temperature on the digital transformation of enterprises. A possible explanation for this is that the implementation of the carbon trading policy allows firms that have exceeded their carbon emission quotas to purchase carbon emission rights through the trading market to compensate for their excess quotas, thus releasing carbon emissions that have been restricted by the government in the context of global warming and reducing the incentive for firms to undergo digital transformation. Of course, this result is somewhat time-sensitive and requires further follow-up and testing.

6.4. Corporate environmental, social, and governance (ESG) performance

Extreme temperatures heighten public environmental awareness, compelling enterprises – particularly highly-polluting firms – to adopt sustainable practices. The ESG principles, formally advanced by the United Nations in 2004, integrate these priorities into corporate governance. Evidence confirms that ESG reduces agency costs, boosts TFP, and enhances innovation,[47] implying that it amplifies extreme temperatures' impact on digital transformation. Based on Fang and Hu's analysis,[48] we measured ESG performance using Huazheng composite ratings and constructed an ESG-extreme temperature interaction term for empirical testing. Column (4) of Table 5 and Figure 5D show that the coefficient of the interaction term is significantly positive, confirming the facilitating effect of ESG performance.

6.5. Urban digital infrastructure

Digital infrastructure construction refers to the construction of digital network infrastructure, big data, artificial intelligence and other fields, which provides strong support for development of the digital economy, smart cities and other fields, favorably contributing to economy, innovation, and environment. Urban digital infrastructure construction promotes the transformation of industrial structure,[49] improves enterprise productivity,[50] reduces the cost of innovation and creativity, enhances the innovation performance of enterprises, and effectively promotes the development of enterprise innovation activities.[51] In addition, digital infrastructure construction significantly promotes China's low-carbon economic growth and brings about technological optimization and industrial upgrading through digital transformation, which, in turn, significantly reduces power consumption and intensity, and thus achieves sustainable economic development.[52,53] It is therefore inferred that urban infrastructure development can enhance the impact of extreme temperatures on the digital transformation of enterprises. To this end, we measured and examined the level of digital infrastructure development (DF) in cities, in reference to Zhang and Fu.[52] Column (7) of Table 5 and Figure 5C show that the coefficient of the interaction term between extreme temperature and digital infrastructure is significantly positive, and the hypothesis is valid that urban digital infrastructure development facilitates the role of extreme temperature on firms' digital transformation. Of course, this result is somewhat time-sensitive and requires further follow-up and testing.

7. Discussion

Our findings revealed that extreme temperature shocks serve as a significant catalyst for digital transformation in China's manufacturing sector, corroborating the growing literature on climate-induced technological adaptation.[11] Recent empirical evidence from Chinese manufacturing firms also demonstrated that persistent heat waves accelerate digital transformation through performance-driven mechanisms.[3] The positive relationship persists across robustness tests, suggesting that manufacturing firms perceive digital transformation as a strategic response to climate disruptions rather than a temporary adjustment, consistent with the climate-economic complexity framework where firms reconfigure global supply chains to mitigate long-term economic risks.[1] This aligns with the organizational resilience theory, where environmental shocks accelerate innovation adoption as firms seek to mitigate operational vulnerabilities through digital technologies that resolve climate-induced efficiency-cost dilemmas,[3] a pathway further reinforced by China's national policy mandating digital-green synergies in manufacturing.[54]

The identified mechanisms – production cost escalation and efficiency reduction – provide empirical support for the "climate pressure-innovation" hypothesis, as demonstrated in Chinese manufacturing contexts where temperature anomalies amplify operational costs due to energy inefficiency and labor productivity loss.[5] As extreme temperatures disrupt traditional production processes, firms appear to compensate by investing in digital technologies that enhance operational flexibility and resource optimization, reflecting a proactive adaptation strategy that strengthens global value chain resilience. This finding extends the win-win hypothesis by demonstrating that environmental pressures specifically drive digital innovation rather than conventional eco-innovation, a distinction critical for designing climate-technology policies that leverage digital infrastructure.[7]

The heterogeneity results offer important nuances. The stronger effect observed in private enterprises and high-tech firms may reflect their greater operational flexibility and innovation capacity compared to SOE. The regional disparity, with more pronounced effects in eastern China, likely stems from better digital infrastructure and greater climate risk exposure in coastal areas. Surprisingly, the moderating effect of carbon trading policies suggests potential policy interference, where market-based climate instruments may inadvertently reduce firms' urgency for digital adaptation – a phenomenon warranting further investigation.

