ARTICLE IN PRESS

Journal of Comparative Economics xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Comparative Economics

journal homepage: www.elsevier.com/locate/jce

The impact of rainfall on productivity: Implications for Chinese manufacturing

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ARTICLE INFO

JEL classification:
D22
D24
Q54
Q56
L60

Keywords:
Climate change
Rainfall
Econometrics
Productivity
Manufacturing
Adaption
Dams
Infrastructure

ABSTRACT

Rainfall affects productivity in many ways. Compared to temperature anomalies, the impacts of precipitation anomalies have been understudied, with existing evidence at the macro level. By combining ground station-level climate data and micro-data from half a million manufacturing firms in China, we uncover that rainfall negatively impacts firms' productivity, with the most significant negative impacts concentrated in extremely heavy rainfall anomalies. Labor-intensive, low-tech, or less productive firms and those located in rainy regions are vulnerable to rainfall extremes. Our estimates are large enough to explain previously observed output losses in cross-country panels. We uncover three primary channels through which manufacturing firms experience productivity loss: reduction in labor, agriculture intermediate inputs and transportation disruptions. We also identify several margins of adaptation. Utilizing the Shared Socioeconomic Pathways Scenarios (SSPs), we estimate the future impact of rainfall on productivity in a cost-benefit analysis. Our projections indicate a substantial output loss of 2.4–14.9 billion CNY by 2100, due to the increase in extreme rainfall events under each scenario with different implementation of environmental policies.

1. Introduction

Global climate change continues to increase the volatility of regional rainfall and may result in heightened uncertainties for sustainable economic growth (Dell, Jones, and Olken, 2012; Kotz, Levermann, and Wenz, 2022). Considerable literature has emphasized the Earth's hydrological cycle caused by anthropogenic human behavior (Min et al., 2011; Madakumbura et al., 2021), particularly in wet and dry areas (Donat et al., 2016). Previous literature has explored the rainfall-output relationship at the macro-level across several contexts. For instance, Barrios et al. (2010) identifies rainfall as a significant impediment to economic growth in sub-Saharan African countries, but not in other countries. Damania et al. (2020) documents concave relationship is observed between GDP per capita and rainfall, with evidence from sub-national data from 1990 to 2014. Similarly, as shown in Online Appendix Fig. A1, our aggregated annual rainfall and aggregated annual value-added exhibit a superficial negative relationship.

In contrast to the wealth of macro-level evidence, micro-level evidence is relatively limited in scope. To our knowledge, the existing detailed evidence focuses on agricultural loss to precipitation (Ortiz-Bobea et al., 2019, Cui 2020; Cui and Xie, 2022). However, the effects of rainfall on manufacturing productivity remain uncertain. This motivates the research questions of this paper: What are the

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https://doi.org/10.1016/j.jce.2025.03.005
Received 5 December 2023; Received in revised form 21 March 2025; Accepted 22 March 2025

specific implications of rainfall for manufacturing plants? Are there any factors that moderate or amplify these effects? Additionally, it is crucial to explore the projected costs associated with extreme precipitation in the future.

To answer these critical questions, we aim to present a nationwide estimate of contemporaneous (including annual rainfall measure, seasonal rainfall measure and rainfall bins) and lagged rainfall effects on Total Factor Productivity (TFP) in China. The empirical analysis in China is valuable in two aspects. First, China is representative of developing countries which suffer from rainfall disasters and countries with similar longitude range (73°33′E-135°05′E) and latitude range (3°51′N-53°33′N). Second, given China's position as a global manufacturing powerhouse, accounting for 22 % of the world's manufacturing outputs (Fu et al., 2021), we have a unique opportunity to investigate the impact of different climate (rainfall) patterns on a diverse range of manufacturing plants. [1]

Using ground station-level nationwide climate data provided by China's National Meteorological Information Center, [2] we match the large-scale manufacturing firms' data compiled by the Annual Surveys of Industrial Firms (ASIF) project. The raw data set contains 568,888 firms, with 2223,406 firm-year observations during 1998–2007. In this dataset, all state-owned manufacturing firms are included. Additionally, all non-state-owned manufacturing firms whose annual sales exceed 5 million CNY (equivalent to 0.7 million USD using the 2007 exchange rate) are also considered. Generally, production values of the dataset account for more than 90 % of China's total industrial outputs (Brandt et al., 2012). [3] Using the fixed-effects panel regression model, we can control time-invariant firms' attributes by adding firm fixed effects, and national shocks to productivity by year fixed effects. Fig. 1 depicts distribution of China's seasonal average rainfall (by monthly average) and the changing trends of monthly rainfall.

Our baseline results reveal that rainfall extremes have a significant negative impact on firm-level productivity. Specifically, a single day of extreme rainfall, defined as more than 250 mm within a 24-hour period, can lead to a productivity loss of 1.77 %. Additionally, a productivity loss of 1.51 % is associated with one more day of rainfall in the range of [100, 250) mm, while a loss of 0.19 % is linked to one more day in the range of [50, 100) mm. However, we do not observe this negative correlation in the [10, 25) and [25, 50) rainfall ranges. This adverse relationship is not limited to extreme rainfall events; we also observe similar detrimental effects associated with our annual rainfall totals, seasonal rainfall totals in summer and autumn, and measures of rainfall anomalies. These findings underscore the critical importance of understanding how varying rainfall patterns can disrupt operational efficiency in firms.

We conduct robustness checks from several perspectives. First, to verify that our results are not sensitive to our baseline econometric models, we adjust the econometric settings, including fixed effects and standard errors. Second, to account for the potential bias introduced by snowfall in winter, we include snowfall depth in our controls to assess whether our winter rainfall estimates are affected. Third, in the rainfall bin measurement, we select 0 (days with zero mm of precipitation), (0, 10] (days with precipitation between 0 and 10 mm), and (10, 25] (days with precipitation between 10 and 25 mm) as the alternative omitted categories to verify the robustness of selecting [0, 10] in our baseline setting. Fourth, although short-term rainfall is considered exogenous, we also incorporate additional controls related to human activities. All these results enhance the credibility of our baseline estimates. Finally, while droughts and flooding events, which also generate significant negative effects, are correlated with rainfall extremes, they do not bias our estimates.

A comprehensive heterogeneity analysis is conducted to explore the differences among firms with various attributes. This analysis provides insights by categorizing industries based on their sensitivity to these factors and examining which are most significant. First, from the perspective of sectoral heterogeneity, our results suggest that industries involved in agricultural processing and outdoor production are more adversely affected by extreme rainfall. Second, considering ownership structure—which includes state-owned, collective-owned, private-owned, and foreign-owned firms—our results indicate that foreign-owned firms are particularly vulnerable to rainfall extremes, while state-owned firms demonstrate greater resilience. Third, we observe significant regional heterogeneity. For example, in southern China, where rainfall is abundant, firms are more susceptible to rainfall extremes. In contrast, in northwest China, extreme rainfall events are virtually absent, and hence firms are less influenced.

Further, we also discuss some potential mechanisms through which rainfall extremes may damage productivity. In literature, labor supply has been verified as an important explanation for temperature (Somanathan et al., 2021). We also find evidence of labor supply as an important explanation for an adverse rainfall extreme-productivity relationship. Additionally, by identifying agriculture-dependent manufacturing, we reveal an agricultural spillover and highlight the linkage between rainfall, agriculture, and manufacturing. Additionally, by identifying the transport-dependent manufacturing firms, our results suggest a possible rainfall-transport disruption-manufacturing linkage.

We also investigate potential adaptations for Chinese manufacturing. First and foremost, we find that Chinese manufacturing firms are inclined to invest in non-productive inputs (such as insurance and stock) to withstand rainfall extremes. Second, by splitting our sample into state-owned and non-state-owned firms, our results suggest that non-state-owned firms are more likely to enter and exit the market as an adaptation to rainfall extremes. Third, at the country level, our findings indicate that infrastructure construction, including anti-flood dams, road infrastructure, and drainage systems, plays a significant role in combating floods. Our results suggest there is a productivity premium for downstream firms compared to upstream firms following the construction of anti-flood dams, as shown by our difference-in-difference strategy. Furthermore, by interacting rainfall bins with highway and drainage lengths, our

[1] Indeed, the correlation between temperature and income has been widely investigated since Huntington (1915) in the cross-sectional dataset, according to Dell et al. (2012). Whereas debate remains how to adapt to the climate phenomenon since whether this correlation is from rainfall directly or via the exogenous third variable like institution which leaves limited room for geographic explanation (Acemoglu et al., 2002). Since we focus on China's context with variant rainfall, the debate is not that challenging.

[2] More information regarding climate data can be assessed from http://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_MUL_MMON_19812010.html.

[3] In 2007, 1 USD=7.6 CNY.

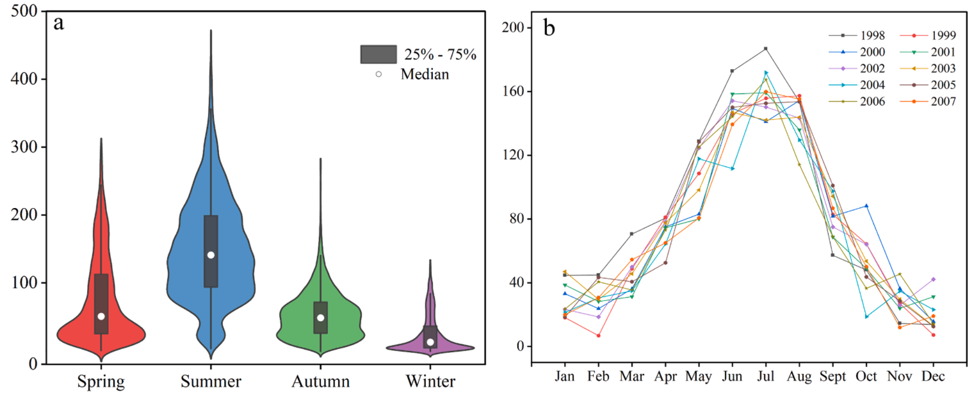

Fig. 1. Distribution of seasonal rainfall (a) and the changing trends of monthly rainfall (b) (mm).

estimates indicate that productivity loss may be mitigated.

Finally, using these estimates and integrating future rainfall data through the end of this century, we can project future output losses in manufacturing due to rainfall. Our results indicate that the reduced output could amount to 6.1 billion CNY (approximately 0.8 billion USD). This translates to an average loss of 17,696 CNY (about 2328.40 USD) per firm for each 1 mm increase in annual rainfall. Moreover, extreme rainfall days can cause even greater damage to manufacturing outputs. For instance, an additional day of rainfall exceeding 250 mm could result in an output loss of approximately 101.1 billion CNY (or around 13.3 billion USD). This implies that a single firm could face a loss of 293,248 CNY (approximately 38,585 USD) due to an extra day of rainfall above 250 mm. For projected outcomes under the SSP1–2.6 scenario, we estimate that the impacts of rainfall events exceeding 250 mm will decrease by over 50 % between 2030 and 2100. Conversely, under the SSP5–8.5 scenario, the impacts of rainfall extremes in 2100 are expected to be twice as large as those estimated in 2030. These findings highlight the critical importance of adopting sustainable practices and transitioning to cleaner, more efficient energy sources to mitigate the risks associated with future rainfall extremes.

Our contribution to climate change literature lies in several aspects. First, we are among the first to perform exhaustive measures for the causal effects of rainfall on productivity at the firm level in manufacturing sectors, adding to our understanding of the impacts of climate change. Though the empirical analysis is in China, our methodology and findings can be applied to other regions and countries with sufficient records and variations on rainfall and manufacturing firms. Second, we delve into the heterogeneous effects of rainfall on different industries, ownership structures, regions, input structure, which helps shed light on channels at work, including labor inputs, agriculture intermediate inputs and transportation disruption. We also examine the effectiveness of potential adaption strategies, including firm level increase in non-productive costs and firm entry and exit decisions, and country-level infrastructure construction including anti-flood dam and improved road infrastructure and drainage systems. Third, we quantify the cost of extreme rainfall in the medium to long term, for the years 2030, 2050, 2080, and 2100, based on four different Shared Socioeconomic Pathways (SSP) scenarios: SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5, which provides crucial input into climate change policymaking.

