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Keywords: Water stress, water runoff, climate change, firm performance, panel model

JEL Classification: L60, O44, O47, Q54, Q25

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Water stress and industrial firm productivity: Evidence from China

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Abstract

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Introduction

The impact of climate change on human society has received growing attention in various disciplines. Studies in economics have focused on temperature anomalies and documented consistent evidence that extreme heat impairs agricultural yield (Burke & Emerick, 2016; Zhang et al., 2017; Cui & Tang, 2024), cognitive performance (Graff Zivin et al., 2018; Graff Zivin et al., 2020; Park et al., 2020; Zhang et al., 2024), industrial production (Zhang et al., 2018; Chen & Yang, 2019; Somanathan et al., 2021) and, ultimately, economic growth (Dell et al., 2012; Burke et al., 2015; Waldinger, 2022). Yet, the effect of water stress, which is another looming challenge due to climate change, remains ambiguous (Dell et al., 2012; Dell et al., 2014; Burke et al., 2015; Kalkuhl & Wenz, 2020). One explanation for the mixed findings in the extant literature is that most studies have proxied water availability using precipitation. While precipitation is a commonly used proxy in agricultural settings, it is less appropriate in industrial contexts because industrial water demand is not seasonal and can be adjusted according to production needs and purposes.

In this study, we employ a novel dataset of water availability – local water runoff – to examine the effect of water stress on firm-level productivity of over a half million formal industrial firms in China. Although precipitation is one of the primary sources of freshwater supply, much of it will run off the land and be transported to other locations, meaning that it is no longer available for local use (Russ, 2020). As such, rainfall poorly approximates the availability of water for nonagricultural uses, such as use in manufacturing or provision of services (Bareille et al, 2024; Russ, 2020). Local water runoff, defined as "*the sum of total discharges from precipitation, snow* *melt or irrigation water that appears in surface streams, rivers drains or sewers*" (Russ, 2020, p.2),[1] can better capture the total amount of water available for industrial activities.

China is ranked sixth globally in total freshwater supply, with surface water being the primary source. However, in per capita terms, water resources are only 28 per cent of the world average, making China one of the most water-stressed countries in the world (Ministry of Water Resources, 2016).[2] Figure A1 in the Appendix plots annual total freshwater withdrawals and the share by different sectors from 1990 to 2019. Between 1990 and 2007, which overlaps the span of our firm-level dataset, industrial water withdrawals increased by 2.5-fold to 140 billion m^3.

Examining the effect of water stress on industrial productivity in China has important implications for our understanding of the effects of climate change on economic growth in China. China's rapid industrialization has been accompanied by intensive, but inefficient, water consumption. An official report by the Ministry of Water Resources (2007) noted that in 2001–2005, water shortage led industrial losses amounted to 1.62 per cent of China's annual GDP.[3] Water stress in China, also has broader implications for the rest of the world. While water stress is often understood as a local issue (Damania et al., 2020), it can propagate to other countries via trade linkages. The potential spillover effects of water stress in China to other countries is arguably far-reaching, given China's dominating role in global supply chains.

[1] This definition is based on the United States Geological Survey (USGS) Water Science School https://water.usgs.gov.au/runoff.html

[2] In 2016, world average per capita water resources was 7831 m^3, while it was only 2,100 m^3 in China.

[3] D'Aquino (2005) estimates that, in 2004, China contributed to 4 per cent of global GDP but consumed 15 per cent of global water resources.

We link deviations in local long-term water runoff, which we term as runoff shock, with data on the plant-level productivity of Chinese industrial firms over the period 1998–2007. The raw, grid-level runoff at monthly frequency is generated by a Global Water Availability Model (GWAM) in combination with a climate model (e.g., Goddard Institute for Space Science (GISS)). Most variables feeding into these models, such as precipitation, temperature and soil composition and moisture, are exogeneous, mitigating endogeneity concerns. Modelling runoffs in the form of deviations from its local long-term trend further reduces this concern. One potential endogeneity concern with water runoff in general is that it can be a function of upstream land use and water withdrawals, meaning that firm use upstream will runoff downstream. We specifically avoid this problem with our runoff dataset because it does not include upstream withdrawals. Moreover, while water distribution from the hydrologic model (GWAM) and climate model factors in land use, it employs a static model that is not impacted by firm-level activity.

To capture potential nonlinear effects of water stress on firm productivity, we construct four categories of runoff shocks.[4] A moderate and negative (positive) shock is defined as local water runoff being between one and two standard deviations below (above) its local long-run average. Similarly, a large negative (positive) shock is defined as local water runoff being at least two standard deviations below (above) its local long-run average.

We find that runoff shocks exert asymmetric effects on firm productivity. Positive runoff shocks exert inconsistent and insignificant effects on firm productivity. By contrast, negative runoff shocks significantly impair firm productivity. A moderate negative shock reduces firm-level

[4] We consider several other specifications to capture the nonlinear relationship between runoff shocks and firm-level total factor productivity (TFP) in robustness checks.

productivity by 1.93 per cent, while large negative runoff shocks reduce firm productivity by 5.40 per cent. These results are well above the estimated impacts of experiencing one more extreme warm day documented in the literature (see e.g., Zhang et al., 2018; Chen & Yang, 2019; Yao et al., 2022). Our own estimates show that an extra extreme warm day, defined as daily mean temperature above 32℃, reduces firm productivity by 0.18 per cent.[5] Back-of-the-envelope calculations show that the productivity loss due to a moderate negative shock to water runoff is equivalent to experiencing 3 – 11 extra days with daily mean temperature above 32℃.

Our main results are robust to numerous checks. The baseline estimates are insensitive to using alternative approaches to calculating TFP, control variables, clustering strategies, functional forms and runoff variables generated by alternative climate models. In particular, we run different horserace specifications that control for competing proxies of water availability. Runoff shocks consistently outperform all other proxies. Our main results are also insensitive to using city-level or monthly-frequency runoff shocks. Our results contrast with the documented effects of precipitation, which are sensitive to different levels of spatial and temporal aggregation (Damania et al., 2020; Kotz et al., 2022). Additionally, our main results are free from potential bias due to firm attrition, time-variant unobservables and spatial spillovers from neighboring counties.

There are several pathways through which local water runoff can affect firm productivity. First, water is one of the most fundamental industrial inputs. Water shortage impedes production,

[5] Following existing studies (see e.g., Zhang et al., 2018; Chen & Yang, 2019; Yao et al., 2022), we categorize the annual distribution of daily mean temperatures into 10 temperature bins, with the bin [15 ◦C 18◦C) omitted as the reference bin. For each temperature bin, its value refers to the number of days with daily mean temperature failing into that bin range. The estimate captures the marginal effect of an extra day with temperature in bin ***m,*** relative to a day in the reference temperature bin.

particularly for water-intensive manufacturing, such as paper and textile products. It also hampers crucial industrial processes, such as steam production and thermal cooling. Second negative shocks to water runoffs cause power disruptions, increasing the prospect of power outages, which increase the costs of firms reliant on electricity (Allcott et al., 2016; Abeberese, 2017; Eyer & Wichman, 2018). A third potential channel is through water-borne diseases, which could impair workers' health and, consequently, firm productivity (World Bank, 2016; Desbureaux & Rodella, 2019). Finally, more recently, climate change induced water stress has been shown to have adverse effects on firm performance via raising the risk premium in the capital market (Hong et al., 2019; Huynh et al., 2020; Javadi & Masum, 2021; Ginglinger & Moreau, 2023).

We explore each of these four specific channels through which local runoff shocks could reduce firm productivity. First, we examine the extent to which negative runoff shocks impair firms' input of water resources in production. Using data on China's industrial firms from the Annual Survey of Industrial Firms (ASIF) matched with China's Environmental Statistics Database, we find that negative runoff shocks significantly reduce firms' total water consumption. This reduction is due to lower freshwater consumption. Firms attempt to recycle more water to mitigate the stress. The results of a two-stage instrumental variable design confirm that lower water input, due to negative runoff shocks, significantly reduce firm productivity.

The second channel works through disrupting power generation. We manually compile a panel of major power plants and find that negative shocks to water runoff significantly reduce power generation. This result is more salient for hydropower plants, and for coal-fired power plants using surface water and water-intensive cooling technology. Using the World Bank China

Enterprise Survey, we show that negative shocks to local water runoff increase the likelihood of firms encountering power outage and listing it as a major obstacle to their business.

The third channel probes the effect of the risk premium due to runoff shocks on firms' financing costs, including cash flow and the cost of raising capital. We find suggestive evidence that negative runoff shocks reduce firms' cash flow and increase their cost of debt.

The fourth channel explores the potential health burden due to local runoff shocks. We first document that negative runoff shocks increase the concentrations of criteria waterborne pollutants, such as COD. However, using the China Health and Nutrition Survey, we find that runoff shocks have insignificant effects on a set of health outcomes. We attribute this finding to relatively higher penetration of tap water and the practice of consuming boiled water in China.

Our study contributes to several strands of literature. First, we add to the relatively small literature that has examined the effect of water stress. Most studies examining water stress have focused on rural and less developed contexts. Rural households and firms in these settings are inherently more vulnerable to water stress (Maccini & Yang, 2009; Rocha & Soares, 2015; Dinkelman, 2017; Desbureaux & Rodella, 2019; Islam, 2019; Díaz & Saldarriaga, 2023). We focus on a completely different setting: the formal industrial sector that is undergoing rapid expansion. While several recent studies have linked climate change induced water stress to formal industrial firms, they focus on physical damage caused by extreme water events, such as storms or typhoons (Elliott et al., 2019; Kotz et al., 2022; Wu et al., 2023; Benincasa et al., 2024). We find that while runoff shocks are less likely to cause physical damage, they can still adversely impact productivity.

Second, our paper speaks to studies using precipitation as a proxy for water availability. While micro-level studies have shown that rainfall anomalies can induce a range of negative effects, the macro-level evidence is inconclusive (Dell et al., 2012; Burke et al., 2015; Damania et al. 2020; Kalkuh & Wenz, 2020; Bareille et al., 2024). Possible explanations for these ambiguous results are that spatial and temporal aggregation in precipitation data is not nuanced enough to capture variation at the local level (Damania et al., 2020; Kotz et al, 2022).

We offer another explanation: precipitation might be a poor proxy for water availability outside rural and agricultural settings. This paper uses a novel, recently constructed water runoff dataset to capture local water availability. We show that water runoff shocks not only exhibit stronger statistical power among alternative proxies for water availability, including precipitation, but are robust to different levels of spatial and temporal aggregation.

Our paper is perhaps closest to Russ (2020) who examines the effect of water runoff on local economic activity/economic growth using a cross-country sample.[6] He finds that globally moderate negative runoff shocks reduce economic activity by 1.4 per cent, while large negative runoff shocks reduce economic activity by 4 per cent. He also finds that these effects are largest in middle income regions of the world. We complement the focus in Russ (2020) on economic activity/economic growth more generally in that we use a large and nationally representative firm-level panel to specifically focus on firm-level productivity in the industrial sector. Our result

[6] Sadoff et al (2015) also examines the relationship between water runoff and economic growth, but they use country-level data on water runoff, which fails to account for variations at the local level. The only other study to use local water runoff is Bareille et al. (2024), who make a distinction between the effect of green water and blue water on economic growth, in which the latter is measured by local runoff water. The focus of their study is not water runoff per se, but the different impacts of blue water and green water.

resonates with the central finding in Russ (2020) that the effects of runoff shocks are asymmetric, while the size effects of the negative shocks are similar in magnitude. Our results are consistent with the finding in Russ (2020) that negative shocks to water runoff imposes a significantly larger effect on middle-income countries, many of which are undergoing rapid industrialization.

Given that firm-level productivity is an important driver of economic growth (see eg. Jorgenson, 1991), our finding – negative runoff shocks adversely impact on firm productivity – points to another potential mechanism underpinning the result in Russ (2020). We explore more and different transmission channels than Russ (2020). In addition to hydropower generation examined in Russ (2020), we explore the role of thermal power generation. Moreover, reflecting that our research question focuses on effects on firm-level productivity, we examine the effect of negative shocks to runoff on constraining water inputs, as well as the potential adverse effects on health and the cost of financing. In-depth knowledge of transmission channels enables policymakers to formulate more effective strategies to cope with future water stress.

1. Datasets

1.1 Local water runoff

The local water runoff dataset used in this study, which spans between 1950 and 2013, is derived from the GWAM. The GWAM uses monthly precipitation, temperature, land use and maximum soil water storage capacity to compute evapotranspiration, transpiration from vegetation and soil moisture added to the soil column, with the remainder of water being runoff. While GWAM factors in upstream land use, it uses a static measure which is not affected by changes in local economic activity. Since upstream water withdrawals are not accounted for, the runoffs can be considered as "*the maximum theoretical amount of water naturally available*"

(Russ, 2020, p.5). The GWAM generates three alternative datasets for water runoff based on one of the following three climate models: Goddard Institute for Space Science (GISS) E2 model, Community Climate System Model Version 4 (CCSM4) or the First Institute of Oceanography-Earth System Model (FIO-ESM). These runoff datasets were evaluated against observational data and other runoff models and found to be highly valid (Hejazi et al., 2014). We present the main results using the runoff data based on GISS and use the other two runoff datasets as robustness checks.

We first merge the grid-level runoff, which are 0.5°×0.5° in size, with an administrative map of China, in order to generate county-level observations.[7] The county-level water runoff is a spatially weighted average of water runoff grid points that fall into the boundary of a county. We replicate this procedure for each county from January 1950 to December 2013. The monthly county-level water runoff is then aggregated to calculate annual water runoff in each county.

Consistent with the approach in Russ (2020), we construct runoff shocks based on z-scores. First, the long-term mean and the standard deviation of water runoff in each county is calculated using annual observations from 1950 to 2013. Second, four shocks are derived for each county from 1998 to 2007. Moderate negative (positive) shocks indicate if water runoff in a particular year is between one and two standard deviations below (above) the local long-run average. Large negative (positive) shocks indicate if water runoff is at least two standard deviations below (above) the local long-run mean. This specification allows for a flexible relationship between water stress and productivity. We consider alternative functional forms in robustness check.

