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Valuing the impact of climate change on China's economic growth☆

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ABSTRACT

There are still many uncertainties regarding the possible influences of global climate change in the mid-latitude regions, owing to rather limited research and lack of empirical evidence. This paper systematically evaluates the economic impact of climate variation by constructing a 27-year panel dataset of 274 prefecture cities and 816 weather stations in China. Our results document some significant climate–economic relationships, with the increase of 1 °C-temperature, 100 mm-rainfall, and 1%-humidity associated with a 0.78% decrease, 0.86% increase and 1.34% decrease in output, respectively. Higher temperature damages are reflected in less-developed regions, while the positive impact of rainfall mainly appear in more-developed regions. Using integrated assessment models, we project that the model-average climate damage of China may account for up to 4.23 percent of GDP by 2100, based on a nonlinear historical climate–economic interaction.

1. Introduction

China is facing unprecedent challenges, given the increasingly severe situation of global warming (Duan et al., 2018). China's surface temperature has been rising by 0.9–1.5 degrees Celsius (°C) since modern industrialization (NCCEC, 2014), and the frequency of extreme weather events related to rainfall has formidably increased within the last 40 years, especially the imbalanced adverse effects across regions, despite no statistically significant evidence on the change in precipitation (IPCC, 2007). By the end of this century, the average temperature in China is expected to rise by 3.9–6.0 °C and is likely to be over 4 °C relative to preindustrial levels. The rainfall will increase by 9%–11%, corresponding to a rise of sea level by 0.4–0.6 meters relative to the 20th century level. As a result, climate damage in China may be more severe

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than the global average level (Ju et al., 2013; NCCEC, 2014), leading to a 2.8–5.7% of cumulative GDP loss (Duan et al., 2021).

The negative role of climate change in economic activities is manifested in many aspects, such as agriculture, industry, ecological system and human health, and such impacts have long been clearly declared in the previous integrated assessment report (AR). For example, AR4 states that "global mean losses could be 1%–5% of GDP for 4 °C of warming..." (IPCC, 2007). Much robust evidence reveals that climate change may cause over 77% of the world's countries to become poorer by the end of this century if no substantial emission control actions are implemented (Burke et al., 2015). Affecting not only the level of output, global warming also damages the economy's ability to grow, and a 1 °C rise in temperature may reduce economic growth by approximately 1.3% (Dell et al., 2012). For China, crop damage associated with climate change during the last decade has reached 595–868 million US dollars (USD); by 2100, the production of corn and soybean may decrease by 3%–12% and 7%–19%, respectively (Chen et al., 2016). A warming climate will greatly increase the future heat-related mortality, particularly for more densely populated cities, given some uncertainties on the possible hedging effects of adaptation capability (Yu et al., 2019; Banerjee and Maharaj, 2020). Climate change may also bring great shocks to the energy system (Rose et al., 2014), and the global electricity demand may grow by 2.8%, on average, in 2100, corresponding to an additional peak capacity cost of 190 billion US dollars (USD) (Auffhammer et al., 2017). Furthermore, investment, trade and political stability are also central channels for global warming to negatively affect the social economy (Hsiang, 2010), especially for less-developed countries, in which each additional rise in temperature damages the aggregated national income by 8.5%, on average (Dell et al., 2009).

Few debates exist concerning the adverse impact of climate change at the global scale, while there are still many uncertainties regarding the possible influences of global warming in the mid-latitude regions, owing to rather limited research and lack of empirical evidence (Diffenbaugh and Burke, 2019). Specifically, what are the possible historical relationships between economic development and climate change for China? An emerging body of study concerns China's future integrated impact assessment and policy options, but to the best of our knowledge, very few attempts seem to have been made to uncover historical climate–economic relations, particularly at country and industrial levels. Overall, only two related studies, i.e., Zhang et al. (2018) and Yuan et al. (2020) are found, but the former focuses on the impact of warming on total factor productivity, while research center of the latter is on the effects of seasonal temperatures. In this context, we first build a two-dimensional database of city-level economic, employment and industrial data and station-level primary and secondary weather data, e.g., temperature, precipitation, relative humidity, and sunshine, air pressure and wind speed, for the period from 1990 to 2016. Regional and industrial heterogeneities of climate impact are further investigated to verify whether the discrepant adverse influences observed between rich countries and poor countries at the global scale still exist across China's different regions. Finally, we incorporate the estimated climate–economic relationship into the frameworks of the integrated assessment model (IAM) and provide multi-model projections on the long-term impacts of global warming on China's economy.

In this study, we find sufficient evidence on the negative role of warming in China's economic output (gross domestic product, GDP), and a 1 °C increase in temperature reduces GDP by 0.78 percentage points, which is literally equivalent to a climate damage of 241.7 billion USD (in 1990 constant prices); our estimate is lower than the average estimate for poor countries, i.e., 1.3 percentage points (Dell et al., 2012). Conversely, there is a positive relationship between precipitation and economy, and a 100 mm rise in rainfall is associated with a 0.86% increase in GDP; we also find a spread of statistically significant impacts of other climate variables, such as humidity and sunshine, on economic development. Furthermore, the nonlinear inverted U-shaped relationships between temperature, precipitation and economy that have been broadly uncovered at the global scale are verified in China (Tol, 2018).

Generally, the adverse climate impact is relatively limited in the short term (within this century), particularly for agricultural or cool countries (Stevanović et al., 2016; Wolfram et al., 2005), which may even benefit from global warming to some extent; however, in the long run, the increasing climate damage will finally offset the short-term positive influences, resulting in significant negative impacts (Heal, 2017). In effect, both the estimated historical relationships between average warming and aggregated economic variables and the IAM-simulated climate–economic interactions concern policy adjustments and designs associated with climate change; however, it is noticeable that the analysis of China's historical climate–economic relationship has long been absent from the empirical literature, with much attention being paid to future simulated climate impacts on the global or regional scales.

In particular, our estimates report significant differences in the effects of climate change across regions, in which economic development plays a formidable role. Specifically, hotter southwest China severely suffers from an average warming, followed by the northwest, while cooler northeast China is less and non-significantly affected by global warming. From the perspective of economic performance, the negative impact of temperature on poor regions is significant and serious, with a 1 °C increase in temperature associated with a 2.34 percentage point decrease in GDP, which is much higher than the projected average impact on rich regions and countries; when considering the positive effect of precipitation, the rich region benefits more than the poor region. Such findings are largely consistent with the global-scale conclusions drawn by Dell et al. (2012) and Hsiang et al. (2017), who reported that an additional temperature rise may reduce the GDP of poor countries by 1.3%, on average, while there may be no significant impacts on rich countries. In fact, more evidence shows that the difference in climate impact between the cooler and warmer regions is relatively limited for the high-latitude hot countries, while in the cooler countries, this discrepancy is generally more significant, and the warm regions benefit more from global warming than the cold regions (Fairbrother and Dixon, 2013). Even within one country, the geographic distribution of climate risk is highly imbalanced, especially when taking nonmarket damages, such as crime, human mortality and coastal storms, into account (Barreca et al., 2016; Nordhaus and Moffat, 2017).

Furthermore, we find significant heterogeneity of climate impacts across typical industries. First, the temperature rise has a negative role in agriculture, with a 1 °C rise in temperature corresponding to a 1.32% decrease in economic output, or approximately 40.9 billion USD (with a share of agricultural GDP of 10% and in 1990 constant prices). Second, precipitation positively affects China's agriculture, and an additional 100 mm of annual rainfall increases GDP by approximately 0.82%. In effect, the extant industry-level research on climate–economic relationships, especially for China, mainly focuses on agriculture (Wang et al., 2009; Xiong et al., 2012; Asseng et al., 2013; Yang et al., 2015). While actually China's industry is more affected by higher temperature, and an additional 1 °C of annual warming is associated with a 2.57% lower economic output, nearly double the corresponding effect on agriculture. This finding has also been verified in Central and Latin American countries, where, as estimated by Hsiang (2010), a 1 °C increase in temperature corresponds more GDP losses to non-agricultural sectors (e.g., industry, service and tourism) than to agriculture, i.e., 0.1% vs. 2.4%, which implies that climate damage would be largely underestimated if agriculture were considered to represent the overall economy.

This study contributes to the existing literature in three ways: first, we develop a systematical empirical model framework by coupling with a large climate–economic database and innovatively examine China's historical climate–economic interactions, particularly in different geographic regions and economic development regions; second, we explore the cross-sector impacts of climate change on economic output and the possible nonlinear relations between critical climate variables and economy, which paves the way for robust parameter calibration and basic assumption input of IAMs that aim at a long-term integrated assessment of climate damages. Despite substantial progress in IAM-based climate damage assessment, the simulated results largely do not match real climate-related damages (Pizer et al., 2014; Burke et al., 2016), and the evolution of climate systems and social-economic systems still faces numerous uncertainties, including climate sensitivity and impacts on sea-level rise, biodiversity, crops and human health, the adaptation capability of human beings arising from the development of adaptation technologies and behaviors, and mitigation activities across countries (Heal, 2017; Pindyck, 2017). The in-depth research on the historical climate–economic relationship is therefore beneficial for filling this gap and contributes to reshaping the simulated future climate–economic interactions with historical evidence. Last, we incorporate the estimated climate–economic relationships into different IAMs and make multi-model comparisons and projections on the future impacts of climate change on China, which greatly supports the decision making of long-term strategies on global warming. The precise assessment of climate impacts is central for policy making to address climate change: if the impact is dramatically negative, then aggressive policies (both mitigation and adaptation) may be needed to hedge against the potential risks (Ju et al., 2013; Chen et al., 2013; Stevanović et al., 2016); if the role of global warming is not significant, then governments' response will be correspondingly conservative (Deschênes and Greenstone, 2007; Wei et al., 2014; Yang et al., 2015). Our results indicate a robust historical relationship between climate change and economic production in the past 30 years and project a long-term role of climate change in economic development until the end of this century, which establishes an effective basis for China's climate policy making.

The remainder of this paper proceeds as below. Section 2 builds conceptual architecture and develops a model for econometric analysis; Section 3 introduces the data processing and provides descriptive statistics on the climate and economic data; the model estimation and results analysis, as well as a discussion of robustness, are presented in Section 4 and Section 5, respectively; Section 6 conducts cross-model projections on the future impacts of global warming on economic performance in terms of the linear and nonlinear relationships between temperature and the economy estimated in this work; and the last section concludes the paper with critical research findings and policy implementations and provides some important caveats for future works.

