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"Climateflation" in China: Could Rising Temperatures Overheat the Economy?

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Abstract

This study examined the inflationary effects of rising temperatures by linking monthly climate variables with consumer price data for 30 large- and medium-sized Chinese cities from January 2004 to December 2019. Lagged one-period temperature had a significant positive effect on current-month price changes. The cumulative estimates indicated that each 1 °C increase during the sample period was associated with a 0.057 percent rise in prices, implying that temperature shocks contributed to consumer price inflation. Mechanism tests showed that higher temperatures reduced output growth and raised production costs, and that greater economic policy uncertainty amplified these effects. When different temperature bins were used as explanatory variables, prices increased linearly with temperatures up to 25–30 °C, then declined at higher temperatures. Temperature effects were stronger in poorer or cooler regions. The findings suggest the need to strengthen monetary policy responses, expand mitigation efforts, and develop climate-adaptive urban systems.

Keywords: climateflation, cumulative estimates, lagged effect, temperature shocks
JEL codes: C51, E31, Q54

I. Introduction

The effects of climate change on human society are becoming increasingly evident with intensifying global warming, generating economic and social uncertainty that is attracting widespread international concern. According to the State of the Global Climate 2022 Report published by the World Meteorological Organization (WMO), the global average surface

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temperature in 2022 was recorded at 1.15 ℃ above the levels observed during the pre-industrial era (1850–1900), and this trend is continuing.

Climate change can entail changes in resource utilization, environmental capacity, and consumption, affecting the industrial layout and operational safety of multiple sectors through the industrial chain. Climate risks have gradually become some of the main risks affecting socioeconomic development (Dutta et al., 2023; Ginglinger and Moreau, 2023) and primarily encompass physical risks and transition risks (Task Force on Climate-related Financial Disclosures, 2017). Physical risks pertain to the potential for direct damage to economic activity caused by climate change or extreme weather events, whereas transition risks arise from government adjustments to emission reduction policies, technological upgrades, and related measures. Drawing on the documented impacts of climate change on agriculture (Chen et al., 2016; World Bank, 2022), industry (Zhang et al., 2018; Chen and Yang, 2019), and business operations (Huang et al., 2018; Javadi and Masum, 2021), climate change can affect inflation significantly. Higher temperatures result in prolonged increases in food and headline inflation over a 12-month period, affecting both high- and low-income countries (Kotz et al., 2024). These price increases challenge inflation-targeting efforts, and the global economy is closely monitoring the implications of climate warming for financial stability (Faccia et al., 2021; Mukherjee and Ouattara, 2021).

The inflationary effects of climate change are anticipated to be particularly pronounced in China. The country's regional warming rate has exceeded the global average significantly during the same timeframe, making it one of the most vulnerable areas affected by global climate change. From 1951 to 2021, China's average annual surface temperature exhibited a clear upward trend, with a warming rate of 0.26 ℃ per decade – well above the global average of 0.15 ℃ per decade (China Meteorological Administration, 2022). As warming in China continues to exceed the global average, the risks associated with climate-induced inflation intensify.

To investigate this, this study considered 30 large- and medium-sized cities in China, constructed a panel dataset from January 2004 to December 2019, and applied a multidimensional fixed effects model to evaluate the inflationary effects of rising temperatures. The marginal effects of average temperature changes, abnormal temperature changes, and temperature bins on price fluctuations were estimated based on monthly city-level data. The main conclusions of this study are as follows. First, the one-period lagged temperature had a notably positive influence on price changes in the current month, with its cumulative effect leading to a price increase of 0.057 percent. Mechanism analysis showed that rising temperatures reduced output growth and increased production costs, and that greater economic policy uncertainty amplified these effects. Second, decomposing consumer prices into subcategories indicated that only food prices were affected. Using multiple temperature bins as independent variables, prices increased linearly with rising temperatures up to 25–30 ℃, then declined at higher levels. Elevated temperatures also had stronger effects in poorer or low-temperature regions compared to wealthier or high-temperature areas, suggesting that wealthier or warmer areas had taken more effective adaptation measures.

This study extends previous research in three directions. First, this study provides a systematic assessment of the temperature effects on inflationary pressures and explores the transmission channels from the perspectives of output effects, cost effects, and policy uncertainty effects. A thorough empirical analysis of the marginal effects of average temperature, abnormal temperature, and temperature bins was conducted. Although prior research has examined the impact of climate change on agriculture (Chen et al., 2016; World Bank, 2022), industry (Zhang et al., 2018; Chen and Yang, 2019), and business operations (Huang et al., 2018; Javadi and Masum, 2021), limited attention has been given to how gradual temperature changes, distinct from the immediate effects of natural disasters, influence price dynamics (Mukherjee and Ouattara, 2021; Semenova, 2024). Studies on the inflationary effects of natural disasters (Ubilava and Holt, 2013; Heinen et al., 2019; Abril Salcedo et al., 2020) are less relevant for understanding these persistent and subtle climate-induced impacts.

Second, this study advances the existing body of research on factors influencing inflation by examining it through the lens of climate physical risks. Previous research explained inflation from various perspectives, such as commodity prices (Kamber and Wong, 2020; Garratt and Petrella, 2022), the output gap (Kuttner and Robinson, 2010), expectations (Siklos et al., 2019), and monetary policy (Gilchrist et al., 2017). However, utilizing monthly data from Chinese cities, this study demonstrates that temperature shocks can contribute to rising prices, enhancing the understanding of "climateflation" in China. The findings indicate that climate-induced price increases can challenge monetary policy formulation. Conventional tools, such as interest rate hikes, target demand-side inflation and are less effective against climate shocks. Persistent tightening may increase the cost of green investments, worsening inflation (Jackson, 2024). Central banks should therefore incorporate climate-related variables, including temperature shocks, into economic assessments and forecasting models (Mukherjee and Ouattara, 2021).

Third, this study confirms the existence of "climateflation" in China, considering both urban climatic and economic conditions. Higher temperatures had a more pronounced impact on price increases in poorer or cooler regions than in wealthier or warmer areas, suggesting that adaptation measures may have been implemented in more affluent and warmer regions. The advantages of capital accumulation, industrial structure, policy efficiency, and market integration in rich/warmer regions have enabled them to form an "adaptive buffer mechanism" against high temperatures. In contrast, due to the lack of these conditions, the prices in poorer/cooler regions are more vulnerable to the shocks of high temperatures. This phenomenon also validates the hypothesis of "climate inequality" in economics. These findings carry important implications for the design of urban climate adaptation strategies (Hettiarachchi et al., 2022; Yari et al., 2024). Although the policy implications are based on China’s experience, they are relevant to other countries.

This paper is organized as follows. Section II provides a comprehensive literature review, summarizing existing research on the economic impacts of climate-related shocks. Section III outlines the data sources and empirical model specifications used in this study. Section IV presents the empirical findings, including benchmark results, robustness checks, mechanism analyses, and heterogeneity assessments based on commodity types, temperature ranges, and climate adaptation strategies. Finally, Section V concludes with a discussion of key insights and policy implications derived from the research.

II. Literature review

The existing literature on climate change impacts has focused primarily on the effects of high temperatures on the agricultural sector, which is particularly sensitive to climate variations. Previous studies have shown that global warming reduced agricultural output and food product yields significantly in various countries (Zhang et al., 2017; Chambers and Pieralli, 2020; Cui, 2020). The China Country Climate and Development Report indicates that, by 2030, rising temperatures will reduce the yields of China’s three major crops by 8 percent (World Bank, 2022). Compared with agriculture, research on the effects of climate change on industry has largely focused on macro-level analyses, with limited empirical investigation at the micro level (Dell et al., 2012). Zhang et al. (2018) found an inverted U-shaped relationship between temperature changes and industrial production in China. From an international trade perspective, Li et al. (2015), Dallmann (2019), and Ouyang et al. (2026) argued that higher temperature fluctuations in either exporting countries or their trading partners led to a decrease in overall bilateral trade.