[7] These grids are centered at the 0.25° and approximately 50km×60km at the equator.

Table 1 displays the incidence of the four types of water runoff shocks in our sample period. Moderate negative runoff shocks are most frequent, with 2514 out of 2851 Chinese counties (88.2 per cent) having at least one moderate negative shock over the sample period. In total, 1592 counties (55.9 per cent) have experienced at least one moderate positive runoff shock. Our identification, therefore, is not dependent upon a small number of counties that have repeatedly encountered runoff shocks. Large runoff shocks, however, are much less frequent. There are only 896 (170) counties that have experienced large positive (negative) runoff shocks.

[Insert Table 1 about here]

Table A1 and Table A2 in the Appendix show the incidence of each of the four types of water runoff shocks using data compiled using the CCSM4 and FIO-ESM climate models. Their frequency distributions of each of the four shocks are similar to that based on the GISS model.

Figure 1 depicts the spatial distribution of the four types of runoff shocks over our sample period. Figure 1 suggests that there is sufficient spatial variation in the incidence of shocks that we can identify the effects of both large and moderate runoff shocks at the same time.

[Insert Figure 1 about here]

1.2 Alternative proxies for water availability and weather controls

Our first alternative proxy for water availability is daily precipitation. We source data on daily precipitation in each of the counties over the sample period from over eight hundred synoptic stations maintained by the China Meteorological Administration (CMA). Readings from the synoptic stations are subject to stringent quality controls. The rate of missing data is less than 0.1 per cent, and the accuracy of the data is assessed to be nearly 100 per cent (Chen & Yang, 2019).

In addition to precipitation, we also employ the Palmer Drought Severity Index (PDSI) as an alternative indicator of water stress. The PDSI is a hydrological measure of supply and demand for soil moisture that captures local water balance. PDSI values are derived from precipitation (water supply) and temperature (potential evapotranspiration) and are normalized to between -10 - indicating extreme water scarcity - and 10 - reflecting a high level of availability of water.

PDSI is obtained from the National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC). It is available at the 0.5° × 0.5° resolution level for each month from January 1901 to December 2020. We merge the PDSI grids with Chinese counties and extract the spatially averaged monthly PDSI for each county.

Table A3 and Table A4 in the Appendix show the frequency of precipitation and PDSI shocks which are defined analogously to water runoff shocks, respectively. Compared to water runoff shocks, precipitation shocks are more likely to capture the wetting trend (wet areas will become wetter), while PDSI shocks are good at capturing the drying trend (dry areas will become dryer).

We control for other daily weather variables: mean temperature, atmospheric pressure, wind speed, the direction of maximum wind speed, relative humidity and sunshine hours at the county level. We source this data over our sample period from the CMA.

1.3 Annual survey of industrial firms

We obtain firm-level data from the Annual Survey of Industrial Firms (ASIF) maintained by the National Bureau of Statistics (NBS) of China. The ASIF covers all industrial firms with annual sales above five million RMB (around USD 0.67 million) from 1998 to 2007.[8] The surveyed firms span 40 industries and collectively are responsible for producing roughly 90 per cent of the total industrial output of China. We include not only manufacturing firms in our sample, but also mining and utility firms that withdraw disproportionally large amounts of water.

We follow the procedure developed in Brandt et al. (2012) to clean the dataset and match industrial firms over time. We rely primarily on firms' legal identification number (IDs) to match them over time. However, IDs are not uniquely assigned to each firm and can change due to merger, acquisition and restructuring. Thus, we also use other information, such as the Chinese name of the firm and its statutory representative and address, to link those firms over time.

We drop observations with missing or negative values for key variables, such as value-added output, employment, and capital stock. We also drop observations that violate basic accounting principles; for instance, when liquid, fixed, or net fixed assets are larger than total assets, and when current depreciation is larger than cumulative depreciation. To mitigate the influence of outliers, we drop observations which are outside the 0.5 and 99.5 percentile range.[9] Our cleaned dataset contains 423,237 unique firms with a total of 181.9 million observations.

[8] Currently, the 2008 – 2013 waves are also available. However, the data after 2008 lack variables of interest such as intermediate inputs. Moreover, Brandt et al. (2017) raise concerns about the data quality in the 2010 wave. In addition, the 2012 data appear to not correctly report the number of workers, because the reported numbers are almost always exactly the same as in the 2011 wave, unlike between other pairs of subsequent years. For these reasons, when using data from the ASIF we focus on the period from 1998 to 2007, as most other studies have done.

[9] Using alternative cutoff values do not change our results.

We exploit ASIF's rich information to estimate firm-level TFP. There are multiple methods for estimating TFP and each of them requires a different set of assumptions. We calculate TFP using the Olley and Pakes (OP) (1996) method for our benchmark analysis. To avoid the functional dependence problem, we apply the ACF correction procedure suggested by Ackerberg et al. (2015), although using OP TFP without the ACF correction produces qualitatively the same results. As a robustness check, we also use TFP based on the Levinsohn and Pertin (LP) (2003) and Syverson (2011) methods. Our main findings are robust to using these alternative approaches.

1.4 China's environmental statistics database

One weakness of ASIF is that information on water consumption is not collected. Thus, we supplement ASIF with China's Environmental Statistics Database (CESD), which records firm-level water consumption and its subcomponents (e.g., freshwater versus recycled water). CESD is maintained by the Ministry of Ecology and Environment (MEE) and has only been made available to the public in recent years. We match ASIF and CESD using firm name, organization code and statutory representative code. Between 1998 and 2007, 204,268 firms appear in both databases. This matched dataset allows us to estimate the direct effect of local water runoff shocks (and our alternative proxies for water stress) on firm-level water consumption. Table A5 in Appendix presents the summary statistics of the main variables used in this study.

1.5 Additional datasets

We use several other datasets in the robustness checks and in the heterogeneity and mechanism analysis. These auxiliary datasets contain information on geological features (accessibility of groundwater, river networks and irrigated farmland), industrial water withdrawals (IWW), power plants, water sources and cooling technologies of power plants, indicators of water quality and potential health effects of water runoff shocks at the county level. We also use a World Bank Enterprise Survey (WBES) to examine the effect of runoff shocks and power outages on production and self-reported business activity of firms in a sample of cities. These datasets are described in Supplementary Information S1 – S6. We refer to them in the robustness section and when presenting the heterogeneity and mechanism analysis.

2. Empirical strategy

We estimate the effects of four types of runoff shocks using the specification below:

$$TFP_{ispt} = \beta RS_{ct}^{+/-1,2} + T_{ct}^{'}\gamma + Z_{it}^{'}\lambda + \alpha_i + \eta_{st} + \delta_{pt} + \varepsilon_{ispt} \tag{1}$$

where *i*, *s*, *p* and *t* are indices denoting firms, two-digit level industries, province and time, respectively. TFP_{ispt} is total factor productivity in logarithm form, estimated using the OP method with ACF correction. We alternatively employ the LP (2003) and Syverson (2011) methods in robustness checks. $RS_{ct}^{+/-1,2}$ refers to the four runoff shocks at the county-year level. For instance, $RS_{ct}^{-1,2}$ refers to a moderate negative shock in which the runoff value is between one and two standard deviations below its local long-term mean. RS_{ct}^{+2} refers to a large positive shock, in which the runoff value is at least two standard deviations above its local long-term mean.

T_{ct} is a set of county-level weather variables, consisting of daily mean temperature, atmospheric pressure, relative humidity, sunshine duration, wind speed and the direction of maximum wind speed. Because part of local water runoff is attributed to precipitation and many studies have proxied water availability with precipitation, we control for annual total precipitation.

We group daily mean temperature into fifteen 3 ◦C wide bins, ranging from below -12 ◦C to above 30 ◦C (see e.g., Zhang et al., 2018; Chen & Yang, 2019; Li et al., 2022). We omit temperature bin [15 ◦C 18 ◦C) to avoid perfect multicollinearity. For other weather controls, we incorporate their mean, squared and cubic terms to account for potential nonlinear effects.

We include a set of fixed effects to improve causal identification. α_i denotes firm fixed effects that capture unobserved time-invariant confounders unique to each firm. η_{st} denotes two-digit industry-by-year fixed effects which account for annual shocks that are unique to each industry. δ_{pt} is province-by-year fixed effects that capture provincial-specific annual shocks.

The matrix Z_{it} contains a set of firm-level controls that are shown to affect firm productivity. We control for firm age, firm size, firm ownership, export status, leverage ratio, intangible assets ratio, whether the firm has multiple plants and the total employment of the two-digit industry to which the firm belongs in the county in which the firm is located (Wang et al., 2018).[10] We cluster standard errors at the firm level to account for possible serial correlation in firm productivity. In sensitivity checks, we consider alternative clustering strategies and the results are robust.

Our identification strategy rests on runoff shocks being exogenous with respect to TFP and being unpredictable in the short to medium-term. As discussed by Russ (2020), one potential source of endogeneity is that firm productivity and water runoff both depend on land use, resulting in simultaneity bias. In our case, the potential for simultaneity bias is mitigated by two

[10] Firm size is measured using the log of total assets. Firm ownership consists of the following categories: state-owned enterprise; collectively owned enterprise; domestically-owned private enterprises; Hong Kong-, Macao- and Taiwan-invested enterprise; foreign-invested enterprise; and domestic join venture.

factors. The first is that in our set up land use is static. The second is that the hydrologic model (GWAM) does not factor in water withdrawals. While levels of upstream water withdrawals are likely to be endogenous with respect to firm productivity, changes in water supplies based on geography and location are exogenous with respect to firm productivity.

Thus, the causal effect of runoff shocks is identified from comparing the same firms that experience different runoff shocks over multiple years, after controlling for other weather variables and numerous unobserved confounders at province-year and industrial-year levels. Our identification strategy exploits the quasi-experimental remaining variation in runoff shocks to explain corresponding variations in firm productivity. Bareille et al (2024) and Russ (2020) show that remaining deviations in water flows after controlling for fixed effects were sufficient to identify the causal effect of water runoffs on growth. We regressed each category of runoff shocks on different combinations of fixed effects, with and without full weather controls. We find that county and year fixed effects collectively explain 12.46 – 17.96 per cent variations of runoff shocks, leaving substantial variations unexplained. After replacing year fixed effects with more stringent province-by-year fixed effects and controlling for weather variables, the remaining variations are still considerable at 54.13 – 68.94 per cent. These results imply that remaining variations in runoff shocks were sufficient to reliably estimate their impacts on firm productivity.

3. Results

3.1 Baseline results

Table 2 reports the impact of the four types of water runoff shocks on firm productivity. Column (1) controls for firm fixed effects and province-by-year fixed effects, in addition to the usual firm-level productivity determinants. Column (2) adds industry-by-year fixed effects. Column (3) is our preferred specification that further incorporates all weather variables.

[Insert Table 2 about here]

We find that runoff shocks exert asymmetric effects on firm productivity. While positive runoff shocks have inconsistent and insignificant effects, negative moderate runoff shocks significantly reduce firm productivity. Specifically, a moderate negative runoff shock significantly reduces firm-level TFP by 1.93 per cent. Experiencing a large negative runoff shock is more detrimental, accounting for a 5.34 per cent reduction in firm-level TFP. Column (4) excludes firms in counties that encountered no runoff shocks over the sample period. The negative runoff shocks impose moderately larger effects, between 2.52 – 6.42 per cent, on firm-level TFP. Column (5) excludes all precipitation controls, and the baseline estimates change a little. This implies that, when runoff shocks are included, precipitation in level form has very limited power in explaining firm-level TFP. This result is to be expected as the runoff modelling process has taken precipitation into account. The final column drops all firm-level variables in order to address concern that doing so is "over controlling" (Dell et al., 2014). The results are qualitatively unchanged.

Using the same ASIF dataset, Wu et al. (2023) estimate the effect of extreme rainfall days, which are defined as days receiving at least 70 mm precipitation, on firm productivity. They find that one additional extreme rainfall day significantly reduces firm-level TFP by 0.21 – 0.57 per cent. One channel through which extreme rainfall adversely affects TFP is via physical damage caused by intensive rainfall. The physical damage could be quickly restored through new capital investments, which boost firm productivity and recover previous loss. This sort of "destructive construction" may explain the smaller detrimental impacts due to intensive rainfall.

Two studies have used the ASIF to estimate the effects of extreme warm days on firm productivity. Zhang et al. (2018) find that an extra day with temperature in excess of 32◦C, relative to an extra day with mild temperature between 10-16◦C, decreases firm productivity by 0.56 per cent. Chen and Yang (2019) report that industrial output would be reduced by 0.21 per cent in response to similar changes. Our own estimates suggest a smaller change – around 0.18 per cent reduction in firm-level TFP.[11] These estimated effects of extreme warm days are consistently smaller than the estimated effects of negative runoff shocks, which are between 1.93 and 5.34 per cent. Back-of-the-envelope calculations demonstrate that the productivity loss due to one more moderate negative runoff is equivalent to experiencing 3 – 11 extra days with mean temperature above 32℃. This provides suggestive evidence that climate change induced water stress could be more devasting than heat stress, at least for industrial firms.[12]

3.2 Heterogeneous effects across sectors

We explore heterogeneous effects across different industrial sectors. Figure 2 depicts point estimates and 95 per cent confidence intervals for negative runoff shocks within each two-digit sector, separately for moderate and large shocks.[13] Figure A2 in the Appendix reports the corresponding results for positive runoff shocks. Two major findings emerge. First, industries that are extremely water intensive, such as electricity generation, water supply and paper

[11] The detailed estimation results are available upon request.
[12] Nevertheless, we recognize that the probability of experiencing one more extreme warm day is much higher than that of experiencing an additional moderate runoff shock on an annual basis.
[13] The regression models underlying Figure 2 are estimated separately for each two-digit sector using our preferred specification.

manufacturing, appear to be immune to local negative runoff shocks. One possible explanation is that firms in these sectors have self-selected into locations with reliable water sources. This explanation is supported by the much larger negative effect on firms with substantial water demand that are unable to self-select on locations. For instance, a moderate negative water runoff shock reduces TFP among coal mining and coal washing firms by 13.83 per cent, which is more than seven times larger than the result for the full sample. Similarly, firms in other water-intensive mining sectors are also more sensitive to negative runoff shocks.