These findings carry important implications for both managers and policymakers. For firms, they highlight digital transformation as a viable strategy for climate risk mitigation, particularly when combined with ESG disclosure and leadership renewal. For policymakers, the results suggest that digital infrastructure development can amplify climate adaptation benefits.

Future research should explore: (i) long-term performance differences between climate-driven versus strategy-driven digital transformation, (ii) potential rebound effects where digital gains offset by increased energy use, and (iii) cross-country comparisons to assess institutional moderators. In addition, qualitative studies could uncover the decision-making processes behind climate-induced digital investments.

8. Conclusion and recommendations

8.1. Conclusion

This study utilized data from A-share listed manufacturing companies from 2011 to 2022 to study the drivers of digital transformation and the role of extreme temperatures. We found that the geographic element of extreme temperatures has a significant role in driving the digital transformation of enterprises, and the cities with frequent extreme temperatures are located in cities where the digital transformation level of manufacturing enterprises is relatively high, *that is*, manufacturing enterprises will respond to extreme temperature events through digital transformation. In terms of the impact mechanism, extreme temperatures increase the production cost and reduce the productivity of manufacturing enterprises, especially TFP, which, in turn, promotes the digital transformation of enterprises. Heterogeneity analysis found that the effect of extreme temperatures on the digital transformation of manufacturing enterprises is more significant in private enterprises, high-tech enterprises and non-highly-polluting enterprises, and geographically the promotion effect is greater in the eastern region. Finally, the moderating effects were tested, and corporate ESG disclosure, younger executive, and digital infrastructure construction have positive moderating effects, while the implementation of carbon trading policy somewhat weakens the digital transformation effect of extreme temperatures.

The findings presented in this paper theoretically enrich the research related to the drivers of corporate digital transformation and the role of extreme temperatures and provide new ideas on how companies can cope with the impact of extreme temperatures and implement digital transformation.

8.2. Recommendations

Several recommendations from this study are as follows:

- Prioritize Internet of Things and AI-driven digital solutions in high-temperature regions to directly counter production cost increases and TFP losses
- Establish cross-ownership alliances with private/hi-tech firms to leverage their demonstrated responsiveness to climate shocks
- Integrate climate-specific digital metrics into ESG disclosures
- Appoint executives under 45 with technical backgrounds to lead transformation initiatives
- Accelerate the convergence of 5G and the industrial internet in the central and western regions to improve digital infrastructure, targeting provinces with high temperature extremes
- Provide tiered subsidies for businesses in hot cities to replicate climate resilience enhancements in the east
- Reform carbon trading mechanisms to allow digital transformation investments to be used as carbon credit to offset the policy disincentives.

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Conflict of interest

At the time of writing this manuscript, Ruling Ma was employed by Hongta Group Yuxi Cigarette Factory, but the company/employer did not play any roles in the study design and writing of the manuscript. No reference to the author's company is made.

Author contributions

Conceptualization: Huan Wang, Ying Ren
Formal analysis: Huan Wang, Dashuai Gao
Investigation: Dashuai Gao, Juping Wu, Ruiling Ma
Methodology: Huan Wang, Juping Wu
Writing–original draft: Huan Wang, Juping Wu, Ying Ren
Writing–review & editing: Dashuai Gao, Juping Wu, Ruiling Ma

Availability of data

The data used in the research for this paper are publicly available. Public company data were obtained from CSMAR (https://data.csmar.com/); weather data from the CMA database; and municipal level control variables from the City Statistical Yearbook (https://www.stats.gov.cn/).