Previous studies have shown that climate physical risks can adversely affect business performance. First, climate change has increased the frequency and intensity of extreme weather events, which reduce the value of corporate assets, including properties, plants, and equipment, and impair overall financial performance (Pinkse and Gasbarro, 2019; Ozkan et al., 2023; Pankratz et al., 2023). Second, Zhang et al. (2018), Letta et al. (2019), and Ding et al. (2021) found that climate change risks, represented by elevated temperatures, can significantly reduce the total factor productivity of enterprises. Finally, climate risks can lead to stricter loan terms, increasing the cost and difficulty of financing for businesses (Javadi and Masum, 2021; Kling et al., 2021; Huang et al., 2022). Overall, climate-related risks exert negative effects on business operations.

Given these sectoral impacts, climate change is likely to play a significant role in influencing inflation. Global warming can reduce agricultural yields, leading to higher food prices, which directly contribute to inflation (Chen et al., 2016; World Bank, 2022). Food consumption constitutes a major component of household consumption. Fluctuations in food prices can influence the consumer price index (CPI) significantly. The positive correlation between elevated temperatures and food prices increases household living costs, ultimately raising overall inflation. Over the past two decades, food price movements have closely mirrored CPI trends, although food prices generally fluctuated more widely than the CPI (Cook and Gale, 2019). Rising temperatures can also reduce industrial productivity, particularly beyond certain thresholds, increasing production costs and exerting upward pressure on prices (Chen and Yang, 2019). Physical risks associated with climate change, including extreme weather events, can also cause significant damage to assets and disrupt supply chains, while financial risks like stricter loan terms raise business costs – both of which are passed on to consumers, further driving inflation (Huang et al., 2018; Javadi and Masum, 2021).

The academic community has long been concerned with climate change impacts on industries and businesses; however, research on its effects on prices and inflation remains limited. Some studies have examined the relationship between natural disasters and prices. Ubilava and Holt (2013) and Abril Salcedo et al. (2020) analyzed the dynamic effects of the El Niño and Southern Oscillation events on the price levels of major food commodities. Heinen et al. (2019) discovered that flooding and hurricane-related shocks significantly influenced inflation across 15 Caribbean nations. Natural disasters typically produce sudden, short-term effects, whereas temperature changes are gradual and persistent. Accordingly, it is reasonable to study the effects of rising temperatures independently from those of natural disasters (Mukherjee and Ouattara, 2021; Semenova, 2024). Nonetheless, research on the price effects of rising temperatures is still relatively scarce.

Climate change risks have regional characteristics, and underdeveloped regions have greater sensitivity to climate change than economically developed regions (Dell et al., 2012). There has long been a notable disparity in temperature between the northern and southern regions of China. Against the background of global warming, cities in the south and north of China may exhibit different climate adaptation behaviors. In particular, cities in the south, which have historically experienced more frequent high temperatures, are very likely to exhibit stronger adaptability (Chen et al., 2023).

III. Data and econometric specification

1. Data

Urban populations constitute over half of the global population, and urban energy consumption and greenhouse gas emissions represent three-quarters of the global totals. Urban activities are both a major driver of climate change and a central focus for strategies to mitigate climate impacts and promote low-carbon development (Mi et al., 2019). The current study used monthly CPI and climate data for 30 large- and medium-sized cities from January 2004 to December 2019 to quantitatively assess the effects of rising temperatures on price changes.[1]

The variation in the logarithm of monthly CPI was constructed using data from China's Economy Prediction System (EPS) database. The CPI captures fluctuations in the prices of goods and services purchased by consumers. Goods were classified into eight categories: (i) food, (ii) tobacco, alcohol, and articles, (iii) clothing, (iv) household facilities, articles, and services, (v) health care and personal articles, (vi) transportation and communication, (vii) entertainment, education, culture articles and services, and (viii) residence. Monthly meteorological data for the 30 cities, including average temperature, precipitation, average relative humidity, and sunshine hours, were obtained from the China Meteorological Data Service Centre (CMDSC).

Table 1 presents the variables used in this study, and Table A1 in the Appendix presents the descriptive statistics of the key variables. From 2004 to 2019, the average monthly price change was 0.162 percent, corresponding to an average annual change of 1.8 percent.[2] Changes in food prices were more volatile and substantially higher than those of the other seven categories. For climate variables (except precipitation), the means were large relative to their variation, indicating that climate conditions were relatively stable. Table A2 in the Appendix provides summary statistics by time period and region.

Table 1. Descriptions of variables

Variable	Description	Data sources
$\Delta \ln cpi$	The logarithmic difference of the CPI (%)	EPS database
Tem	Average temperature (°C)	CMDSC
Pre	Precipitation (mm)	CMDSC
Sun	Sunshine hours (hour)	CMDSC
Hum	Average relative humidity (%)	CMDSC
L1.*Tem*	One-month lagged temperature	CMDSC
L2.*Tem*	Two-month lagged temperature	CMDSC
Abtem	Abnormal temperatures	CMDSC
IND	Industrial output growth	EPS database
AGR	Agricultural output growth	EPS database
PPPI	Industrial producer purchase price index	EPS database
PEPI	Industrial producer ex-factory price index	EPS database
EPU	Economic policy uncertainty index	EPU index
d_{rich}	Rich region dummy (rich = 1, poor = 0)	EPS database
$d_{high\text{-}tem}$	High-temperature region dummy (high temperature = 1, low temperature = 0)	CMDSC

Note: CMDSC, China Meteorological Data Service Centre; CPI, consumer price index; EPS, China's Economy Prediction System; EPU, Economic policy uncertainty.

[1]The 30 large- and medium-sized cities covered in this study include: Beijing, Changchun, Changsha, Chengdu, Chongqing, Fuzhou, Guangzhou, Guiyang, Haikou, Hangzhou, Harbin, Hefei, Hohhot, Jinan, Kunming, Lanzhou, Nanchang, Nanjing, Nanning, Shanghai, Shenyang, Shijiazhuang, Taiyuan, Tianjin, Urumqi, Wuhan, Xi'an, Xining, Yinchuan, and Zhengzhou.

[2]In the subsequent empirical analysis, the difference in logarithmic values is multiplied by 100.

2. Econometric specification

The inflationary effects of rising temperatures were evaluated based on the random fluctuations in temperature over time. To account for concurrent variations in other climatic factors, precipitation, average relative humidity, and sunshine hours were included as additional climate variables. The impact of climate change on price changes may not be immediate, as time lags may arise from physical processes (e.g., production cycles), buffer mechanisms (e.g., inventory), decision lags (e.g., enterprise adjustments), or data characteristics (e.g., cumulative effects) (Chen and Yang, 2019; Heinen et al., 2019; Chandio et al., 2020; Mukherjee and Ouattara, 2021; Zouabi and Dimou, 2025). Analyzing lagged effects of temperature shocks often provides a more accurate representation of causal relationships than focusing solely on current-period effects. The dynamic effect model was specified as follows:

$$\Delta \ln cpi_{itm} = \sum_{s=0}^{s} \alpha_s^T Tem_{itm-s} + \sum_{s=0}^{s} \alpha_s^W \boldsymbol{W}_{itm-s} + \mu_{it} + \gamma_{im} + \delta_{tm} + \varepsilon_{itm}, \tag{1}$$

where cities are indexed by i, years are indexed by t, months within the year are indexed by m, and s denotes the lag order. For city i at month m of year t, $\Delta\ln cpi$ indicates the difference in log CPI, and Tem is the average temperature. The sum of precipitation, average relative humidity, and sunshine hours were incorporated and represented by $\boldsymbol{W}_{itm}$. The lagged values of climate variables were also included to examine whether price changes in month m were influenced by climate variations in previous months. μ_{it} denotes city–year fixed effects, which account for annual shocks that are city specific, such as urban public policies. γ_{im} denotes city–month fixed effects, and was used to capture month-specific shocks within a given city, such as monthly urban events and input prices. Month–year fixed effects δ_{tm} was incorporated to allow for all the time-varying factors affecting consumer prices that are common across cities. ε_{itm} represents the error term. Standard errors were clustered at the city level to address potential autocorrelation within each individual city.