2. Empirical strategy

2.1. Empirical framework

Human capital is one of the core engines driving economic growth and a main channel for climate change to affect economic production (Sudarshan et al., 2014). Scientific evidence reveals that temperatures over 26 °C may significantly decrease humans' cognitive performance and activity efficiency and the marginal utility of leisure (Graff Zivin and Neidell, 2014), which greatly emphasizes the importance of the human capital in the unbiased estimation of climate damage (Hsiang, 2010; Dell et al., 2012). We therefore refer to Dell et al. (2012) and develop our empirical model framework from the typical reduced production function:

$$Y_{it} = A_{it} L_{it}^{\alpha} \tag{1}$$

Where i and t denote city and year, respectively; Y is economic output (GDP); L and A denote human capital and productivity, respectively; $0 < \alpha < 1$, which represents decreasing return to scale in human capital. Taking the logarithm of both sides of formula (1), we can obtain:

$$Ln\left(Y_{it}\right) = Ln\left(A_{it}\right) + \alpha Ln\left(L_{it}\right) \tag{2}$$

According to Bond et al. (2007), the current output is closely related to that of the previous period, in addition to the current human capital and productivity; combining with formula (2), we can obtain a dynamic panel model described as follows:

$$Ln\left(Y_{it}\right) = \rho Ln\left(Y_{it-1}\right) + \beta \Delta Ln\left(A_{it}\right) + \gamma \Delta Ln\left(L_{it}\right) + \varsigma_{it} \tag{3}$$

Where ς represents the random error term. Given the formidable impacts of climate change on both human capital and productivity (Burke et al., 2015; Zhang et al., 2018), we then approximately obtain the following relation equations:

$$\Delta Ln\left(A_{it}\right) = k_i + \sum_j \beta^j \mathbb{W}_{it}^j + \delta' \mathbb{T}_{it} + \varphi' \mathbb{X}_{it} + \nu_{it} \tag{4}$$

$$\Delta Ln\left(L_{it}\right) = l_i + \sum_j \gamma^j \mathbb{W}_{it}^j + \tau' \mathbb{T}_{it} + \pi' \mathbb{X}_{it} + \zeta_{it} \tag{5}$$

where k and l represent specific factors that affect the changes in technological advancement and human capital across cities; $\mathbb{W}$ shows primary climate variables, i.e., temperature, precipitation and relative humidity; and $\mathbb{T}$ gives control climate variables, including sunshine, air pressure and wind speed. $\mathbb{X}$ denotes the other important control variables that may play formidable roles in China's economy, such as distances between cities to shipping points and fixed asset investment. Globally, the majority of rich countries are located in the temperate zone or frigid zone (e.g., North America and Europe), while countries around the equator are mostly poor (e.g., African countries); this may not be true for China since most of the wealthy provinces are situated in relatively hot regions (e.g., South and East China), while the northern regions with cooler weather are less developed. China's traditional economic development patterns could tell most of the story; that is, the degree of transportation convenience (the distance to river or ports) plays a central role in regional economic development (Baum-Snow and Turner, 2017). In this context, we include the distance from cities to typical ports as one of the core control variables to control its possible influence on economic performance. Capital is also one of critical factors for economic production, but capital stock data are mostly unavailable; therefore, we consider fixed-asset investment in our model instead. ν and ζ are random error terms.

By putting formulas (4) and (5) into (3), we can obtain our main empirical model:[1]

$$Ln\left(Y_{it}\right) = y_0 + \rho Ln\left(Y_{it-1}\right) + \sum_j \theta^j \mathbb{W}_{it}^j + \lambda' \mathbb{T}_{it} + \xi' \mathbb{X}_{it} + c_i + \varepsilon_{it} \tag{6}$$

where y_0 is constant term; $\theta^j = \beta^j + \gamma^j$ is a semi-elasticity parameter, indicating the variation rate of the dependent variable per additional climate indicator; $\lambda' = \tau' + \delta'$ and $\xi' = \varphi' + \pi'$ are coefficients for climate control variables and other economy-related control variables, respectively. $c_i = k_i + l_i$ represents city-specific factor; ε is a random error term.

2.2. Regression methods

As we can see from (6), the lagged item of the dependent variable appears on the right-hand side, which may lead to endogeneity of the regression. In this circumstance, the traditional ordinary least square (OLS) method may bias the estimation, and the corresponding statistical inferences may be invalid as well. We therefore attempt to estimate the climate–economic relationship by employing the instrumental variable (IV) method and generalized method of moments (GMM) to reduce the possible bias resulting from endogeneity. A difference GMM (Dif. GMM) adopts the lagged dependent variable before period $t-2$ as the instrumental variable of the first-order lagged difference to obtain consistent and valid estimations. However, for finite samples, the difference GMM is sensitive to weak instruments, which may also lead to biased results (Arellano and Bover, 1995). The system GMM (Sys. GMM), which adds the level equation to the first differenced equation so as to make a joint estimation, can overcome the above difficulties of difference GMM.

3. Data and summary statistics

3.1. Data descriptions

We build an economic panel of 275 cities from 1990 to 2016, in which GDP and fixed asset investment are adjusted by the 1990 CPI deflator. City-level employment and real GDP across industries are used to explore the channels of climate–economic impacts, and we use urban on-the-job employees as a proxy of general employment, owing to data availability. Actually, industry-level GDP data are also inaccessible for some cities, which inevitably leads to a decrease in the data sample for channel analysis. All economic data are from national and provincial statistical yearbooks (NBS, 2017). Because missing data are severe for cities in Tibet, we do not consider such samples in the current research framework.

[1] We could actually use per capita GDP on the left-hand side of model (6), but the statistical caliber of population for many cities changed from registered to permanent after 2010, which greatly biased the trajectories of population evolution; we therefore use real GDP instead of per capita GDP, and this processing is consistent with Zhang et al. (2018).

Weather data are primarily collected from the *China Surface Daily Weather Dataset (V3.0)* released by the National Meteorological Center (NMC),[2] which includes daily temperature, precipitation, humidity, evaporation, sunshine, air pressure and wind speed data from 824 standard weather stations since 1951, and we use only the station-level weather data from 1990–2016 to match the economic data. Specifically, there exist withdrawal and changes in locations for some stations during the target period, which causes missing data and inconsistent statistical caliber to some extent; as a consequence, we finally adopt the weather data of 816 stations.

We transform the station-day weather data to the city level using inverse-distance weights between the station and the geographic centroid of each city (Mendelsohn et al., 1994; Deschênes and Greenstone, 2011). Given that the closer stations report more climate information on the center, the more distant stations should have lower weights in aggregation (Zhang et al., 2018). Specifically, we first identify the city center of gravity and the geographic distribution of the surrounding weather stations based on the ArcGIS software; then, we make a circle for each target city with the geographic centroid as the center and the maximal distance to the city boundary as the radius, and we consider the number of weather stations that are located in the circle. Next, we calculate the weights by inversing the distances R between each weather station and the geographic centroid. Then, the station-level weather data can be converted into city levels (see Figure B1 in the Supplementary Material for details). Finally, the daily city-level weather data are aggregated into year or season scales in terms of the given standards for different research aims (see Table A1 in the Supplementary Material for details). In the robustness analysis, we adopt different weighting methods, i.e., the inverse square root distance $(1/\sqrt{R})$ and the inverse squared distance $(1/R^2)$, to construct city-level yearly or quarterly weather data, and yearly mean temperature and rainfall data at 0.5*0.5 degree resolution are used to test the robustness of our main panel results.

Import–export trade has long been one of the driving forces for China's economic development, in which port trade plays a formidable role; in this circumstance, whether a city has a port or how close the city is to the nearby ports directly determines its economic growth to a large extent (Baum-Snow and Turner, 2017). We therefore construct a "city-port transportation distance" indicator by measuring the highway mileage between a city and its nearest port (waydist).[3] For the highway mileage, we first vectorize the *China Map* for each year and obtain preliminary transportation data. We then conduct nearest neighbor analysis by using the ArcGIS tool to calculate the highway distance between each city and its nearest port.

3.2. Summary statistics

The descriptive relationships between variations in temperature, precipitation and relative humidity and variations in logarithmic GDP (*Log output*) across cities are depicted in the scatter diagram, i.e., Fig. 1, Panel A to Panel C. The heights from cities to the horizontal zero line show the variations of climate variables, comparing the last five-year period (2012–2016) to the first five-year period (1990–1994), and the distances between cities and the vertical zero line denote the variations in *Log output* during the two periods.

From Panel A of Fig. 1, we find that the mean temperature in the majority of cities is rising, but there is substantial heterogeneity in specific warming increases, with the largest increases reaching 2–3 °C, such as in Anyang, Shiyan, Zunyi, Shangqiu, Xi'an, Xianyang and Suqian cities. There are also few cities encountering a decline in average temperature, but such cities are mostly located in South and Northeast China, with the magnitude of decrease less than 1 °C. Precipitation increases in most of the cities during the past decades (Panel B), particularly in Nanping, Foshan, Beihai and Heze cities, in which rainfalls increase by over 400 mm; approximately one-third of the sample cities experienced a decrease of precipitation, with the maximal decline reaching up to 200 mm, corresponding to Kaifeng and Changzhou cities. In Panel C, it is easy to observe that the relative humidity in most cities reduces, especially in some cities in Henan Province, such as Kaifeng, Xinxiang and Zhengzhou cities, where the magnitude of decrease reaches more than 8%; only a small number of cities experienced a rising average relative humidity, such as Anyang, Xi'an, Zunyi, Sanya and Suqian cities, with the maximal increase up to 5%. In sum, although we can expect tentative directional impacts of critical climate variables on economic output from the descriptive statistics, some exceptions prevent us from drawing a definitive conclusion, which indicates the need for further investigation of China's historical climate–economic relationships.

Fig. 2 sketches the time trends of variations in mean temperature (Panel A), precipitation (Panel B) and relative humidity (Panel C) on the country level; in these panels, large Xs denote annual averages of climate variables, and green dots give variance of logarithmic output, corresponding to the left Y-axis and right Y-axis, respectively. Fig. 1 indicates a rough average increase of 0.884 °C in temperature, a decrease of 1.84% in relative humidity, and a slight increase in rainfall. As shown in Panel A and Panel B, in the overwhelming majority of years, fluctuations of *Log output* are contrary to the variations in temperature and consistent with the variations in rainfall, which may indicate the negative role of temperature and the positive role of precipitation in economic output to some extent. As we can observe in Panel C, the relative humidity changes mostly in an opposite trend with the changes in *Log output*, especially after 1995, which also provides some implied evidence of the possible negative impacts of humidity on China's economy.

[2] All the weather data here can be accessed via *China Meteorological Data Sharing Service System* (CMDSS), http://cdc.cma.gov.cn/.

[3] We choose 8 typical ports established before 1990 in terms of throughput performance (turnover capacity): Shanghai, Shenzhen, Ningbo, Qingdao, Tianjin, Guangzhou, Xiamen and Dalian.