Second, water stress imposed significant effects on a range of manufacturing sectors. Several high value-added manufacturing sectors, including electronic devices and transport equipment, are quite sensitive to moderate negative runoff shocks. The estimated reductions are between 4.48 and 5.35 per cent in firm-level TFP, more than twice the average effect (1.93 per cent). While these manufacturing sectors are not leading water consumers, they usually have stringent standards of water quality. Negative runoff shocks are associated with not only lower water availability, but poorer water quality due to the effect of weakened dilution (Jiang, 2009). Thus, firms have to purify the water in order to maintain water quality requirements.[14]

3.3 Relevance of specific geographical features

We next examine how access to groundwater, access to river networks and being located in a county with more irrigated agricultural land affects the effect of water runoff shocks on TFP. Supplementary Information S1 describes the datasets used to capture accessibility of county-level

[14] Moderate positive runoff shocks boost firm-level TFP in some water-intensive sectors, such as pharmaceuticals, paper and electrical devices and transport equipment. This mirrored pattern suggests that our findings are unlikely to be due to unobserved confounders. The results are available upon request.

groundwater, county-level river networks and the percentage of irrigated and rainfed cropland at the county level, together with their sources. Table A6 in the Appendix reports the results.

Groundwater is an important substitute for surface water (Bareille et al, 2024). Columns (1) and (2) in Table A6 classify all counties into two groups with high and low degrees of accessibility to groundwater. Groundwater accessibility depends not only on the quantity of water reservoirs, but also takes account of the geological complexity involved in extracting water (Bareille et al., 2024). Being located in a county with poor access to groundwater exposes firms to a larger productivity loss from a negative runoff shock. A negative runoff shock reduces firm-level TFP by 3.05 – 8.19 per cent in counties with below-median level groundwater access.

Columns (3) and (4) in Table A6 classify our sample according to the density of the river network in the county in which they are located. Negative runoff shocks have a larger impact in counties with denser river networks. A possible explanation for this seemingly surprising result is that it reflects self-selection with respect to where firms choose to locate. Firms with large water demand may choose to locate closer to rivers, but have to cope with unpredictable runoff shocks. We find that moderate and positive runoff shocks marginally boost firm productivity in more river dense counties, a result that is consistent with the self-selection explanation.

Columns (5) and (6) in Table A6 examine how the prevalence of irrigated agricultural land affects the relationship between water runoff shocks and TFP. On one hand, agricultural runoffs may benefit water-intensive industrial activities, such as providing water for thermal cooling. On the other hand, farmers may compete with industrial firms for freshwater. Our results support the competition story. We find that negative runoff shocks have a stronger adverse effect on firm productivity in counties with a larger share of irrigated agricultural land.[15]

3.4 Heterogeneous effects across firm ownership and region

Finally, we explore heterogeneous effects across firm ownership and the region in which the firm is located.[16] Results are reported in Table A7. Our baseline results are mainly driven by private-owned enterprises (POEs). State-owned enterprises (SOEs) and foreign-invested firms (FIEs) are immune to negative runoff shocks. There is a political pecking order among firms with different ownership in China. SOEs and FIEs often receive preferential treatment in accessing various resources, from banking loans to land rights (Huang, 2003). Our results are suggestive that the preferential treatment along these dimensions could extend to accessing natural resources, reflected in water rights. Regarding regional heterogeneity, we find that negative runoff shocks significantly impair firm productivity in all regions except the east and the northeast, implying that the productivity loss from negative water runoff shocks are widespread across the country.

4. Robustness checks

4.1 Alternative approaches to firm-level productivity

We begin through examining the robustness of our results to alternative methods of estimating TFP. Column (1) of Table 3 replicates our baseline estimates using the OP method with AFC for comparison. Column (2) uses the OP method without AFC correction. Columns (3) and (4)

[15] Nevertheless, we should not place too much emphasis on this finding because irrigation infrastructure is endogenously determined.

[16] We categorize the 31 provinces in mainland China into seven macro regions: Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia in the North; Liaoning, Jilin and Heilongjiang in the Northeast; Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi and Shandong in the East; Henan, Hubei and Hunan in the Central; Guangdong, Guangxi, Hainan in the South; Chongqing, Sichuan, Guizhou, Yunan and Tibet in the Southwest; Shaanxi, Gansu, Qinghai, Ningxia Hui and Xinjiang in the Northwest.

use TFP estimates based on the LP (2003) and Syversion (2011) methods, respectively. The results are qualitatively similar, suggesting our results are not dependent on how TFP is estimated.

[Insert Table 3 here]

In column (5), we follow Zhang et al. (2018) and Chen and Yang (2019) and use real industrial output as the dependent variable. Moderate negative runoff shocks also significantly reduce industrial output. The magnitude, however, is only half of that on firm-level TFP. This result is to be expected as firms could turn to more costly water sources (e.g., buying water from utility firms) in order to maintain production, but this adjustment could hamper production efficiency.

4.2 Alternatives for calculating water runoff

Columns (6) and (7) of Table 3 use water runoff variables calculated using the CCSM4 and FIO-ESM climate models. The results are qualitatively similar to those in Column (1).

Column (8) of Table 3 uses a shorter time span, 1965-2013, to construct water runoff shocks. The shorter time span excludes the potential influence of a series of droughts that devasted China during the Great Leap Forward between 1958 and 1961. The effect of negative runoff shocks becomes larger and remains highly significant. Following Holtermann (2020), we also use numerous alternative time spans, such as those preceding 1998 and moving average mean and standard deviation, to construct runoff shocks. Our results are insensitive to these changes.[17]

[17] These results are available upon request.

After 2000, the runoff modelling process utilized updated but cross-sectional land use data. One may be concerned that this change could introduce endogeneity and bias our estimates downward. To examine this issue, Column (9) in Table 3 excludes the sample before 2000. Reassuringly, the estimates are qualitatively similar to the baseline results in Column (1).

4.3 Checks on country-specific confounding factors

Counties with large administrative areas contain more grid points and the spatial aggregation procedure may average out local runoff variations. Thus, we a follow the suggestion in Clò et al. (2024) to drop large counties. Column (10) in Table 3 excludes counties in the top 35 percentile in terms of size of administrative area. The estimates become slightly larger.[18]

One of our identification assumptions is that runoff shocks in a county are not associated with unobserved factors that could influence firm productivity. A possible threat to our identification strategy could be a transitory shock taking place in some counties that are more likely to encounter runoff shocks; thus, generating a spurious relationship between runoff shocks and firm-level TFP. This is more likely to happen if similar firms self-select into certain areas based on unobservable local characteristics that are also correlated with resilience (or vulnerability) to ambient water stress. To address this concern, we interact a large set of geographical and predetermined macroeconomics variables with a quadratic time trend.[19] The last column of Table 3 shows that adding these interaction terms does not alter our results.

[18] Almost all large counties are in western China and only a small number of formal industrial firms were established there. Despite that we have used a large cutoff value, the sample size is reduced moderately, from 1,819,904 to 1,537,410. We also employed more and less conservative cutoff values and the results are unaltered.

[19] For geographic variables, we collect groundwater accessibility, river network density, share of irrigated agricultural land, land roughness, average elevation, river network density, rainfed/irrigated agricultural land and the longitude and latitude of county centroid. For predetermined macroeconomic variables, we collect city-level real GDP, industrial output share, number of FIEs, number of major SOEs, real fiscal revenue and expenditure, real fixed investment,

4.4 Sensitivity to functional form and clustering

One might argue that the use of one and two standard deviations as the cutoffs to define moderate and large runoff shocks is arbitrary. We first use a more flexible functional form that specifies ten z-score bins, each with width of 0.5 of a standard deviation. Figure A3 depicts the results. We find consistent evidence that only negative runoff shocks impair firm productivity. Our results imply that firms would begin to feel the negative productivity impact once the magnitude of the shock exceeds one standard deviation, consistent with our baseline results.

We next consider other nonlinear specifications including piecewise linear and second to sixth order polynomial functions in Figure 3. Our main finding remains robust.

[Insert Figure 3 here]

In Appendix Table A8, we progressively add lagged runoff shocks up to three years to accommodate the dynamic effects of water stress.[20] The effects of current moderate negative runoffs are stable and highly significant, although the large negative runoff shocks lose significance after deeper lags are included. Some lagged runoff shocks turn to promoting firm productivity. We attribute this result to a learning effect, in which firms gain relevant experience, which enable them to ameliorate the effect of water stress on productivity.

number of formal sector employees, all of which are for 1995, the year that sweeping economic reforms were set out. We also use the same set of macroeconomic variables observed in 1994, 1996 and 1997 and get qualitatively very similar results.

[20] Specifications with deeper lag structure return similar results. The results are available upon request.

In our main results, we cluster the standard errors at the firm level. We re-estimate our preferred specification with standard errors clustered at different levels. Table A9 in the Appendix reports the results. Our results are robust to different clustering strategies.

We finally examine the sensitivity of our baseline estimates to excluding provinces (municipality) and industries on a case-by-case basis to see if firms in any province or industry are driving the results. Results in Appendix Figure A4 and Figure A5 suggest this is not the case.

4.5 Alternative proxies of water availability

To examine the performance of our water runoff measure with other proxies of water availability, we run a set of horserace regressions. Table 4 reports the results.

[Insert Table 4 here]

Column (1) replicates our baseline results for comparison. Column (2) additionally controls for county-level PDSI, a hydrological measure of local water balance. The effects of the four water runoff shocks are almost identical to our baseline results. Column (3) instead controls for PDSI shocks which are defined analogously to water runoff shocks. The four PDSI shocks exert a small effect on firm-level TFP and only one of them is marginally significant. By contrast, the effects of negative moderate water runoff shocks are almost identical to our baseline results.

Column (4) replaces PDSI shocks with precipitation shocks. We still find that negative water runoff shocks maintain their power in explaining firm-level TFP. This is not surprising as the runoff modelling process has taken not only local rainfall, but also the rainfall in surrounding higher land into account. In column (5), we include water runoff, PDSI and precipitation shocks in the same specification. Runoff shocks have the strongest effects on TFP in this horserace specification.

In columns (6), we follow the approach in Kotz et al. (2022) and control for rainfall bins. Modelling rainfall in this more flexible form does not alter the effects of negative runoff shocks. Figure A6 in the Appendix plots the estimated coefficients of different rainfall bins. Moderate rainfall days boost firm-level TFP, but extreme rainfall days significantly reduce firm productivity. In column (7), we just control for the number of days with 70 – 100 mm rainfall and the number of days with rainfall above 100 mm to account for the potential physical damage associated with extreme water events. The effects of water runoff shocks remain qualitatively the same.

In the last column, we use the most demanding horserace specification, which simultaneously include runoff shocks, PDSI shocks, precipitation shocks, rainfall bins and number of extreme rainfall days. The coefficients on negative runoff shocks remain stable and highly significant. Other water availability proxies, except the number of extreme rainfall days, exert a small and insignificant effect on firm productivity. These results imply that runoff shocks outperform all other competing proxies of water availability that are commonly used in the literature in the statistical sense.[21] This result is in line with Sadoff et al. (2015), who documented that water runoff outperforms nine hydro-climactic indices in explaining economic growth.

[21] While number of extreme rainfall days has large and significant effects on firm-level TFP, we find that they are not consistent across different specifications. These results are available upon request.

4.6 Different levels of spatial and temporal aggregation

Our runoff shocks are constructed at the county-level, which is fairly disaggregated by China's administrative structure. Damania et al. (2020) noted a paradox that precipitation measured at a more aggregated level has weaker power in explaining economic growth. To check whether our results would be weakened by using runoff shocks at higher levels of spatial aggregation, we construct city-level runoff shocks and re-estimate our preferred specification.

[Insert Table 5 here]

Table 5 reports the results. Column (1) is our baseline estimates for comparison. Column (2) uses city-level runoff shocks. We find that negative runoff shocks still significantly reduce firm productivity. Alternatively, using city-level water runoff shocks constructed using the CCSM4 and FIO-ESM climate models also produces qualitatively the same results.[22]

In column (3), we construct runoff shocks at the county-month cell level. Monthly shocks are calculated in the same way as annual shocks. Because firm-level variables are only available at the annual level, we change the definition of $RS_{ct}^{-/+1,2}$ and $RS_{ct}^{-/+2}$ to the number of months in each year in which runoff is between one and two standard deviations, or greater than two standard deviations away from the local long-term monthly mean. We find the consistent result that only negative runoff shocks significantly reduce firm productivity.

[22] The results are available upon request.

4.7 Spatial spillovers of runoff shocks

We have so far ignored spatial spillover effects of runoff shocks in surrounding areas. Neighboring counties that encountered water shortage may intensify competition for water, which may indirectly affect firms' TFP. The total productivity loss from negative runoff shocks might be underestimated without accounting for these spillover effects (Marbler, 2024). We augment Eq. (1) with four spatially weighted runoff shocks to control for potential spillovers,

$$TFP_{ispt} = \beta RS_{ct}^{+/-1,2} + \kappa WRS_{ct}^{+/-1,2} + T_{ct}^{'}\gamma + Z_{it}^{'}\lambda + \alpha_i + \eta_{st} + \delta_{pt} + \varepsilon_{ispt} \qquad (2)$$

W refers to the spatial weighting matrix that is used to capture the potential influence of runoff shocks in surrounding counties. κ are corresponding coefficients to be estimated. We use four different spatial weighting matrices. The first one is based on contiguity, with border-sharing counties assigned positive weights. For the remaining three we employ inverse-distance weighting with alternative distance thresholds. We start with 50km, which is aligned with the distance between any pair of runoff grids in the raw runoff dataset. We employ 100km and 200km thresholds to examine the robustness of using the 50km threshold.