The remainder of the paper is structured as follows: Section 2 briefly introduces the background and data sources. Following that, we present the econometric framework and different rainfall measures in Section 3. The subsequent section (Section 4) reports our baseline results. In Section 5, we include a series of robustness checks, while the heterogeneity analysis is provided in Section 6. Possible channels and adaptations are discussed in Sections 7 and 8. In Section 9, we simulate the impacts of future rainfall extremes until the end of this century using the SSP scenario. The following section (Section 10) provides a cost-benefit analysis, before the final section (Section 11) concludes.

2. Background and data sources

2.1. Historical and projected climate data

We use the daily ground station-level climate data derived from the Chinese Meteorological Science Data Center (CMSDC) and the China Meteorological Data Sharing Service System (CMDSSS). This center clusters fundamental statistical indicators of climate, including atmospheric pressure, relative humidity, rainfall, temperature, wind direction and speed, sunshine duration in 820 weather stations across the country. It also contains basic station-level location information (longitude and latitude), enabling us to continue the matching procedure in the county administrative region. In our sample, for the 2591 counties covered, rainfall and other climate data in counties with multiple stations are averaged to obtain county-year observations. The climate data is inputted for a few counties without weather stations using data from the nearest station. In order to construct the firm-year panel data, we derive the county-level location of each firm and then match this with the county-year panel data. Additionally, our analysis adds the square terms of climate controls to account for nonlinearity.

One aim of this article is to project the further effects of extreme rainfall on output and productivity, which requires predictions for the future daily rainfall distribution. These predictions come from the Coupled Model Intercomparison Project (CMIP6), which has been commonly used in recent literature (Newell et al., 2021). In CMIP6, climatic variables such as maximum/minimum temperature and precipitation were projected by the Statistical DownScaling Model (SDSM) under all shared socioeconomic pathway-representative concentration pathway (SSP1–1.9, SSP1–2.6, SSP2–4.5, SSP3–7.0, SSP4–3.4, SSP4–6.0, SSP5–3.4, and SSP5–8.5). In this article, we have selected the most used SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5 scenarios to assess the future climate effects.

2.2. Firm-level data

In our sample, we manually collect and clean the firm-level data from the Annual Survey of Industrial Firms (ASIF) Database, the most representative large-scale micro-data in China compiled by the National Bureau of Statistics (NBS) during 1998–2007. The dataset incorporates all state-owned and private firms whose annual production values are above 5 million CNY (0.66 million USD dollars in the 2007 exchange rate). The original uncleaned dataset contains 2223,406 plant-year observations for 568,888 unique firms. This dataset has been widely utilized in empirical and theoretical research. Although outliers are present, we can employ the basic cleaning procedure outlined in Brandt et al. (2012), and Fu et al. (2021) to remove these unreliable observations. Specifically, we exclude key accounting books with missing values and zero values, such as value-added, labor, and capital. Additionally, we exclude enterprises with less than 8 workers, as they may lack reliable accounting systems. Furthermore, we eliminate financial indicators from certain observations that violate basic accounting rules, such as total assets being smaller than components of net assets (liquid assets, fixed assets, and net fixed assets), or cumulative depreciation being smaller than current depreciation. Finally, we convert nominal values into real values using industry-level price indicators, as recommended in the literature (Yu et al., 2015). Another issue we need to emphasize is the occurrence of data entry errors and reporting errors. To address this, we adopt the approach used by Cai and Liu (2009) to trim the bottom and top 0.5 % of data, which helps to exclude these potential biases. We finally have 1559,844 enterprise-year observations with 353,885 unique manufacturing firms after carefully cleaning unreliable observations (for detailed cleaning procedure, please refer to Fu et al., 2021). Table 1 provides detailed summary statistics for our dataset.

In literature, many approaches (e.g., index number estimates of productivity, Olley-Pakes and Ackerberg-Caves-Frazer productivity measures) have been widely investigated in computing productivity and proven comparable (Brandt et al., 2012). Hence, in our analysis, we use the Olley-Pakes (OP) approach as the baseline for comparison and the Levinsohn- -Petrin (LP) and index number estimate for robustness. When computing productivity using the Cobb-Douglas production function, unreliable results may be generated because the existing and entering firms may suffer from low and high productivity, respectively. Additionally, firms' inputs can be endogenously determined by the observed productivity. More information on this estimator can be obtained from Olley and Pakes (1996).

The OP estimator addresses the potential endogeneity issue (simultaneity) mentioned earlier by employing investment as the proxy of residual productivity shock. Furthermore, the survival probability is employed to alleviate the selection bias. The LP estimator is like the OP estimator, and the only difference is that LP uses the intermediate inputs as the proxy of residual productivity shock (Levinsohn and Petrin, 2003). Besides, labor productivity (Value added/Labor) is also employed for robustness. The detailed mathematical expressions are shown in Online Appendix Part B.

2.3. Determinants of rainfall patterns in China

Climate variables exhibit substantial natural variability over time and space (Wang et al., 2023; Zheng et al., 2023), driven by complex atmospheric and oceanic processes (Gimeno et al., 2012; Cai et al., 2014; Konapala et al., 2020; Zeng et al., 2023). This natural variability is largely independent of human activities, at least in the short to medium term, supporting the assumption of exogeneity. Therefore, in economic and climate change literature, the exogeneity of weather and climate variables, such as temperature and rainfall, is often a key assumption (Hsiang, 2010; Deschênes and Michael, 2007; Dell, 2012; Cui and Xie, 2022; Cui and Zhong, 2024).

However, it is important to note that the exogeneity of climate variables is not without debate. Human activities, such as cloud seeding may have a more direct influence on local rainfalls. Nonetheless, cloud seeding accounts for less than 1 % of total rainfall in China, making it unlikely to significantly affect our results.[4]

In Fig. 1, we review the spatial and temporal patterns of rainfall in China. As seen, rainfall in China primarily occurs in the summer (June, July, and August), reaching 120–160 mm per month. In comparison, winter rainfall (December, January, and February) only reaches 0–40 mm. Furthermore, Panel (a) of Fig. 4 indicates significant regional heterogeneity; for example, South China experiences an annual total 1730 mm of rainfall, while the northwestern region has only 399 mm. To account for this varied spatial-temporal trend, we include region-specific polynomial time trends (Chen et al., 2016; Kalkuhl and Wenz, 2020) in our regressions.

[4] According to a National Communication on Climate Change Report (https://unfccc.int/sites/default/files/resource/China_NC4_Chinese.pdf), the total annual precipitation resources in China in 2020 amounted to 6,592.6 billion cubic meters, equivalent to approximately 6592 billion tons. Meanwhile, in 2013, China produced around 55 billion tons of artificial rain each year (https://qz.com/1241066/china-is-engineering-the-biggest-project-yet-to-force-rainfall).

Table 1
Summary of data sets.

	Observation	Mean	Standard devi.	Minimum	Maximum
Panel of Plants data					
TFP (log) (OP estimate)	1,559,844	2.61	1.02	−3.65	8.17
TFP (log) (LP estimate)	1,559,844	5.09	1.03	0.04	10.20
Labour Productivity (log) (Value added/Labour)	1,559,844	3.77	1.10	−2.85	10.02
Value added (log) (thousand CNY)	1,559,844	8.57	1.28	4.16	13.01
Capital (log) (thousand CNY)	1,559,844	8.54	1.50	3.94	12.80
Labour (log) (Person)	1,559,844	4.80	1.04	2.30	8.38
Investment (log) (thousand CNY)	1,559,844	6.91	1.70	−4.60	12.36
Intermediate inputs (log) (thousand CNY)	1,559,844	9.57	1.24	4.88	13.88
Inventory (log) (thousand CNY)	1,419,964	7.55	1.73	0.00	14.60
Insurance (log) (thousand CNY)	1,559,459	1.30	1.83	0.00	11.05
Age (log) ($Year^{current}$-$Year^{founding}$)	1,559,844	2.00	0.79	0.00	3.40
Weather Data					
Rainfall (mm)	1,559,844	1087.68	479.04	25.44	2681.16
Rainfall-Spring (mm)	1,559,844	274.38	193.26	1.02	993.33
Rainfall-Summer (mm)	1,559,844	510.3	225.39	9.63	1635.39
Rainfall-Autumn (mm)	1,559,844	187.95	106.68	0.00	1200.78
Rainfall-Winter (mm)	1,559,844	115.02	94.11	0.00	497.7
Rain day -above 250 mm (days)	1,559,844	0.004	0.07	0.00	2.00
Rain day -100–250 mm (days)	1,559,844	0.32	0.71	0.00	9.00
Rain day -50–100 mm (days)	1,559,844	2.30	2.29	0.00	15.00
Rain day -25–50 mm (days)	1,559,844	7.86	4.87	0.00	31.00
Rain day -10–25 mm (days)	1,559,844	21.80	9.86	0.00	60.00
Air pollution ($\mu g/m^3$)	1,559,844	49.28	15.27	1.10	116.00
Nightlight	1,559,844	18.85	17.96	0	63

Sources:
1. Plant-level data is from China's Annual Survey of Industrial Firms (ASIF) compiled by the National Bureau of Statistics. Sample period: 1998–2007. Our ASIF data is obtained from http://microdata.sozdata.com/index.html#/Single/Basic?year=2013.
2. Weather data: Our weather data is derived from Chinese Meteorological Science Data Center (CMSDC) based on ground-station observations, which can be derived from https://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_MUL_MMON_19812010.html. Satellite nightlight data is from https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html#AVSLCFC.
3. Geographic Data of Firms: Following Meng (2013) and Chen (2021), we employ the detailed data sets of our county-level GIS boundary data (https://www.resdc.cn/Datalist1.aspx?FieldTyepID=20,0) in the last year of our sample, i.e., 2007 and then match them to our geocoded firms.

3. Econometric model

Our article estimates the effects of rainfall in three aspects: on an annual, seasonal and rainfall bin basis.

3.1. Annual rainfall measure

$$lnTFP_{it} = \alpha Annual\_Rain_{it} + \beta C_{it} + f(x) + \gamma_i + \delta_r + \theta_t + \varepsilon_{it} \quad (1)$$

Indicators *i, r*, and *t* denote firm, industry, and year respectively. ln ($TFP_{i,t}$) is the natural log form of productivity level for firm *i* in year *t*. $Annual\_Rain_{it}$ represents the rainfall of the region where firm *i* is located in year *t*. Similarly, $C_{i,t}$, clusters the controls in the contemporaneous years. *f(x)* contains the quadratic forms of all climate variables, including temperature, wind speed, sunshine duration, wind direction, relative humidity, and air pressure.

In addition, we add three fixed effects to control unobservables, involving firm fixed effects, year fixed effects and (two-digital) industry fixed effects.[5] Specifically, α_i denotes firm fixed effects. β_r controls the industry fixed effects. ϑ_t represents the year fixed effects. While $\varepsilon_{i,t}$ captures the error term and is clustered at the firm-level to allow serial correlation within a firm.

3.2. Season rainfall measure

To account for the nonlinear effects of seasonal rainfall, we first cluster 12 months into four seasons, including spring, summer, autumn, and winter. According to Chen and Yang (2019), March-May are clustered to the spring, June - August are clustered to the summer, September - November are clustered to the autumn, and December - February in the last year are clustered to the winter. On this basis, we construct the regression based on the season:

$$lnTFP_{it} = \alpha Season\_Rain_{its} + \beta C_{its} + f(x) + \gamma_i + \delta_r + \theta_t + \varepsilon_{it} \quad (2)$$

[5] Since 12% observations ever changed their industries, we control industry fixed effects and firm fixed effects simultaneously.

Where index s denotes the season. $Season\_Rain_{its}$ represents the rainfall in season s, year t, at where firm i is located.

3.3. Rainfall bin

Beyond the seasonal rainfall, we further examine the rainfall bin effects on productivity of manufacturing firms. The daily rainfall data is employed to examine the nonlinear effects of each rainfall range separately. On this basis, we construct the rainfall bin regression:

$$lnTFP_{it} = \sum_{j} \alpha Bin\_Rain_{itj} + \beta C_{it} + f(x) + \gamma_i + \delta_r + \theta_t + \varepsilon_{it} \tag{3}$$

Where definitions of climate measures are consistent with those in Eq. (1). We now use Bin_Rain_j as an indicator representing the number of days falling in each rainfall bin j. Then, we consider five threshold measures of the distribution of daily rainfall, including >=250 mm, [100, 250), [50, 100), [25, 50), [10, 25) and [0, 10) (considered as the reference category). According to the China Meteorological Administration, daily accumulated rainfall within 0–10 mm range is classified as drizzle, within 10–25 mm range is called moderate rain, within 25–50 mm range is called heavy rain, within 50–100 mm range is called torrential rain, within 100–250 mm is called downpour and above 250 mm is called extraordinary storm.