References

1. KotzM, LevermannA, WenzL. The economic commitment of climate change. *Nature*. 2024;628(8008):551-557. doi: 10.1038/s41586-024-07219-0
2. Dell M, Jones BF, Olken BA. Temperature and income: Reconciling new cross-sectional and panel estimates. *Am Econ Rev*. 2012;102(3):923-937. doi: 10.1257/aer.99.2.198
3. Stott P. Climate change. How climate change affects extreme weather events. *Science*. 2016; 352(6293):1517-1518. doi: 10.1126/science.aaf7271
4. Barnes EA. Revisiting the evidence linking Arctic amplification to extreme weather in midlatitudes. *Geophys Res Lett*. 2013;40(17):4734-4739. doi: 10.1002/grl.50880
5. Schlenker W, Roberts MJ. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proc Natl Acad Sci U S A*. 2009;106(37):15594-15598. doi: 10.1073/pnas.0906865106
6. Chen S, Chen X, Xu J. Impacts of climate change on agriculture: Evidence from China. *J Environ Econ Manag*. 2016;76:105-124. doi: 10.1016/j.jeem.2015.12.003
7. Hsiang SM. Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proc Natl Acad Sci U S A*. 2010;107(35):15367-15372. doi: 10.1073/pnas.1009510107
8. Zhang P, Deschenes O, Meng K, Zhang J. Temperature effects on productivityand factor reallocation: Evidence from half a million Chinese manufacturing plants. *J Environ Econ Manag*. 2018;88:1-17. doi: 10.1016/j.jeem.2017.11.001
9. Yang L, Shi J, Chen X. The impact of temperature changes on China's industrial production and its mechanism analysis. *Chin Econ Q*. 2020;20(5):299-320.
10. Challinor AJ, Watson J, Lobell DB, Howden SM, Smith DR, Chhetri N. A meta-analysis of crop yield under climate change and adaptation. *Nat Clim Chang*. 2014;4(4):287-291. doi: 10.1038/nclimate2153
11. IPCC. *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report. "Key Risks Across Sectors and Regions*". Ch. 16. United States: IPCC; 2022.
12. Deryugina T, Hsiang SM. *Does the Environment Still Matter? Daily Temperature and Income in the United States National Bureau of Economic Research 2014*. (Working Paper No. 20750). 2014. doi: 10.3386/w20750
13. Weibing L, Siyuan C. On whether temperature change affects the location of enterprises with enterprise-level micro data based on emission peak and carbon neutrality. *Jinan J*. 2023;45(11):114-132. doi: 10.11778/j.jnxb.20231110
14. Tang W, Yang M, Duan H. Temperature and corporate tax avoidance: Evidence from Chinese manufacturing firms. *Energy Econ*. 2023;117:106456. doi: 10.1016/j.eneco.2022.106456
15. Kahn ME, Zhao D. The impact of climate change skepticism on adaptation in a market economy. *Res Econ*. 2018;72(2):251-262. doi: 10.1016/j.rie.2017.12.001
16. Kjellstrom T, Briggs D, Freyberg C, Lemke B, Otto M, Hyatt O. Heat, humanperformance, and occupational health: A key issue for the assessment of globalclimate change impacts. *Annu Rev Public Health*. 2016;37(1):97-112. doi: 10.1146/annurev-publhealth-032315-021740
17. Zhang J, Yang S, Suo C. Experimental study on the physiological and psychological effects of high-temperature and high-humidity environments on miners. *Chin Saf Sci J*. 2015;(1):23-28.
18. Somanathan E, Somanathan R, Sudarshan A, Tewari M. The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *J Polit Econ*. 2021;129(6):1797-1827. doi: 10.1086/715239
19. Pankratz N, Bauer R, Derwall J. Climate change, firm performance, and investor surprises. *Electron J*. 2023;69(12):7352–7398. doi: 10.2139/ssrn.3437178
20. Yu Y, Huang J, Zhou T. The impact of extreme temperature on labor wage: Evidence from Chinese manufacturing firms. *Glob Environ Chang*. 2023;83:102768.