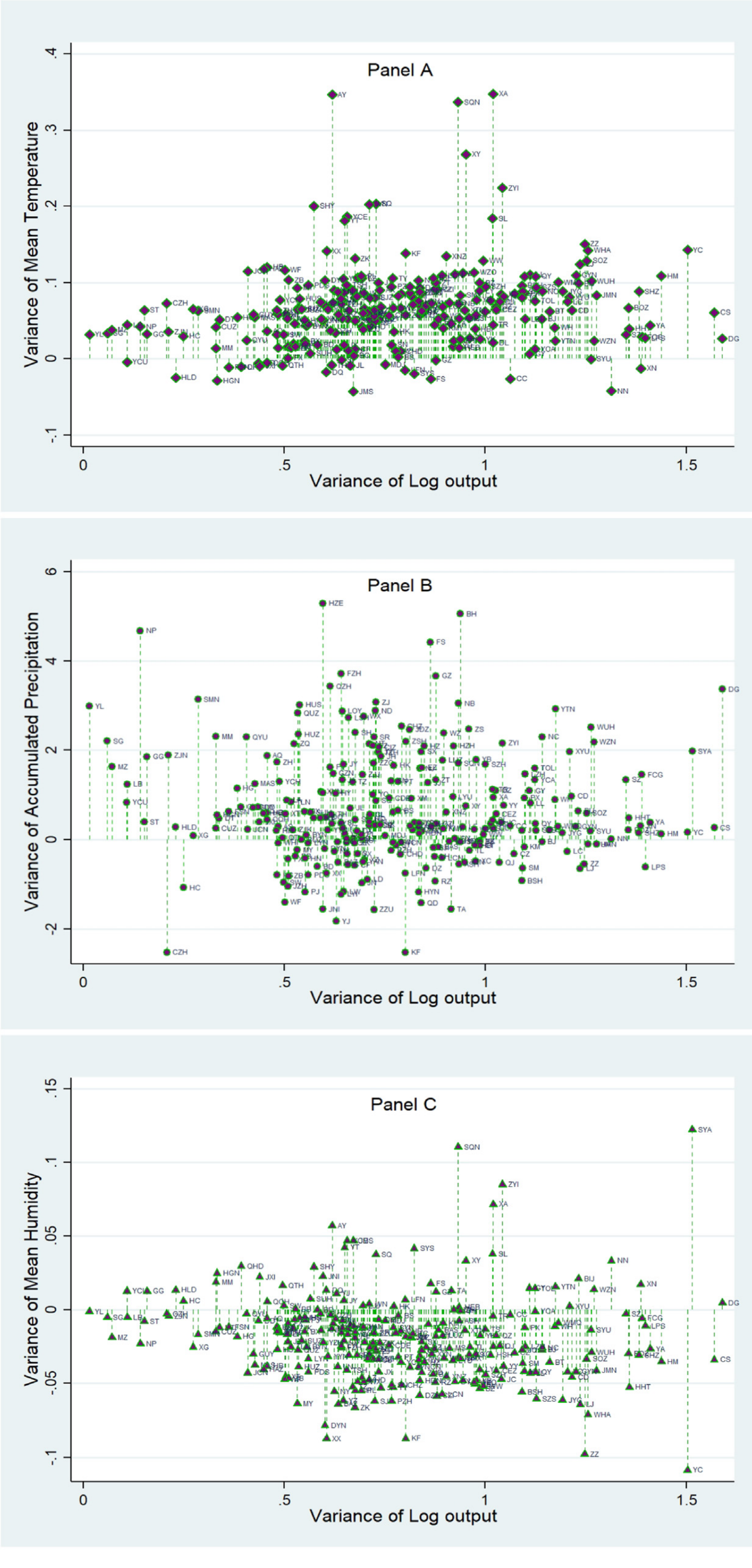

Fig. 1. Variations of temperature, precipitation and relative humidity across cities. ***Notes:*** City codes are used in this figure, see Figure A2 of the Appendix for more details.

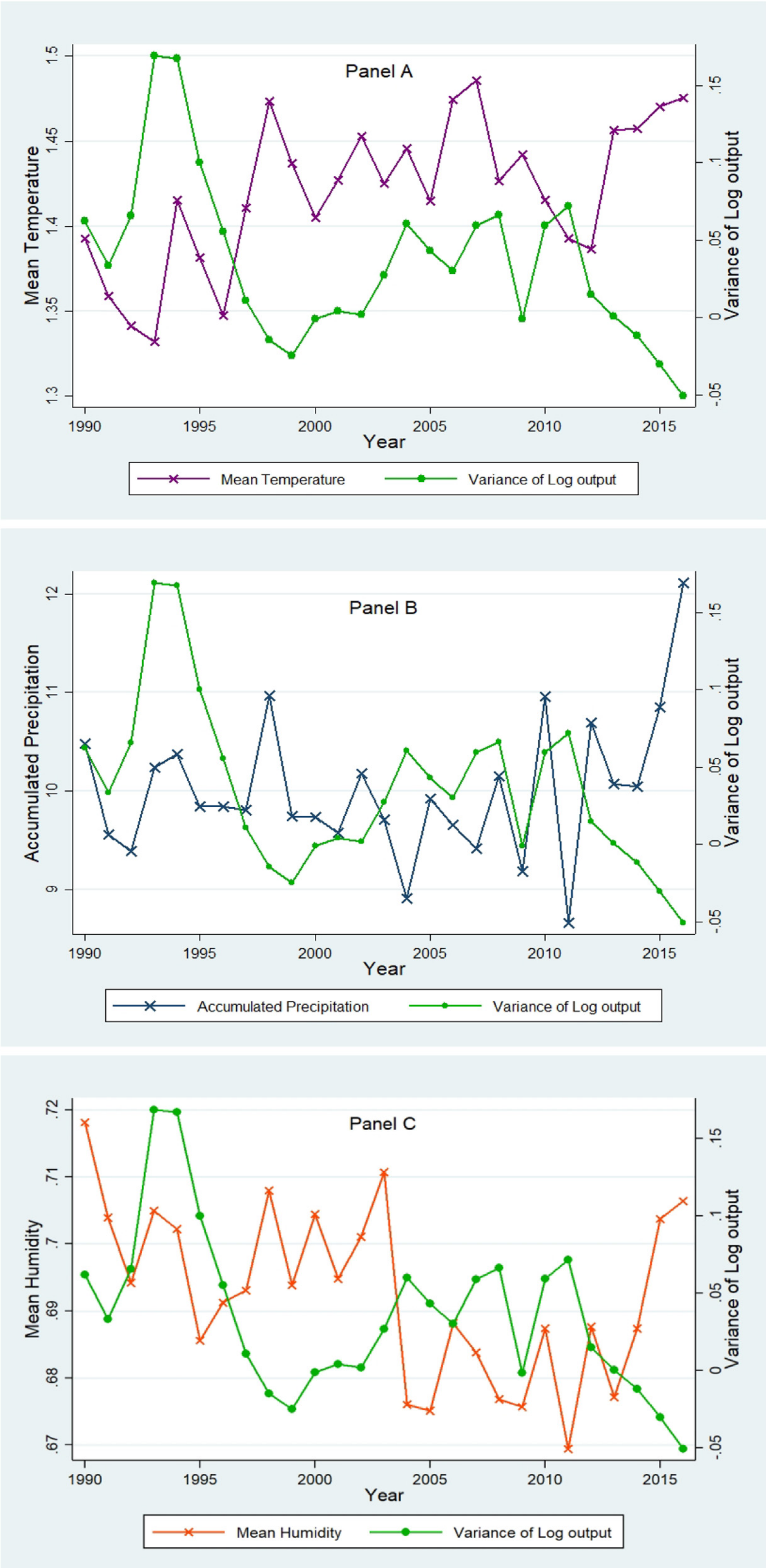

Fig. 2. Country-level time trends of variations in primary climate variables and output.

Table 1
Descriptive statistics of extended primary climate variables.

Variable	Obs	Mean	Std. Dev	Min	Max	Cv
Mean Temperature (unit:10 °C)	7497	1.4234	0.5195	0.0396	2.7001	0.3652
Q1	7497	1.4585	0.4679	0.0862	2.7822	0.3213
Q2	7497	2.4793	0.3134	0.3402	3.0026	0.1262
Q3	7497	1.5014	0.5609	−0.0331	2.7636	0.3738
Q4	7497	0.2250	0.8441	−2.3570	2.3568	3.7513
Accumulated Rainfall (unit:100 mm)	7497	10.0249	5.6432	0.4503	37.1449	0.5632
Q1	7497	2.5008	2.1304	0.0000	18.0530	0.8521
Q2	7497	4.8709	2.6732	0.1810	25.7273	0.5490
Q3	7497	1.8053	1.2665	0.0010	14.0164	0.7021
Q4	7497	0.8479	0.9224	0.0000	5.2110	1.0873
Mean Humidity (unit:100×percentage)	7497	0.6932	0.0983	0.0953	0.9138	0.1420
Q1	7497	0.6474	0.1446	0.0845	0.9508	0.2241
Q2	7497	0.7423	0.0933	0.1006	0.9313	0.1262
Q3	7497	0.7104	0.0883	0.0902	0.9147	0.1242
Q4	7497	0.6723	0.1112	0.0918	0.8860	0.1650
Days of High Temperature	7497	38.1285	30.6013	0.0000	165.0000	0.8031
Days of Low Temperature	7497	17.2785	32.4139	0.0000	144.0000	1.8760
Days of Strong Rainfall	7497	2.2900	2.8253	0.0000	22.0000	1.2342
Days of Weak Rainfall	7497	270.0980	37.4549	154.0000	355.0000	0.1390
Days of High Humidity	7497	109.3268	65.5550	0.0000	346.0000	0.6000
Days of Low Humidity	7497	23.8335	38.5069	0.0000	365.0000	1.6161

***Notes*:** Cv represents the coefficient of variation, and Q1, Q2, Q3 and Q4 represent the first quarter (spring), the second quarter (summer), the third quarter (autumn) and the fourth quarter (winter), respectively, in each year.

The descriptive statistics of the extended climate variables of temperature, rainfall and relative humidity are summarized in Table 1. By comparing the coefficient of variance for temperature and precipitation, we find that the largest dispersion appears in the fourth quarter (winter), which means that these two climate variables deviate greatly from their yearly or regional averages in this season; on the contrary, the dispersion of these two variables in the second quarter (summer) is the least. In contrast, the deviation of relative humidity is relatively lower across all seasons. For extreme climate indicators, low temperature, strong rainfall and low humidity encounter large dispersion.