3.4. Lagged effects

To investigate the lagged effects or accumulative effects of rainfall, we add one-year lag for the rainfall bin by modifying Eq. (3), which can be characterized as:

$$lnTFP_{it} = \sum_{j} \alpha_0 Bin\_Rain_{itj} + \sum_{j} \alpha_1 L.Bin\_Rain_{i,t-1,j} + \beta C_{it} + f(x) + \gamma_i + \delta_r + \theta_t + \varepsilon_{it} \tag{4}$$

Where $L.Bin\_Rain^{j}_{i,t-1}$ denotes a count, for firm i, of the number of days falling in rainfall bin j in the prior year t-1. Our outcome of interest and climate variables are the same as those defined in Eqs. (1) and (3). Our results suggest there are limited lagged effects for rainfall extremes on manufacturing. Results are reported in Online Appendix Part C.

3.5. Rainfall anomalies

In this section, we primarily investigate the effects of rainfall anomalies on productivity. We propose three strategies for measuring rainfall anomalies. The first strategy involves including two dummy variables that represent rainfall anomalies (less than -5 mm and greater than 5 mm), with one omitted as the reference category (between -5 mm and 5 mm). [6]

$$lnTFP_{it} = \alpha_1 D(>5mm)_{it} + \alpha_2 D(<-5mm)_{it} + \beta C_{it} + f(x) + \gamma_i + \delta_r + \theta_t + \varepsilon_{it} \tag{5}$$

D_{it} represents three dummy variables: $D(>5mm)_{it}$, $D(-5\ to\ 5)_{it}$, and $D(<-5mm)_{it}$. $D(>5mm)_{it}$ equals 1 if the annual rainfall anomalies for firm i in year t exceed 5 mm and 0 otherwise. $D(-5\ to\ 5)_{it}$ equals 1 if the annual rainfall anomalies fall within the range of [-5, 5] mm, and 0 otherwise. $D(<-5mm)_{it}$ equals 1 if the annual rainfall anomalies are less than -5 mm and 0 otherwise.

In addition to the rainfall deviation from the historic average, we further employ the seasonal regression and standardized monthly rainfall deviations approach, following Kotz et al. (2022), to measure rainfall deviations. $Rain_{imt}$ is employed to denote the annual measure of standardized monthly rainfall deviations, RS_{it} can be formulated and decomposed as:

$$RS_{it} = \sum_{m=1}^{12} \frac{R_{imy} - \overline{R_{im}}}{\sigma_{im}} \frac{\overline{R_{im}}}{\overline{RA_i}} = \sum_{spring}^{m=3,4,5} \frac{R_{imy} - \overline{R_{im}}}{\sigma_{im}} \frac{\overline{R_{im}}}{\overline{RA_i}} + \sum_{summer}^{m=6,7,8} \frac{R_{imy} - \overline{R_{im}}}{\sigma_{im}} \frac{\overline{R_{im}}}{\overline{RA_i}} + \sum_{autumn}^{m=9,10,11} \frac{R_{imy} - \overline{R_{im}}}{\sigma_{im}} \frac{\overline{R_{im}}}{\overline{RA_i}} + \sum_{winter}^{m=12,1,2} \frac{R_{imy} - \overline{R_{im}}}{\sigma_{im}} \frac{\overline{R_{im}}}{\overline{RA_i}} \tag{6}$$

where R_{imy} is the current mean of monthly rainfall totals of regions where firm i located; $\overline{R_{im}}$ and σ_{im} is the historic mean and historical standard deviation of monthly rainfall totals of the region where firm i located; while $\overline{RA_i}$ is the historical mean of annual rainfall totals of the region where firm i located. The annual standard deviation is decomposed to four seasons, which are of our interest. This measure captures monthly rainfall anomalies from their climatological means, weighted by the climatological contribution of monthly rainfall to the annual rainfall. Detailed results are reported in Online Appendix Part D.

3.6. Droughts and floods

Though our daily rainfall data captures the extreme rain days, while only reflects 18.7 % flooding (Patel, 2024). Also, even no rainfall days cannot embody sufficient information on droughts, which require consistent water scarcity and rainfall variations (Desbureaux and Rodella, 2019). To better understand the potential manufacturing loss relevant to those extreme climate events, we further investigate drought and flooding effects on manufacturing productivity.

[6] Our results remain consistent across alternative thresholds (±3mm, ±7mm).

Existing literature has inconsistent definitions on "drought" and "flood" (Patel, 2024). IPCC (2022) defines flood as the inundation of normally dry land, while drought as a period of abnormally dry weather long enough to cause a serious hydrological imbalance. Here, due to the lack of the most accurate official data, we manually combine the two most used datasets: the Dartmouth Flood Observatory Archive and the EM-DAT International Disaster Database (Brakenridge, 2023; Guha-Sapir et al., 2023) to measure flood events, while using the EM-DAT International Disaster Database to measure drought events. [7]

$$lnTFP_{it} = \sum_j \alpha Flood_{itj} + \sum_j \alpha Drought_{itj} + \beta C_{it} + f(x) + \gamma_i + \delta_r + \theta_t + \varepsilon_{it} \tag{7}$$

Where the number of flooding events and droughts in year t for firm i belonging to industry j, are incorporated in $Flood_{itj}$ and $Drought_{itj}$.

4. Empirical results

4.1. Rainfall effects

4.1.1. Annual baseline

Assessing the rainfall distribution associated with each firm, we can identify the annual rainfall effects (measured by monthly average) on the firm's annual productivity (shown in Panel A of Table 2). With different specifications across Columns (1) - (3), we uncover that rainfall adversely affects the productivity gains in China's manufacturing firms significantly, ranging from 0.02–0.07 %/1mm. When adding the square term of rainfall in Column (4), the observed effect is -0.10 %. This effect is substantial since the firms may suffer as high as 1.0 % productivity loss with a 10 mm increase in rainfall. The above results are consistent with prior literature. As a reference, in Dell et al. (2012), rainfall is adversely associated with annual growth rate by 8.3 %/100 mm.

4.1.2. Non-linear effects

In the above-mentioned estimates, rainfall variables enter linearly, which may arise dubiety. In the following sub-sections, beyond the quadratic term, we further investigate the possibility of non-linear effects by proposing two strategies: seasonal regression and rainfall bin.

4.1.2.1. Seasonal rainfall effects. Since significant seasonal heterogeneity exists in China regarding rainfall (as shown in Fig. 1), we further estimate the effects of rainfall on productivity by season. On average, the accumulated rainfall in summer is 451.47 mm, while in winter it is 75.6 mm in our sample. Panel B of Table 2 provides detailed estimates of the seasonal rainfall effects on productivity changes. In our preferred specification (Column 7), which controls for fixed effects, climate variables, and their quadratic terms, we find that in spring and winter, manufacturing firms' productivity does not respond significantly to rainfall. [8] Significant adverse effects of rainfall are observed in summer, reaching 0.04 %. In autumn, a significant 0.08 % productivity loss is associated with rainfall.

4.1.2.2. Rainfall bin effects. In order to further explore the possibility of non-linear effects, we employ more flexible extreme rainfall bins beyond seasonal rainfall changes. [9] Using daily rainfall data from the China Meteorological Data Sharing Service System (CMDSSS), we calculate the number of days each firm experiences at each rainfall level. [10] On this basis, we repeat the panel regression, allowing daily rainfall to vary arbitrarily within each rainfall range. Specifically, we consider each range defined by the China Meteorological Administration, including 0–10 mm (considered the omitted category), 10–25 mm, 25–50 mm, 50–100 mm, 100–250 mm, and above 250 mm. [11]

Fig. 2 plots the coefficients for these variables. Results in panel A imply that heavier rainfall is closely associated with a decline in productivity. Firms with a larger fraction of heavy rain days experienced more significant negative effects. The results also indicate that the negative rainfall-productivity relationship is mainly driven by extreme rainfall (in the 100–250 mm range and above 250 mm). These conclusions also apply to panel B, which employs output as the outcome of interest. Notably, our results indicate that a slight increase in rainfall does not facilitate manufacturing economic production, at least for some sectors. By collecting county-level agricultural production data, we found that rain days falling within the (0, 10) and [10, 25) mm ranges promote agricultural economic development (see Online Appendix Table E1). However, this increase does not spill over to the manufacturing sector, even for agriculture-dependent manufacturing firms (see Column 1 of Table 6). For rainfall amounts above 50 mm, we observe significant negative effects on both agriculture and manufacturing. We retain the binned regressions in the main text and provide specifications

[7] There are many missing values for detailed county for EM-DAT, we manually match corresponding counties that exposed to droughts and floods.

[8] There is significant productivity changes associated with a 1 mm increase in rainfall under other specifications (columns 4-5). The difference mainly arises from the quadratic term, indicating that nonlinear rainfall effects could bias our estimates in columns (1) - (3) and (4) - (5).

[9] For example, Somanathan et al. (2022) observe nonlinear effects of temperature on Indian manufacturing factories, while Kotz et al. (2022) identify nonlinear rainfall effects on global economic production.

[10] It should be noted that our productivity data are measured at the annual level, and we are unable to precisely identify the detailed effects of the distribution of rainy days on daily productivity.

[11] According to the China Meteorological Administration, daily accumulated rainfall (measured within 24 hours from 8 AM to 8 AM) is categorized into different levels based on the amount of rainfall.

Table 2
Annual and Seasonal rainfall effects on firm performance (dependent variable is residual logged TFP).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Total factor productivity (OP estimate)					
Panel A: Annual measure							
Rainfall	−0.0002***	−0.0006***	−0.0007***	−0.0010***			
	(0.0000)	(0.0000)	(0.0000)	(0.0001)			
$(\text{Rainfall})^2$				1.17e-06**			
				(5.01e-07)			
Panel B: Seasonal measure							
B.1 Spring Rainfall					0.0002***	−0.0004***	−0.00003
					(0.0000)	(0.0000)	(0.0001)
B.2 Summer Rainfall					−0.0001***	−0.0001***	−0.0004***
					(0.0000)	(0.0000)	(0.0000)
B.3 Autumn Rainfall					−0.0003***	−0.0006***	−0.0008***
					(0.0000)	(0.0000)	(0.0001)
B.4 Winter Rainfall (last year)					−0.0002***	−0.0002***	−0.00004
					(0.0000)	(0.0000)	(0.0001)
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Observation	1559,844	1,59,844	1,59,844	1,59,844	1,59,844	1,59,844	1,59,844
Quadratic terms	No	No	Yes	Yes	No	No	Yes
Climate controls	No	Annual	Annual	Annual	No	Seasonal	Seasonal
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column in each sub-panel represents a separate regression, indicating the coefficient estimates of the annual or seasonal rainfall variables. Column (1) reports rainfall effects on residual firm TFP without any weather controls but with firm fixed effects, industry fixed effects and year fixed effects. Column (2) reports rainfall effects on residual firm TFP, with climate controls added. Column (3) incorporates quadratic terms for these climate variables, excluding rainfall, while Column (4) includes estimates with quadratic terms for all climate variables. Climate covariates in these columns include annual temperature, annual wind speed, annual sunshine duration, annual wind direction, annual relative humidity, and annual air pressure. Column (5) reports seasonal rainfall effects on residual firm TFP without any climate controls but with firm fixed effects, industry fixed effects, and year fixed effects. Column (6) provides seasonal rainfall effects on residual firm TFP, with climate controls added. Column (7) adds the quadratic terms of climate variables. The seasons are categorized as follows: Spring comprises March to May, Summer covers June to August, Autumn includes September to November, and Winter covers December to February. Since winter mainly exerts its effects on productivity in the following year, we employ the winter rainfall in the last year as the explanatory variable. Climate covariates in these columns include seasonal temperature, seasonal wind speed, seasonal sunshine duration, seasonal wind direction, seasonal relative humidity, and seasonal annual air pressure. Standard errors are clustered at the firm level. These estimated rainfall effects can be interpreted as the percentage changes in firm TFP with a 1 mm increase in rainfall.
*denotes significant at 10 % level,
** at 5 % level.
*** at 1 % level.

with annual and seasonal rainfall measures in Online Appendix Part F.