doi: 10.1016/j.gloenvcha.2023.102768

21. Acevedo S, Mrkaic M, Novta N, Pugacheva E, Topalova P. The effect of weather shocks on economic activity: What are the channels of impact? *J Macroecon*. 2020;65:103207.
doi: 10.1016/j.jmacro.2020.103207
22. Feng S, Krueger AB, Oppenheimer M. Linkages among climate change, crop yields, and Mexico-US cross-border migration. *Proc Natl Acad Sci*. 2010;107(32):14257-14262.
doi: 10.1073/pnas.1002632107
23. Feng S, Oppenheimer M, Schlenker W. *Weather Anomalies, Crop Yields, and Migration in the US Corn Belt National Bureau of Economic Research*. (NBER Working Paper No. 17734); 2015.
doi: 10.3386/w17734
24. Gray CL, Mueller V. Natural disasters and population mobility in Bangladesh. *Proc Nat Acad Sci*. 2012;109(16):6000-6005.
doi: 10.1073/pnas.1115944109
25. Dasgupta S, Van Maanen N, Gosling SN, Piontek F, Otto C, Schleussner CF. Effects of climate change on combined labour productivity and supply: An empirical, multi-model study. *Lancet Planet Health*. 2021;5(7):e455-e465.
doi: 10.1016/S2542-5196(21)00170-4
26. Diffenbaugh NS, Burke M. Global warming has increased global economic inequality. *Proc Natl Acad Sci*. 2019;116(20):9808-9813.
doi: 10.1073/pnas.1816020116
27. Burke M, Dykema J, Lobell DB, Miguel E, Satyanath S. Incorporating climateuncertainty into estimates of climate change impacts. *Rev Econ Stat*. 2015;9(2):461-471.
doi: 10.1162/REST_a_00462
28. Letta M, Tol RSJ. Weather, climate, and total factor productivity. *Environ Resour Econ*. 2019;73(1):283-305.
doi: 10.1007/s10640-018-0268-2
29. Zivin JG, Hsiang SM, Neidell M. Temperature and human capital in the short and long run. *J Assoc Environ Resour Econ*. 2018;5(1):77-105.
doi: 10.1086/694177
30. Deschenes O, Moretti E. Extreme weather events, mortality, and migration. *RevEcon Stat*. 2009,91(4):659-681.
doi: 10.1162/rest.91.4.659
31. Warnken J, Bradley M, Guilding C. Exploring methods and practicalities of conducting sector-wide energy consumption accounting in the tourist accommodation industry. *Ecol Econ*. 2004;48(1):125-141.
doi: 10.1016/j.ecolecon.2003.09.008
32. Zhang C, Liao H, Mi Z. Climate impacts: Temperature and electricity consumption. *Nat Hazard*. 2019;99(3):1259-1275.
doi: 10.1007/s11069-019-03676-3
33. Wu X, Miao Q, Gu X, Wang J w, Liu W, Li L. Analysis of the impact of climate change on industry and energy in the Yangtze River Delta region. *J Nanjing Univ Inform Sci Technol*. 1999;(S1):541-546.
doi: 10.13878/j.cnki.dqkxxb.1999.s1.014
34. Addoum JM, Ng DT, Ortiz-Bobea A. Temperature shocks and establishment sales. *Rev Fin Stud*. 2020;33(3):1331-1366.
doi: 10.1093/rfs/hhz127
35. Brauner P, Dalibor M, Jarke M, *et al*. A computer science perspective on digital transformation in production. *ACM Trans Int Things*. 2022;3(2):1-32.
doi: 10.1145/3505256
36. Zhang Y, Shi Z, Shi Y, Chen J. Enterprise digital transformation and production efficiency: Mechanism analysis and empirical research. *Econ Res J*. 2022;35(1):2781-2792.
doi: 10.1080/1331677X.2021.1980731
37. WU F, Hu H, Lin H, Ren X. Enterprise digital transformation and capital market performance: Empirical evidence from stock liquidity. *J Manag World*. 2021;37(7):130-144.
doi: 10.19744/j.cnki.11-1235/f.2021.0097
38. Wang H, Yan Z, Guo G, Zhang T, Liu Z, Chen M. Digital infrastructure policy and enterprise digital transformation: Empowerment or "Burden"? *J Quant Technol Econ*. 2023;40(5):5-23.
doi: 10.13653/j.cnki.jqte.20230314.002
39. Yuan C, Xiao SS, Geng CX. Digital transformation and enterprise division of labor: Specialization or vertical integration? *China Ind Econ.* 2021;(9):137-155.
doi: 10.19581/j.cnki.ciejournal.2021.09.007
40. Zhao C, Wang W, Li X. How does digital transformation affect total factor productivity of enterprises? *Fin Trade Econ*. 2021;42(7):114-129.
doi: 10.19795/j.cnki.cn11-1166/f.20210705.001
41. Zhou Y, Ren G. Change in extreme temperature event frequency over Chinese mainland, 1961-2008. *Clim Res*. 2011;50(2-3):125-139.
doi: 10.3354/cr01053
42. Alexander LV, Zhang X, Peterson TC, *et al*. Global observed changes in dailyclimate extremes of temperature and precipitation. *J Geophys Res Atmos*. 2006;111(D5):D05109.
doi: 10.1029/2005JD006290
43. Pan X, Zhai P. Selection and analysis of extreme temperature values. *Meteorology.* 2002;28(10):28-31.
44. Song J, Chen J. Exploring dimensions and developing scales for service capabilities of manufacturing enterprises under the WSR framework. *Manag Rev*. 2021;33(5):87-96.
45. Verhoef PC, Broekhuizen T, Bart Y, *et al*. Digital transformation: A multidisciplinary reflection and research Agenda. *J Bus Res*. 2019;12(1):35-83.
doi: 10.1016/j.jbusres.2019.09.022
46. Wu Y, Ding L, Song X, Chen J. Top management team