Following Hu and Li (2019) and Zivin et al. (2020), the temperature variables were defined as a vector comprising several temperature bins, as illustrated in Equation (2):

$$\Delta \ln cpi_{itm} = \sum_{s=0}^{s} \beta_s^T Tbin_{itm-s}^T + \sum_{s=0}^{s} \beta_s^W \boldsymbol{W}_{itm-s} + \mu_{it} + \gamma_{im} + \delta_{tm} + \varepsilon_{itm}, \tag{2}$$

where $Tbin^T$ denotes a dummy variable indicating whether monthly average temperatures fall within the Tth temperature bin. The monthly average temperatures were categorized into seven distinct intervals, each spanning 5 °C in range. $Tbin^1 = 1$ when the monthly average temperature was below 0 °C, $Tbin^2 = 1$ when it fell within the interval [0, 5) °C, and so forth. To avoid multicollinearity, the temperature bin below 0 °C was used as the reference category. Estimates for the remaining temperature intervals measure the marginal impact on price changes associated with an additional month in the Tth bin, relative to a month characterized by an average temperature below 0 °C. Additional climate variables and the three types of interactive fixed effects included in Equation (2) were defined consistently with Equation (1).

To investigate whether the estimated temperature effect varied across different types of cities during the sample period, the heterogeneity analyses were divided into two categories – economic status and climatic conditions – and a set of dummy variables was constructed. If a city had above-median average per capita GDP over the period 1999–2003, it was classified as belonging to the relatively highly developed region (the rich region). If the city had above-median average temperature over the period 1999–2003, it was classified as belonging to the high-temperature group. All regressions implemented Equation (3) and controlled for additional climate variables and the three types of interactive fixed effects:

$$\begin{aligned}\Delta \ln cpi_{itm} = {} & \sum\nolimits_{s=0}^{s} \theta_s^T Tem_{itm-s} + \sum\nolimits_{s=0}^{s} \theta_s^v Tem_{itm-s} \boldsymbol{d}_{feature} \\ & + \sum\nolimits_{s=0}^{s} \theta_s^W \boldsymbol{W}_{itm-s} + \mu_{it} + \gamma_{im} + \delta_{tm} + \varepsilon_{itm},\end{aligned} \tag{3}$$

where $\boldsymbol{d}_{feature}$ denotes dummies reflecting different features, i.e., economic status (d_{rich}) and climatic conditions ($d_{high\text{-}tem}$), and θ^v measures the changes in the consumer price due to the temperature variation for the high group in comparison to the low group.

IV. Empirical results

1. Benchmark results

The effects of temperature shocks on price changes were evaluated using models that incorporated both current and lagged values of climate variables, including average temperature, precipitation, sunshine hours, and average relative humidity. Table 2 presents the estimation results for the temperature effects on monthly price changes. Column (1) includes all climate variables in the current period to assess the inflationary impacts of temperature shocks. Two additional model specifications were examined to assess the effects of lagged temperature. Column (2) adds one lag of the climate variables to Equation (1), and column (3) includes two lags. As a result, the first month of the sample period was excluded in column (2), and the first two months were excluded in column (3). Table 2 also reports the cumulative effect of temperature shocks on price changes, calculated as the sum of the current and lagged temperature coefficients. Three types of interactive fixed effects were incorporated in all columns.

Although lag lengths of up to 5 months were tested, only results for no lags, a 1-month lag, and 2-month lags of the climate variables are reported. Further lags were found to be statistically insignificant and were excluded from the analysis. Column (1) of Table 2 shows that the simultaneous temperature effect was not significant. After including one lag in column (2), the effect emerged after 1 month.

Holding all other variables constant, a 1 °C increase in *Tem* led to a 0.0465 percent rise in prices after 1 month. The cumulative effect was significantly positive, with a 1 °C temperature increase producing a 0.0371 percent rise in the CPI. After including two lags in column (3), a 1 °C temperature increase caused a 0.046 percent rise in prices 1 month later. From a cumulative perspective, a 1 °C temperature increase over the sample period was associated with a 0.0571 percent rise in prices, indicating that rising temperatures exerted inflationary pressures. With the increasing frequency of climate change and global warming, temperature effects on price pressures are becoming increasingly evident. Given the severity and prevalence of rising temperatures, these inflationary impacts should be regarded as sustained and systematic phenomena rather than merely short-term and transient price changes.

Table 2. Effect of temperature shocks on price changes

Variable	$\Delta \ln cpi$		
	(1)	(2)	(3)
Tem	–0.0066 (0.0125)	–0.0094 (0.124)	0.0063 (0.0142)
L1.*Tem*		0.0465*** (0.120)	0.0459*** (0.0109)
L2.*Tem*			0.0049 (0.0139)
Other climate variables	Yes	Yes	Yes
Cumulative temperature effect	–0.0066 (0.0125)	0.0371** (0.0138)	0.0571*** (0.0204)
R^2	0.686	0.689	0.655
Observations	5,280	5,280	4,800

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. Standard errors in parentheses are clustered at the city level. Other climate variables include precipitation, average relative humidity, and sunshine hours as climate variables. Definitions of variables are reported in Table 1. Column (1) includes other climate variables in the current period. Column (2) includes both the current values and one lagged term of other climate variables. Column (3) incorporates the current values and two lagged terms of other climate variables. The cumulated effect of temperature shocks on price changes was calculated by summing the temperature variable along with its lagged values. All regressions incorporate city–year fixed effects, city–month fixed effects, and month–year fixed effects.

2. Robustness test

The reliability of the findings was assessed by examining the robustness of the estimated effects of temperature shocks on price changes with respect to variations in variable processing, estimation methods, and sample adjustments.

Provincial aggregation. Monthly data from 2006 to 2019 on the CPI and climate variables were collected for 30 provincial regions of China to test whether climate-induced inflation was also evident at the provincial level. In column (1) of Table 3, only average temperature and its lagged values were included as explanatory variables to estimate inflationary effects. Column (2) presents results obtained using lagged climate variables. The regression results in Table 3 indicate that, consistent with city-level evidence, the 1-month lagged temperature variable was significantly positive, and the cumulative effect of temperature shocks increased prices from 0.0436 percent in column (1) to 0.0490 percent in column (2).

Table 3. Results using provincial panel data

Variable	Δln*cpi*	
	(1)	(2)
Tem	–0.0169** (0.0063)	–0.0023 (0.0081)
L1.*Tem*	0.0479*** (0.0073)	0.0487*** (0.0070)
L2.*Tem*	0.0126 (0.0087)	0.0025 (0.0111)
Other climate variables	No	Yes
Cumulative temperature effect	0.0436*** (0.0135)	0.0490*** (0.0135)
R^2	0.769	0.776
Observations	4,340	4,340

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. Standard errors within parentheses are clustered at the provincial level. Definitions of variables are reported in Table 1. Column (1) excludes the current and lagged terms of other climate variables, while column (2) includes their current and two lagged terms. The regressions incorporate province–year fixed effects, province–month fixed effects, and month–year fixed effects.

Alternative climate risk measurement. To verify that the regression results remained robust under different variable settings, the period from January 1984 to December 1999 was used as a reference period to calculate abnormal temperatures for the purpose of measuring climate risk (Hong et al., 2019; Choi et al., 2020). Specifically, abnormal temperatures were determined by calculating the difference between the average temperature of a specific month in a certain city and the average temperature for that same month during the city's historical reference period. This difference was then divided by the standard deviation of the temperatures recorded for that month within the historical reference period. The variable *Abtem* measures the fluctuation or anomaly of the monthly average temperature in a city relative to the historical average level.