4.2. Rainfall anomalies

Apart from examining the “level effects” of rainfall, we also provide estimates of productivity responses to rainfall anomalies in Table 3. We create two dummy variables: the first variable equals one if a firm’s rainfall anomalies are less than -5 mm, while the second equals one if the anomalies are greater than 5 mm. The remaining range of [-5 mm, 5 mm] is treated as the reference category. The results suggest that, relative to the reference category, rainfall anomalies lead to significant productivity declines. For example, firms experiencing positive annual rainfall anomalies of greater than 5 mm suffer an additional 2.62 % productivity loss. Conversely, firms experiencing annual rainfall anomalies of less than -5 mm see an additional 0.47 % productivity gain compared to the [-5 mm, 5 mm] range. These findings help explain the macro effects of rainfall anomalies (e.g., Kotz et al., 2022). In Appendix Part D, we assess the robustness of our results using alternative measures of rainfall deviations, as well as examining the effects of seasonal rainfall deviations.

4.3. Drought and flooding effects

Another concern in the interpretation of our results is that rainfall might be correlated with drought and floods, which affect productivity in their distinctive ways. While rainfall, droughts, and floods are interconnected, they should not be seen as closely correlated due to their distinct mechanisms and influencing factors. Rainfall is a direct measure of precipitation, whereas droughts indicate prolonged periods of insufficient rainfall, and floods result from excessive rainfall or other contributing factors, such as tidal surges. According to Patel (2024), 44.7 % of floods are linked to tidal surges, 18.7 % are associated with heavy rainfall, 16.8 % can be attributed to river erosion or embankment failures, 7.6 % result from dam failures, and 1.1 % are related to waterlogging. In Online Appendix Part K, we examine whether rainfall extremes affect the productivity of firms differently based on their vulnerability to

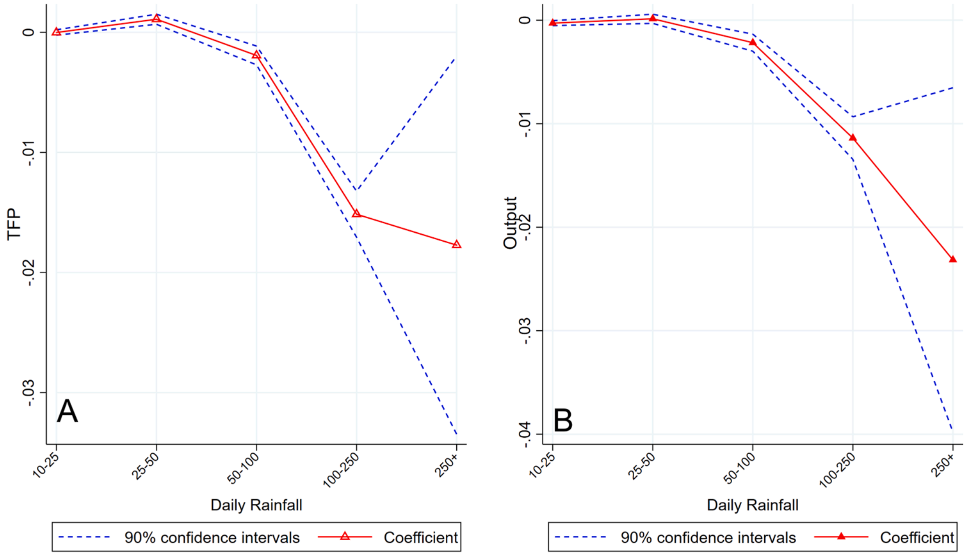

Fig. 2. Regression coefficients for each rainfall bin

Note: Each Fig. represents a separate regression, showing the coefficient estimates for rainfall bins. These estimated effects can be interpreted as the percentage changes in firm Total Factor Productivity (TFP) (A) and outputs (B) with an additional day in each bin. All regressions include firm fixed effects, industry fixed effects, and year fixed effects, climate controls and the quadratic terms of these controls. Climate covariates include temperature, wind speed, sunshine duration, wind direction, relative humidity, and air pressure. Standard errors are clustered at the firm level. Regression coefficients for each rainfall bin are highlighted in red, while the 90 % confidence bands are shown as dotted blue lines.

Table 3
Rainfall anomalies effects on productivity and output.

	(1)	(2)
	TFP (OP)	Output (log)
> 5mm	−0.0262***	−0.0265***
	(0.0027)	(0.0028)
[−5 mm,5 mm]	reference category	
< −5mm	−0.0047***	−0.0015***
	(0.0015)	(0.0004)
Observation	1559,844	1,59,844
Quadratic terms	Yes	Yes
Climate controls	Yes	Yes
Firm Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes

Note: Each Panel in each column represents a separate regression, indicating the coefficient estimates of annual rainfall variables. Columns (1)-(2) report effects of rainfall anomalies on productivity and output, respectively. Specifically, we divide rainfall anomalies into three categories, including <-5 mm, [-5 mm, 5 mm] and >5mm. The [-5 mm, 5 mm] rainfall anomalies range is considered as the reference category. All regressions include firm fixed effects, industry fixed effects, and year fixed effects, climate controls and the quadratic terms of these controls. Climate covariates include temperature, wind speed, sunshine duration, wind direction, relative humidity, and air pressure. Standard errors are clustered at the firm level.
*denotes significant at 10 % level,
**at 5 % level.
*** at 1 % level.

flooding.

Therefore, to separately assess the effects of drought and flooding, we obtain flood data from EM-DAT: The CRED/OFDA International Disaster Database and Global Flood Database (https://global-flood-database.cloudtostreet.ai/#interactive-map). The database is assembled from a variety of sources, such as UN agencies, non-governmental organizations, reinsurance companies, research institutes, and news agencies. As for droughts, we directly obtain drought event data from the International Disaster Database.

Column (1) in Table 4 reports drought effects on productivity, indicating one more drought event may induce 2.01 % productivity loss. In Column (2), we introduce flooding effects on manufacturing productivity. In Column (3), we simultaneously report drought

Table 4
The effects of droughts and flooding on productivity.

TFP	(1)	(2)	(3)
Drought	-0.0201***		-0.0199***
	(0.0060)		(0.0060)
Flooding		-0.0183*	-0.0183*
		(0.0095)	(0.0095)
Cluster	Firm	Firm	Firm
Observation	1559,844	1,59,844	1,59,844
Quadratic terms	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes

Note: Each column represents a separate regression. Column (1) reports drought events effects on productivity; Columns (2) reports flood events effects on productivity, while Column (3) simultaneously reports drought and flooding event effects on the manufacturing productivity. All regressions include firm fixed effects, industry fixed effects, and year fixed effects, weather controls and the quadratic terms of these controls. Data Source: EM-DAT: The CRED/OFDA International Disaster Database and Global Flood Database (https://global-flood-database.cloudtostreet.ai/#interactive-map). These estimated rainfall effects can be interpreted as the percentage changes in firm TFP with a one day increase in each rainfall bin. Climate covariates include temperature, wind speed, sunshine duration, wind direction, relative humidity, and air pressure. Standard errors are clustered at the firm level.

* denotes significant at 10 % level.

**at 5 % level.

*** at 1 % level.

and flooding effects on the manufacturing. These results all suggest that drought and flooding, though partly correlated with rainfall extremes, generate significant negative effects on productivity.

5. Robustness

5.1. Econometric specification

We aim to strengthen the robustness of our econometric settings and productivity measures by conducting a variety of checks. In Appendix Table L1, we impose stricter restrictions on econometric models and clustering to assess the robustness of our framework (rainfall bin). Column (1) includes industry × year fixed effects to control for biases common to firms within a specific year but varying across industries, thus helping to eliminate the influence of industry-specific policies. In Column (2), we introduce region × year fixed effects to account for provincial shocks that impact all firms within a given region in a particular year. Additionally, since our climate covariates are matched at the county-year level through interpolation, the standard errors may be biased due to unobservable macro factors (Kloek, 1981; Moulton, 1986). Because multi-dimensional clustering is not standardized, we explore two approaches for robustness checks. Column (3) clusters the error term within firms and at the county-year level to address spatial correlation, while Column (4) clusters the error term within firms and at the industry-year level. The results confirm the robustness of our baseline findings. In Appendix Table F1, we apply these alternative econometric settings to seasonal regressions, further validating our baseline results.

Appendix Table L2 examines alternative productivity measures using the LP estimator and the index approach (labor productivity). The results in Columns (1) and (2) indicate that our original productivity (OP) approach remains relatively robust. We also include corresponding covariates to account for confounding effects such as economic development, pollution, and firm age. The results confirm the robustness of our baseline findings. In Columns (3)-(6), we introduce nightlight data as covariates to exclude economic confounding factors (Cao and Birchenall, 2013), include air pollution as covariates to account for its effects on productivity (Xue et al., 2021), and consider firm age to account for specific firm attributes (Acemoglu and Cao, 2015), respectively. The reported results demonstrate their relative robustness. In Appendix Table F2, we perform seasonal regressions using these robustness checks, and the results add credibility to our baseline results.

5.2. Snowfall

We also evaluate whether including snowfall (measured by snow depth) as a covariate biases our winter estimates. Appendix Table L4 presents the results, which indicate that our findings remain robust even when accounting for snowfall and its quadratic term as covariates.

5.3. Alternative reference category

The reference group for temperature and rainfall is typically chosen based on the level that has minimal impact on the outcomes. In this paper, the reference group consists of the interval for rainfall of less than 10 mm per day (including 0 mm). This approach aligns with Cui and Zhong (2024). However, in our context, this reference group may not be ideal for comparison, as extremely low rainfall can also affect economic activities, such as contributing to droughts.

To assess the robustness of the reference category selection, we propose several alternative settings. First, in Column (1) of Appendix Table L5, we maintain six rainfall bins consistent with our baseline setting: [0, 10), [10, 25), [25, 50), [50, 100), [100, 250), and ≥250 mm, treating [10, 25) as the omitted category. Furthermore, to account for temporary, extremely low rainfall, Columns (2) to (4) utilize seven rainfall categories: 0, (0, 10), [10, 25), [25, 50), [50, 100), [100, 250), and ≥250 mm, while considering 0, (0, 10), and [10, 25) as the reference categories, respectively. The results across Columns (1) to (4) indicate that the effects of rainfall extremes, including ≥250 mm, [100, 250), and [50, 100), are not significantly affected by changes in the reference bin.

5.4. Additional controls

The annual baseline results may raise concern because the coefficients in the first row of Table 2 vary significantly with alternative controls, which should have a limited impact when the same fixed effects are applied. To address these potentially confounding factors, Appendix Table L6 introduces several additional controls, including region-specific time trends, topographic features, nightlight data, land use, and air pollution. The results indicate that our baseline findings remain robust.

6. Heterogeneity

6.1. Sectoral heterogeneity

ASIF encompasses a wide range of industries, including more than 40 two-digit sectors, enabling us to conduct a comprehensive analysis of sectoral heterogeneity. Online Appendix Tables G1 and G2 present the binned rainfall results (days with more than 250 mm of rain) and annual rainfall results on the productivity of each two-digit manufacturing industry. We also incorporate fixed effects and covariates in these estimates, with 90 % confidence bands provided.

For brevity, we only present a selection of representative industries, as illustrated in Fig. 3(a). In particular, two-digit industries engaged in agricultural processing (-18. 2% per day with more than 250 mm of rain) and outdoor industrial production (-15.9 % per day with more than 250 mm of rain) experience significant damage from extreme rainfall days. Additionally, manufacturing firms producing high-value products also face productivity declines. For instance, craftworks manufacturing (−12.2 % per day with more than 250 mm of rain) and computers and electronic products manufacturing (−10.7 % per day with more than 250 mm of rain) are especially vulnerable to extreme rainfall events. [12]

Conversely, the Medical Goods Manufacturing sector benefits from extreme rain days, one possible explanation is that heavy rainfalls increase the demand for medical goods (Lai et al, 2020), which in turn promotes the medicine production expansion and innovation. In this case, we believe demand shifts can lead to productivity gains for several reasons. First, heavy rainfall increases the demand for medical goods (Lai et al., 2020), which in turn promotes the expansion and innovation of medicine production. Second, increased demand enables better utilization of idle production capacity, prompting companies to activate resources and facilities that were previously underused. This helps firms to achieve economies of scale, as higher production volumes reduce average costs per unit by spreading fixed costs over more items. Most of these conclusions remain valid when we use annual rainfall as the measure.