heterogeneity and performance of cross-border M&A. *SAGE Open*. 2023;13(2):1-21. doi: 10.1177/215824402311775
47. Li J, Yang Z, Chen J, Cui W. Research on the mechanism of ESG promotingcorporate performance: Based on the perspective of corporate innovation. *Sci Sci Technol Manag*. 2021;42(9):71-89.
48. Fang X, Hu D. Corporate ESG performance and innovation: Evidence from A-share listed companies. *Econ Res J*. 2023;58(2):91-106.
49. Ma Q, He L, Yuan E. New infrastructure construction and urban industrial structure upgrading: A quasi-natural experiment based on the "Broadband China" pilot. *Fin Econ Sci*. 2021;(4):76-90.
50. Guo J, Guo M, Guo S. How does digital infrastructure construction affect totalfactor productivity of enterprises? A quasi-natural experiment based on the "Broadband China" strategy. *Secur Market Herald*. 2021;(6):13-23.
51. Xu Y, Liu Y. Digital infrastructure construction and enterprise technological innovation: Empirical evidence from the "Broadband China" demonstration city policy. *J Nanjing Univ Fin Econ*. 2022;(4):77-87.
52. Zhang J, Fu K. Can information network infrastructure construction drive urbaninnovation? A quasi-natural experiment based on the "Broadband China" strategy pilot. *Ind Econ Res*. 2021;19(5):1-14.
53. Wang Q, Hu A, Tian Z. Digital transformation and electricity consumption: Evidence from the Broadband China pilot policy. *Energy Econ*. 2022;115:106346. doi: 10.1016/j.eneco.2022.106346
54. Ministry of Industry and Information Technology. *Guiding Opinions on Accelerating Green Development of Manufacturing Industry*; 2024. Available from: https://www.gov.cn/zhengce/zhengceku/202401/content_6923456.htm [Last accessed on 2025 May 30].