4. Results and analysis

4.1. Main panel results: Impacts of climate change on national output

Temperature and precipitation play strong roles in economic production, which has long been agreed upon in the extant research (Dell et al., 2009; Lanzafame, 2014; Burke et al., 2015; Barreca et al., 2016; Graff Zivin et al., 2018); however, other climate variables, such as humidity, sunshine and wind, may also noticeably affect economic performance (Zhang et al., 2018). For example, the possible impacts of temperature rise, such as climate-related death rate and economic welfare, would be greatly overestimated without the measurement of humidity (Barreca, 2012). Our results also emphasize the important roles of climate variables in addition to temperature and precipitation (Table 2).[4] Specifically, in the only temperature and rainfall case, a 1 °C rise in warming is associated with 3.01 percentage point lower output (in column 1); when adding relative humidity, this impact reduces to 1.89% (column 2); if controlling for all the other climate variables, i.e., illumination time, air pressure and wind speed, a one-degree increase in temperature will reduce GDP by 0.78 percentage points at the 5% significance level (column 5), which is somewhat lower than the estimated climate impact on the US, i.e., 1.2% of GDP (Hsiang et al., 2017). The impacts of rainfall on the economy are consistently significant at the 1% level, and in the only temperature and precipitation case, a 100 mm increase in rainfall corresponds to an increase of 0.31 percentage points in GDP; when turning to the full climate variable case, this positive effect will further increase to 0.86% (column 5 in Table 2). Additionally, our results report statistically significant influences of relative humidity on output, with an additional 1% of humidity is associated with a 1.34% decrease of GDP (column 5); we can also observe the significant roles of sunshine and air pressure in economic performance from estimates in Table 2.

Weather factors are likely to interact with each other, and so might the economic effects of climate change. For instance, precipitation provides the source of higher humidity, which in turn strengthens the effects of higher temperature, particularly on labor input and efficiency (Barreca, 2012). In this context, we try to examine the interactive impacts of primary weather variables, as reported in Table 3. Columns 2 and 3 show the estimates by interacting temperature with humidity and precipitation, respectively; columns 3 and 4 show the impacts of humidity–rainfall interaction and three-way interactions among temperature, precipitation and humidity. Compared to the no interaction case (Column

[4] We made unit root tests for Log output, Log fixcapi and Log waydist before our main regressions, and those panels are stationary in general (Table A3 of the Supplementary Material), which effectively helps avoiding spurious regressions resulting from the possible existence of unit roots.

Table 2
Main panel results: effects of climate change on output.

Log output	Temp & Preci (1)	Add Humidity (2)	Add Sunlight (3)	Add Pressure (4)	Add Wind (5)
Temperature	−0.3009***	−0.1889***	−0.0673**	−0.0886***	−0.0775**
	(0.0580)	(0.0489)	(0.0341)	(0.0339)	(0.0349)
Precipitation	0.0031*	0.0115***	0.0079***	0.0086***	0.0086***
	(0.0016)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Humidity		−0.9978***	−1.3071***	−1.3058***	−1.3417***
		(0.1289)	(0.1604)	(0.1547)	(0.1604)
Sunlight			−0.0842***	−0.1682***	−0.1772***
			(0.0152)	(0.0298)	(0.0310)
Air pressure				1.0677***	1.0557***
				(0.2143)	(0.2152)
Wind speed					0.0015
					(0.0017)
L1: Log output	0.8423***	0.8238***	0.8178***	0.8158***	0.8141***
	(0.0224)	(0.0196)	(0.0204)	(0.0189)	(0.0192)
Log waydist	−0.0972***	−0.0860***	−0.0842***	−0.0523***	−0.0498***
	(0.0180)	(0.0175)	(0.0152)	(0.0163)	(0.0162)
Log fixcapi	0.0156***	0.0110**	0.0069	0.0066	0.0070
	(0.0049)	(0.0044)	(0.0048)	(0.0046)	(0.0046)
AR(2)(ρ-value)	0.668	0.757	0.907	0.878	0.824
Hansen Test(ρ-value)	0.124	0.849	0.808	0.908	0.909
Observations	7063	7063	7063	7063	7063

***Notes*:** The dependent variable is logarithmic output (GDP); temperature, precipitation and relative humidity are independent variables; and the other climate factors are control variables. The *Log fixcapi* represents logarithmic city-level fixed-asset investment. Temperature, relative humidity, air pressure and wind speed are annual averages of daily mean data, while precipitation and sunlight hour data are annual cumulants of daily cumulative data. All the data for climate variables is inverse-distance weighted. Robust standard errors are in parentheses. In columns (1)–(5), all estimates are achieved using the system GMM method. AR(2) examines the serial correlations of residuals in second difference. The Hansen test examines the exogeneity of difference GMM instruments (H_0 the instruments are exogenous). ***Significance at the 1% level, **Significance at the 5% level, *Significance at the 10% level.

5 in Table 2), we can obtain the following findings: first, the weather interactive items play a consistently negative role in economic output, which stresses the existence of interactive effects; second, the interactions with temperature affect the warming–economic relationships differently in terms of both magnitude and statistical significance, while interactions with rainfall consistently reinforce the positive effect of precipitation on GDP; third, interacting temperature with precipitation slightly reduces the impacts of warming on economy, which implies the positive hedging effect of rainfall to some extent; fourth, interacting humidity with the other weather variables causes a significant decrease in the impact of relative humidity on GDP, and this may imply some overestimation of the economic influence of humidity if interaction items are not considered.

Table 4 empirically informs the economic impacts of climate change across seasons, and quarter 1 (Q1) to quarter 4 (Q4) represent the four seasons, i.e., spring, summer, autumn and winter, respectively. Similar to the layout of Table 2, column 1 is the only warming and precipitation case; the effects of adding relative humidity are summarized in column 2; columns 3 and 4 report the results by controlling air pressure and wind speed; and column 5 shows the estimates under the full climate variable case. As we can observe, warming plays a consistently negative role in output in the first quarter, with a 1 °C temperature rise producing a 1.33–1.66 percentage point reduction in GDP; this effect turns to be significantly positive when moving to the second and third quarters. The first three quarters are a critical period for China's economic production in both agriculture and industry, which largely explains the sensitive and significant influences of warming on output. Higher temperatures in spring disturb the growth cycle of crops, and this finally turns into a decrease in agricultural output. Moreover, spring is the high-incidence season of epidemics, and higher temperatures may prevent the effective control of infectious diseases; as a result, both labor input and efficiency may be negatively affected. In contrast, summer and autumn are the mature periods for most crops, and warming increases in such seasons contribute to increases in agricultural yields. Our results are largely in line with Liu et al.'s (2004) study on agriculture, in which they find a negative role of warming in spring and a positive role in autumn.

Despite the prevalent positive influence of precipitation on average, the quarterly impact of precipitation in spring is estimated to be negative, with an extra 100 mm of rainfall associated with a 0.75% reduction in GDP, which is significant at the 1% level. Similar to the effect of warming, higher precipitation in spring may worsen the conditions for agricultural and industrial production, especially for rainy South and East China (which are also China's main production areas), and the increase in rainfall may negatively affect the labor input and productivity in the service sector. The significant economic impacts of relative humidity mainly appear in the first and second quarters, with a 1% increase in humidity reducing GDP by 0.23–0.25 percentage point in the first quarter, which is statistically distinguishable at the 1% level, and increasing GDP in the second quarter with magnitude and significance equivalent to those in the first quarter. On the year-average level, this positive influence of humidity is completely offset by the strong negative effects, which leads to a negative effect

Table 3
Effects of climate change on output: climate interactions.

Log output	(1)	(2)	(3)	(4)
Temperature	−0.0158	0.3324**	−0.1166***	−0.0475
	(0.0532)	(0.1593)	(0.0305)	(0.0413)
Precipitation	0.0241***	0.0104***	0.0460***	0.0206***
	(0.0082)	(0.0020)	(0.0155)	(0.0060)
Humidity	−1.3368***	−0.3475	−0.7849**	−1.1814***
	(0.1553)	(0.3883)	(0.3115)	(0.1921)
Temp × Preci	−0.0078**			
	(0.0039)			
Temp × Humidity		−0.6196***		
		(0.2303)		
Humidity × Preci			−0.0471**	
			(0.0191)	
Temp × Preci × Humidity				−0.0075**
				(0.0034)
L1: Log output	0.8159***	0.8228***	0.8286***	0.8204***
	(0.0192)	(0.0189)	(0.0190)	(0.0189)
Log waydist	−0.0506***	−0.0535***	−0.0489***	−0.0499***
	(0.0158)	(0.0151)	(0.0151)	(0.0155)
Log fixcapi	0.0070	0.0056	0.0050	0.0063
	(0.0046)	(0.0045)	(0.0042)	(0.0044)
AR(2)(ρ-value)	0.931	0.879	0.961	0.944
Hansen Test(ρ-value)	0.746	0.890	0.875	0.821
Observations	7063	7063	7063	7063

Notes: The dependent variable is logarithmic annual output (GDP). Data processing for both GDP and climate variables are the same as in Table 1. Columns (1)-(3) are estimates under interactions between pairs of critical climate variables, i.e., temperature, precipitation and humidity. The model used in column (4) includes all the permutation interactions among the three climate variables. All the other climate variables are controlled in the estimates. Robust standard errors are in parentheses. All estimates are achieved using system GMM method. AR(2) examines the serial correlations of residuals in the second difference. The Hansen test examines the exogeneity of the difference GMM instruments (H_0: the instruments are exogenous). ***Significance at the 1% level, **Significance at the 5% level, *Significance at the 10% level.

of humidity on the economy (as portrayed in Table 2). Specifically, the increase in relative humidity damages people's ability to sweat and cool, which proves to be harmful for health and reduces labor efficiency (Barreca, 2012); in addition, higher humidity provides a fertile environment for bacteria and dust mites, particularly in the epidemic-sensitive spring, which inevitably increases the risk of infection and social control costs (Shaman and Kohn, 2009).

Global-scale research has revealed that the world's economy is the most productive when the mean temperature is approximately 13 °C, and extremely high or low temperatures are harmful to the growth of crops and the work efficiency of laborers (Diffenbaugh and Burke, 2019). Given this background, we try to incorporate extreme weather variables, i.e., temperature, rainfall and relative humidity, in the panel framework to examine the economic influences of extreme weather that may be covered or neglected by the mean climate performance. As abbreviated in Table 5, Maxi and Mini represent the number of days that the mean temperature is higher than 32 °C and lower than -12 °C, respectively; when moving to the precipitation (24 h cumulant), these two thresholds are chosen to be 50 mm and 1 mm, versus 80% and 40% for the relative humidity (daily average). Column 1 in Table 5 reports the estimates with temperature, precipitation and relative humidity as independent variables, and columns 2, 3, and 4 present the results by controlling for sunshine, air pressure, and wind speed separately. We find that extreme heat plays a negative role in output, with an additional day of extreme heat reducing GDP by 0.0006 percentage point (Column 4). In fact, the economic impacts of extreme heat are different across sectors, particularly for industry, whose GDP loss reaches 0.45% corresponding to an additional day of extreme heat (Zhang et al., 2018). The increase in extreme low temperature days positively affects economic production, despite the insignificance of the coefficient. Table 2 reports the positive impacts of precipitation on the economy, which is consistent with the effects of heavy rainfall in direction. As the point estimate reveals in Table 5, an additional day of heavy rainfall is associated with a 0.0092 percentage point increase in output. Thus, in addition to natural hazards, such as floods and landslides, resulting from frequent precipitation within a short period, more days of effective rainfall greatly contributes to alleviating the shortage of water resources and benefits economic development.