Next, we explore sectoral heterogeneity along several dimensions (see Online Appendix Tables G3 and G4, and Fig. 3b-g for more details). To assess whether labor-intensive industries are more adversely affected, we classify all industries into labor-intensive and capital-intensive categories. [13] The results indicate that labor-intensive firms are vulnerable to both moderate and heavy rain days, while capital-intensive firms demonstrate resilience to extreme rainfall events. Specifically, an additional day with more than 250 mm of rain reduces the productivity of labor-intensive firms by 5.84 %, whereas capital-intensive industries show no significant productivity response. Furthermore, an additional day of rainfall in the 100–250 mm range leads to a 2.21 % productivity decline for labor-intensive firms, while capital-intensive firms experience only a 0.4 % loss. For the 50–100 mm rainfall bin, labor-intensive firms incur a 0.16 % productivity loss for each additional rain day, while capital-intensive firms remain unaffected.

Second, we examine how technologies can aid firms in adapting to climate change. The results indicate that low-tech firms experience a productivity loss of 2.65% due to each additional day of rainfall exceeding 250 mm, and a 1.62 % loss for each additional

[12] In the craftworks industry, rainfall can negatively impact productivity in several ways compared to other manufacturing sectors. First, we find that the craftworks industry is heavily dependent on agricultural inputs, as indicated by the input-output table (2007 version) and the sources of its subsectors. Specifically, within 135 sectors, agricultural outputs consumed by this industry account for 1.21%, significantly higher than the average of 0.3%. Second, the craftworks industry is more labor-intensive. On average, the labor input for the ASIF is 218.95, while for the craftworks industry, it is 245.94 (see Online Appendix Table H1). In the case of computer and electronic product manufacturing, our findings suggest that labor dynamics and increased management costs (see Columns 3-4, Online Appendix Table H2) are critical factors in the negative correlation between rainfall and productivity. Moreover, the sector's reliance on Just-In-Time production exacerbates the impact of supply chain and transport disruptions caused by extreme rainfall (Koks et al., 2019; Sodhi and Choi, 2022; Sapot, 2024).

[13] We classify industries into labor-intensive and capital-intensive categories based on their labor engagement in production activities. If the ratio of the wage bill to output is higher than the median for all industries, we categorize that industry as labor-intensive. Conversely, industries with a ratio that is below the median are classified as capital-intensive.

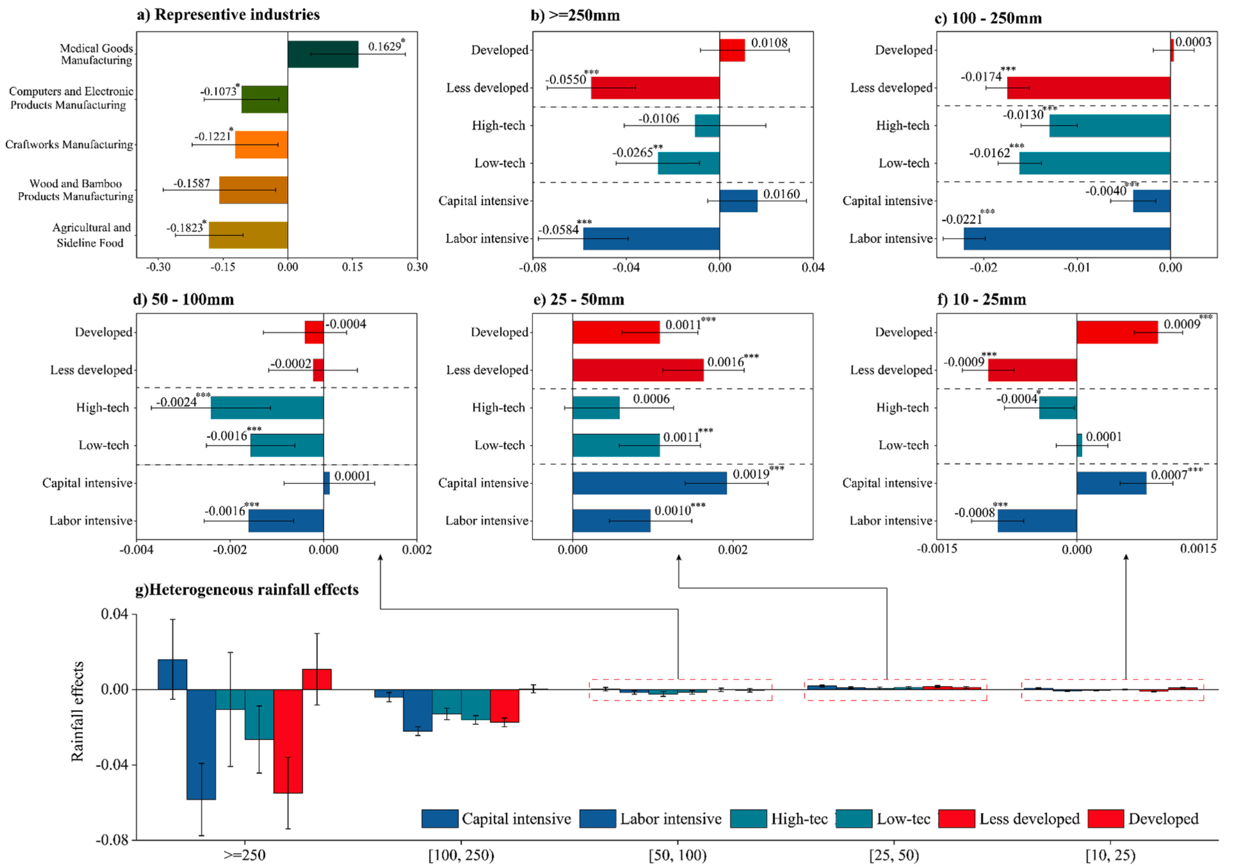

Fig. 3. Heterogeneous rainfall effects on productivity by industry

Note: Panel (a) displays the coefficients of rainfall impact for representative industries resulting from one day of rainfall exceeding 250 mm. Panels (b) to (f) illustrate the heterogeneous effects of rainfall across various rainfall bins. The heavy blue histograms in Panels (b) to (f) present the rainfall effects categorized by labor intensity. Firms are classified as "labor intensive" or "capital intensive" based on whether their labor intensity (measured as wage bill/output) is above or below the median (Zhang et al., 2018). The light blue histograms show the heterogeneous rainfall effects for firms based on their technology levels. The classification of technology intensity follows the OECD definitions found at https://www.oecd.org/sti/ind/48350231.pdf. In line with Fu, Viard, and Zhang (2021), industries that employ high and medium-high technologies are grouped as high-tech industries, while those using medium-low and low technologies are classified as low-tech industries. The red histograms categorize firms into developed and less developed based on their outputs per capita. Less developed firms have outputs per capita below the median, whereas developed firms have outputs above the median. All regressions account for firm fixed effects, industry fixed effects, year fixed effects, climate controls, and the quadratic terms of these controls. The estimated effects for each rainfall bin can be interpreted as percentage changes in firm total factor productivity (TFP) associated with a one-day increase in each rainfall category. Climate covariates include temperature, wind speed, sunshine duration, wind direction, relative humidity, and air pressure. Standard errors are clustered at the firm level, and coefficients along with 90 % confidence bands are provided. In our sample, there are 721,153 observations for capital-intensive firms and 715,998 for labor-intensive firms. High-tech firms comprise 559,138 observations, while low-tech firms include 987,101 observations. Additionally, less developed firms account for 715,637 observations, compared to 725,919 observations for developed firms.

* denotes significant at 10 % level.

** at 5 % level.

*** at 1 % level.

day of rainfall in the 100–250 mm range. In contrast, high-tech firms do not show significant productivity changes in response to these extreme rainfall events. Third, we investigate whether firms with higher outputs per capita are more resilient to rainfall extremes. The findings reveal that developed firms generally do not respond significantly to increases in heavy rainfall days (in the above-250 mm, 100–250 mm, and 50–100 mm ranges). In comparison, less developed firms suffer a 5.50 % productivity loss from each additional day of rainfall above 250 mm and a 1.74 % decrease for each additional day in the 100–250 mm range. These results suggest that capital-intensive, high-tech, and more developed firms are better able to adapt to extreme rainfall events than their counterparts. Additionally, as shown in Fig. 3g, non-extreme rainy days (below 100 mm) have limited effects on productivity.

6.2. Ownership heterogeneity

Next, we examine heterogeneity by ownership type. Results presented in Table 5 indicate that foreign firms are the most affected by extreme rainy days. Specifically, an additional day with more than 250 mm of rain leads to a 12.91 % productivity loss, while an additional day with rainfall between 100–250 mm results in a 2.89 % productivity decrease. In contrast, private firms experience productivity reductions of 3.92 % and 1.31 % for an additional day with more than 250 mm and between 100–250 mm of rain, respectively. Collectively owned manufacturing firms show no significant response to days with more than 250 mm of rain, and their response to days with 100–250 mm of rain is small in magnitude, significant only at the 10 % level. State-owned firms, however, do not exhibit a significant response to rainy days in these ranges. One possible explanation for these differences is that foreign firms may have limited experience with local extreme weather conditions, which could hinder their adaptation capabilities. Conversely, state-owned firms might be more likely to adhere closely to government guidelines for managing extreme weather events or may benefit from government support during such occurrences.

6.3. Regional heterogeneity

Given China's vast territorial expanse across diverse latitudes and longitudes, understanding regional heterogeneity is essential for analyzing how firms respond to rainfall in different areas. We classify China's territory into seven regions based on geographical distribution, which allows us to identify potential regional variations.[14] Panel A illustrates the geographic distribution of these regions along with the average annual total rainfall in our sample.

Our findings reveal that manufacturing firms are particularly susceptible to rainfall extremes in wetter regions, while light rainy days may actually benefit drier areas. Fig. 4 examines the impact of rainfall on productivity across different regions (for extended data, see Online Appendix Table G4). The results indicate that the negative effects of extreme rainy days are primarily driven by firms located in rainy regions. For example, manufacturing firms in the southern regions experience an average of 0.018 days with rainfall exceeding 250 mm and 0.855 days with rainfall between 100–250 mm. In contrast, the national averages for these rainfall categories are only 0.004 and 0.327 days, respectively. Consequently, in the south, firms face a productivity loss of 5.31 % (see Panel B of Fig. 4) due to one additional day of rainfall above 250 mm, while an extra day of rainfall between 100–250 mm is associated with a 1.84 % productivity loss (see Panel C). This phenomenon suggests that, despite being accustomed to wet conditions, manufacturing firms in these areas struggle to adapt adequately to extreme rainfall events. It is also noteworthy that there are no recorded extreme rain days in the northeast and northwest regions.

In dry regions, manufacturing firms tend to benefit from light rain days. For instance, firms in the central region experience an average of only 0.002 days with above-250 mm of rain and 0.243 days with 100–250 mm of rain. In the northwest, manufacturing firms do not encounter any days with above-250 mm rainfall and average only 0.020 days with 100–250 mm rain. Quantitatively, firms in both the central and northwest regions respond positively to 10–25 mm rain days, showing productivity increases of 0.22 % and 0.28 % respectively (see Panel F).

Additionally, rather than selecting specific samples for the heterogeneity analysis, we present results that include the interaction term for all samples. This approach offers a comprehensive view of how rainfall affects industrial production. The findings are detailed in Online Appendix Table G5, and they align with the conclusions drawn previously.

7. Mechanisms

This section examines the channels through which rainfall impacts Total Factor Productivity (TFP) at the firm level. We aim to explore a variety of potential channels, including reductions in labor, effects on agricultural productivity (Cui, 2020; Cui and Xie, 2022), and transport disruptions within manufacturing firms (Zhang et al., 2018). By investigating these channels, we seek to contextualize our findings within the broader macro-level literature on the impacts of rainfall and to derive important policy implications.