Table A10 in the Appendix presents the results. Runoff shocks in surrounding counties have insignificant effects on firm-level TFP, regardless of the weighting method and threshold distance used. Meanwhile, the effects of runoff shocks within a country on TFP of firms in that county are stable and remain significant, suggesting that spatial spillovers are not biasing our main results.[23]

[23] We also employed the Spatial Durbin Model (SDM) to examine spatial spillovers. To do so, we constructed county-level TFP by averaging firm-level TFP within the same county. We find the reassuring result that spatially weighted runoff shocks in other counties failed to alter our baseline results. The regression results are available upon request.

4.8 Placebo test

To demonstrate that our main finding is not due to unobserved factors, we randomly reassign the runoff shocks among Chinese counties. The randomization process is limited within each year. For instance, runoff shocks observed in 2002 are randomly assigned to different counties in that year.[24] This setting still allows for county-level drying or wetting trends. We repeat this procedure and re-estimate our preferred specification five hundred times to increase the power of the test. Figure 4 plots the distribution of the estimates of negative runoff shocks, separately for large and moderate shocks.[25] The placebo estimates are clustered around zero and only a few of them have larger values than our baseline estimates.

[Insert Figure 4 here]

4.9 Firm attrition

Will local runoff shocks push firms to relocate or cease operation? If this is the case, our baseline results are lower bounds, as we only observe firms that survived after encountering runoff shocks. Alternatively, runoff shocks may adversely affect firms' sales. If this is the case, sales of some firms may fall below 500 million RMB, which is the threshold for inclusion in the ASIF survey. We perform two exercises to probe this issue. First, we create a dependent variable, which is a dummy indicating whether the firm is present in the panel on an annual basis (Yes=1). Table A11 in the Appendix shows that negative runoff shocks exert a small, but negative and

[24] The underlying premise is that, if the baseline results are driven by some preexisting differential trends between counties and not by the runoff shocks, some of the placebo estimates would be significant.

[25] The placebo estimates for positive runoff shocks are consistently insignificant. Results are available upon request.

significant effect on the survival dummy variable, implying that runoff shocks may lead some affected firms to leave the ASIF panel. This result implies that our baseline estimates in Table 2 are likely to be lower bounds for the true runoff shock effects.

Second, we employ increasingly balanced samples to re-estimate our preferred specification. In Appendix Table A12, we report the results using ten different samples, corresponding to the condition that the sampled firms appeared at least between two to ten times over the study period. The sample will be fully balanced when we retain firms that were surveyed annually between 1998 and 2007. Our baseline estimates survived in most columns. Note that, when we use the fully balanced panel, runoff shocks no longer exert any significant effect on firm productivity. We check the firm and sector composition of the fully balanced sample and find that most of them are SOEs and were located in the utility sector which, as we have shown above in the heterogeneity analysis in Section 3.2, are largely immune to local runoff shocks.

5. Mechanisms

In this section, we explore the mechanisms underlying the negative effect of water runoff on firm productivity. We empirically test four channels: the constraint on water input, disrupted power generation, health burden and the financing cost via the risk premium.

5.1 Water input constraint

Water is used directly as an input in manufacturing goods, such as beverages, textile and paper products. Water is also used in various industrial processes. Apart from generating steam and cooling, it is used for washing minerals and extracting oil and natural gas from shale rock. Other industrial processes, like diluting and fabricating, are also water intensive.

Negative water runoff shocks imply less available water for withdrawal. Local firms may be unable to source sufficient water for their industrial activities or face higher costs to obtain enough water. In that context, firms are forced to adjust production plans, which may compromise production productivity, at least in the short term.

We perform three sets of analysis to examine whether constraint on water as an input into production is a mechanism underlying our results. First, we use the ASIF-CESD matched dataset to estimate industrial-level water intensity and perform a subsample analysis. Table A13 in the Appendix reports the results. Panel A divides ASIF firms into four groups by quantiles of industrial-level water intensity.[26] Consistent with our previous heterogeneity results, the effects are non-linear. Firms in the third quantile suffered the largest productivity loss, while firms in the most water intensive industries in the fourth quantile are resilient to moderate water deficit. In panel B, we find consistent results classifying the ASIF firms according to the US industrial-level water intensity estimates. Che and Zhang (2018) state that US industries are subject to less market distortions and consequently the water intensity estimates are less biased.

In the second set of analysis, we estimate the effect of runoff shocks on firm-level water consumption, distinguishing between freshwater and recycled water. Table 6 reports the results.

[26] The CESD dataset contains firm-level water consumption information that enables us to estimate industrial-level water intensity, defined as total water use per every 100,000 RMB of real output. Industrial output across different years is deflated into constant price. A high quantile indicates higher water intensity.

[Insert Table 6 about here]

We find that negative runoff shocks significantly reduce firm-level total water consumption. The estimates are stable across different specifications. A negative moderate runoff shock reduces total water consumption by between 3.24 – 4.14 tons. This result is due to lower freshwater withdrawal. Columns (4) – (6) show that a negative moderate runoff shock is associated with 3.47 – 4.37 tons lower freshwater withdrawal. Firms may recycle water to cope with the water deficit. Columns (7) – (9) provide some suggestive evidence. The impact of negative moderate runoff shocks turns positive, albeit the coefficients are less precisely estimated.

We next change the dependent variable to the number of wastewater treatment devices and associated volume of wastewater being treated. Table A14 in the Appendix reports the results. We find consistent evidence that firms treated more wastewater and discharged lower amount of wastewater in response to a negative moderate runoff shock.

Third, we test whether unexpectedly lower water runoffs will dampen firm-level TFP through reducing firms' water consumption. We use a two-stage regression analysis. In the first stage, we instrument firm-level water consumption, distinguishing between total water and freshwater, with county-level runoff shocks. In the second stage, firm productivity is regressed on exogenous firm-level water consumption predicted by local runoff shocks. Table 7 reports the results.

[Insert Table 7 about here]

In Column (1), we use firm-level total water consumption. The first-stage results show that moderate negative runoff shocks significantly reduce firm-level water consumption. In the second stage, lower water consumption appears to reduce firm-level TFP, yet the estimate is insignificant. The Cragg-Donald Wald F statistic is small and well below the rule of thumb critical value. Column (2) reports the results using freshwater withdrawal. While the second stage estimate remains insignificant, the coefficient becomes larger in magnitude and is more precisely estimated. Additionally, the Cragg-Donald Wald F statistic becomes larger, and the Anderson LM statistic indicates that our two-stage specification is no longer under identified.

There are two explanations for this finding. First, the working sample only contains 25,290 unique firms, accounting for only 5.98 per cent of firms in the ASIF survey (423,237 firms). Second, there is likely to be selection bias in that those firms in the matched sample may be more likely to report their water consumption. A reasonable expectation is that only water-intensive firms would record their water consumption. We checked the industrial distribution of retained firms and find that many of them belong to the utility and mining sectors. These utilities, as we have shown, are more likely to self-select into locales with reliable water sources.

We next use a novel, recently constructed, grid-level industrial water withdrawals (IWWs) dataset. Supplementary Information S2 describes the dataset in detail. Using this dataset enables us to retain all industrial firms from the baseline sample. The dataset has a spatial resolution of $0.1° \times 0.1°$ and is available from 1965 to 2020 for mainland China. We spatially matched grid points of IWWs to Chinese counties using ArcGIS. Table A15 in the Appendix reports the estimated effect of runoff shocks on county-level IWW. IWW is an index number, meaning that the estimates are not comparable to that of using firm-level water consumption. The findings, nevertheless, are consistent with our general conclusion that that negative water runoff shocks, particularly moderate ones, significantly reduce county-level industrial water withdrawal.

The final column of Table 7 presents the parallel two-stage estimation results. County-level IWWs are instrumented by four categories of runoff shocks in the first stage. The predicted county-level IWWs are used to explain firm-level TFP. Both large and moderate negative runoff shocks significantly reduce IWWs, while positive runoff shocks increase IWWs. The Cragg-Donald Wald F statistic suggest that runoff shocks are strong instruments for county-level industrial water withdrawal. The second stage results show that less industrial water withdrawal would significantly reduce firm-level productivity.

Overall, these results provide consistent evidence for the conclusion that negative runoff shocks lower firms' water input, which, in turn, reduce their TFP.

5.2 Disrupting power generation

The power sector is the second largest water user, after agriculture. In 2017, China's power sector withdrew 62.7 billion m^3 of freshwater (Jin et al., 2021). Electricity is a strong complement to capital in industrial production, and other inputs cannot easily be substituted for electricity (Atkeson & Kehoe, 1999; Fried & Lagakos, 2023). Outages, therefore, lower firm productivity by creating idle resources in the short run (Fried & Lagakos, 2023). Many firms use generators to produce their own electricity, insuring themselves against outages (Allcott et al., 2016; Abeberese, 2017; Eyer & Wichman, 2018). However, generators are expensive and reduce investment in other productive assets. The cost of self-generated electricity is also substantially higher than the cost of grid electricity. Fried and Lagakos (2023) show that using a generator as a strategy to address power disruption can lead to large productivity losses in the long run.

We first examine whether negative water runoff shocks are detrimental to power generation. Since water is used for different purposes, we separate our analysis for thermal power and hydropower plants. For thermal power plants, water is used for generating steam and cooling.[27] For hydropower plants, electricity is generated from the physical force of water flows, which drive turbines that are connected to generators. We manually compile a panel of major power plants with installed generation capacity above 100MW from the *China Compendium of Statistical Materials of Electric Power Industry*. We search for the location of each plant employing Baidu map, a leading Chinese navigation service provider. We cross checked the returned addresses from this exercise with information in the *Global Database of Power Plants,* compiled by the World Resources Institute and the *Global Coal Plant Tracker,* compiled by the Global Energy Monitor, which provide either addresses or coordinate information for nearly all large power plants. Supplementary Information S3 provides more information on these datasets.

In Table 8 we report the results when annual generated electricity is regressed on local runoff shocks. Column (1) uses all types of power plants. Column (2) considers coal and nuclear power plants. The last column examines hydropower plants only. Moderate negative runoff shocks significantly reduce the amount of electricity generated by all categories of power plants. Positive runoff shocks boost hydropower generation, which is in line with expectations. These results suggest that local negative water runoff is detrimental to power generation.

[27] Water use in thermal power generation can be characterized by a consumption component, where water is evaporated and not returned, and a withdrawal component, where water is extracted and the thermally polluted outlet water is then returned to the water source.

[Insert Table 8 about here]

We next exploit information on thermal power plants' water source and cooling technology to understand how runoff shocks impede their power generation.[28] Thermal power plants usually withdraw water from four sources: surface water, groundwater, reclaimed water and seawater. The first category is largely captured by local water runoff. There are three common cooling technologies: once-through cooling, closed-loop (wet tower) cooling and air cooling. Once-through cooling technologies are most water intensive (Jin et al., 2021). Thermal power plants that are reliant on surface water and once-through cooling technology are be expected to be the most susceptible to the impact of negative runoff shocks on their ability to supply power.

We collect water sources and cooling technologies for a subset of major coal-fired plants from *Materials of National Energy Efficiency Benchmarking Competition for Thermal Power Units 2012*. While this dataset is cross-sectional, water sources and cooling technologies rarely change over the designated service life. We interact runoff shocks with dummies denoting water source and cooling technology. Table A16 in the Appendix reports the results. Column (1) includes the interaction term between runoff shocks and a dummy set equal to 1 if the power plant is mainly reliant on surface water. We find that power plants relying on surface water significantly lower their power generation in response to moderately negative runoff shocks. Column (2) interacts runoff shocks with a dummy set equal to 1 for power plants that employ once-through cooling technology. Power plants adopting once-through cooling technology are also vulnerable to

[28] Water use varies by installed capacity, fuel types and cooling technologies adopted by power plants (Eyer & Wichman, 2018; Zhang et al., 2018; Jin et al., 2021).

negative runoff shocks, but the coefficient of the interaction term is insignificant. In Appendix Table A17, we replicate the interaction analysis for alternative water sources and cooling technologies and find that most interactions with negative runoff shocks have a small and insignificant effect on power generation. The interaction term of moderate water deficit with groundwater has a positive and marginally significant effect on power generation, which implies that access to groundwater mitigates the negative impact of local water deficit for power plants.

While we show negative runoff shocks impede power generation, firms may not necessarily experience power outages as inter-regional grid transmission may mitigate local power stress.[29] This is not a major issue because inter-provincial grid transmission remains low in China. In 2011, four years after our sample period, only 13.7 per cent of total national electricity was transported inter-provincially. The share grew slowly to 16 per cent in 2017 (Zhang et al., 2017; Jin et al., 2021).

We examine whether runoff shocks make firms experience more power outages. Unfortunately, CESD does not collect data on electricity consumption. We instead use three waves of the World Bank China Enterprise Survey (WBCES) carried out in 2002, 2005 and 2012. Supplementary Information S4 provides detailed information about this survey. The WBES records whether the firm had encountered power outages in the previous (financial) year. If the answer is yes, it then asks whether the firm has suffered production loss. Another question that the WBCES asked owners/senior managers is whether power disruption represents a major obstacle to their business. We regress these variables on local water runoff shocks.

[29] Within each grid, the transmission of power is frequent and with minimal congestion. However, in the absence of long-distance transmission direct current lines, the transfer of electric power cross grids has been difficult. As a result, in tight markets, cities are able to provide power to other cities located within the same regional grid through load management, but the sharing of power across grids to meet peak demand is impossible in most cases (see Fisher-Vanden et al., 2015).

Table 9 reports the results. Note that we use city-level runoff shocks because WBCES only provides the city location of surveyed firms. As WBCES only surveyed a small number of cities, we are not able to estimate the effects of all runoff shocks.[30] Column (1) shows that negative runoff shocks significantly increase the probability of the firm experiencing power outage in the previous (financial) year. However, as shown in Column (2), the negative impact is unlikely to induce production loss, possibly due to the use of backup generators or other adaptation strategies. As we note above, no production loss does not necessarily imply no productivity impact. Investing and running backup generators could divert productivity resources, dampening firm-level TFP in the long run (Fried & Lagakos, 2023). We find that moderate positive runoff shocks significantly reduce the probability of suffering power-related production loss. In the final column, we find that if the firm experienced more negative runoff shocks, the owner/senior manager in the firm was more likely to answer that power outage as a major obstacle to running the business.