The empirical findings, as illustrated in Table 4, indicate that the estimated coefficient of the one-period lag of abnormal temperature (L1.*Abtem*) was still significantly positive, that is, the probability of being in "climateflation" also increased in response to the abnormal temperature shock.

Table 4. Results using abnormal temperature

Variable	Δln*cpi*	
	(1)	(2)
Abtem	–0.0142 (0.0107)	0.0037 (0.0092)
L1.*Abtem*	0.0304*** (0.0098)	0.0292** (0.0118)
L2.*Abtem*	0.0116 (0.0070)	0.0015 (0.0070)
Other climate variables	No	Yes
Cumulative temperature effect	0.0278** (0.0135)	0.0343* (0.0177)
R^2	0.647	0.653
Observations	4,800	4,800

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. Standard errors in parentheses are clustered at the city level. Definitions of variables are reported in Table 1. Column (1) excludes the current and lagged terms of other climate variables, while column (2) includes their current and two lagged terms. The regressions incorporate city–year fixed effects, city–month fixed effects, and month–year fixed effects.

Alternative clustering strategies. Alternative clustering strategies were employed to assess the sensitivity of the results. The error term ε_{itm} may exhibit spatial correlation across cities within a given year and serial correlation within cities over time. Following the two-way clustering methodology of Cameron et al. (2011), standard errors were clustered at both the city and year levels to account for spatial and serial correlation. The results in Table 5 show that the 1-month lagged temperature coefficient was statistically significant at the 1 percent level. This finding is consistent with the benchmark regression results, reinforcing their robustness.

Table 5. Results using the two-way clustering approach

Variable	Δln*cpi*	
	(1)	(2)
Tem	–0.0175 (0.0138)	0.0063 (0.0151)
L1.*Tem*	0.0436*** (0.0134)	0.0459*** (0.0145)
L2.*Tem*	0.0158 (0.0105)	0.0049 (0.0142)
Other climate variables	No	Yes
Cumulative temperature effect	0.0420** (0.0189)	0.0571*** (0.0180)
R^2	0.648	0.655
Observations	4,800	4,800

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. Standard errors in parentheses are clustered by city and year. Definitions of variables are reported in Table 1. Column (1) excludes the current and lagged terms of other climate variables, while column (2) includes their current and two lagged terms. The regressions incorporate city–year fixed effects, city–month fixed effects, and month–year fixed effects.

Subsample analysis. China's CPI statistical survey rotates its base period every 5 years to ensure that the goods and services included are representative and reflect recent changes in consumer behavior. The price index with 2015 as the base period was compiled and released from January 2016. Compared with the previous base period, notable changes occurred in CPI categories, including the merger of "food" and "tobacco and alcohol" into "food, tobacco, and alcohol"; the separation of "medical care and personal goods" into "daily necessities and services," "medical care," and "other goods and services"; the division of "entertainment, education, and cultural goods and services" into "education, culture, and entertainment" and "other goods and services;" and the separation of "household equipment and maintenance services" into "daily necessities and services" and "other goods and services." To eliminate the potential bias introduced by this base period adjustment, Equation (1) was re-estimated after excluding samples from January 2016 to December 2019. Column (1) of Table 6 shows that the lagged and cumulative effects of temperature on price changes remained significantly positive.

Exclusion of municipalities. A directly administered municipality is an administrative city that operates under the direct jurisdiction of the central government. It plays a crucial role in politics, economy, science, culture, transportation, and various other sectors within the country. Given the special administrative status of those municipalities, directly under the central government, significant differences exist between them and ordinary prefecture-level cities in terms of institutional environment, policy support, resource acquisition, and environmental regulations (Yang and Zhou, 2022). It may therefore be speculated that the influence of increasing temperatures on CPI inflation could vary between municipalities and prefecture-level cities. To mitigate the influence of the unique characteristics of municipalities on the conclusions drawn from this study, Equation (1) was re-estimated after removing the samples from the four municipalities, to avoid the corresponding conclusion bias. Column (2) of Table 6 presents the regression results following the exclusion of municipalities. The cumulative effect of warmer temperatures created significant price pressures in ordinary prefecture-level cities, excluding estimation errors caused by the special characteristics of municipalities, consistent with the conclusions of this study.

Global food crisis effect. During the period 2007–2008, a global food crisis occurred, leading countries to control grain imports and exports strictly in response to rising international grain prices. The resulting food shortage and soaring prices posed more serious threats than the global financial and capital market turbulence caused by the subprime crisis (You, 2009; Kumar and Quisumbing, 2013). To mitigate the potential interference of the global food crisis on the climate inflation effect, Equation (1) was re-estimated after excluding samples from January 2007 to December 2008. Column (3) of Table 6 presents the estimation results for this model. The one-period lagged temperature coefficient remained significantly positive at the 1 percent level, indicating that the findings were robust and not driven by the global food crisis.

Table 6. Robustness checks based on sample adjustment

Variable	Δln*cpi*		
	Excluding the samples from 2016 to 2019	Excluding the municipalities	Excluding the samples from 2007 to 2008
	(1)	(2)	(3)
Tem	0.0059 (0.0163)	0.0067 (0.0159)	0.0020 (0.0125)
L1.*Tem*	0.0488*** (0.0140)	0.0457*** (0.0117)	0.0396*** (0.0113)
L2.*Tem*	0.0144 (0.0173)	0.0058 (0.0145)	0.0070 (0.0120)
Cumulative temperature effect	0.0691*** (0.0237)	0.0582** (0.0219)	0.0486** (0.0183)
R^2	0.675	0.656	0.672
Observations	3,600	4,160	4,200

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. Standard errors in parentheses are clustered at the city level. Definitions of variables are reported in Table 1. The regressions incorporate the current values and two lagged terms of other climate variables, while accounting for city–year fixed effects, city–month fixed effects, and month–year fixed effects.

3. Mechanism analysis

An open question remains regarding the mechanism through which temperature changes affect price fluctuations. The literature on this topic is relatively limited. One obvious way in which rising temperatures induce inflationary pressures is through the negative effects on economic output. Climate shocks influence production, business operations, financing, and investment, which are ultimately reflected in output fluctuations (Shen et al., 2024). Output indicators can therefore capture the adverse impacts of temperature changes on the production sector.

Table 7 reports the estimated temperature effects on industrial and agricultural output.[3] The results in column (1) show that the 1-month lagged temperature shock was negatively associated with industrial output growth (*IND*). Agricultural output, which is directly linked to basic consumption needs, influences costs along the industrial chain and supports overall CPI stability (Faccia et al., 2021; Peersman, 2022; Ginn, 2024). Column (2) presents the estimated effects of temperature shocks on changes in agricultural output value (*AGR*). The lagged estimates indicate that the damaging impact of temperature shocks was significant. These findings suggest that higher temperatures can impair economic production and disrupt market supply and demand, ultimately contributing to higher prices and increased inflation (Bartos, 2022; Intergovernmental Panel on Climate Change, 2022).

[3]Due to data limitations, output indicators and climate variables are measured at the provincial level.

Table 7. Temperature shocks and output growth

Variable	*IND*	*AGR*
	(1)	(2)
Tem	–0.0014 (0.0010)	–0.0001 (0.0001)
L1.*Tem*	–0.0016** (0.0007)	–0.0011*** (0.0003)
L2.*Tem*	–0.0003 (0.0005)	–0.0011*** (0.0002)
R^2	0.808	0.817
Observations	4,733	2,159

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. Standard errors are reported in parentheses and are clustered at the province level. *IND* represents industrial output growth, and *AGR* represents agricultural output growth. Definitions of other variables are reported in Table 1. The regressions incorporate the current values and two lagged terms of other climate variables, while accounting for city–year fixed effects, city–month fixed effects, and month–year fixed effects.

Cost is another mechanism through which rising temperatures generate inflationary pressure. Higher global temperatures increase the costs of food, goods, and services (Mukherjee and Ouattara, 2021; Kotz et al., 2024). Food prices are especially significant for headline inflation because they account for a large share of consumption and reflect essential demand. Higher temperatures also increase energy and manufacturing costs through greater cooling needs and stress on infrastructure. Rising global temperatures therefore create a cumulative cost effect that increases expenses for households and firms.