7.1. Labor supply

Rainy days may also impact productivity if increased heavy rainfall impedes factor accumulation, which in turn may harm productivity growth. Rainfall primarily exerts its adverse effects on labor. Somanathan et al. (2021) reveal that hotter days are associated with labor supply decline via absenteeism, and this mechanism holds true for China's manufacturing sectors during rainy days. For example, an additional day falling into the above-250 mm rainfall range results in a 2.95 % reduction in labor supply in manufacturing firms, as provided in Column (1) of Table 6. By categorizing industries, we further find that extreme rainfall-induced labor loss is significant in labor-intensive firms, with a decrease of 4.31 % per day for rainfall exceeding 250 mm (Column 2).

[14] Provinces included in each region can be assessed at: https://en.wikipedia.org/wiki/List_of_regions_of_the_People's_Republic_of_China

Table 5
Heterogeneous rainfall effects on productivity by ownership type.

	(1)	(2)	(3)	(4)
	Total Factor Productivity (OP estimate)			
	Collective	Foreign	Private	State-owned
>=250mm	−0.0280	−0.1291***	−0.0392**	0.0041
	(0.0312)	(0.0190)	(0.0172)	(0.0289)
[100, 250)	−0.0072*	−0.0289***	−0.0131***	−0.0028
	(0.0037)	(0.0030)	(0.0017)	(0.0038)
[50, 100)	0.0004	0.0020	−0.0035***	0.0038***
	(0.0014)	(0.0013)	(0.0007)	(0.0015)
[25, 50)	0.0019***	0.0009	0.0018***	0.0008
	(0.0007)	(0.0007)	(0.0004)	(0.0008)
[10, 25)	−0.0001	−0.0016***	0.0001	0.0001
	(0.0004)	(0.0004)	(0.0002)	(0.0004)
Cluster	Firm	Firm	Firm	Firm
Observation	175,054	207,637	588,540	170,500
Quadratic terms	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes

Note: Each column represents a separate regression, indicating the coefficient estimates of rainfall bin variables. Columns (1) - (4) report heterogeneous rainfall effects by ownership, with collective-owned firms in Column (1) and foreign-owned firms in Column (2), private-owned firms in Columns (3) and state-owned firms in Column (4). All regions include firm fixed effects, industry fixed effects, and year fixed effects, climate controls and the quadratic terms of these controls. These estimated rainfall bin effects can be interpreted as the percentage changes in firm TFP with one day increase in each rainfall bin. Climate covariates include temperature, wind speed, sunshine duration, wind direction, relative humidity, and air pressure. Standard errors are clustered at the firm level.

* denotes significant at 10 % level.

** at 5 % level.

*** at 1 % level.

7.2. Agriculture spillover

The agricultural sector provides essential raw materials for manufacturing firms, and all manufacturing industries in our sample are directly or indirectly linked to agriculture. Literature suggests an inverted U-shaped relationship between rainfall and agricultural yields (Elisabeth et al., 2019). Column (3) of Table 6 examines how rainfall affects firms with direct agricultural inputs. [15] The results indicate that manufacturing firms with direct agricultural inputs are particularly sensitive to heavy rainfall. Specifically, an additional day of rainfall exceeding 250 mm leads to a 2.56 % decline in productivity. In contrast, one day of rainfall in the 100–250 mm range results in a 1.60 % productivity loss, while a day of rainfall between 50–100 mm corresponds to a 0.41 % decline in productivity.

7.3. Transport disruptions

Transport infrastructure, particularly low-quality roads, is highly vulnerable to natural hazards such as flooding, tropical cyclones, and earthquakes (Cho et al., 2001; Koks et al., 2019). Approximately 7.5 % of all transport assets are exposed to severe flood events that occur once every hundred years (Koks et al., 2019). In China, directly measuring a firm's reliance on road transportation is challenging. To address this, we construct an industry-level transport reliance measure to capture the degree of dependence on road transportation, following Wu et al. (2023). To investigate potential transportation difficulties during heavy rains, we select industries with significant transportation activities based on the Input-Output Table in China and the transport reliance rate (Wu et al., 2023). Results presented in Column (4) of Table 6 indicate that one additional day of rainfall of 250 mm or more may result in a 6.47 % productivity loss for transport-dependent firms, compared to 1.77 % in the baseline.

8. Adaption

8.1. Non-productive costs: insurance and stocks

We first aim to investigate how manufacturing firms adjust management cost structures in response to rainfall. Given the substantial impacts of rainfall, it is important to explore the adaptation strategies that firms employ to mitigate these negative effects. Table 7 outlines potential solutions. Specifically, Columns (1) and (2) present findings on the roles of insurance and stock as climate

[15] We determine whether a firm has direct agricultural inputs using China's Input-Output Table from 2007. More information can be retrieved from https://data.stats.gov.cn/files/html/quickSearch/trcc/trcc04.html.

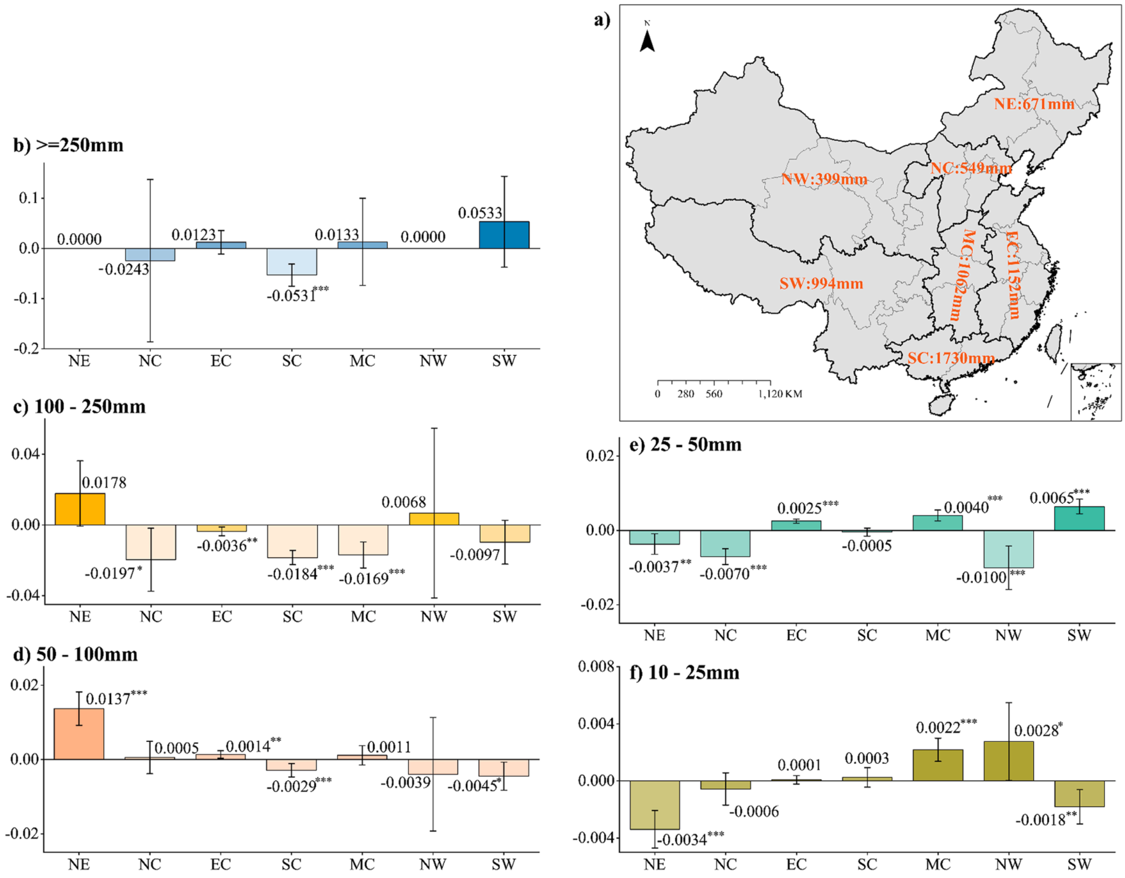

Fig. 4. Heterogeneous rainfall effects on productivity by region

Note: As shown in Panel A, we classify China's territory into seven regions based on geographical distribution to identify potential regional heterogeneity. The annual total rainfall for each region is also reported in this panel. The regions are defined as follows: NE: Northeast (including Heilongjiang, Jilin, Liaoning, and Eastern Inner Mongolia); NC: North of China (including Beijing, Tianjin, Shanxi, Hebei, and Middle Inner Mongolia); EC: East of China (including Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Shandong, and Fujian); SC: South of China (including Guangdong, Guangxi, and Hainan); MC: Middle of China (central, including Henan, Hubei, and Hunan); NW: Northwest (including Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Western Inner Mongolia); SW: Southwest (including Chongqing, Sichuan, Guizhou, and Yunnan). All regions account for firm fixed effects, industry fixed effects, year fixed effects, weather controls, and the quadratic terms of these controls. The estimated rainfall bin effects can be interpreted as the percentage changes in firm total factor productivity (TFP) associated with a one-day increase in each rainfall bin. Climate covariates include temperature, wind speed, sunshine duration, wind direction, relative humidity, and air pressure. Standard errors are clustered at the firm level. The observations for each region are as follows: NE: 113,152 observations; NC: 167,171 observations; EC: 796,177 observations; SC: 194,851 observations; MC: 161,785 observations; NW: 39,953 observations; SW: 85,573 observations.
* denotes significant at 10 % level.
** at 5 % level.
*** at 1 % level.

change mitigation strategies, partially corroborated by Ramelli et al. (2021). [16] Results indicate, in order to resist the negative effects of heavy rainfall (such as above-250 mm rainfall bin and 100–250 mm rainfall bin), firms choose to increase the insurance as a countermeasure. Whereas, in light or moderate rainy days (25 - 50 mm rainfall bin and 10 - 25 mm rainfall bin), firms choose to reduce insurance and stock to improve the operation efficiency of capital since rainfall effects are marginal these days.

Additionally, we examine the effects of rainfall on productivity while accounting for the increase in non-productive adaptation costs by including insurance and stock as covariates. The results presented in Columns (3) and (4) indicate that the negative impacts of extreme rainfall days are mitigated compared to the baseline results. Specifically, when insurance is included as a covariate, the coefficient for rainfall exceeding 250 mm decreases by 23 % (from 0.0177 to 0.0136) and becomes non-significant. Similarly, when inventory is considered as a non-productive input that mitigates the effects of extreme rainfall, the coefficient decreases by 0.001 and is

[16] In our article, "stock" refers to the total inventory held by a firm, while "insurance" specifically pertains to property insurance. McKinsey has explored how the insurance industry can play a pivotal role in combating climate change. For more details, please visit https://www.mckinsey.com/industries/financial-services/our-insights/how-insurance-can-help-combat-climate-change.

Table 6
Potential channels: reduction in labor input, agriculture spillover and transport disruption.

	(1) Labor (log)	(2) Labor (log) (Sample=Labor-intensive firms	(3) TFP (Sample = with Ag input)	(4) TFP (Sample=firms relying on transport)
>=250mm	−0.0295***	−0.0431***	−0.0256**	−0.0647***
	(0.0056)	(0.0072)	(0.0127)	(0.0207)
[100, 250)	0.0023	0.0018*	−0.0160***	−0.0072***
	(0.0018)	(0.0010)	(0.0007)	(0.0024)
[50, 100)	0.0004	0.0007*	−0.0041***	−0.0004
	(0.0003)	(0.0004)	(0.0007)	(0.0010)
[25, 50)	−0.0001	−0.0004**	0.0012***	0.0001
	(0.0002)	(0.0002)	(0.0004)	(0.0005)
[10, 25)	−0.0002*	−0.0005***	−0.0002	−0.0009***
	(0.0001)	(0.0001)	(0.0002)	(0.0003)
Cluster	Firm	Firm	Firm	Firm
Observation	1,559,418	709,749	735,519	363,531
Quadratic terms	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes

Note: Each column in each panel represents a separate regression, indicating the coefficient estimates of the rainfall bin variables. Columns (1) and (2) report potential channels through labor reductions associated with each rainfall bin, including labor for all firms and labor for labor-intensive firms. Column (3) presents productivity responses for agriculture-dependent firms, which confirm the agricultural spillover effect. Column (4) reports productivity responses for transport-dependent firms, verifying transport disruption effects. The classification of agriculture-dependent firms is based on China's Input-Output Table (2007 version), while transport-dependent firms are classified according to Wu et al. (2023). All regressions include firm fixed effects, industry fixed effects, and year fixed effects, climate controls and the quadratic terms of these controls. These estimated rainfall bin effects can be interpreted as the percentage changes in outcomes with one day increase in each rainfall bin. Climate covariates include temperature, wind speed, sunshine duration, wind direction, relative humidity, and air pressure. Standard errors are clustered at the firm level.