Table 5 also uncovers a negative impact of extremely high humidity and a positive impact of extremely low humidity on output, and both are statistically significant at the 1% level; an additional day of extremely high humidity and low humidity is associated with a 0.0005 lower and 0.0014 higher GDP, respectively. Although the increase in average humidity in the crop growing season may play a positive role in yields, with a 1% increase in mean relative humidity corresponding to 0.61%, 0.75% and 0.96% growth in maize, rice and wheat (Chen et al., 2016); the impact of extremely high humidity is negative. Higher relative humidity makes it colder in winter and hotter in summer, which may reduce labor intensity and efficiency to a large degree; the interaction of high temperature with high humidity increases the death rates associated with climate change, while low humidity, drying and cool air should be effective to hedge against this risk (Barreca, 2012; Graff Zivin and Neidell, 2014). Overall, agriculture is not dominant in China (7.9% in 1990 and 40.9% in 2016), which means that the positive effect resulting from the increase in relative humidity may be largely offset by the corresponding negative effect, which tells the story that higher humidity damages China's economy.

Table 4
Effects of climate change on output: roles of seasons.

Log output	Temp & Preci (1)	Add Humidity (2)	Add Sunlight (3)	Add Pressure (4)	Add Wind (5)
Temperature:					
Q1	−0.1658***	−0.1325***	−0.1407***	−0.1396***	−0.1379***
	(0.0257)	(0.0255)	(0.0241)	(0.0257)	(0.0250)
Q2	0.1237***	0.1007**	0.1091**	0.1180*	0.1191**
	(0.0322)	(0.0458)	(0.0458)	(0.0606)	(0.0592)
Q3	0.0942***	0.1205***	0.1109**	0.1092**	0.1091**
	(0.0355)	(0.0376)	(0.0402)	(0.0452)	(0.0443)
Q4	−0.0521***	−0.0157	−0.0170	−0.0179	−0.0180
	(0.0161)	(0.0139)	(0.0138)	(0.0149)	(0.0148)
Precipitation:					
Q1	−0.0113***	−0.0065***	−0.0075***	−0.0075***	−0.0075***
	(0.0028)	(0.0025)	(0.0022)	(0.0022)	(0.0021)
Q2	0.0112***	0.0037*	0.0015	0.0016	0.0016
	(0.0020)	(0.0020)	(0.0018)	(0.0017)	(0.0017)
Q3	0.0025	0.0099	0.0084	0.0083	0.0082
	(0.0027)	(0.0063)	(0.0066)	(0.0069)	(0.0067)
Q4	−0.0002	0.0108**	0.0063	0.0064	0.0062
	(0.0041)	(0.0047)	(0.0045)	(0.0046)	(0.0045)
Humidity:					
Q1		−0.2352***	−0.2516***	−0.2505***	−0.2519***
		(0.0488)	(0.0525)	(0.0508)	(0.0501)
Q2		0.2185***	0.2300***	0.2511***	0.2454***
		(0.0828)	(0.0769)	(0.0793)	(0.0803)
Q3		−0.0177	−0.0855	−0.0788	−0.0831
		(0.1160)	(0.0963)	(0.1043)	(0.0998)
Q4		−0.1625	−0.1453	−0.1448	−0.1467
		(0.0914)	(0.0937)	(0.0990)	(0.0968)
L1: Log output	0.7399***	0.7971***	0.8125***	0.8123***	0.8122***
	(0.0184)	(0.0167)	(0.0143)	(0.0143)	(0.0142)
Log waydist	−0.0745***	−0.0432***	−0.0464***	−0.0449***	−0.0440***
	(0.0156)	(0.0115)	(0.0121)	(0.0122)	(0.0116)
Log fixcapi	0.0260***	0.0167***	0.0130***	0.0131***	0.0132***
	(0.0041)	(0.0036)	(0.0030)	(0.0031)	(0.0032)
AR(2)	0.677	0.751	0.817	0.790	0.785
Hansen Test	0.998	0.868	0.867	0.869	0.872
Observations	7063	7063	7063	7063	7063

***Notes*:** Climate variable data, such as temperature, rainfall and relative humidity, are quarterly averaged, and Q1, Q2, Q3 and Q4 represent the first quarter, the second quarter, the third quarter and the fourth quarter, respectively. The other climate variables, including sunlight, pressure and wind speed, are annually averaged with inverse-distance weights. In columns (1)-(5), system GMM methods are employed, controlling all the other climate variables. Asterisks indicate significance at the 1% (***), 5% (**), and 10% (*) levels for the coefficients. Values in parentheses are standard errors. AR(2) examines the serial correlations of residuals in the second difference. The Hansen test examines the exogeneity of difference GMM instruments (H_0: the instruments are exogenous).

4.2. Effects on economic regions of China

The regional impact of climate change is closely related to the level of economic development (Burke et al., 2015); generally, less-developed areas are more vulnerable to climate damage risk due to their hotter locations and incomplete adaptation capacity (Dell et al., 2012). Global-scale research also indicates that in years when the weather is warmer than the historical average level, cooler countries benefit more from global warming, while hotter countries may encounter slower economic growth, which implies that global warming is likely to exacerbate economic inequality across countries (Diffenbaugh and Burke, 2019). Then, is this global-scale finding still true across China's regions? To address this concern, we divide all the provinces into three large regions, i.e., west, center and east, corresponding to a less-developed (poor), medium-developed and higher-developed (wealthy) economic level (the detailed region divisions are described in Table A4 of the Supplementary Material).

As shown in Table 6, columns (1a), (2a) and (3a) give the estimates under the mean weather scenario, and columns (1b), (2b) and (3b) report the economic impacts of extreme weather. As previously defined, extreme weather is proxied by the days that the weather variable is higher or lower than the given thresholds (see Table A1 of the Supplementary Material for definitions). Although extreme weather may not uncover the influence of the full exposure of weather during the course of a day, it sufficiently supplements the possible effects that could be neglected by the mean weather (Zhang et al., 2018). According to the estimates of mean warming, a 1 °C-temperature rise produces a 2.34 percentage point reduction in GDP of the less-developed region, which is much higher than the country-average warming impact; temperature rise also plays a negative role in the economy of the higher-developed region, but both the magnitude and significance are much lower than those of the less-developed region. Our results provide substantial evidence on the findings of Dell et al.

Table 5
Effects of climate change on output: extreme weather.

Log output	(1)	(2)	(3)	(4)
Temperature:				
Maxi	−0.0007*	−0.0003	−0.0005*	−0.0006**
	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Mini	0.0006	0.0001	0.0001	0.0001
	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Precipitation:				
Maxi	0.0081***	0.0079***	0.0090***	0.0092***
	(0.0028)	(0.0029)	(0.0026)	(0.0026)
Mini	−0.0003	−0.0003	−0.0002	−0.0001
	(0.0004)	(0.0002)	(0.0004)	(0.0004)
Humidity:				
Maxi	−0.0003	−0.0003*	−0.0005***	−0.0005***
	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Mini	0.0009***	0.0009***	0.0014***	0.0014***
	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Sunlight		−0.0641*	−0.0998***	−0.1092***
		(0.0367)	(0.0290)	(0.0323)
Air pressure			0.7138***	0.7032***
			(0.1648)	(0.1644)
Wind speed				0.0010
				(0.0014)
L1: Log output	0.8148***	0.8165***	0.8069***	0.8083***
	(0.0172)	(0.0172)	(0.0166)	(0.0166)
Log waydist	−0.0705***	−0.0645***	−0.0536***	−0.0521***
	(0.0137)	(0.0142)	(0.0140)	(0.0138)
Log fixcapi	0.0144***	0.0126***	0.0112**	0.0115**
	(0.0049)	(0.0048)	0.0050	(0.0049)
AR(2)(ρ-value)	0.973	0.805	0.908	0.948
Hansen Test(ρ-value)	0.999	0.994	0.997	0.998
Observations	7063	7063	7063	7063

***Notes*:** Maximum and minimum data of independent variables, i.e., temperature, precipitation and humidity, are the number of days with the daily maximum and minimum observations met with the given thresholds. For temperature, the upper bound is 32 degrees Celsius, and the lower bound is -12 degrees Celsius; for rainfall, the relative thresholds are 50 mm per day and 1mm per day; for humidity, the two bounds are 80% and 40%, respectively. The estimates in columns (1)-(4) are made under the basic method of system GMM. Robust standard errors are in parentheses. AR(2) examines the serial correlations of residuals in the second difference. The Hansen test examines the exogeneity of the difference GMM instruments (H_0: the instruments are exogenous). ***Significance at the 1% level, **Significance at the 5% level, *Significance at the 10% level.

(2012) and Pretis et al. (2018) from the country perspective, i.e., poor regions are more vulnerable than wealthy regions to global warming, and climate change may trigger 'new poor' in the poor regions. Globally, poor countries are mostly located in hotter regions, such as the equatorial African countries, and China's western provinces also face unfavorable weather conditions. In addition, poor countries usually face high exposure to climate risk and have poor adaptation ability, which may explain the large damage to the poor region (Hsiang et al., 2017). What is different from the results at the global scale is that many hotter provinces are also wealthy regions, such as South China, which may differ from the global-level estimates to some extent. Actually, such hotter and richer provinces are mostly along the coast or rivers; they suffer from global warming but benefit more from convenient transportation, which proves to be a driving force for economic development. As a result, the positive effect of superior geographic position partly offsets the negative effect of global warming (which is why we incorporate the distance to ports as one of the control variables in our model). For the straightforward distribution of climate impacts across economic regions, please refer to Figure B4 of the Supplementary Material.

The positive impacts of rainfall on output are greatly significant and consistent across economic regions. For example, a 100 mm increase in precipitation is associated with a 0.67 percentage point higher GDP in East China and a 0.5 percentage point higher GDP in West China. Higher relative humidity has a significant negative effect on the economy of the east and center of China; an additional 1% of humidity will reduce GDP by 0.76% and 0.77%, respectively, while the negative economic impact of humidity on the west is not significant. China is along the coast, while the center typically features lakes or rivers. As a result, both East and Central China are wet, and the further increase in humidity may reduce labor intensity and efficiency, which in turn negatively affects economic production. For the dry western regions, increasing humidity may have positive effects on agricultural production but may also have negative effects on the industry and service sectors, which brings uncertainty to the net impact on output. By combining the warming effect and precipitation effect across regions, we can conclude that the wealthy regions gain more from the positive impact of climate change, while the poor regions suffer more from the negative influence, which largely verifies the global-scale finding; i.e., climate change may intensify regional economic inequality (Hsiang, 2010; Diffenbaugh and Burke, 2019).