To evaluate the impact of rising temperatures on production costs, the analysis employed two variables with a strong direct correlation with the CPI: the industrial producer purchase price index (PPPI) and the industrial producer ex-factory price index (PEPI) (Wen et al., 2019; Chen and Zhu, 2021; Sun et al., 2023). The PPPI captures price changes in production inputs such as raw materials and fuels, and the PEPI captures price changes in products at the production stage and in upstream industries. As the cost origin of enterprise production, shifts in the PPPI are transmitted to the PEPI through cost pass-through. Changes in the PEPI then propagate along the industrial chain to the consumer side and generally move in tandem with the consumer price index. Table 8 reports the regression results of temperature effects on production costs. The 1-month lagged effect of temperature shocks on the PPPI and the PEPI was significantly positive (columns (1)–(2)), indicating that heat waves led to an increase in direct costs associated with producing goods or services, such as raw material costs and fuel costs.

The intensification of inflation under economic policy uncertainty has become a central concern for government agencies, researchers, and market participants (Phan et al., 2021; Wang and Weng, 2024). In practical terms, repeated shifts in policy direction, frequent adjustments to regulatory instruments, and the waiting period preceding major policy announcements can all amplify inflationary pressures through multiple mechanisms. For firms, uncertainty increases the costs of holding raw material inventories and raises long-term investment risks, prompting some to pass these pressures on by increasing product prices.

Table 8. Temperature shocks and production costs

Variable	PPPI	PEPI
	(1)	(2)
Tem	0.0007** (0.0003)	0.0007 (0.0009)
L1.*Tem*	0.0008* (0.0005)	0.0014** (0.0006)
L2.*Tem*	0.0002 (0.0003)	0.0006 (0.0011)
R^2	0.986	0.871
Observations	2,670	2,480

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: ** and * represent significance at the 5 and 10 percent levels, respectively. Standard errors are clustered at the city level. The regressions incorporate the current values and two lagged terms of other climate variables, while accounting for city–year fixed effects, city–month fixed effects, and month–year fixed effects. Definitions of variables are reported in Table 1. PEPI, producer ex-factory price index; PPPI, producer purchase price index.

This study used the monthly economic policy uncertainty index (*EPU*) for China, developed by Baker et al. (2016), to assess whether the inflationary effects of temperature shocks depended on policy uncertainty. Temperature variables were interacted with the uncertainty measure, and Table 9 reports the results. Column (1) presents estimates based on the interaction between the one-period lagged temperature and economic policy uncertainty. Column (2) reports estimates using the interactions between temperature variables and economic policy uncertainty. Column (1) shows positive estimates for the interaction term L1.*Tem* × *EPU*. Column (2) shows that the interaction term was still significantly positive, indicating that temperature shocks exerted a stronger influence on price fluctuations under higher policy uncertainty. Stabilizing policy expectations and calibrating the pace of regulation have therefore become important issues in current macroeconomic management.

Unlike the immediate impacts of natural disasters (e.g., Ubilava and Holt, 2013; Heinen et al., 2019; Abril-Salcedo et al., 2020), this study showed that climate physical risks drove inflation in China, primarily through supply-side shocks induced by gradual temperature fluctuations. This research extended the analysis of Mukherjee and Ouattara (2021) and Semenova (2024) by exploring the transmission channels of "climateflation" from the perspectives of output effects, cost effects, and policy uncertainty effects. Another strand of the literature (e.g., Bolton and Kacperczyk, 2023; Bua et al., 2024; Kaur and Ahmed, 2025) focused on the price effects of climate transition risks, such as climate policy adjustments.

Using the same model specification adopted in this study, the monthly climate policy uncertainty index for China, constructed by Ma et al. (2023), was employed to assess the price effects of transition risks. The results indicated that the contemporaneous, lagged, and cumulative effects of climate policy uncertainty on price changes were all insignificant, suggesting that the price effects of transition risks were limited (Table A3 in the Appendix).

Table 9. Temperature shocks and economic policy uncertainty

Variable	Δln*cpi*	
	(1)	(2)
Tem × EPU		0.0000 (0.0001)
L1.*Tem × EPU*	0.0003** (0.0001)	0.0003** (0.0001)
L2.*Tem × EPU*		–0.0000 (0.0001)
R^2	0.656	0.656
Observations	4,800	4,800

Sources: Authors' calculations based on the CMDSC, EPU index, and EPS databases.

Notes: ** represents significance at the 5 percent level. Standard errors in parentheses are clustered at the city level. Definitions of variables are reported in Table 1. The regressions incorporate the current values and two lagged terms of other climate variables, while accounting for city–year fixed effects, city–month fixed effects, and month–year fixed effects.

4. Heterogeneous effects

(1) Effects across consumer price index categories

The CPI encompasses the prices of goods and services categorized into eight segments. For all eight CPI categories, which are shown in Table 10, there was no simultaneous impact, but there was a lagged impact. As column (1) shows, the coefficient estimates of L1.*Tem* on food price changes were significantly positive, suggesting that food price changes are positively correlated with higher temperatures in month $m - 1$. Specifically, a 1 °C increase in L1.*Tem* was linked to a 0.136 percent rise in food prices. As column (6) indicates, the impact of temperature shocks in month $m - 2$ on the current period's price changes for household facilities, articles, and services was positive at the 10 percent level of significance during the sample period. Keeping all other variables constant, each additional 1 °C increase in L2.*Tem* in month $m - 2$ was found to create price pressures in month m by 0.017 percent.

In terms of the cumulative effect, the results of decomposition into categories showed that there was only an effect on food prices, and prices of the other seven major categories were not affected. The cumulative impact on food prices entailed that each 1°C rise in temperature resulted in a price increase of 0.142 percent. Generally speaking, CPI is mainly composed of two categories, food and nonfood, with food accounting for nearly 30 percent of the total. In recent years, because of shifts in the consumption structure of residents, the proportion of food has declined and the proportion of nonfood has gradually increased. However, in terms of driving the inflation surge, the impact of food is much greater than that of nonfood items (Faccia et al., 2021; Fan et al., 2023; Zhou and Chen, 2023). The main reason is that nonfood prices are relatively stable and not affected significantly by temperature, whereas food prices are more volatile and adjust more quickly. The impact on CPI price fluctuations is therefore mainly reflected in food prices.

Table 10. Heterogeneity in the temperature effects across consumer price index categories

	Food	Clothing	Residence	Transportation and communication	Tobacco, alcohol, and articles	Household facilities, articles, and services	Health care and personal articles	Entertainment, education, culture articles, and services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tem	–0.0041	0.0073	–0.0133	0.0071	–0.0124	0.0072	–0.0049	0.0046
	(0.0330)	(0.034)	(0.0153)	(0.0169)	(0.0124)	(0.0168)	(0.0167)	(0.0286)
L1.*Tem*	0.136***	–0.0015	–0.0002	–0.0261	0.0055	–0.0023	0.0044	0.0243
	(0.0314)	(0.0242)	(0.0090)	(0.0199)	(0.0115)	(0.0177)	(0.0125)	(0.0218)
L2.*Tem*	0.0102	0.0316	0.0194	–0.0166	–0.0086	0.0172*	0.0452	0.0129
	(0.0253)	(0.0262)	(0.0240)	(0.0129)	(0.0100)	(0.0093)	(0.0396)	(0.0206)
Cumulative temperature effect	0.142***	0.0374	0.0059	–0.0356	–0.0154	0.0220	0.0447	0.0418
	(0.0340)	(0.0463)	(0.0332)	(0.0235)	(0.0178)	(0.0238)	(0.0366)	(0.0417)
R^2	0.718	0.488	0.431	0.389	0.480	0.286	0.274	0.374
Observations	3,600	4,800	4,800	4,800	3,600	3,600	3,600	4,800

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: *** and * represent significance at the 1 and 10 percent levels, respectively. Standard errors, shown in parentheses, are clustered at the city level. The dependent variable is monthly price changes for eight CPI categories. Definitions of variables are reported in Table 1. All regressions incorporate the current values and two lagged terms of other climate variables, while accounting for city–year fixed effects, city–month fixed effects, and month–year fixed effects.