* denotes significant at 10 % level.

** at 5 % level.

*** at 1 % level.

significant only at the 10 % level.

8.2. Firm entry and exit decisions

Firm entry and exit account for a significant portion of aggregate productivity growth (Asturias et al., 2023). Climate change and the reallocation of resources among firms may induce substantial firm entry and exit (Linnenluecke et al., 2011; Anouliès, 2017; Cascarano et al., 2022). To explore this adaptation strategy in response to extreme rainfall, we directly examine the effects of extreme rainfall on the fraction of firms entering or exiting (measured by the proportion of entering or exiting firms to total firms) at the county level. To explore heterogeneity, we split our sample into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs).

Results in Columns (1) and (2) of Table 8 report estimates for the fraction of SOE and non-SOE firms entering the market, while Columns (3) and (4) report estimates for the fraction of SOE and non-SOE firms exiting. Rainy days with precipitation exceeding 250 mm may significantly reduce the firm entry fraction for non-SOE firms by 1.57 % per day (see Column 2) at the county level, whereas SOE firms are more resilient. Columns (3) and (4) suggest that the fraction of non-SOE firms exiting will increase by 2.18 % per day (Column 4), while the fraction of SOE firms exiting will decrease by 1.5 % per day (Column 3).

8.3. Infrastructure construction

8.3.1. Anti-flood dam construction

Large-scale infrastructure construction (e.g., dams) emerges as a practical solution capable of protecting downstream agricultural and manufacturing production against rainfall shocks (Duflo and Pande, 2007). In this section, we investigated the role of anti-flood dams as practical solutions for protecting downstream agricultural production from rainfall shocks. We matched geocoded anti-flood dams with the locations of our manufacturing firms and gridded rainfall data to assess how these dams mediate the effects of extreme rainfall.

To conduct this analysis, we first identified the year of construction for each dam, including only those built before 2007, as our ASIP dataset covers the period from 1998 to 2007. Next, we overlaid a water basin system layer onto the township GIS map, focusing on regions with at least one river. Using each dam as a centroid, we included firms within a 25-km radius. We classified the grade-ten water basins as upstream or downstream and assigned this status to the firms located within these basins (data obtained from HydroSHED).

We employed three sets of analyses. In Panel A of Table 9, we directly analyzed the responses of firm-level productivity centered around the selected anti-flood dams. The results indicate that one additional day of rainfall exceeding 250 mm leads to a 12.8 %

Table 7
Potential adaptation strategies for rainfall extremes: non-productive costs.

	(1) Insurance (log)	(2) Stock (log)	(3) TFP	(4) TFP
>=250mm	0.1226***	0.0107	−0.0136	−0.0167*
	(0.0208)	(0.0132)	(0.0095)	(0.0096)
[100, 250)	0.0067***	0.0030*	−0.0145***	−0.0150***
	(0.0025)	(0.0016)	(0.0012)	(0.0012)
[50, 100)	0.0040***	0.0000	−0.0018***	−0.0019***
	(0.0011)	(0.0007)	(0.0005)	(0.0005)
[25, 50)	−0.0020***	0.0005	0.0011***	0.0011***
	(0.0006)	(0.0003)	(0.0003)	(0.0003)
[10, 25)	−0.0018***	−0.0011***	0.00003	0.00003
	(0.0004)	(0.0002)	(0.0001)	(0.0001)
Insurance (log)			0.000015***	
			(0.0000)	
Stock (log)				2.95e-06***
				(1.45e-07)
Cluster	Firm	Firm	Firm	Firm
Observation	1,559,418	1,559,418	1,559,418	1,559,418
Quadratic terms	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes

Note: Each column in each panel represents a separate regression, indicating the coefficient estimates of the rainfall bin variables. Columns (1) and (2) report estimates of potential adaptation strategies including firm-level insurance and stock. Columns (3) - (4) add insurance and stock as additional controls. Insurance and stock data is from ASIF. All regressions include firm fixed effects, industry fixed effects, and year fixed effects, climate controls and the quadratic terms of these controls. These estimated rainfall bin effects can be interpreted as the percentage changes in firm TFP with one day increase in each rainfall bin. Climate covariates include temperature, wind speed, sunshine duration, wind direction, relative humidity, and air pressure. Standard errors are clustered at the firm level.

* denotes significant at 10 % level.

**at 5 % level.

*** at 1 % level.

Table 8
Rainfall effects on firms' decisions to enter or exit the market.

	(1)	(2)	(3)	(4)
	County-year sample			
	Fraction of SOE firms entering	Fraction of non-SOE firms entering	Fraction of SOE-firms exiting	Fraction of non-SOE firms exiting
>=250mm	−0.0087	−0.0157**	−0.0150***	0.0218**
	(0.0058)	(0.0080)	(0.0044)	(0.0120)
[100, 250)	−0.0010	0.0002	0.0015*	0.0010
	(0.0010)	(0.0016)	(0.0007)	(0.0017)
[50, 100)	0.0010**	0.0006	0.0010***	0.0016**
	(0.0004)	(0.0006)	(0.0003)	(0.0006)
Cluster	County	County	County	County
Observations	22,727	22,727	22,785	22,785
Quadratic terms	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes

Note: Each column represents a separate regression, indicating the coefficient estimates of rainfall bin variables. Columns (1)-(4) are county-year data, which aggregate all firms to the county level. Sample period: 1999–2007 in Columns (1) and (2) to measure entry from the prior year; 1998–2006 in Columns (3) and (4) to measure exit in the following year. All regressions include county fixed effects and year fixed effects, climate controls and the quadratic terms of these controls. These estimated rainfall effects can be interpreted as the percentage changes in the fraction of SOE/non-SOE entering/exiting firms with 1 day increase in each rainfall bin. Climate covariates include temperature, wind speed, sunshine duration, wind direction, relative humidity, and air pressure. Their quadratic terms are also included. Standard errors are clustered at the county level.

* denotes significant at 10 % level.

** at 5 % level.

*** at 1 % level.

Table 9
Infrastructure (Anti-flood dam) mediating rainfall extremes.

	(1)	(2)	(3) Downstream TFP	(4) Downstream Labor	(5) Downstream Capital	(6)	(7)	(8)
Panel A: interaction term strategy								
Rain day (>250mm)	−0.128***	−0.097***						
	(0.030)	(0.034)						
Rain day × upstream		−0.066*						
		(0.039)						
Panel B: upstream rainfall effects on downstream manufacturing								
Upstream rain day (>250mm)			−0.003	0.005*	0.003			
			(0.004)	(0.003)	(0.004)			
Panel C: DID strategy								
Difference-in-difference						0.05*	0.13**	0.50**
						(0.03)	(0.06)	(0.21)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth (km)	25	25	25	25	25	25	15	5
Dam Construction Time	1950–2007	1950–2007	1950–2007	1950–2007	1950–2007	1998–2007	1998–2007	1998–2007
Observation	49,607	49,607	49,607	49,607	49,607	9509	2290	294

Notes: We conduct a separate regression for each column in each panel of the table. The dependent variable TFP is estimated using the OP method proposed by Olley and Pakes (1996). Panel A reports estimate by interacting with the upstream dummy variable. In Column (1), we report the effects of one additional extreme rain day (with over 250 mm rainfall within 24 hours) on firm-level TFP. In Column (2), we examine whether the extreme rainfall days have a greater impact on TFP for upstream firms, by interacting rainfall days and upstream dummy variable. In Panel B, we report estimates regarding the upstream rainfall effects on downstream productivity (Column 3) and inputs (Columns 4 and 5). In Panel C, we conduct a difference-in-difference (DD) strategy that compares the firm-level performance of upstream and downstream areas of the dam after the dam construction (relative to before). We select dams designed for flood resistance constructed between 1999–2006 which enable us to identify firms that experience both the pre- and post-construction periods. Dams are selected from Global Reservoir and Dam database (GRanD), with detailed locations and functions provided. By geocoding each firm's location, we can project it within the grade-ten river basin at that specific point. We first categorize the grade-ten water basin as downstream/upstream, subsequently assigning this status to the firms within these basins (basin data is procured from HydroSHED). This helps us identify the upstream and downstream status of one firm, relative to the anti-flood dam. Specifically, in Column (6), our bandwidth is established at 25 km, encompassing samples from both downstream and upstream within a 25-km range of the dams. In Column (7), the bandwidth is narrowed to 15 km, and further to 5 km in Column (8). All regressions include firm fixed effects, industry fixed effects and year fixed effects. We cluster standard errors at the firm level, which are reported in the parentheses.

*** significant at 1 % level.
** significant at 5 % level.
* significant at 10% level.

productivity decline (Column 1). Furthermore, when we interact extreme rainfall days with the upstream dummy variable, the results shown in Column (2) reveals that upstream manufacturing firms, compared to their downstream counterparts, may experience an additional 6.6 % productivity loss.

In Panel B, we examined the effects of upstream rainfall on downstream firm performance and input structure. Our findings suggest that upstream rainy days do not significantly impact downstream firms' productivity (Column 3) or capital (Column 5), which is suggestive of the role of dams in protecting downstream firms from upstream rainfalls.

Finally, in Panel C, we employed a difference-in-differences (DID) strategy to compare the performance of upstream and downstream manufacturing firms before and after dam construction. In Column (6), our results indicate a 5 % productivity premium for downstream firms compared to upstream firms. When we narrow the bandwidth to 15 km in Column (7), the productivity premium for downstream firms increases to 13 %. Further narrowing the bandwidth to 5 km in Column (8) reveals a more pronounced 50 % productivity difference. These results demonstrate that dam construction protects downstream manufacturing firms from extreme rainfall, compared to upstream firms.

8.3.2. Improved road infrastructure and drainage systems

Improved and reliable transport infrastructure is essential for a thriving economy, as it ensures access to markets, employment opportunities, and social services (Limao and Venables, 2001; Zhu et al., 2025). Sustainable Development Goal (SDG) 9 emphasizes the need for enhanced access to sustainable transport infrastructure in low- and middle-income countries. Another important aspect of adaptive infrastructure is the construction of drainage systems, which helps remove excess water from the land (Bibi et al., 2023).

To examine whether improved road infrastructure and drainage systems help mitigate the risks associated with extreme rainfall, we gathered city-level data on road infrastructure (highways) and drainage systems, aligning it with our manufacturing firms. We further interact highway and drainage length to our rainfall bin variables. Results for highways and drainpipe length are reported in Columns (1) and (2) of Table 10, respectively. Due to sample loss from missing city data, we combined rainfall amounts of >=250 mm and [100, 250) into one >=100 mm bin. Both the rainfall-highway and rainfall-drainpipe interaction terms are positive and significant, while the

Table 10
Potential adaptation strategies for rainfall extremes: highway and drainpipes.

	(1) TFP	(2)
Panel A: Highway		
>=100mm*highway	0.0051**	
	(0.0022)	
[50, 100) *highway	0.0077***	
	(0.0007)	
>=100mm	−0.0159***	
	(0.0010)	
[50, 100)	−0.0035***	
	(0.0004)	
Panel B: Drainpipes		
>=100 mm* drainpipes		0.0218***
		(0.0056)
[50, 100) * drainpipes		0.0091***
		(0.0019)
>=100mm		−0.0054***
		(0.0010)
[50, 100)		−0.0017***
		(0.0003)
Cluster	Firm	Firm
Observation	1,517,452	1,526,650
Quadratic terms	Yes	Yes
Climate controls	Yes	Yes
Firm Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes

Note: Each column in each panel represents a separate regression, indicating the coefficient estimates of the rainfall bin variables. Columns (1) and (2) report estimates of potential adaptation strategies including city-level highway and drainpipes. City-level per capita highway length data is from China City Statistical Yearbook while per capita drainpipe length is from China City Construction Statistical Yearbook. All regressions include firm fixed effects, industry fixed effects, and year fixed effects, climate controls and the quadratic terms of these controls. These estimated rainfall bin effects can be interpreted as the percentage changes in firm TFP with one day increase in each rainfall bin. Climate covariates include temperature, wind speed, sunshine duration, wind direction, relative humidity, and air pressure. Standard errors are clustered at the firm level.
* denotes significant at 1 0% level.
** at 5% level.
*** at 1% level.

rainfall effects on productivity elasticity are negative. These estimates suggest that improved transport infrastructure and drainage systems can effectively mitigate the impacts of extreme rainfall.