[Insert Table 9 about here]

5.3 Financing cost

Climate change induced water deficit may lower firm productivity through adversely affecting the firm's financial position. For instance, it could reduce cash flow by pushing firms to take more expensive water sources and/or costly adaptive strategies. Being vulnerable to negative water runoff shocks may expose firms to higher capital cost in the financial market. Anecdotal evidence suggests that investors have started to acknowledge the growing impact of

[30] For instance, WBCES surveyed 120 Chinese cities in 2005, and none of them experienced a large negative runoff shock, making it impossible to estimate its coefficient.

climate change in altering the capital cost in financial markets. A theoretical model by Chen et al. (2012) demonstrates that the risk premium would increase immediately following water related natural disasters. Using firm-level data from the US, Huynh et al. (2020) present evidence that drought increases the costs of business operations and consequently brings about intertemporal risks to affected firms. Uncertainty as to occurrence and potential impact also contributes to the risk premium (Aguilar-Gomez et al., 2024).

We test whether, and to what extent, runoff shocks reduce firms' cash flow and increase their capital cost. Due to data constraints, we use the cost of debt to gauge the burden of raising external capital. Table 10 reports the results. We first estimate the impact of water runoff shocks on firms' cash flow. Column (1) shows that moderate negative runoff shocks significantly lower firms' cash flow, albeit the magnitude is small. In Column (2) the dependent variable is the cost of debt. Following the literature (e.g., Pittman & Fortin, 2004; Zhang, 2008; Armstrong et al., 2010), we use the ratio of net financial expenses to total liabilities as a proxy for the cost of debt financing. Additionally, in the process of debt financing, firms incur not only interest expenses but also other financial costs, such as bank fees. Therefore, this ratio is calculated as the total of interest expenses, fees and other financial costs divided by total liabilities. A higher ratio indicates a higher cost of debt. Moderate negative runoff shocks significantly increase the cost of debt financing. Yet large negative runoff shocks reduce it. We attribute this contrasting result to the possibility that stronger negative shocks could be a catalyst for government intervention, manifest in special loans with lower interest rates. In Column (3), when we exclude SOEs, which are the main beneficiaries of these policies, the mitigating effect on the cost of debt disappears.

[Insert Table 10 about here]

5.4 Health burden

Studies in public heath point out that water-related extreme events, such as flooding and drought, can adversely affect human health by increasing the survival rate of pathogens and vectors (Cann et al., 2013; Levy et al., 2016). Extended dry events are known to reduce steam flows and increase the concentration of effluent-derived pathogens via a weakened dilution effect. Consuming contaminated water has been shown to impair human health and, hence, labor productivity (Baisa et al., 2010; Rocha & Soares, 2015; Li et al., 2024). Similarly, excessive wet events can directly mobilize pathogens and vectors in the environment and increase runoff of water from fields, thus transporting them into surface water. For instance, heavy runoff can overwhelm water treatment facilities and lead to sewage overflows and even changes in the direction of the flow of water. The resulting cross-contamination between sewage and clean water resources is a cause of gastrointestinal illnesses (Cann et al., 2013).

We first examine the effect of water runoff shocks on local water quality. To do so, we regress four benchmark indicators of water quality - chemical oxygen demand (COD), dissolved oxygen (DO), ammonia nitrogen (NH_4), and pH which measures the acidity of the water - on local runoff shocks. Supplementary Information S5 describes China's automatic water quality monitoring network and each of the four benchmark indicators. We first average station-week level water quality data to station-month level and then regress them on monthly local runoff shocks. Using station-year level data of water quality would substantially reduce the sample size.

Table A18 in the Appendix reports the results. In Columns (1) – (4), we find negative runoff shocks significantly increase the concentration of both COD and NH_4 and also make the water more acidic. While the coefficient on DO is imprecisely estimated, the negative sign provides consistent evidence that unexpectedly low water runoff would deteriorate water quality. In Columns (5) – (8), we add weather controls, that influence water quality, as a robustness check (Lin et al., 2024). We still find consistent evidence. Additionally, positive runoff shocks, regardless of their magnitude, produce much smaller and insignificant effects on water quality, suggesting that the weakened dilution effect could be the mechanism underpinning our findings.

Next, we examine whether lower water quality has an adverse effect on health and lowers labor productivity. Lacking worker-level health information from the ASIF, we use the China Health and Nutrition Survey (CHNS) to examine the potential health burden of lower water quality. Supplementary Information S6 provides more information about the CHNS.

We estimate whether experiencing runoff shocks adversely affects the health of respondents in the CHNS. Results are reported in Table 11. Column (1) regresses self-reported health status on runoff shocks. The dependent variable is coded as one if respondents believe that they are relatively unhealthy. In the next three columns, we estimate whether local runoff shocks increase the probability that respondents report having diarrhea, rash and eye problems. Each of these health problems are closely related to consuming unsanitary water. Column (5) estimates the effect of runoff shocks on worker absenteeism. We find that all runoff shocks exert small and insignificant effects on these outcomes. Columns (6) – (10) replicate the analysis but use monthly runoff shocks to accommodate the fact that each health related questions referred to four weeks before the interviews. The coefficients on water runoff continue to be insignificant. There are two potential reasons for this result. First, China has a relatively high penetration rate of tap water. Second, most Chinese people consume boiled water which eliminates most pathogens.

[Insert Table 11 about here]

5.5 Can our results help explain why negative runoff shocks lower economic growth?

We examine whether industrial productivity is a mechanism linking runoff shocks and local economic growth. Both Russ (2020) and Bareille et al (2024) find that negative runoff shocks significantly lower local economic growth, while the effects of positive runoff shocks are less robust. We first estimate the effects of runoff shocks on local economic growth. For comparison purposes, we follow Russ (2020) and use night luminosity strength to gauge local economic activities. Table A19 in the Appendix reports the results. Column (1) excludes weather controls. In column (2) we add all weather controls. We find that a moderate runoff shock reduces local economic growth by 1.15 – 1.34 per cent, while a large negative runoff shock reduces local economic growth by 4.79 – 5.22 per cent. These estimates are quite close to those reported in Russ (2020), who found that a moderate negative runoff shock lowered economic growth by 1.41 per cent, while a large negative runoff shock lowered economic growth by 4.07 per cent.

In columns (3) and (4), we incorporate city-level manufacturing TFP, calculated using the Olley & Pakes (1996) method.[31] City-level manufacturing TFP exerts a positive and significant impact on local economic growth, consistent with theoretical predictions (Solow, 1956; Romer, 1986); however, the estimated effects of negative runoff shocks become much smaller in magnitude and are insignificant. This finding implies that industrial productivity is a channel explaining the finding in previous studies that negative runoff shocks adversely affect local economic growth.

[31] We cannot estimate county-level TFP because we lack key variables, such as sectoral-level fixed capital investment.

Conclusion

Climate change poses a significant threat to the environment, livelihoods and economic development of local communities around the world. Developing effective mitigation strategies for climate change lies in a sound understanding of its impact on various aspects of society and economy. Studies in the economics literature have documented consistent evidence regarding the detrimental effect of climate change on economic growth, yet the effect of climate change induced water stress on firm-level productivity remains ambiguous. This study investigates this important question in the context of China. It uses a unique dataset that consists of a half million industrial firms matched to fine-scale water runoff data over the period 1998–2007.

Our study contributes to existing research in several aspects. First, most scholars have examined the effect of water stress on agricultural activities, but we focus on a different setting: the formal industrial sector in a developing country that is undergoing major transition. Second, while an emerging body of literature has studied the impact of water stress on physical damage of formal industrial firms, we focus on firm's productivity loss caused by water availability. Third, we construct and employ a novel water runoff dataset to capture local water availability. Compared with the conventional proxy in the literature (i.e., precipitation), water runoff which consists of various discharges including groundwater and rainfall, is a better measure for capturing the total amount of water available for industrial activities.

Our main conclusion is that runoff shocks exert an asymmetric effect on firm productivity. Positive runoff shocks exert an inconsistent and insignificant effect on firm productivity. In contrast, a negative runoff shock significantly reduces firm-level TFP by 1.93 to 5.40 per cent, depending on the magnitude of the shock. Numerous robustness checks suggest that our findings are plausibly causal. We also demonstrate that the effect of negative runoff shocks is heterogeneous across different industries and areas. First, water intensive industries are seemingly immune to negative runoff shocks. In contrast, manufacturing industries, which usually have a high standard for water quality, experience a significant effect of negative runoff shocks. Second, firms in counties with a higher degree of groundwater accessibility are better at coping with negative runoff shocks, while firms in counties with denser river networks and a higher share of irrigation land are more vulnerable to runoff shocks. We find that constraints on water inputs, power generation disruption and, to a lesser degree, the cost of finance are important channels through which negative runoff shocks influence firm productivity. We find no empirical support that adverse effects of runoff shocks on human health is a transmission channel.

Our findings carry important policy implications for social and economic policy. First, besides the documented detrimental effect in rural and developing settings in which household and firm activities are largely agricultural, our results show that water stress also has a nontrivial negative effect on firm productivity. In the aftermath of COVID-19, despite multiple economic stimulus packages, China and other developing economies have experienced declining consumption, production and other economic activities, resulting in slower economic growth. Our finding is particularly relevant and have important implication for policy makers in these countries. Water stress affects productivity, which lends support to the need for an enhanced water resources management strategy to boost economic growth. The negative effect of water stress on power generation suggests that policies aimed at promoting sustainable energy infrastructure development could potentially compensate power generation loss due to water stress and in so doing provide reliable energy for local firms, thereby increasing productivity. Second, the results of the heterogeneity analysis suggest that social and economic policies aimed at addressing water stress need to consider differences across industries and regions. For example, farmers in areas where there is a higher share of irrigation land may compete with local firms for water resources, so local government could design market where public goods such as water rights are traded.

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Main tables

Table 1: Frequency of runoff shocks, predicted by the GISS climate model.

Frequency	Moderate positive shocks	Moderate negative shocks	Large positive shocks	Large negative shocks
0	1027	848	1955	2681
1	1053	1072	838	164
2	606	554	58	6
3	134	254	0	0
4	25	84	0	0
5	6	36	0	0
6	0	3	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0
10	0	0	0	0
Total	2,851	2,851	2,851	2,851

Notes: This table presents the frequency of the distribution of four types of county-level runoff shocks, 1998-2007. Runoff data is from the GISS climate model. Moderate positive (negative) shocks indicate if runoff in a particular year is between one and two standard deviations above (below) the long-run average for a particular county. Large positive (negative) shocks indicate if runoff is at least two standard deviations above (below) the long-run mean for that county.

Table 2: Baseline results

Runoff shocks	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RS_{ct}^{-2}	-0.0551***	-0.0648***	-0.0540***	-0.0640***	-0.0534**	-0.0549***
	(0.0208)	(0.0207)	(0.0208)	(0.0211)	(0.0208)	(0.0208)
$RS_{ct}^{-1,2}$	-0.0163***	-0.0169***	-0.0193***	-0.0252***	-0.0189***	-0.0190***
	(0.0034)	(0.0033)	(0.0034)	(0.0041)	(0.0034)	(0.0034)
$RS_{ct}^{+1,2}$	-0.0014	0.0018	0.0012	0.0007	0.0013	0.0011
	(0.0040)	(0.0039)	(0.0040)	(0.0043)	(0.0040)	(0.0040)
RS_{ct}^{+2}	-0.0045	-0.0025	-0.0089	-0.0107	-0.0083	-0.0089
	(0.0062)	(0.0060)	(0.0062)	(0.0066)	(0.0062)	(0.0062)
Constant	2.6571***	2.7210***	5.2281**	10.5941***	5.6759***	5.1679**
	(0.0337)	(0.0329)	(2.1105)	(2.4856)	(2.1031)	(2.1100)
Adj-R^2	0.6983	0.7154	0.7155	0.7167	0.7155	0.7152
Firm-level controls	Yes	Yes	Yes	Yes	Yes	No
Weather controls	No	No	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	No	Yes	Yes	Yes	Yes	Yes
# of Obs.	1,819,904	1,819,904	1,819,904	1,504,896	1,819,904	1,819,904

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Firm-level TFP is estimated using the Olley & Pakes (1996) method, with the ACF correction. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells in that county. Firm-level controls are firm age, leverage ratio, intangible assets ratio, firm size captured by the log value of total assets, ownership dummies, export status, whether the firm has multiple plants and the total employment of the firms' 2-digit industry in the same county. Weather controls consist of fifty 3 ◦C wide bins (ranging from below -12 ◦C to above 30 ◦C, with the bin 15-18 ◦C omitted as the reference group), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed and the direction of maximum wind speed. Column (5) excludes precipitation related variables.