Given that the analysis above showed that temperature shocks had a greater impact on food prices than on the CPI (Cook and Gale, 2019), this study examined the temperature effects on the price indices of different food categories. The types of food surveyed by the CPI include six subcategories: fresh vegetables, aquatic products, eggs, fresh fruits, grains, and poultry. The results in Table A4 in the Appendix indicate heterogeneous effects of temperature across food categories. The cumulative effect of growing temperatures on the prices of fresh vegetables, eggs, and fresh fruits was significantly positive (columns (1)–(3)), whereas the cumulative effect on the prices of aquatic products, grains, and poultry was not significant (columns (4)–(6)).

(2) Effects across temperature bins

Several temperature bins were employed as explanatory variables to examine the potential nonlinear relationship between temperature ranges and price fluctuations. Equation (2) was systematically estimated by designating different temperature intervals as the reference group. When the bin below 0 °C was used as the reference, the estimates for the other temperature intervals were positive, indicating that, relative to a month with an average temperature below 0 °C, additional months in higher temperature intervals were associated with positive marginal impacts on price changes. Equation (2) was estimated with two lags of the climate variables, using the temperature bins as the independent variables.

Table 11 shows the binned estimates of price changes. The one-period lagged temperature bins exhibited a significantly positive correlation with price changes. Figure 1 illustrates the lagged effects on monthly price changes using temperature bins with a range of 5 °C.[4] The horizontal axis indicates the temperature bin, and the vertical axis shows the difference in the logged monthly CPI. As Figure 1 shows, the relationship between temperature bin and price changes was nonlinear. When the average temperature ranged from above 0 °C to below 5 °C, temperature shocks had no significant impact on prices. Once the temperature exceeded 5 °C, the influence of temperature shocks on price fluctuations became markedly more pronounced. Consumer prices exhibited a nearly linear increase with rising temperatures up to [25, 30) °C, but after surpassing 30 °C, there was a sharp decline in prices. Compared with a month with an average temperature below 0 °C, an additional month within the [25, 30) °C range was associated with a price increase of about 0.597 percent, while an additional month above 30 °C increased prices by 0.475 percent, holding all other variables constant.

Table 11. Binned estimates of the effects of temperature shocks on price changes

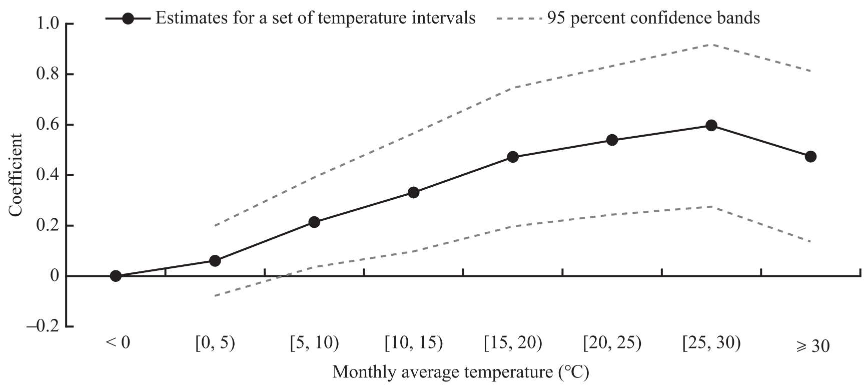
Dependent variable: $\Delta \ln cpi$					
Default: *Tem* < 0 °C					
Tem ∈ [0, 5) °C	0.159* (0.087)	L1.*Tem* ∈ [0, 5) °C	0.061 (0.068)	L2.*Tem* ∈ [0, 5) °C	0.016 (0.071)
Tem ∈ [5, 10) °C	0.195 (0.141)	L1.*Tem* ∈ [5, 10) °C	0.214** (0.087)	L2.*Tem* ∈ [5, 10) °C	0.059 (0.094)
Tem ∈ [10, 15) °C	0.303* (0.166)	L1.*Tem* ∈ [10, 15) °C	0.332*** (0.114)	L2.*Tem* ∈ [10, 15) °C	0.095 (0.124)
Tem ∈ [15, 20) °C	0.202 (0.180)	L1.*Tem* ∈ [15, 20) °C	0.472*** (0.134)	L2.*Tem* ∈ [15, 20) °C	0.052 (0.161)
Tem ∈ [20, 25) °C	0.117 (0.185)	L1.*Tem* ∈ [20, 25) °C	0.538*** (0.144)	L2.*Tem* ∈ [20, 25) °C	0.016 (0.159)
Tem ∈ [25, 30) °C	0.116 (0.210)	L1.*Tem* ∈ [25, 30) °C	0.597*** (0.157)	L2.*Tem* ∈ [25, 30) °C	0.027 (0.166)
Tem ⩾ 30 °C	0.136 (0.242)	L1.*Tem* ⩾ 30 °C	0.475*** (0.165)	L2.*Tem* ⩾ 30 °C	–0.033 (0.191)
Observations	4,800	R^2	0.655		

Sources: Authors' calculations based on the CMDSC and EPS databases.

Note: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. Standard errors in parentheses are clustered at the city level. The regression incorporates the current values and two lagged terms of other climate variables, while accounting for city–year fixed effects, city–month fixed effects, and month–year fixed effects.

[4]The binned estimates with a range of 3 °C are available from the authors upon request.

Figure 1. One-month lagged temperature effects

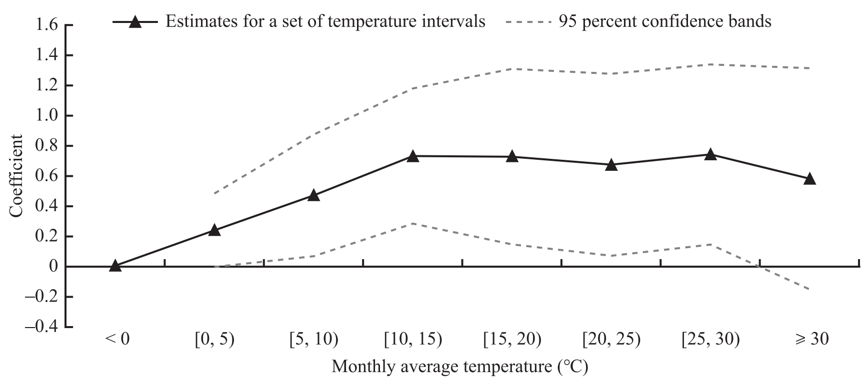


Sources: Authors' calculations based on the CMDSC and EPS databases.

Note: Figure 1 illustrates the 1-month lagged effect on monthly price changes utilizing temperature bins.

Figure 2 illustrates the cumulative effects of temperature on monthly price fluctuations using designated temperature bins. Compared with a month with an average temperature below 0 °C, the cumulative impacts on price changes associated with an additional month in other temperature intervals were significantly positive, except for the [0, 5) °C and [30, 35) °C bins. Specifically, an additional month in the [10, 15) °C range was associated with a price increase of approximately 0.720 percent, while an additional month in the [25, 30) °C range corresponded to an increase of 0.740 percent, relative to a month with an average temperature below 0 °C.

Figure 2. Cumulative temperature effects



Sources: Authors' calculations based on the CMDSC and EPS databases.

Note: Figure 2 illustrates the cumulative effect on monthly price changes using temperature bins.

(3) Effects in cities with distinct economic and weather conditions

The study measured the average impact of temperature shocks on price changes across cities, demonstrating that higher temperatures generated inflationary pressures. However, the temperature effects may differ depending on city characteristics. The parameter estimates for cumulative temperature effects across regions were obtained by evaluating Equation (3) while incorporating two lags of the climate variables (Tables 12 and 13). In each column of these tables, the coefficients on the temperature variables represent the effect for the default group.