9. Impacts of further climate change

Using the point estimates obtained from the rainfall bins regression, we can calculate the marginal effects of each extreme rainfall day under different specifications, with baseline estimates reported according to Eq. (5). This allows us to quantify the potential effects of future climate change. Projections of future climate variables are derived from the Shared Socioeconomic Pathways (SSPs) scenarios developed in relation to the Sixth IPCC Report (IPCC AR6). These scenarios consist of four basic pathways: SSP5–8.5, SSP3–7.0, SSP2–4.5, and SSP1–2.6, which are based on projected population growth, economic development, technological change, and the adoption of clean and resource-efficient technologies (O'Neill et al., 2014; O'Neill et al., 2017; Riahi et al., 2017; O'Neill et al., 2020).[17] In brief, SSP5–8.5 represents the most severe environmental degradation, while SSP1–2.6 reflects the most effective environmental protection measures. The SSP scenarios correspond to high, medium-high, medium-low, and low carbon dioxide emissions by the end of this century. The projections for rainfall variables include daily rainfall totals for various timeframes: short-term (beginning of the century, 2030), short-medium term (mid-century, 2050), medium-long term (near the end of the century, 2080), and long-term (end of the century, 2100).

To quantify the potential impacts of future extreme rainfall events, we employ a two-step approach. First, we calculate the projected changes in the number of extreme rainfall days by subtracting the rainfall extremes from the future projected values. This process enables us to gauge the magnitude of changes in extreme rainfall events that are anticipated. Next, we use the estimated effects of extreme rainfall on productivity, derived from our regression analysis, to compute firm-specific predicted changes in productivity

[17] Our dataset is from WCRP Coupled Model Intercomparison Project (Phase 6) (https://esgf-node.llnl.gov/projects/cmip6/).

and output. These predictions are then weighted by each firm's share of total output, allowing us to estimate the overall impacts of future rainfall extremes on China's industrial output. By employing this methodology, we can effectively assess the potential consequences of increased extreme rainfall events on productivity and output across various industries in China.

Our findings, presented in Table 11, indicate that adopting a sustainable and environmentally friendly development pathway, as represented by the SSP1–2.6 scenario, can significantly mitigate the impacts of extreme rainfall by the year 2100. Specifically, the impact of rainfall events exceeding 250 mm on output is projected to decrease by more than 5 0% by 2100 compared to 2030 projections. This suggests that with appropriate measures in place, the potential negative consequences of extreme rainfall can be effectively managed. In contrast, if global socio-economic development continues to rely heavily on the intensified exploitation of fossil fuel resources, particularly coal, and promotes an energy-intensive lifestyle—as depicted in the SSP5–8.5 scenario—the impacts of future rainfall extremes may become uncontrollable. Under the SSP5–8.5 scenario, the effects of rainfall extremes in 2100 are expected to be twice as large as those observed in 2030. These results underscore the critical importance of adopting sustainable practices and transitioning toward cleaner, more efficient energy sources to mitigate the risks associated with future rainfall extremes. By doing so, we can minimize adverse impacts on industrial output and foster a more resilient and sustainable future.

10. Cost-benefit analysis

How large are the magnitude of these rainfall effects on China's manufacturing industry? According to our baseline, results indicate output could be reduced by 0.1 4% due to the rainfall (see Online Appendix Table I1). [18] Hence, the reduced output could be 12.64 million CNY*344,956*0.1 4%= 6.1 billion CNY (or equivalent to 0.8 billion dollars). This also suggests, on average for one firm, 17,696 CNY (2328.4 USD) loss is associated with 1 mm annual rainfall increase. Extreme rainfall days bring more damage to manufacturing outputs. For example, one more above 250 mm rain day induces output loss as high as 12.64 million CNY*344,956*2.3 2%= 101.1 billion CNY (or equivalent to 13.3 billion USD). This implies one firm could lose 293,248 CNY (38,585 USD) due to an additional day with above 250 mm rain. The coefficients are reported in Table I2. While one more 100–250 mm rain day results in 12.64 million CNY*344,956*1.1 4%= 49.7 billion CNY (or equivalent to 6.5 billion USD) loss. On average, one firm's output will be reduced by 144,096 CNY (18,960 USD).[19]

In terms of sectors, we observe heterogeneous effects of extreme rain days on outputs, as shown in Tables I3 and I4. Notably, Agricultural and Sideline Food manufacturing firms experience the most significant output loss during extreme rainy days (above 250 mm). Quantitatively, this translates to an average output loss of 12.8 million CNY * 17. 0% = 2.2 million CNY (equivalent to 0.3 million USD) for a single firm in this industry. Considering there are 20,772 firms within this industry, the overall output loss amounts to 2.2 million CNY * 20,772 = 45.7 billion CNY (equivalent to 6.0 million USD). In the Metal Products and Machinery and Equipment Repair Industry, the average loss per firm is 7.7 million CNY * 12. 9% = 1.0 million CNY (equivalent to 0.1 million USD), resulting in an overall output loss of 1.0 million CNY * 4472 = 4.5 billion CNY (equivalent to 0.6 million USD). Conversely, Medical Goods Manufacturing benefits from rainy days, with the average output for a firm in this industry potentially increasing by 329.7 million CNY * 17. 1% = 56.4 million CNY (equivalent to 7.4 million USD), and the overall value for the industry estimated at 56.4 million CNY * 6191 = 349.2 million CNY (equivalent to 46.0 million USD).

In addition to extreme rainy days, annual average rainfall also influences output losses or gains for each industry. Based on our estimates, an increase of 1 mm in rainfall could result in output losses of 452.0 million CNY (equivalent to 59.5 million USD) for Agricultural and Sideline Food manufacturing firms, indicating a potential output loss of 21,760 CNY (equivalent to 2863.2 USD) per firm. Similarly, industries involved in outdoor production activities also experience output losses due to rainfall increases. For example, a 1 mm increase in rainfall could lead to an output loss of 152.2 million CNY (equivalent to 20.02 million USD) for all Furniture Manufacturing firms, 25.23 million CNY (equivalent to 3.32 million USD) for Wood and Bamboo Products Manufacturing firms, and 185.1 million CNY (equivalent to 24.36 million USD) for Wood and Bamboo Products Manufacturing firms.

Based on this framework, a cost-benefit analysis can be conducted for any region or industry within our study.

11. Concluding remarks

By combining the Annual Survey of Industrial Firms (ASIF) data, which includes half a million firms, with ground station-level climate data, this study utilizes a large microdata set to estimate the effects of rainfall on economic productivity at the firm level. By considering Total Factor Productivity (TFP), we move beyond merely measuring economic output; we also account for the quantity and quality of inputs, technological advancements, and management practices. This broader perspective enables a more comprehensive understanding of the factors that drive productivity, providing valuable insights into how rainfall impacts economic performance at the firm level.

In our empirical analysis, we document patterns consistent with previous literature that identify significant negative impacts of rainfall on output in the manufacturing sector (Damania, 2020; Kotz et al., 2022). Focusing on seasonal rainfall effects, we confirm findings from Kotz et al. (2022) that indicate wet days in autumn have a significant adverse effect on GDP. Specifically, we observe that intense rainfall in both summer and autumn reduces firms' productivity. Our rainfall bin regressions indicate that the negative

[18] Detailed estimates are presented in Appendix Tables I1 and I2.

[19] Of course, we would not expect these extreme rainy days all happen simultaneously across the entire country. These results should be understood as the outcomes of one additional extreme rainy day that happened at different times in different places.

Table 11
Effects of projected extreme rain days (>250 mm, 100–250 mm and 50–100 mm) on TFP and output under different SSP scenarios (%).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total Factor Productivity (OP estimate)				Outputs			
	SSP1–2.6	SSP2–4.5	SSP3–7.0	SSP5–8.5	SSP1–2.6	SSP2–4.5	SSP3–7.0	SSP5–8.5
Panel A: >250mm								
2030	0.0216	0.0006	0.0030	0.0355	0.0283	0.0008	0.0039	0.0465
2050	0.0076	0.0192	0.0169	0.0006	0.0100	0.0252	0.0222	0.0008
2080	0.0425	0.0146	0.0030	0.0030	0.0557	0.0191	0.0039	0.0039
2100	0.0099	0.0425	0.0564	0.0750	0.0130	0.0557	0.0739	0.0983
Panel B: 100–250 mm								
2030	0.2284	0.1947	-0.0034	0.5831	0.1724	0.1470	-0.0026	0.4402
2050	0.1808	0.3394	0.4385	0.2641	0.1365	0.2562	0.3310	0.1994
2080	0.2799	0.3057	0.2443	0.2403	0.2113	0.2308	0.1844	0.1814
2100	0.2482	0.4424	0.7099	1.0131	0.1874	0.3340	0.5360	0.7649
Panel C: 50–100 mm								
2030	0.0271	0.0296	-0.0340	0.1328	0.0313	0.0342	-0.0394	0.1538
2050	0.0196	0.0450	0.1320	0.0580	0.0227	0.0521	0.1529	0.0671
2080	0.0754	0.1014	0.0762	0.0849	0.0874	0.1174	0.0882	0.0983
2100	0.0468	0.1380	0.2363	0.2954	0.0542	0.1598	0.2736	0.3420

Note: The projected impacts of future rainfall extremes on productivity and outputs are reported under four scenarios (SSP1–2.6, SSP2–4.5, SSP3–7.0 and SSP5–8.5), in percentage term. The projected extreme rain days are computed employing the further extreme rain days minus the extreme rain days in our sample. Columns (1) – (4) reports effects on TFP, while Columns (5) – (8) introduces effects on outputs.

relationship between rainfall and productivity is primarily driven by heavy rain days. Additionally, to investigate the short-term cumulative effects of rainfall, we extend the analysis to include lagged terms from previous years. However, our results suggest that no clear pattern is evident regarding the lagged effects of rainfall on productivity.

Moreover, our extensive microdata enables us to examine the diverse responses to extreme rainfall across different sectors. We find that some sectors experience greater productivity losses due to rainfall than others, particularly those that rely heavily on agricultural inputs or outdoor activities. In terms of firm ownership, foreign and private manufacturing firms are particularly vulnerable to extreme rainy days, while collectively owned and state-owned firms demonstrate relative resilience. Regarding regional heterogeneity, areas that are prone to rain suffer more during extreme rainfall events. Additionally, we identify three primary channels through which manufacturing firms experience productivity loss: labor supply, agricultural intermediate inputs and transportation disruptions. We also recognize that increases in non-productive costs at the firm level and strategic firm entry/exit decisions serve as effective mitigation strategies. Furthermore, country-level infrastructure improvements—such as the construction of anti-flood dams, enhanced road infrastructure, and better drainage systems—play a crucial role in mitigating the impacts of extreme weather.

Our cost-benefit analyses suggest that one additional above-250 mm rain day induces manufacturing firms' output loss by 2.32%, or 38,585.26 USD for each firm, on average. Although our analyses are applied to China's manufacturing firms, the results can provide important implications worldwide because of China's most prominent role in the global supply chain. In addition, our paradigm or research design can be applied to any country with sufficient climate data and plant-level surveys.

CRediT authorship contribution statement

Xiaodong Chen: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Yatang Lin:** Writing – review & editing, Validation, Supervision. **Pengyu Zhu:** Validation, Supervision, Project administration.

Acknowledges

We extend our gratitude to the Editor, Hongbin Li, and the two anonymous referees for their insightful comments, which have greatly enhanced this paper. The authors are also grateful for the financial support provided by the Hong Kong RGC Research Fellow scheme (Project No.: HKUST RFS2425-6H03).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jce.2025.03.005.

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