Table 3: Robustness checks

Runoff shocks	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Baseline	OP TFP (no ACF)	LP TFP	Syverson TFP	industrial output	CCSM4	FIO-ESM	1965-2013	Excluding pre 2000 obs.	Remove large counties	Preexisting maro*trend controlled
RS_{ct}^{-2}	-0.0540***	-0.0615***	-0.0334*	-0.0369*	-0.0170	-0.0386***	-0.0530***	-0.0851***	-0.0561**	-0.0747***	-0.0506**
	(0.0208)	(0.0237)	(0.0193)	(0.0192)	(0.0189)	(0.0075)	(0.0045)	(0.0203)	(0.0219)	(0.0266)	(0.0208)
$RS_{ct}^{-1,2}$	-0.0193***	-0.0189***	-0.0132***	-0.0139***	-0.0059**	-0.0255***	-0.0083**	-0.0228***	-0.0146***	-0.0208***	-0.0188***
	(0.0034)	(0.0037)	(0.0032)	(0.0032)	(0.0025)	(0.0027)	(0.0033)	(0.0036)	(0.0037)	(0.0038)	(0.0034)
$RS_{ct}^{+1,2}$	0.0012	-0.0020	0.0070*	0.0060	0.0103***	0.0019	-0.0004	0.0034	-0.0042	0.0013	-0.0005
	(0.0040)	(0.0043)	(0.0038)	(0.0038)	(0.0038)	(0.0046)	(0.0034)	(0.0038)	(0.0045)	(0.0046)	(0.0040)
RS_{ct}^{+2}	-0.0089	-0.0211***	-0.0015	-0.0042	-0.0028	0.0046	0.0075	0.0150	-0.0038	-0.0100	-0.0097
	(0.0062)	(0.0068)	(0.0058)	(0.0058)	(0.0057)	(0.0081)	(0.0059)	(0.0078)	(0.0064)	(0.0075)	(0.0062)
Constant	5.2281**	4.3002*	5.8723***	5.7676***	6.1426***	5.5066***	5.5045***	5.3735**	5.8366**	3.8917	4.6745**
	(2.1105)	(2.3178)	(2.0393)	(2.0250)	(2.0410)	(2.1100)	(2.1103)	(2.1085)	(2.3628)	(3.7805)	(2.1144)
Adj-R^2	0.7155	0.5728	0.6956	0.6814	0.7669	0.7155	0.7155	0.7155	0.7235	0.7154	0.7156
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	1,819,904	1,819,904	1,819,904	1,819,904	1,819,904	1,819,904	1,819,904	1,819,904	1,524,268	1,537,410	1,819,904

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Firm-level controls are firm age, leverage ratio, intangible assets ratio, firm size captured by the log value of total assets, ownership dummies, export status, whether the firm has multiple plants and the total employment of the firms' 2-digit industry in the same county. Weather controls consist of fifty 3 ◦C wide bins (ranging from below -12 ◦C to above 30 ◦C, with the bin 15-18 ◦C omitted as the reference group), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

Table 4 Alternative water proxies

	(1) Baseline	(2) PDSI level	(3) PDSI shocks	(4) Precipitation shocks	(5) PDSI shocks & Precipitation shocks	(6) Rainfall bins	(7) # of extreme rainfall days	(8) All proxies included
RS_{ct}^{-2}	-0.0540***	-0.0557***	-0.0546***	-0.0526**	-0.0518**	-0.0527**	-0.0534**	-0.0518**
	(0.0208)	(0.0208)	(0.0208)	(0.0208)	(0.0208)	(0.0208)	(0.0208)	(0.0208)
$RS_{ct}^{-1,2}$	-0.0193***	-0.0187***	-0.0187***	-0.0187***	-0.0188***	-0.0191***	-0.0190***	-0.0188***
	(0.0034)	(0.0035)	(0.0035)	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)
$RS_{ct}^{+1,2}$	0.0012	0.0014	0.0016	0.0012	0.0014	0.0007	0.0013	0.0014
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
RS_{ct}^{+2}	-0.0089	-0.0096	-0.0095	-0.0077	-0.0078	-0.0055	-0.0085	-0.0080
	(0.0062)	(0.0063)	(0.0063)	(0.0062)	(0.0063)	(0.0062)	(0.0062)	(0.0063)
$PDSI_{ct}^{-2}$			0.0230*		0.0227*			0.0226*
			(0.0134)		(0.0133)			(0.0133)
$PDSI_{ct}^{-1,2}$			-0.0070		-0.0068			-0.0067
			(0.0058)		(0.0049)			(0.0049)
$PDSI_{ct}^{+1,2}$			-0.0006		0.0032			0.0031
			(0.0059)		(0.0059)			(0.0059)
$PDSI_{ct}^{+2}$			0.0137		0.0066			0.0063
			(0.0178)		(0.0178)			(0.0178)
$Pres_{ct}^{-2}$				-0.0112	-0.0113			-0.0115
				(0.0082)	(0.0082)			(0.0082)
$Pres_{ct}^{-1,2}$				0.0008	0.0006			0.0006
				(0.0027)	(0.0027)			(0.0027)
$Pres_{ct}^{+1,2}$				-0.0031	-0.0032			-0.0031
				(0.0030)	(0.0030)			(0.0030)
$Pres_{ct}^{+2}$				-0.0045	-0.0052			-0.0049
				(0.0052)	(0.0052)			(0.0052)
70–100 mm							-0.0847**	-0.0834**
							(0.0412)	(0.0412)
>100 mm							-0.1012**	-0.1002*
							(0.0504)	(0.0504)
	5.2281**	6.1084***	6.2176***	5.7479***	5.8333***	4.5622**	5.7164***	5.8686***
	(2.1105)	(2.1163)	(2.1173)	(2.1071)	(2.1079)	(2.1147)	(2.1023)	(2.1071)
Adj-R^2	0.7155	0.7155	0.7155	0.7155	0.7155	0.7155	0.7155	0.7155
# of Obs.	1,819,904	1,819,904	1,819,904	1,819,904	1,819,904	1,819,904	1,819,904	1,819,904

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Firm-level TFP is estimated using the Olley & Pakes (1996) method, with the ACF correction. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Column (6) specifies precipitation in rainfall bins, with critical thresholds set at 0.1, 1, 3, 10, 20, 50, 70, and 100 mm, following Kotz et al. (2020). All specifications contain weather controls, firm-level variables, firm FE, province-by-year FE and industry-by-Year FE.

Table 5: Different levels of spatial and temporal aggregation

Runoff shocks	**(1)**	**(2)**	**(3)**
	Baseline	**City-level shocks**	**Monthly frequency shocks**
RS_{ct}^{-2}	-0.0540***	-0.0632***	-0.0822***
	(0.0208)	(0.0184)	(0.0095)
$RS_{ct}^{-1,2}$	-0.0193***	-0.0093***	-0.0051***
	(0.0034)	(0.0033)	(0.0013)
$RS_{ct}^{+1,2}$	0.0012	-0.0136***	-0.0022
	(0.0040)	(0.0039)	(0.0013)
RS_{ct}^{+2}	-0.0089	0.0029	0.0024
	(0.0062)	(0.0051)	(0.0022)
Constant	5.2281**	5.3188**	5.8949***
	(2.1105)	(2.1104)	(2.1120)
Adj-R^2	0.6983	0.7155	0.7155
Firm-level controls	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes
Industry-by-Year FE	No	Yes	Yes
# of Obs.	1,819,904	1,819,904	1,819,904

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Firm-level TFP is estimated using the Olley & Pakes (1996) method, with the ACF correction. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. The city-level runoff shocks are constructed in the same way. Firm-level controls are firm age, leverage ratio, intangible assets ratio, firm size captured by the log value of total assets, ownership dummies, export status, whether the firm has multiple plants and the total employment of the firms' 2-digit industry in the same county. Weather controls consist of fifty 3◦C wide bins (ranging from below -12 ◦C to above 30 ◦C, with the bin 15-18 ◦C omitted as the reference group), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed. In Column (3), $RS_{ct}^{-/+1,2}$ and $RS_{ct}^{-/+2}$ refers to the number of months in year *t* where runoff is between 1 and 2, or greater than 2 standard deviations away from the long run mean.

Table 6: Runoff shocks and firm-level water consumption

Runoff shocks	Total industrial water consumption (1)	(2)	(3)	Freshwater withdrawal (4)	(5)	(6)	Recycled water usage (7)	(8)	(9)
RS_{ct}^{-2}	0.0486	0.0404	0.0418	0.1201	0.1123	0.1146	-0.0121	-0.0315	-0.0171
	(0.0708)	(0.0708)	(0.0708)	(0.0787)	(0.0786)	(0.0786)	(0.1154)	(0.1160)	(0.1160)
$RS_{ct}^{-1,2}$	-0.0414***	-0.0338**	-0.0324**	-0.0437***	-0.0347**	-0.0353**	0.0050	0.0086	0.0221
	(0.0161)	(0.0159)	(0.0161)	(0.0163)	(0.0162)	(0.0163)	(0.0272)	(0.0272)	(0.0274)
$RS_{ct}^{+1,2}$	0.0222	0.0219	0.0232	0.0209	0.0207	0.0212	-0.0017	-0.0024	0.0036
	(0.0183)	(0.0183)	(0.0183)	(0.0188)	(0.0188)	(0.0189)	(0.0305)	(0.0305)	(0.0305)
RS_{ct}^{+2}	0.0165	0.0138	0.0130	0.0140	0.0125	0.0103	0.0093	0.0018	0.0020
	(0.0292)	(0.0292)	(0.0294)	(0.0299)	(0.0299)	(0.0301)	(0.0508)	(0.0508)	(0.0509)
Constant	10.7314***	7.1729***	-2.0852	10.2065***	6.9179***	-6.7312	6.4733***	1.9929***	6.1365
	(0.0026)	(0.1502)	(5.5994)	(0.0027)	(0.1514)	(5.9048)	(0.0046)	(0.2706)	(12.7512)
Adj-R^2	0.7685	0.7694	0.7694	0.7423	0.7434	0.7434	0.7551	0.7559	0.7560
Firm-level controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Weather controls	No	No	Yes	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	269,814	268,498	268,498	269,438	268,139	268,139	266,666	265,570	265,570

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Firm-level industrial water consumption, as well as freshwater and recycled water consumption, are obtained from ASIF-CESD matched dataset. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Firm-level controls are firm age, leverage ratio, intangible assets ratio, firm size captured by the log value of total assets, ownership dummies, export status, whether the firm has multiple plants and the total employment of the firms' 2-digit industry in the same county. Weather controls consist of third-order polynomials in mean temperature, cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

Table 7: IV results – firm-level water consumption

	(1) Total water consumption	(2) Freshwater withdrawal	(3) County-level IWWs
Runoff shocks	***First-stage***	***First-stage***	***First-stage***
RS_{ct}^{-2}	-0.0536	-0.2382**	-6.4772***
	(0.0963)	(0.0989)	(3.1111)
$RS_{ct}^{-1,2}$	-0.0352**	-0.0357**	-4.8202***
	(0.0172)	(0.0175)	(0.4777)
$RS_{ct}^{+1,2}$	0.0133	0.0098	1.9227***
	(0.0196)	(0.0199)	(0.5563)
RS_{ct}^{+2}	0.0210	0.0039	10.755***
	(0.0327)	(0.0330)	(0.8561)
	Second-stage	***Second-stage***	***Second-stage***
Predicted: Firm water consumption	-0.0507	-0.1193	
	(0.2101)	(0.1540)	
IWWS			-0.0018***
			(0.0004)
Cragg-Donald Wald F statistic	1.33	2.527**	69.89***
Anderson canon. corr. LM statisti	7.125	13.55***	366.809***
Firm-level controls	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes
# of Obs.	208,643	207,484	1,697,234

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. The first stage utilizes four runoff shocks as IVs for firm-level water consumption. In the second stage, firm-level TFP is regressed on the predicted firm-level water consumption. Firm-level controls are firm age, leverage ratio, intangible assets ratio, firm size captured by the log value of total assets, ownership dummies, export status, whether the firm has multiple plants and the total employment of the firms' 2-digit industry in the same county. Weather controls consist of third-order polynomials in mean temperature, cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed and the direction of maximum wind speed.

Table 8: Effects of runoff shocks on power generation

	All types		Thermal power		Hydropower	
Runoff shocks	(1)	(2)	(3)	(4)	(5)	(6)
RS_{ct}^{-2}	-0.1368	-0.1036	-0.0332	0.0317	N.A.	N.A.
	(0.0930)	(0.1376)	(0.0639)	(0.1357)	(N.A.)	(N.A.)
$RS_{ct}^{-1,2}$	-0.3560***	-0.3711***	-0.4106***	-0.4250***	-0.2967	-1.5615***
	(0.0762)	(0.0750)	(0.0990)	(0.0981)	(0.2126)	(0.0782)
$RS_{ct}^{+1,2}$	0.0234	0.0266	0.0117	0.0006	0.3471**	0.7028***
	(0.0643)	(0.0639)	(0.0800)	(0.0779)	(0.1381)	(0.1170)
RS_{ct}^{+2}	0.1463	0.1140	0.1452	0.0884	0.3324*	4.3540***
	(0.1109)	(0.1030)	(0.1215)	(0.1112)	(0.1808)	(0.3643)
Constant	8.8086***	168.1588	8.8633***	-2.8e+02	8.4820***	7.6e+03***
	(0.0141)	(323.6186)	(0.0179)	(439.9655)	(0.0477)	(550.8685)
Adj-R^2	0.6350	0.6468	0.4946	0.5135	0.8470	0.9920
Weather controls	No	Yes	No	Yes	No	Yes
Power plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
# of power plants	220	220	194	194	26	26
# of Obs.	1,116	1,116	946	946	170	170

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the power plant level. The dependent variable is the annual amount of electricity generated in logarithm form. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Weather controls consist of third-order polynomials in mean temperature, cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed and the direction of maximum wind speed.