Table 12 presents the heterogeneity analysis of temperature effects on price changes by economic conditions. Using Equation (3), the average per capita GDP from 1999 to 2003 was calculated and interacted with the contemporaneous and lagged temperature variables. Column (1) of Table 12 indicates that a 1 °C increase in temperature in poorer regions was associated with a 0.046 percent rise in prices after one month. The parameter estimates for the interaction term (L2.$Tem \times d_{rich}$) between the rich region dummy (d_{rich}) and the two-period lagged temperature showed that higher economic status reduced the lagged effect of temperature shocks.

Regarding cumulative effects, economically disadvantaged regions experienced a more pronounced increase in price changes following an escalation in temperature. In contrast, wealthier areas were better positioned to adapt to climate warming through costly mitigation measures, such as climate-resilient infrastructure and the development of new crop varieties (Kumar and Khanna, 2019; Letta and Tol, 2019; Rode et al., 2021).

Table 12. The effect of temperature shocks on price changes by economic conditions

Variable	Δln*cpi*	
	(1)	(2)
Tem	0.0068 (0.0171)	0.0062 (0.0187)
L1.*Tem*	0.0461*** (0.0133)	0.0455*** (0.0125)
L2.*Tem*	0.0151 (0.0142)	0.0147 (0.0133)
$Tem \times d_{rich}$	–0.0010 (0.0182)	–0.0011 (0.0173)
L1.$Tem \times d_{rich}$	–0.0007 (0.0121)	–0.0006 (0.0132)
L2.$Tem \times d_{rich}$	–0.0209* (0.0111)	–0.0212* (0.0101)
Cumulative temperature effect in rich regions	0.0454* (0.0234)	0.0467* (0.0245)
Cumulative temperature effect in poor regions	0.0681*** (0.0213)	0.0663*** (0.0203)
R^2	0.655	0.654
Observations	4,800	4,800

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: *** and * represent significance at the 1 and 10 percent levels, respectively. Standard errors in parentheses are clustered at the city level. Definitions of variables are reported in Table 1. Column (1) presents the heterogeneous results when rich regions have above-median average per capita GDP from 1999 to 2003. Column (2) displays the heterogeneous results when rich regions are defined based on their coastal location. The regressions incorporate the current values and two lagged terms of other climate variables, while accounting for city–year fixed effects, city–month fixed effects, and month–year fixed effects.

Column (2) of Table 12 reports the heterogeneity results based on a geographical definition of rich regions, distinguishing coastal from inland regions. Coastal areas play a central role in China's economic development and their geographical advantages and resource endowments give them distinct economic characteristics. The estimates show that in inland and poorer regions, a 1 °C temperature increase was associated with a cumulative rise in consumer prices of 0.0663 percent, compared with 0.0467 percent in coastal areas. This indicates that geographically disadvantaged regions faced a larger and statistically significant inflationary effect.

Table 13. The effect of temperature shocks on price changes by weather conditions

Variable	$\Delta \ln cpi$	
	(1)	(2)
Tem	0.0147 (0.0157)	0.0148 (0.0157)
L1.*Tem*	0.0402*** (0.0118)	0.0401*** (0.0121)
L2.*Tem*	0.0094 (0.0149)	0.0061 (0.0152)
$Tem \times d_{high\text{-}tem}$	–0.0268* (0.0151)	–0.0275* (0.154)
L1.$Tem \times d_{high\text{-}tem}$	0.0166 (0.0127)	0.0161 (0.0135)
L2.$Tem \times d_{high\text{-}tem}$	–0.0122 (0.0123)	–0.0010 (0.0128)
Cumulative temperature effect in high-temperature regions	0.0419 (0.0256)	0.0485* (0.0249)
Cumulative temperature effect in low-temperature regions	0.0643*** (0.0216)	0.0609** (0.0263)
R^2	0.655	0.655
Observations	4,800	4,800

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. Standard errors, shown in parentheses, are clustered at the city level. Column (1) presents the heterogeneous results when high-temperature regions have above-median average temperatures from 1999 to 2003. Column (2) displays the heterogeneous results when high-temperature regions are defined based on the Huai River–Qin Mountains line. The regressions incorporate the current values and two lagged terms of other climate variables, while accounting for city–year fixed effects, city–month fixed effects, and month–year fixed effects.

The analysis focused on heterogeneity across regions with different long-term temperature levels to examine the extent of climate adaptation. Regions with high temperatures may possess a greater capacity to manage elevated temperatures than those with low temperatures. For instance, cities that have historically encountered warmer temperatures may implement various adaptation measures to mitigate the effects of future heat events, such as stockpiling essential resources and developing climate-resistant crops (Zhou and Turvey, 2014; Li et al., 2024). To assess this mechanism, the average temperature from 1999 to 2003 was calculated and interacted with contemporaneous and lagged temperature variables in Equation (3). Column (1) of Table 13 shows that the parameter estimates for the interaction term $Tem \times d_{high\text{-}tem}$ between the current temperature and the high-temperature region dummy $d_{high\text{-}tem}$ were negative, indicating that high-temperature regions were better able to mitigate heat stress than low-temperature regions.

Equation (3) was then modified to include interaction terms between the temperature variables and a dummy variable identifying high-temperature cities. This classification is based on the Huai River–Qin Mountains line, a natural boundary separating the cooler northern regions from the warmer southern regions (Chen and Yang, 2019). Column (2) of Table 13 presents the estimated outcomes for these interaction terms.

The results show that higher temperatures produced a stronger cumulative impact on price pressures in low-temperature regions than in high-temperature regions. Although no direct evidence was found that adaptation to warming had been initiated in regions characterized by high thermal conditions, the parameter estimates for the cumulative effects presented in this study indicate that certain forms of climate adaptation may have been actively implemented in the warmer areas to attenuate the positive impacts of heat waves on price pressures (Yang et al., 2022).

V. Conclusions and discussion

The existing literature on the economic effects of climate change focused mainly on outcomes such as output growth, corporate performance, business operations, and energy poverty, with limited attention to how climate change, particularly temperature shocks, affects prices and inflation. This study aimed to address this gap. It examined 30 large and medium-sized Chinese cities, using panel data on price indices and climate conditions from January 2004 to December 2019 and applying a multidimensional fixed effects model to assess how temperature shocks contribute to consumer price inflation.

The research findings indicate the following. First, 1-month lagged temperatures had a significant positive effect on current-month price changes, with a cumulative increase of 0.057 percent. These results suggest that rising temperatures generated inflationary pressures, which remained robust across multiple checks. Mechanism analyses show that higher temperatures significantly raised production costs and reduced output growth, with climate-induced price increases being larger under greater economic policy uncertainty.

Second, the effect was observed only for food prices, with no significant impact on the other seven major categories of goods and services. In the case of food, a 1 °C temperature increase corresponded to a 0.142 percent rise in prices. Using temperature bins as the independent variables, prices increased linearly with temperature up to approximately 25–30 °C, followed by a marked decline at higher levels.

Finally, higher temperatures exerted a stronger effect on price increases in poorer or low-temperature regions than in richer or high-temperature areas. This pattern suggests that adaptation measures may have already been proactively implemented in more affluent and warmer regions of China.

The findings of this study have a clear theoretical and practical significance. Although the implications were drawn from China's experience, they are also applicable to other regions. First, the research findings highlight the significance of temperature shocks as a sustained driver of inflation. As climate change accelerates and temperatures rise, the inflationary effects of rising temperatures are expected to intensify. Temperature shocks, by triggering inflationary pressures, can significantly undermine central banks' capacity to sustain low inflation rates and ensure price stability. In response, incorporating climate-related risks into monetary operations through stress testing and scenario analysis can strengthen financial system resilience in the face of systemic and uncertain climate shocks (Battiston et al., 2021).