Extreme weather plays a limited role in the regional economy by showing a small effect in magnitude and substantially less significance. For the more-developed regions, an additional day of extreme high temperature corresponds to a 0.0005

Table 6
Effects of climate change on regions under different economic development levels.

Log output	East China		Midland China		West China	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Temperature:	−0.1046**		0.0161		−0.2340***	
	(0.0437)		(0.0236)		(0.0516)	
Maxi		−0.0005*		0.0001		−0.0010
		(0.0003)		(0.0002)		(0.0008)
Mini		−0.0007		0.0004		0.0009*
		(0.0005)		(0.0004)		(0.0005)
Precipitation:	0.0067***		0.0034***		0.0050*	
	(0.0016)		(0.0014)		(0.0028)	
Maxi		0.0059***		0.0015		0.0030
		(0.0021)		(0.0018)		(0.0042)
Mini		−0.0002		−0.0007*		−0.0001
		(0.0004)		(0.0004)		(0.0008)
Humidity:	−0.7631**		−0.7730***		0.1236	
	(0.3823)		(0.1075)		(0.4203)	
Maxi		−0.0003		−0.0007***		0.0003
		(0.0003)		(0.0002)		(0.0003)
Mini		0.0015**		0.0006***		0.0007**
		(0.0006)		(0.0002)		(0.0004)
L1: Log output	0.8043***	0.8457***	0.8692***	0.8430***	0.8128***	0.8196***
	(0.0447)	(0.0407)	(0.0196)	(0.0179)	(0.0270)	(0.0354)
Log waydist	−0.1990***	−0.1393***	0.0021	−0.0103	−0.0523**	−0.0357
	(0.0485)	(0.0355)	(0.0274)	(0.0310)	(0.0275)	(0.0329)
Log fixcapi	0.0074	0.0032	0.0033	0.0059	0.0261***	0.0237***
	(0.0146)	(0.0158)	(0.0033)	(0.0041)	(0.0076)	(0.0085)
AR(2)(ρ-value)	0.855	0.907	0.441	0.556	0.295	0.321
Hansen Test(ρ-value)	0.498	1.000	0.932	0.999	0.985	1.000
Observations	2548	2548	2652	2652	1863	1863

***Note*:** Climate variables, such as temperature, air pressure, wind speed and humidity, are annually averaged on the daily mean data, and rainfall and sunlight data are the annual average of daily cumulative observations. According to differences in economic development level (e.g., per capita income), rich regions, average-income regions and poor regions correspond to the east, center and west of China (Regional distributions are summarized in Table A2). As above, all estimates are achieved using the system GMM method.AR(2) examines the serial correlations of residuals in the second difference. The Hansen test examines the exogeneity of the difference GMM instruments (H_0: the instruments are exogenous). ***Significance at the 1% level, **Significance at the 5% level, *Significance at the 10% level.

percentage point reduction in GDP, and an additional 100 mm of precipitation is associated with a 0.0059 percentage point GDP growth. We find little evidence of the significant economic impact of extremely lower precipitation. With respect to the cross-regional impacts on output, the mean weather effect is highly in line with that of the extreme weather, in terms of both the significant and nonsignificant estimates (Table 6). This result partly reflects the robustness of our empirical estimates and partly shows that less- or undeveloped regions suffer more from adverse climate events due to limited economic ability and incomplete adaptation capability.[5] In addition, the negative effect of extremely high humidity on output is only significant in the center, but the positive impact of extremely low humidity is significant across all three economic regions, which supports the country-average influence of extremely low humidity (Table 5).

4.3. Heterogeneity in the effects on climatic regions

Existing studies have shed light on the geographically imbalanced distribution of climate impacts in the US (Wang et al., 2017; Hsiang et al., 2017); therefore, it is reasonable to expect that this heterogeneity in climate effects also exists in China, a more climate-vulnerable country than the US. Actually, China covers a vast geographic area, and its regions largely differ in climate conditions, industrial structure and economic situation, which may all contribute to heterogeneous climate effects. We report the cross-regional impacts of climate change on output in Table 7, with columns 1 to 7 corresponding to east, northwest, northeast, north, central, south and southwest China (the detailed regional divisions can be referred to in Table A5 of the Supplementary Material). The estimates inform the most negative economic impact of warming in west China (northwest and southwest), followed by north and central China, while the south and northeast regions suffer less from the temperature rise, despite the insignificance of the effects. As shown in the data description (Figure B2 of the Supplementary Material), the mean temperature is higher in southwest China and lower in northeast China; as a consequence, an additional temperature rise negatively affects the hotter regions but has a smaller effect on the cooler regions (Zhang et al., 2018). Furthermore, both the northwestern and southwestern regions are relatively poor in

[5] Notably, extreme weather here is defined in terms of the given threshold, while different from the common-sense extreme events, such as the large-scale blackout and production halts in central China resulting from the sleet in 2008 and the waterlogging diseases owing to the typhoon "Shanzhu" in the Pearl River Delta in 2018.

Table 7
Effects of climate change on output across geographic regions.

Log output	Northeast (1)	Northwest (2)	North (3)	Central (4)	South (5)	Southwest (6)	East (7)
Temperature	−0.0007	−0.1736***	−0.1809*	−0.1354**	−0.1011	−0.1683*	0.0417
	(0.0534)	(0.0632)	(0.1008)	(0.0658)	(0.1345)	(0.0878)	(0.0481)
Precipitation	0.0092**	0.0090*	0.0077	0.0087***	0.0052**	−0.0152***	0.0039***
	(0.0046)	(0.0053)	(0.0202)	(0.0016)	(0.0025)	(0.0050)	(0.0013)
Humidity	0.5615*	−0.1223	−1.9091**	−0.8628***	−0.5588**	0.0847	−1.0710***
	(0.2789)	(0.2982)	(0.8843)	(0.1563)	(0.2437)	(0.0592)	(0.1532)
Sunlight	0.1284	−0.0439	−0.1041	−0.0152	−0.0435	−0.0159	−0.0536*
	(0.0810)	(0.0535)	(0.1130)	(0.0311)	(0.0602)	(0.0395)	(0.0286)
Air pressure	0.8423	0.4712	2.6761*	0.0782***	1.2196	0.4724	0.6956***
	(0.5380)	(0.3117)	(1.5589)	(0.0176)	(2.8094)	(0.4340)	(0.2184)
Wind speed	0.0023	−0.0022	−0.0180	0.0002	0.0015	−0.0002	0.0045**
	(0.0038)	(0.0024)	(0.0114)	(0.0021)	(0.0033)	(0.0046)	(0.0019)
L1:Log output	0.6770***	0.9170***	0.7659***	0.8984***	0.8305***	0.8699***	0.8053***
	(0.0329)	(0.0406)	(0.2065)	(0.0311)	(0.0417)	(0.0697)	(0.0200)
Log waydist	−0.1011***	−0.0203	−0.0211	−0.0189	−0.0781***	0.0316	−0.0523
	(0.0390)	(0.0432)	(0.0518)	(0.0473)	(0.0268)	(0.0923)	(0.0363)
Log fixcapi	0.0333***	0.0300	−0.0012	0.0012	0.0179*	0.0267	0.0115**
	(0.0076)	(0.0181)	(0.0299)	(0.0049)	(0.0101)	(0.0278)	(0.0052)
AR(2)	0.621	0.114	0.990	0.730	0.729	0.463	0.000
HansenTest	0.999	0.989	1.000	0.999	0.982	1.000	0.972
Observations	936	754	754	1040	858	797	1924

Note: Climate variables, such as temperature, air pressure, wind speed and humidity, are annually averaged on the daily mean data, and rainfall and sunlight data are the annual average of daily cumulative observations. According to differences in economic development level (e.g., per capita income), rich regions, average-income regions and poor regions correspond to the east, center and west of China (Regional distributions are summarized in Table A2). As above, all estimates are achieved using the system GMM method.AR(2) examines the serial correlations of residuals in the second difference. The Hansen test examines the exogeneity of the difference GMM instruments (H_0: the instruments are exogenous). ***Significance at the 1% level, **Significance at the 5% level, *Significance at the 10% level.

China, which may also contribute to the larger negative impacts of temperature rise (Table 6). In contrast, temperature increases in cooler regions may improve the climate conditions required by agricultural, industrial and service production and save considerable heat costs, which explains the lower economic effects of warming (Fairbrother and Dixon, 2013). Interestingly, as a hotter region, south China non-significantly suffers from global warming, which seems to be somewhat contradictory to the general finding we obtain above. Actually, this result indicates substantial trade-offs between the negative impacts of warming increase and the positive hedging effects. On the one hand, a higher mean temperature indeed means a larger magnitude of climate impact, which explains the negative estimate in column (5) of Table 7. On the other hand, wealthy regions suffer less from the impact of temperature rise, as we uncovered in Table 6, and this provides a positive effect to hedge against the negative climate impact; in addition, we can observe that the average temperature fluctuates more in south China, which may reinforce this hedging effect to some extent. Consequently, the hedging positive effect of higher economic performance in south China overlaps with the negative effect of its higher mean temperature, suggesting that the region-level impact of global warming depends on economic development level and geographic climate conditions.

The influences of precipitation in most regions are positive and statistically significant, as portrayed in Table 7. For example, a 100 mm increase in rainfall is associated with a 0.92, 0.90 and 0.87 percentage point higher GDP in northeast, northwest and central China, respectively; these results are greatly consistent with the country-average estimates in both direction and magnitude, as shown in Table 2. Notably, we cannot repeat the finding obtained in Table 6, i.e.; the significant positive effect of rainfall mainly appears in more-developed regions, while in less- or undeveloped regions, this effect is negative or nonsignificant, and the distribution of the positive impacts of rainfall relies more on the geographic location and its corresponding climate conditions. An increase in mean relative humidity may play a formidable negative role in the production of north, east and central China, with an additional 1% of humidity associated with a 1.90, 1.07 and 0.86 percentage point lower output, respectively, at the 1% level of significance, which is also highly parallel with the results shown in Table 6. In fact, east, north and central China are wet regions, being located either along the coast or in the lake and river districts, and further increases in humidity negatively affect labor input and efficiency, which in turn leads to a net adverse impact on output. The straightforward distribution of climate impacts across geographic regions is portrayed in Figure B5 of the Supplementary Material.

4.4. Nonlinear relations between climate change and economy

Although this study is conducted based on the assumption of a linear climate–economy relationship, climate, especially warming and rainfall, may have nonlinear effects on economic production (Wolfram and Mendelsohn, 2009). Burke et al. (2015) found nonlinear temperature–economy relationships in both wealthy and poor countries, and the difference in the

Table 8
Possible nonlinear interaction between climate change and economy.