Table 9: Runoff shocks and power outages experienced by firms

	(1)	(2)	(3)
Runoff shocks	Power outage (Yes=1)	Related loss (Yes=1)	Major obstacle (Yes=1)
RS_{ct}^{-2}	N.A.	N.A.	N.A.
	(N.A.)	(N.A.)	(N.A.)
$RS_{ct}^{-1,2}$	0.2818***	0.0931	0.0818**
	(0.0552)	(0.0897)	(0.0383)
$RS_{ct}^{+1,2}$	0.0642	-0.3818***	N.A.
	(0.1397)	(0.1333)	(N.A.)
RS_{ct}^{+2}	0.0138	0.0779	-0.0095
	(0.0619)	(0.0596)	(0.0714)
Constant	-3.4881	3.3963	-0.5470
	(7.2666)	(7.6950)	(7.6207)
Adj-R^2	0.2130	0.2289	0.3061
Firm-level controls	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes
# of Obs.	15,418	15,418	9,121

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Runoff data is from the GISS climate model and is calculated for each city based on the spatially weighted average of gridcells falling into that city. The firm-level dataset is the WBES. Firm controls are firm age, number of formal employees, total sales of all products, whether the firm has loans and state ownership. Weather controls consist of third-order polynomials in mean temperature, cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

Table 10: Runoff shocks and the cost of finance

Runoff shocks	**(1)** Cash flow	**(2)** Cost of debt	**(3)** Cost of debt (No SOEs)
RS_{ct}^{-2}	0.0005	-1.1755*	-0.3841
	(0.0019)	(0.6037)	(0.7115)
$RS_{ct}^{-1,2}$	-0.0007**	0.3331**	0.4032**
	(0.0003)	(0.1596)	(0.1949)
$RS_{ct}^{+1,2}$	-0.0004	-0.0396	-0.0474
	(0.0004)	(0.0452)	(0.0541)
RS_{ct}^{+2}	-0.0008	0.3346**	0.3484*
	(0.0006)	(0.1603)	(0.1813)
Constant	0.5970***	-4.2307	-15.5762
	(0.1465)	(18.0611)	(22.8465)
Adj-R^2	0.5429	0.4684	0.4511
Firm-level controls	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes
# of Obs.	1,302,901	1,323,359	1,136,906

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Runoff data is from the GISS climate model and is calculated for each city based on the spatially weighted average of gridcells falling into that city. Firm controls consist of firm age, number of formal employees, total sales of all products, whether the firm has loans and state ownership. Weather controls consist of third-order polynomials in mean temperature, cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

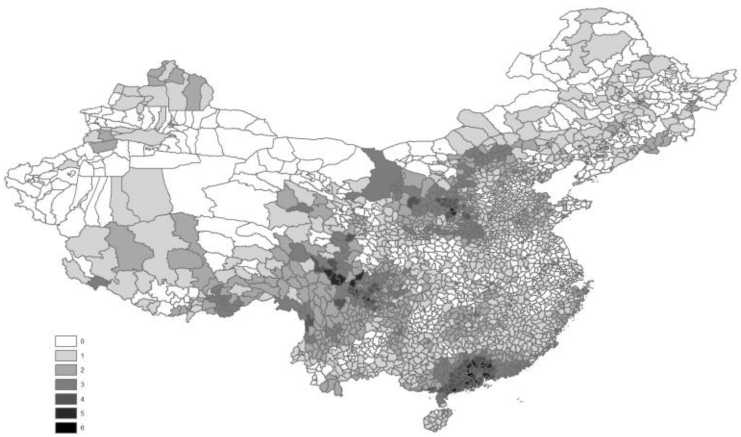
Table 11: Runoff shocks and individual-level health and absenteeism outcomes

Runoff shocks	Annual runoff shocks					Monthly runoff shocks				
	(1) Unhealthy	(2) diarrhea	(3) Eye	(4) Rash	(5) Absence	(6) Unhealthy	(7) diarrhea	(8) Eye	(9) Rash	(10) Absence
RS_{ct}^{-2}	-0.0057	0.0031	0.0313*	0.0885	0.0035	N.A.	N.A.	N.A.	N.A.	N.A.
	(0.0203)	(0.0418)	(0.0185)	(0.0786)	(0.0182)	(N.A.)	(N.A.)	(N.A.)	(N.A.)	(N.A.)
$RS_{ct}^{-1,2}$	0.0026	0.0040	0.0015	-0.0022	0.0028	0.0135	-0.0076	0.0035	0.0025	0.0074
	(0.0074)	(0.0048)	(0.0026)	(0.0021)	(0.0062)	(0.0107)	(0.0070)	(0.0035)	(0.0035)	(0.0084)
$RS_{ct}^{+1,2}$	-0.0204**	0.0021	0.0013	-0.0023	-0.0015	0.0038	-0.0022	-0.0010	0.0014	-0.0038
	(0.0089)	(0.0036)	(0.0022)	(0.0016)	(0.0071)	(0.0064)	(0.0034)	(0.0020)	(0.0016)	(0.0056)
RS_{ct}^{+2}	-0.0232	-0.0025	0.0025	0.0012	-0.0003	0.0089	0.0015	-0.0032	-0.0011	-0.0118*
	(0.0208)	(0.0110)	(0.0045)	(0.0043)	(0.0189)	(0.0089)	(0.0051)	(0.0030)	(0.0024)	(0.0067)
Constant	14.1426	65.6846**	-2.6933	5.4647	14.9193	9.2015	59.8603*	-14.2346	10.4776	16.3989
	(14.0242)	(33.1595)	(12.7151)	(12.1623)	(10.2444)	(14.1738)	(33.2090)	(12.3414)	(11.9027)	(10.7415)
Adj-R^2	0.0745	0.1301	0.0371	0.1133	0.1718	0.0752	0.1328	0.0525	0.1139	0.1560
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	38,859	54,059	54,052	54,053	48,382	38,449	51,485	51,479	51,479	45,880

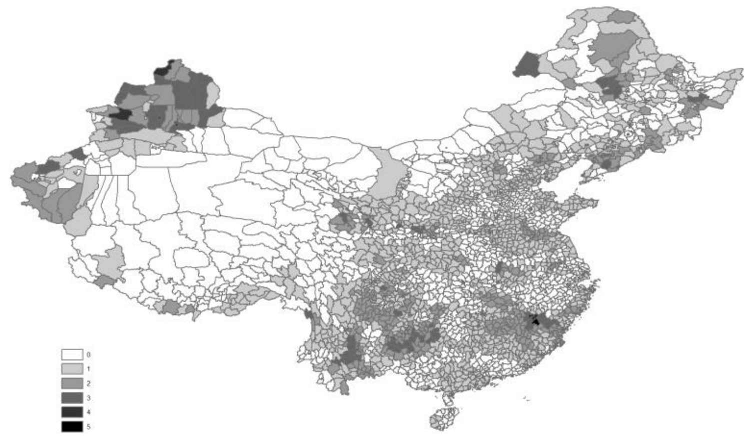
Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the respondent level. Runoff data is from the GISS climate model and is calculated for each city based on the spatially weighted average of gridcells falling into that city. Demographic controls are the respondent's age, number of formal schooling years and whether the respondent has an urban hukou (household registration). Weather controls consist of third-order polynomials in mean temperature, cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed and the direction of maximum wind speed.

Main figures

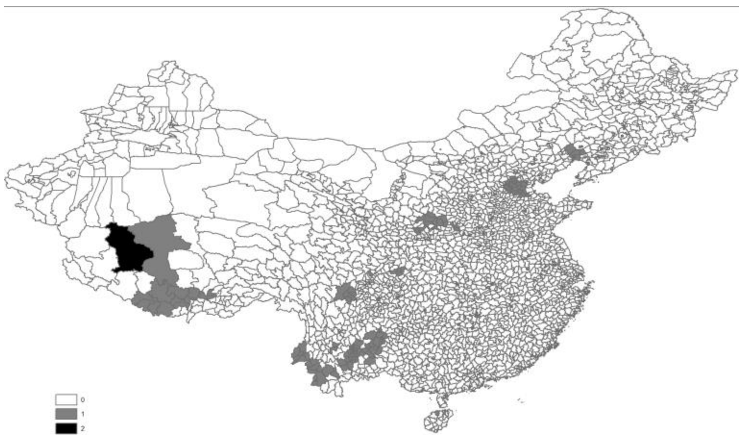
Figure 1: Spatial distribution of runoff shocks over the 1998 – 2007 period (mainland China only)



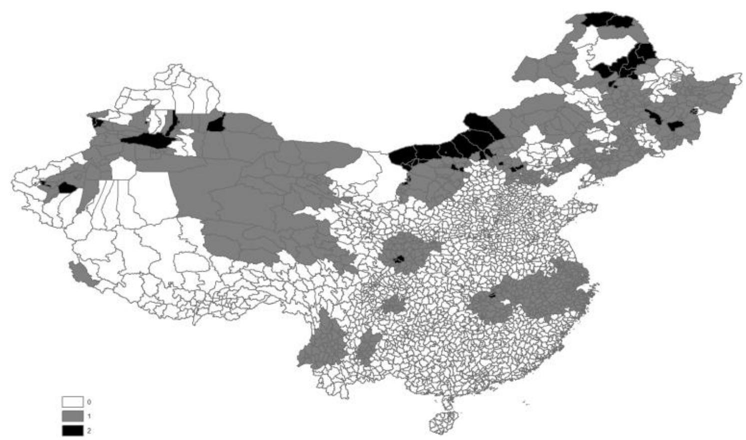
1a. Negative and moderate runoff shocks



1b. Positive and moderate runoff shocks

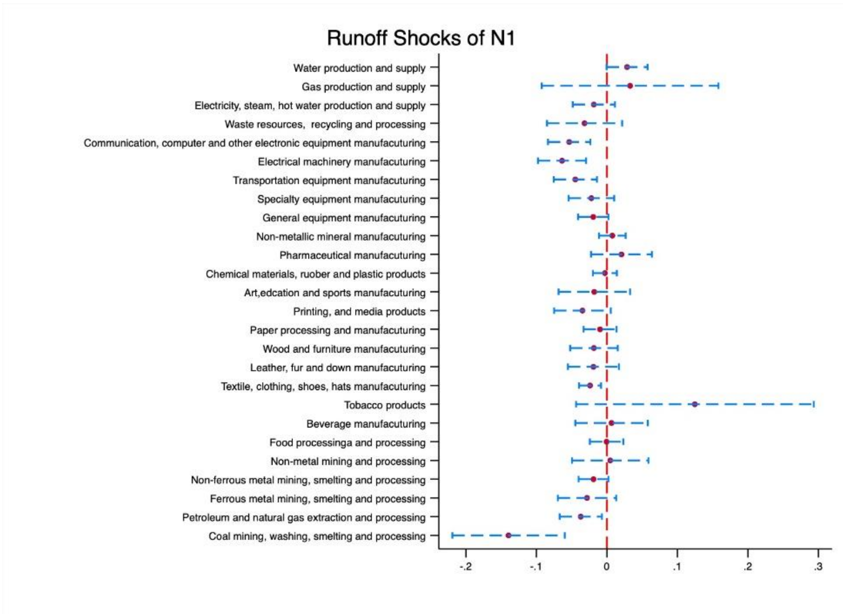


1c. Negative and large runoff shocks

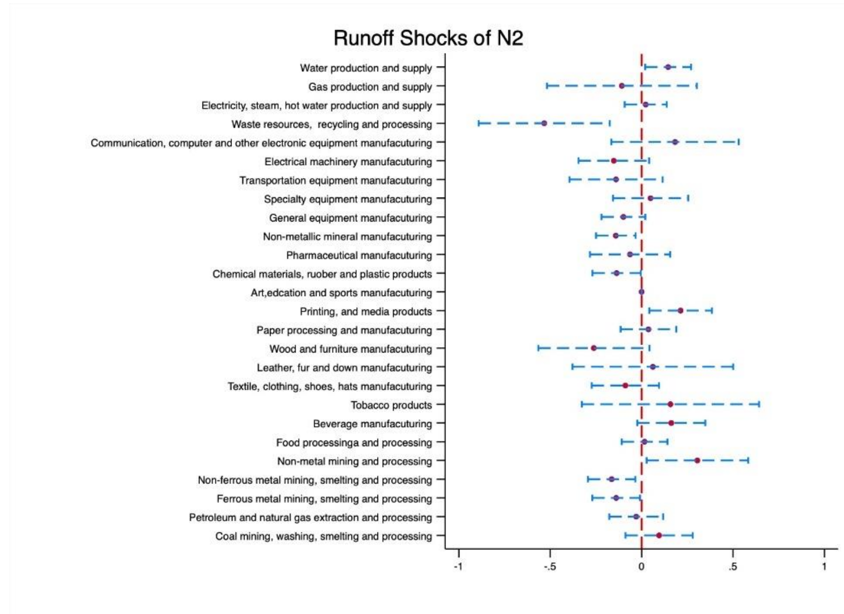


1d. Positive and large runoff shocks

Figure 2: Heterogeneous negative runoff effects by two-digit industrial sectors



2a: Negative moderate runoff shock effects across industries



2b: Negative large runoff shock effects across industries

Figure 3: Results of other nonlinear specifications

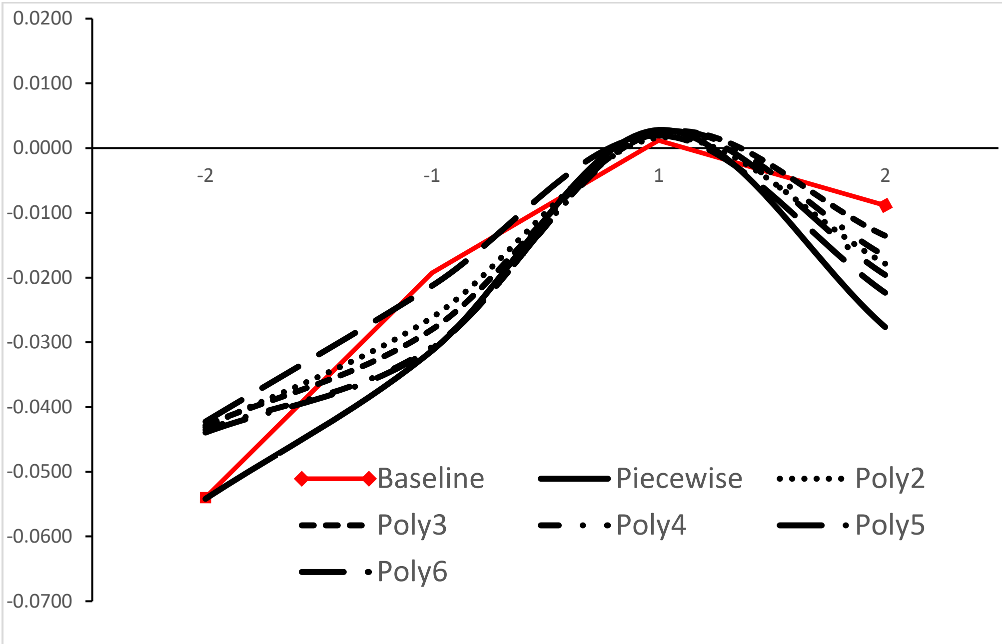
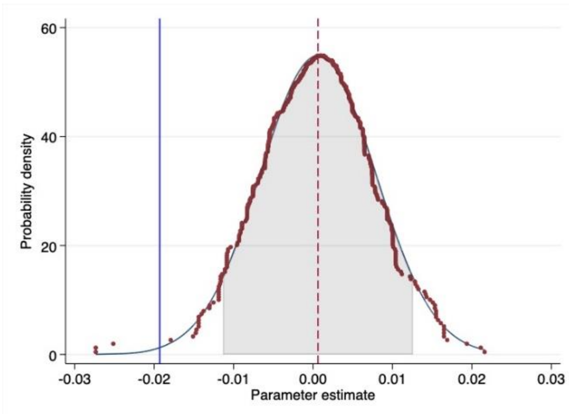
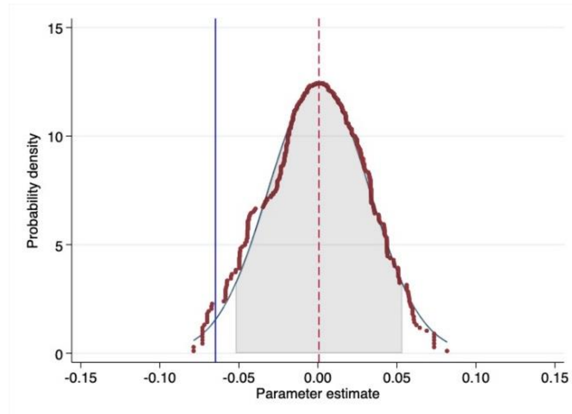