Second, it is essential for China's cities to develop pertinent mitigation and adaptation strategies. These include initiatives such as the advancement of clean energy and support for research and development in low-carbon technologies (Probst et al., 2021). Among the different categories of goods and services, food should be given the highest priority due to its essential role in people's lives and its high susceptibility to climate change. Given that the rate of temperature increase in China exceeds the global average (China Meteorological Administration, 2022), the promotion of regional integration and the reduction of the wealth gap should include closer consideration of the effect of temperature warming on increasing wealth inequality.

Third, the development of climate-resilient cities should be accelerated, with adaptation strategies tailored to regional conditions (Yari et al., 2024). In China, economically underdeveloped and northern regions are more sensitive to temperature fluctuations, and larger price increases may coincide with lower real output growth. Cities should learn from southern, high-temperature areas and design climate adaptation plans suited to their local circumstances. Efforts should focus on building "climate-adaptive cities" and strengthening urban resilience to address the challenges of global warming.

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Appendix

Table A1. Descriptive statistics for the main variables

Variable	Mean	Standard deviation	Min.	Max.	Observations
Panel A: Monthly price changes (%)					
All	0.162	0.768	–3.769	4.628	5,280
Food	0.291	2.071	–10.384	11.659	3,960
Tobacco, alcohol, and articles	0.143	0.569	–2.597	6.449	3,960
Clothing	0.161	1.943	–11.118	14.833	5,280
Household facilities, articles, and services	0.115	0.628	–3.780	4.689	3,960
Health care and personal articles	0.140	0.611	–4.216	13.561	3,960
Transport and communication	–0.095	0.714	–20.537	3.826	5,280
Entertainment, education, culture articles, and services	0.004	1.411	–9.778	12.848	5,280
Residence	0.219	0.780	–9.210	8.268	5,280
Panel B: Climate variables					
Average temperature (°C)	15.872	9.964	–19.400	32.600	5,280
Precipitation (mm)	81.011	95.339	0.000	1,212.900	5,280
Sunshine hours (hour)	170.450	66.728	0.000	908.000	5,280
Average relative humidity (%)	65.579	13.946	22.000	94.000	5,280

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: This table presents descriptive statistics for the monthly data spanning from 2004 to 2019. Panel A illustrates the monthly price fluctuations for the overall index, as well as for eight categories. Panel B details climate variables, including average temperature, precipitation levels, average relative humidity, and hours of sunshine.

Table A2. Descriptive statistics by different time periods and regions

	Type	Mean	Standard deviation	Min.	Max.
Panel A					
Price changes (%)	2006–2010	0.220	0.930	–3.600	4.628
	2011–2015	0.140	0.622	–2.962	3.212
	2016–2019	0.164	0.591	–1.766	2.901
Average temperature (°C)	2006–2010	15.925	9.887	–16.700	32.400
	2011–2015	15.670	10.033	–19.400	32.600
	2016–2019	16.076	9.967	–17.100	31.900
Precipitation (mm)	2006–2010	77.064	95.084	0.000	1,212.900
	2011–2015	83.264	97.060	0.000	968.000
	2016–2019	86.932	99.799	0.000	676.100
Sunshine hours (hour)	2006–2010	167.661	63.941	5.900	362.600
	2011–2015	169.333	72.296	0.000	908.000
	2016–2019	174.446	64.511	8.200	350.400
Relative humidity (%)	2006–2010	64.987	13.056	22.000	90.000
	2011–2015	66.110	14.283	24.000	94.000
	2016–2019	66.521	14.670	26.000	93.000
Panel B					
Price changes	low-temperature regions	0.149	0.817	–3.769	3.902
	high-temperature regions	0.176	0.715	–2.884	4.628
Average temperature	low-temperature regions	12.110	10.765	–19.400	30.500
	high-temperature regions	19.635	7.374	0.300	32.600
Precipitation	low-temperature regions	47.413	62.066	0.000	968.000
	high-temperature regions	114.609	109.872	0.000	1,212.900
Sunshine hours	low-temperature regions	198.061	59.668	2.400	362.600
	high-temperature regions	142.838	61.817	0.000	908.000
Relative humidity	low-temperature regions	57.877	13.831	22.000	91.000
	high-temperature regions	73.281	8.892	30.000	94.000
Price changes	poor regions	0.175	0.770	–3.769	4.417
	rich regions	0.150	0.765	–3.600	4.628
Average temperature	poor regions	15.916	9.680	–19.400	32.600
	rich regions	15.829	10.241	–16.700	32.300
Precipitation	poor regions	79.036	94.986	0.000	1,212.900
	rich regions	82.986	95.669	0.000	834.600
Sunshine hours	poor regions	169.035	68.411	0.000	908.000
	rich regions	171.865	64.983	13.000	362.600
Relative humidity	poor regions	66.835	13.819	24.000	94.000
	rich regions	64.323	13.961	22.000	93.000

Sources: Authors' calculations based on the CMDSC and EPS databases.

Note: Rich regions are defined based on their coastal location, and high-temperature regions are defined based on the Huai River–Qin Mountains line.

Table A3. Results using climate policy uncertainty

Variable	Δln*cpi*		
	(1)	(2)	(3)
Tem	0.0063 (0.0142)		0.0065 (0.0142)
L1.*Tem*	0.0459*** (0.0109)		0.0458*** (0.0108)
L2.*Tem*	0.0049 (0.0139)		0.0047 (0.0141)
CPU		–0.0116 (0.0117)	–0.0099 (0.0115)
L1.*CPU*		–0.0171 (0.0172)	–0.0165 (0.0177)
L2.*CPU*		0.0058 (0.0192)	0.0059 (0.0189)
Cumulative temperature effect	0.0571*** (0.0205)		0.0570*** (0.0204)
Cumulative CPU effect		–0.0230 (0.031)	–0.0205 (0.0303)
R^2	0.655	0.694	0.655
Observations	4,800	4,800	4,800

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: *** represents significance at the 1 percent level. Standard errors, indicated within parentheses, are clustered at the city level. The findings reported in column (1) are derived from estimating Equation (1), incorporating two lags of average temperature. Column (2) reports the estimates from an analogous specification, in which the two lags of average temperature are replaced by two lags of *CPU*. Column (3) displays results from a model that jointly includes two lags of both average temperature and the CPU index. *CPU* represents climate policy uncertainty. Definitions of other variables are reported in Table 1. The regressions incorporate the current values and two lagged terms of other climate variables, while accounting for city–year fixed effects, city–month fixed effects, and month–year fixed effects.

Table A4. Heterogeneity in the temperature effects across food categories

	Fresh vegetables	Eggs	Fresh fruits	Aquatic products	Grain	Poultry
	(1)	(2)	(3)	(4)	(5)	(6)
Tem	–0.515*** (0.128)	0.054 (0.056)	0.109 (0.094)	–0.053 (0.045)	0.022 (0.018)	0.022 (0.035)
L1.*Tem*	1.248*** (0.107)	0.162*** (0.053)	0.146 (0.109)	–0.052 (0.044)	–0.001 (0.017)	0.024 (0.038)
L2.*Tem*	–0.520*** (0.156)	0.063 (0.088)	0.125 (0.151)	0.033 (0.038)	0.010 (0.020)	–0.025 (0.039)
Cumulative temperature effect	0.213* (0.121)	0.279** (0.109)	0.380** (0.185)	–0.072 (0.067)	0.031 (0.036)	0.021 (0.068)
R^2	0.803	0.801	0.658	0.545	0.403	0.818
Observations	3,300	3,300	3,300	3,300	3,300	3,300

Sources: Authors' calculations based on the CMDSC and EPS databases.

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent levels, respectively. Standard errors in parentheses are clustered at the city level. Definitions of variables are reported in Table 1. All regressions incorporate the current values and two lagged terms of other climate variables, while accounting for city–year fixed effects, city–month fixed effects, and month–year fixed effects.

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