Log output	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Temperature	0.3119*	0.3151*	−0.1464***	−0.0699**	−0.1725***	−0.0784***
	(0.1938)	(0.1831)	(0.0345)	(0.0253)	(0.0314)	(0.0236)
Precipitation	0.0073***	0.0062***	0.0179**	0.0195**	0.0090***	0.007***
	(0.0017)	(0.0017)	(0.0077)	(0.0093)	(0.0017)	(0.0019)
Humidity	−0.4813*	−0.8077**	−0.5523**	−0.9053***	2.1028	1.4481
	(0.2748)	(0.3195)	(0.2661)	(0.2924)	(1.5202)	(1.3517)
Temperature^2	−0.1764**	−0.1461**				
	(0.0700)	(0.0708)				
Precipitation^2			−0.0003	−0.0004		
			(0.0002)	(0.0003)		
Humidity^2					−1.9508**	−1.6814**
					(0.9836)	(0.8465)
Includes other vars.	No	Yes	No	Yes	No	Yes
L1:Log output	0.8363***	0.8322***	0.8400***	0.8356***	0.8501***	0.8408***
	(0.0156)	(0.0157)	(0.0150)	(0.0156)	(0.0154)	(0.0160)
Log waydist	−0.0785***	−0.0537***	−0.0693***	−0.0422***	−0.0658***	−0.0503***
	(0.0141)	(0.0138)	(0.0142)	(0.0137)	(0.0146)	(0.0126)
Log fixcapi	0.0135***	0.0092*	0.0115***	0.0081*	0.0091***	0.0062
	(0.0044)	(0.0052)	(0.0038)	(0.0048)	(0.0035)	(0.0046)
AR(2)	0.852	0.855	0.962	0.961	0.694	0.902
Hansen Test	0.986	0.983	0.967	0.871	0.956	0.949
Observations	7063	7063	7063	7063	7063	7063

Notes: In this nonlinearity estimate, the independent variable is still log annual GDP, with the dependent variables being temperature, precipitation and humidity (columns (1a), (2a) and (3a)), and controlling for the other climate variables, including sunshine, air pressure and wind speed (columns (1b), (2b) and (3b)), respectively. In addition, we independently introduce quadratic items for temperature (columns (1a) and (1b)) and precipitation (columns (2a) and (2b)), respectively, and simultaneously consider the quadratic items for temperature, precipitation and relative humidity in the estimates of columns (3a) and (3b). Standard errors are in parentheses. ***Significance at the 1% level, **Significance at the 5% level, *Significance at the 10% level.

estimated climate damages resulting from these two relationships reaches 50–100 percentage points. In this circumstance, we attempt to examine whether county-specific deviations from economic growth trends are nonlinearly associated with deviations from the trends of critical climate variables; to further explore this possibility, we reconsider the impacts of climate change on output by adding the quadratics to the regression model and carrying out panel analysis. As summarized in Table 8, columns (1a) and (1b), (2a) and (2b), (3a) and (3b) report the estimates by incorporating the quadratics of temperature, precipitation and relative humidity, respectively. We find preliminary evidence on the consistently significant inverted U-shaped relationship between temperature and economy; i.e., warming may positively affect China's economic output until it arrives at the turning point, 10.78 °C, and this threshold is somewhat lower than that at the global level, 13 °C (Burke et al., 2015). The data descriptions show that China's average temperature during the considered timeframe is 14.32 °C, which notably passes the turning point and further supports the baseline negative estimates of warming. Table 8 provides little evidence on the nonlinear precipitation–economy relationship but substantial evidence on the nonlinearity of the humidity–economy interaction. In fact, the potential relationship between climate change and economy is far from definitive, as different datasets, panel divisions and model designs may yield different conclusions; as we can see at the global scale, Burke et al. (2015) stressed the importance of a nonlinear warming–economic interaction, while Dell et al. (2012) argued that they find little evidence for substantial nonlinearity.

5. Robustness

We will make several robustness checks in this section, involving alternative panel specifications, estimation methods and data samples. The alternative panel specifications mainly refer to the selection of weights used to transform the station-level daily weather data into the yearly city level, and the weights here are calculated by the inverse distances between the weather station and the geographic centroid of each city. Although this approach is commonly used (Mendelsohn et al., 1994; Zhang et al., 2018), the inverse-distance weights are largely subjective and may bring some uncertainty to the estimates (Dell et al., 2014). We therefore consider two alternative specifications in addition to the baseline, i.e., inverse square root distance and inverse squared distance, to construct city-level weather data. The main results are summarized in panel A of Table 9, of which columns (2a) and (2b) correspond to the estimates under the alternative weights. We also show the previous results under the baseline specification from Table 2 to facilitate comparison. We do not find substantial effects of alternative weights on the model estimates in magnitude or significance. For example, under the baseline case, an extra temperature rise is associated with a 0.78 percentage point reduction in GDP, and this estimate is 0.80 and 0.77 when moving to the two alternative weighting cases, and both estimates are at the 1% level of significance. The results on precipitation and humidity also suggest that our estimates are not sensitive to the alternative specifications.

Table 9
Robustness checks for panel results across model specifications.

Panel A	Baseline weights		Squared weights		Radical weights	
	Sys. GMM (1a)	Dif. GMM (1b)	Sys. GMM (2a)	Dif. GMM (2b)	Sys. GMM (3a)	Dif. GMM (3b)
Temperature	-0.0775^{**}	-0.2808^{***}	-0.0795^{**}	-0.2873^{***}	-0.0772^{**}	-0.2795^{***}
	(0.0349)	(0.0490)	(0.0367)	(0.0513)	(0.0341)	(0.0483)
Precipitation	0.0086^{***}	0.0129^{***}	0.0083^{***}	0.0128^{***}	0.0088^{***}	0.0131^{***}
	(0.0018)	(0.0020)	(0.0020)	(0.0021)	(0.0018)	(0.0019)
Humidity	-1.3417^{***}	-1.3724^{***}	-1.2941^{***}	-1.3328^{***}	-1.3555^{***}	-1.3908^{***}
	(0.1604)	(0.1636)	(0.1511)	(0.1582)	(0.1666)	(0.1678)
Sunlight	-0.1772^{***}	-0.0174	-0.1680^{***}	-0.0095	-0.1788^{***}	-0.0214
	(0.0310)	(0.0250)	(0.0294)	(0.0245)	(0.0317)	(0.0259)
Air pressure	1.0557^{***}	1.2313^{***}	1.1128^{***}	1.2591^{***}	1.0262^{***}	1.2300^{***}
	(0.2152)	(0.1908)	(0.1919)	(0.1796)	(0.2305)	(0.2025)
Wind speed	0.0015	0.0007	0.0015	0.0004	0.0014	0.0008
	(0.0017)	(0.0012)	(0.0015)	(0.0011)	(0.0017)	(0.0012)
L1:Log output	0.8141^{***}	0.8231^{***}	0.8140^{***}	0.8233^{***}	0.8152^{***}	0.8229^{***}
	(0.0192)	(0.0193)	(0.0205)	(0.0206)	(0.0187)	(0.0187)
Log waydist	-0.0498^{***}	0.0035	-0.0475^{***}	-0.0055	-0.0508^{***}	0.0028
	(0.0162)	(0.0124)	(0.0157)	(0.0141)	(0.0165)	(0.0118)
Log fixcapi	0.0070	0.0117^{**}	0.0072	0.0119^{**}	0.0067	0.0116^{**}
	(0.0046)	(0.0049)	(0.0048)	(0.0051)	(0.0045)	(0.0047)
AR(2)	0.824	0.152	0.883	0.173	0.772	0.133
Hansen Test	0.909	–	0.894	–	0.920	–
Observations	7063	6791	7063	6791	7063	6791
Panel B	Station-level data			0.5×0.5 degree grid data		
	Sys. GMM (4a)	Dif. GMM (4b)	Sys. GMM (4c)	Sys. GMM (5a)	Dif. GMM (5b)	Sys. GMM (5c)
Temperature:						
Mean	-0.3009^{***}	-0.4745^{***}		-0.3778^{***}	-0.4699^{***}	
	(0.0580)	(0.0641)		(0.0683)	(0.0763)	
Maxi			-0.0013^{***}			-0.0012^{***}
			(0.0004)			(0.0004)
Mini			0.0008			0.0009
			(0.0007)			(0.0010)
Precipitation:						
Mean	0.0031^{*}	0.0010		0.0039^{**}	0.0035^{*}	
	(0.0016)	(0.0017)		(0.0016)	(0.0020)	
Maxi			0.0144^{***}			0.0157^{***}
			(0.0029)			(0.0031)
Mini			0.0013^{***}			0.0012^{***}
			(0.0003)			(0.0004)
L1:Log output	0.8423^{***}	0.8555^{***}	0.8173^{***}	0.8312^{***}	0.8380^{***}	0.7904^{***}
	(0.0224)	(0.0240)	(0.0205)	(0.0233)	(0.0243)	(0.0182)
Log waydist	-0.0972^{***}	0.0021	-0.0630^{***}	-0.1156^{***}	0.0027	-0.0713^{***}
	(0.0180)	(0.0107)	(0.0177)	(0.0206)	(0.0110)	(0.0172)
Log fixcapi	0.0156^{***}	0.0201^{***}	0.0186^{***}	0.1858^{***}	0.0235^{***}	0.0273^{***}
	(0.0049)	(0.0052)	(0.0053)	(0.0051)	(0.0050)	(0.0041)
AR(2)	0.668	0.063	0.809	0.435	0.040	0.894
Hansen Test	0.124	–	0.892	0.324	–	0.910
Observations	7063	6791	7063	6803	6541	6803

***Notes*:** In the baseline scenario, climate data are weighted by the inverse distance between stations and the geographic centroid; columns (2a) and (2b) use squared inverse-distance weights versus radical inverse-distance weights in the estimates of columns (3a) and (3b). Annual average data are used in Panel A, including the annual averages of daily mean temperature, daily mean relative humidity, daily mean pressure and daily mean wind speed, and daily cumulative rainfall and sunshine hours. In Panel B, the numbers of days that the maximum (minimum) data above (below) the given thresholds are employed. AR(2) and Hansen test act as before. Standard errors are in parentheses. ***Significance at the 1% level, **Significance at the 5% level, *Significance at the 10% level.

The robustness checks on alternative datasets are reported in panel B of Table 9. Our baseline data are abstracted from weather stations distributed in different cities, and although we tease out the stations that may entail entry and exit problems during the sample period, the number of stations may become a new data limitation and then bias our estimates (Dell et al., 2012; Auffhammer et al., 2013). We therefore use the yearly mean temperature and rainfall data at the 0.5*0.5 degree resolution to test the robustness of our main panel results. As shown in panel B, columns (4a) and (4c) are estimates based on the mean and extreme station-level data, while columns (5a) and (5c) give the relevant results based on grid weather data. As we can observe from the mean warming scenario, the estimates based on grid data continue to show substantial negative impacts on output, with no change in significance from the station-level data, although the estimated effect appears to be somewhat larger. When turning to the impacts of mean precipitation, the grid data results are also consistent with those of the station data, with a slight increase in magnitude and statistical significance. In addition, the estimations on extreme grid weather data strengthen our basic results from another side (Columns (4c) and (5c)). An additional day of extreme high temperature reduces GDP by 0.0012–0.0013 percentage points, according to both the grid- and station-level datasets; this consistency in both magnitude and significance persists when moving to the impacts of rainfall. As a consequence, our results are hardly driven by different data sources.

Finally, the robustness check on method is conducted by reconsidering the main panel analysis using difference GMM. As shown in Table 9, columns (1b), (2b) and (3b) in panel A, and columns (4b) and (5b) in panel B are estimates under the difference GMM approach, and we repeat the baseline estimates under system GMM (columns (1a–5a) and columns (4c–5c)) for convenience of comparison. The point estimates are highly comparable in influence direction and significance across the various alternative specifications for both methods, although the effect magnitude typically increases using the difference GMM. This consistency still exists when considering the alternative datasets (Panel B), despite the fact that the warming impact appears to be somewhat higher and the impact of precipitation lower under the difference GMM method, simultaneously with a reduction in the estimates' precision, as compared to the system GMM approach. Overall, our results are robust to the chosen panel regression method.

6. Predicted damage due to global warming

Based on the empirical temperature–economy relationship, we can derive a "damage function" in the integrated assessment model by linking global warming to possible climate damage in China. More direct evidence has shown that the temperature–economy relationship is likely to be linear (Dell et al., 2012), but nonlinear assumption has also been broadly adopted, particularly in IAMs (Burke et al., 2015; Nordhaus and Moffat, 2017), and our estimate provides evidence for this nonlinearity. Given this basis, we project China's warming damages based on both the linear and nonlinear historical relationship between temperature and economic output estimated in this work; by aggregating a set of typical IAMs, i.e., WITCH, AIM/CGE, GCAM, IMAGE, MESSAGE and REMIND, we extend the projection to the end of this century. The detailed method and cross-model projections are depicted in the Supplementary Material AIII.

There exists substantial heterogeneity in the projected warming damages across various IAMs, which are due partly to the discrepant expectations of the IAMs concerning China's economic growth and partly to the different projections on future temperature changes. Additionally, the estimated GDP loss per capita in Fig. 3 is closely related to the pathways of future population growth. As we can observe, China's climate damage will dramatically increase over time given the sustained temperature rise; seen from cross-model averages, this damage may expand from 0.55 percentage point of GDP in 2030 to 2.58 percentage points in 2100, given the linear temperature–economic interaction, and the largest warming-related GDP loss is as high as 2.96 percentage points, corresponding to the GCAM. By contrast, China's per capita climate damage is estimated to be between 70 USD and 82 USD in 2030, with the cross-model average being 70.7 USD, and this model-average impact would increase from 251 USD in 2050 to approximately 1199 USD in 2100. Different from the gross climate damage, the largest per capita damage corresponds to the MESSAGE and IMAGE models, rather than the GCAM. Actually, what drives this discrepancy is not the possible difference in cross-model assumptions on population pathways but dominantly the distinguishing expectations of China's future economic development since the population pathways in MESSAGE and IMAGE are largely similar, while their projections on economic growth are much more optimistic than those of the other IAMs (Luderer et al., 2018).

The model difference in climate damage under the nonlinear warming–economy relationship is highly consistent with that under the linear interaction; however, the magnitude of the estimated damage is dramatically larger. As sketched in Fig. 3, climate damage in the nonlinear case reaches up to 4.98 percentage points of GDP in 2100, with a model-average level of 4.23 percentage points, which is 38.9 percentage points higher than that in the linear case. When moving to the per capita situation, the model-average damage will increase from 367 USD in 2050 to 1948 USD in 2100, which are 45.8 and 62.6 percentage points higher than the estimates in the linear case. We therefore can conclude that climate damage may be significantly underestimated if estimates are purely based on the assumption of a linear temperature–economy relationship, suggesting positive insights for both IAM-based climate impact assessment and policy making for global warming. In addition, according to the model averages, China's damage resulting from global warming is estimated to be significantly more severe than the simulated damage at the global level (Stern, 2008), which also underscores the great importance of China's rapid and substantial climate-addressing actions.

7. Conclusions

The effectiveness of climate policy making strictly relies on the quantified assessment of climate impacts, which in turn depends on precise analysis of the historical climate–economy relationships (Hsiang et al., 2017). However, the widespread aspects of climate-related effects and the possible interventions of production mode adjustments, changes in habitual behaviors and adaptation capability may all make it challenging to estimate such impacts (Dell et al., 2012), especially when exploiting the possible climate–economic relationships at the national/regional scales (Nordhaus and Moffat, 2017). In this work, we examine the Chinese historical relationship between climate change and economy and explore the presence of heterogeneous effects in economic and geographic regions, which are not captured by the current IAM-based climate–economic analysis.

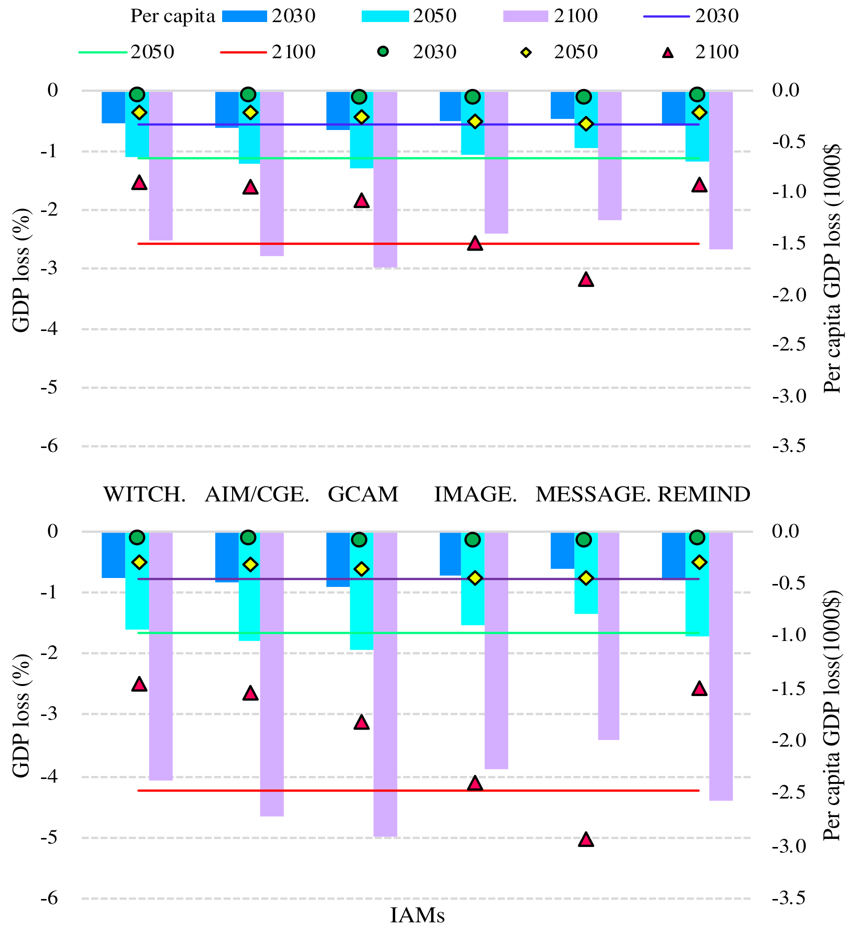

Fig. 3. China's damage projections arising from estimated economy–warming relationship. ***Notes***: The upper and lower subfigures portray the forecasts under the linear and nonlinear warming–economy interactions, respectively. Bars show percentages of GDP loss; blue, red and black lines are cross-model means of GDP loss in 2030, 2050 and 2100; green circles, yellow squares and brown triangles present per capita GDP loss in target years.

We find substantial evidence on the impacts of warming shocks on national economic performance, with a 1 °C increase in temperature associated with a 0.78 percentage point reduction in GDP, which, literally, is equivalent to a GDP loss of 241.7 billion USD, given the average GDP level and temperature rise during the time horizon considered in this work. In contrast, rainfall negatively affects economic output, with an additional 100 mm precipitation increasing GDP by 0.86 percentage points; our estimates also suggest a negative role of humidity in the economy, with a 1.34 percentage point reduction in output for each additional 1% increase in relative humidity. We also find statistically significant effects of extreme weather change on national economic output, which are largely consistent with the basic impacts of mean weather shocks, despite slight differences in magnitude. Mostly importantly, our results confirm that the global-scale conclusion drawn by Dell et al. (2012) is still true for China, i.e., temperature rise has a greater effect on the less-developed regions, with an additional 1 °C corresponding to a decrease of approximately 2.3 percentage points in output.

Our work shows substantial evidence of the heterogeneity of climate impacts in geographic regions and industrial sectors. Hotter south China suffers the most from a temperature rise, and the negative effect is much smaller in cooler regions, such as northeast and central China, suggesting that the magnitude of the warming effect is governed not only by economic development levels but also by mean weather conditions. The economic influence of relative humidity also reflects this point; i.e., coastal, riverside or lakeside regions, such as central, north and east China, are significantly and negatively affected by the increase in humidity, with each additional 1% of humidity associated with 0.83, 1.02 and 1.06 percentage point reductions in output, respectively. Additionally, our work underscores the important roles of potential channels in climate damage estimation. Specifically, temperature rise significantly reduces agricultural and industrial output, with a one-degree increase in temperature associated with 1.32 and 2.57 percentage point decreases in GDP, respectively, for these two sectors. The impact on agriculture is closer in magnitude to the average welfare loss estimated at the global scale (Stevanović et al., 2016), while our estimated effect on industry is smaller than the estimates of Zhang et al. (2018).

Based on our county-level empirical estimates, we construct a true 'damage function' that maps the economic loss in China due to future global warming. We therefore predict the possible GDP loss by 2100 under different scenarios of temperature change and make corresponding comparisons across models. We find that the model-average climate damage of China may account for 2.58 percentage points of GDP by 2100 in terms of the linear warming–economy interaction, with a relative per capita GDP loss of 1198 USD. Most importantly, this climate damage could be severely understated by 38.9 and 62.6 percentage points in gross and per capita terms compared to the case of a nonlinear temperature–economy relationship.

Still, several limitations exist for this research. Although climate change is mostly exogenous to economic growth, there are possibilities that exist endogeneity problems in our regressions, given the increasingly complicated dynamics between climate change and economy; and some attention may therefore need to pay in the future research. Further, we tried to reduce the uncertainty of long-term projections by employing multi-model framework (Revesz et al., 2014), still, we have to assume a constant climate–economic relationship in terms of the historical estimates, and the changes in some typical indicators, like technological advance and population, are also left out in the current study, which may affect the forecasts as well.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eap.2022.01.019.

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