Figure 4: Placebo test, negative runoff shocks



3a: Negative moderate runoff shocks



3b: Negative large runoff shocks

Appendix

Appendix Tables

Table A1: Frequency of runoff shocks predicted by the CCSM4 climate model

Frequency	Moderate positive shocks	Moderate negative shocks	Large positive shocks	Large negative shocks
0	1257	337	1929	2289
1	1020	812	862	492
2	426	752	58	68
3	126	581	2	2
4	21	249	0	0
5	1	86	0	0
6	0	29	0	0
7	0	4	0	0
8	0	1	0	0
9	0	0	0	0
10	0	0	0	0
Total	2,851	2,851	2,851	2,851

Notes: This table shows the frequency of the distribution of four types of county-level runoff shocks, 1998-2007. Runoff data is from the CCSM4 climate model. Moderate positive (negative) shocks indicate if runoff in a particular year is between one and two standard deviations above (below) the long-run average for a particular county. Large positive (negative) shocks indicate if runoff is at least two standard deviations above (below) the long-run mean for that county.

Table A2: Frequency of runoff shocks, predicted by the FIO-ESM climate model

Frequency	Moderate positive shocks	Moderate negative shocks	Large positive shocks	Large negative shocks
0	843	721	1467	2582
1	970	1163	1083	244
2	557	662	287	25
3	293	246	14	0
4	125	28	0	0
5	52	1	0	0
6	11	0	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0
10	0	0	0	0
Total	2,851	2,851	2,851	2,851

Notes: This table shows the frequency of distribution of four types of county-level runoff shocks, 1998-2007. Runoff data is from the FIO-ESM climate model. Moderate positive (negative) shocks indicate if runoff in a particular year is between one and two standard deviations above (below) the long-run average for a particular county. Large positive (negative) shocks indicate if runoff is at least two standard deviations above (below) the long-run mean for that county.

Table A3: Frequency of precipitation shocks

Frequency	Moderate positive shocks	Moderate negative shocks	Large positive shocks	Large negative shocks
0	732	445	1836	2574
1	988	873	974	272
2	774	890	41	5
3	261	477	0	0
4	81	131	0	0
5	11	35	0	0
6	4	0	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0
10	0	0	0	0
Total	2,851	2,851	2,851	2,851

Notes: This table show the frequency of distribution of four types of county-level precipitation shocks. Moderate positive (negative) shocks indicate if annually accumulated precipitation in a particular year is between one and two standard deviations above (below) the long-run average for a particular county. Large positive (negative) shocks indicate if annually accumulated precipitation is at least two standard deviations above (below) the long-run mean for that county.

Table A4: Frequency of PDSI shocks

Frequency	Moderate positive shocks	Moderate negative shocks	Large positive shocks	Large negative shocks
0	1323	385	2613	2106
1	807	499	191	562
2	444	641	27	139
3	149	458	20	44
4	70	427	0	0
5	31	210	0	0
6	16	89	0	0
7	10	62	0	0
8	1	80	0	0
9	0	0	0	0
10	0	0	0	0
Total	2,851	2,851	2,851	2,851

Notes: This table shows the frequency of distribution of four types of county-level PDSI shocks. Moderate positive (negative) shocks indicate if PDSI in a particular year is between one and two standard deviations above (below) the long-run average for a particular county. Large positive (negative) shocks indicate if PDSI is at least two standard deviations above (below) the long-run mean for that county.

Table A5: Summary statistics

Variable	# of Obs.	Mean	Std. Dev.	Min	Max
Firm level					
TFP-OP (with ACF correction)	1,819,904	2.7374	1.6225	-13.0892	16.1645
TFP-OP (no ACF correction)	1,819,904	3.4461	1.4168	-13.1744	16.1645
TFP-LP (with ACF correction)	1,819,904	5.3238	1.7052	-11.6027	20.6690
TFP (Syverson, 2011)	1,819,904	5.0512	1.4443	-8.8206	16.1645
ln_real industrial output	1,819,904	8.4934	1.6817	0	18.9093
Intangible asset ratio [a]	1,819,904	0.014646	0.0515323	-3.895468	1.966667
Firm size [b]	1,819,904	9.680196	1.499325	0.6931472	20.15211
Leverage ratio [c]	1,819,904	0.5987419	3.618402	-51.25	4838.333
Firm age	1,819,904	12.07827	12.08864	1	64
Ownership [d]	1,819,904	2.356314	0.8846943	1	3
Export status	1,819,904	0.2493873	0.4326585	0	1
Multi-plant firm	1,819,904	0.0194461	0.1380867	0	1
Two-digit industrial employees [e]	1,819,904	5464.578	22094.76	0	473,553
County level					
Large & negative RS	1,819,904	0.0018	0.0421	0	1
Moderate & negative RS	1,819,904	0.1217	0.3270	0	1
Large & positive RS	1,819,904	0.0651	0.2467	0	1
Moderate & positive RS	1,819,904	0.0478	0.2133	0	1
Mean daily air pressure	1,819,904	993.6356	41.65244	607.5818	1017.165
Mean daily mean temperature	1,819,904	16.20547	4.300087	-3.747661	26.67957
Mean wind speed	1,819,904	0.2359034	0.0684099	0.052806	0.6688175
Mean direction of max wind speed	1,819,904	7.747974	1.118733	3.605479	13.14795
Mean sunshine duration	1,819,904	5.309767	1.089393	1.965617	9.813926
Mean relative humidity	1,819,904	71.30153	7.475549	30.38783	86.82956
Annually accumulated precipitation	1,819,904	1104.282	514.8377	13.38893	3753.087
≧30℃	1,819,904	12.00434	12.11337	0	62
[27℃ 30℃)	1,819,904	39.554	28.31099	0	182
[24℃ 27℃)	1,819,904	47.33637	18.45937	0	143
[21℃ 24℃)	1,819,904	45.51939	11.56142	0	172
[18℃ 21℃)	1,819,904	38.88802	11.19395	0	140
[15℃ 18℃)	1,819,904	32.84644	9.263242	0	112
[12℃ 15℃)	1,819,904	29.67274	8.610463	0	105
[9℃ 12℃)	1,819,904	27.62036	11.28637	0	116
[6℃ 9℃)	1,819,904	26.6091	14.13053	0	97
[3℃ 6℃)	1,819,904	22.63459	13.78316	0	95
[0℃ 3℃)	1,819,904	17.11129	14.48486	0	100
[-3℃ 0℃)	1,819,904	10.8119	13.75123	0	82
[-6℃ -3℃)	1,819,904	6.006322	10.53911	0	70
[-9℃ -6℃)	1,819,904	3.389341	7.666996	0	58
[-12℃ -9℃)	1,819,904	2.036635	6.088056	0	60
<-12℃	1,819,904	3.041551	12.77321	0	140

Note: [a] the ratio is defined as intangible assets divided by total assets; [b] total assets in logarithm form; [c] leverage ratio is total debt divided by total assets; [d] 1=SOEs, 2=foreign firms 3=domestically-owned private firms; [e] total employment of the firms' 2-digit industry in the same county.

Table A6: Effect of water runoff shocks on TFP by different geographic characteristics

	Groundwater		River density		Irrigated land	
Runoff shocks	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Low	High	Low	High	Low	High
RS_{ct}^{-2}	-0.0819***	-0.0068	-0.0227	-0.0670**	0.0002	-0.1531***
	(0.0263)	(0.0357)	(0.0257)	(0.0275)	(0.0265)	(0.0365)
$RS_{ct}^{-1,2}$	-0.0305***	0.0103	0.0011	-0.0305***	-0.0049	-0.0246***
	(0.0039)	(0.0086)	(0.0070)	(0.0041)	(0.0065)	(0.0042)
$RS_{ct}^{+1,2}$	-0.0036	0.0076	-0.0095	0.0084*	0.0171**	-0.0082*
	(0.0044)	(0.0104)	(0.0073)	(0.0049)	(0.0070)	(0.0050)
RS_{ct}^{+2}	-0.0109	0.0091	-0.0111	-0.0095	-0.0112	-0.0021
	(0.0071)	(0.0174)	(0.0097)	(0.0087)	(0.0102)	(0.0082)
Constant	7.9279**	2.5889	8.2972***	11.9562**	4.5853	4.2781
	(3.5762)	(4.3597)	(2.9699)	(6.0860)	(2.9594)	(4.6545)
Adj-R^2	0.7128	0.7300	0.7216	0.7139	0.7332	0.7094
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	1,495,351	324,553	498,040	1,314,488	507,275	1,312,629

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Firm-level TFP is estimated using the Olley & Pakes (1996) method, with the ACF correction. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Firm-level controls consist of firm age, leverage ratio, intangible assets ratio, firm size captured by the log value of total assets, ownership dummies, export status, whether the firm has multiple plants and the total employment of the firms' 2-digit industry in the same county. Weather controls consist of fifty 3 ◦C wide bins (ranging from below -12 ◦C to above 30 ◦C, with the bin 15-18 ◦C omitted as the reference group), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed and the direction of maximum wind speed.

Table A7: Heterogeneity by ownership and the region in which the firm is located

	Ownerships			Regions						
Runoff shocks	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	SOEs	**FIEs**	**POEs**	**North**	**Northeast**	**East**	**Central**	**South**	**Southwest**	**Northwest**
RS_{ct}^{-2}	-0.0151	-0.0228	-0.0642**	-0.1141	0.1371***	.	.	-0.1580	-0.0995***	-0.0713
	(0.0445)	(0.0761)	(0.0249)	(0.0750)	(0.0409)	.	.	(0.2199)	(0.0287)	(0.0961)
$RS_{ct}^{-1,2}$	-0.0130	0.0001	-0.0244***	-0.0461***	-0.0174	0.0011	-0.0307***	-0.0430***	-0.0027	0.0107
	(0.0091)	(0.0104)	(0.0040)	(0.0145)	(0.0190)	(0.0053)	(0.0114)	(0.0074)	(0.0111)	(0.0188)
$RS_{ct}^{+1,2}$	0.0042	-0.0066	-0.0006	0.0312**	-0.0192	0.0117**	-0.0302**	0.0424***	0.0360**	-0.0016
	(0.0097)	(0.0125)	(0.0046)	(0.0155)	(0.0169)	(0.0053)	(0.0136)	(0.0158)	(0.0156)	(0.0172)
RS_{ct}^{+2}	0.0299	-0.0337	-0.0140**	-0.0398**	-0.0449***	-0.0104	0.0079	.	-0.1028***	0.0743***
	(0.0182)	(0.0217)	(0.0069)	(0.0198)	(0.0139)	(0.0104)	(0.0212)	.	(0.0287)	(0.0242)
Constant	8.2025**	-1.1217	3.6812	10.9534	30.4447	32.4724***	93.6275***	-370.0***	0.6625	18.8880**
	(4.0322)	(7.5490)	(2.6293)	(11.8161)	(64.5062)	(9.0341)	(33.5074)	(606.2159)	(5.0829)	(7.5836)
Adj-R^2	0.7490	0.7274	0.7061	0.6482	0.6828	0.7469	0.6830	0.7059	0.7294	0.7099
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	246,461	206,595	1,366,848	204,480	122,444	825,356	201,122	232,647	109,830	88,071

Note: ***p < 0.01, **p < 0.05, *p < 0.1. SOEs, FIEs and POEs refer to state-owned enterprises, foreign invested enterprises and private owned enterprises, respectively. Robust standard errors in parenthesis are clustered at the firm level. Firm-level TFP is estimated using the Olley & Pakes (1996) method, with the ACF correction. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Firm-level controls are firm age, leverage ratio, intangible assets ratio, firm size captured by the log value of total assets, ownership dummies, export status, whether the firm has multiple plants and the total employment of the firms' 2-digit industry in the same county. Weather controls consist of fifty 3 ◦C wide bins (ranging from below -12 ◦C to above 30 ◦C, with the bin 15-18 ◦C omitted as the reference group), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

Table A8: Incorporating lagged runoff shocks

Runoff shocks	(1)	(2)	(3)	(4)
RS_{ct}^{-2}	-0.0540***	-0.0462**	-0.0372	-0.0338
	(0.0208)	(0.0228)	(0.0236)	(0.0241)
$RS_{ct}^{-1,2}$	-0.0193***	-0.0188***	-0.0165***	-0.0170***
	(0.0034)	(0.0037)	(0.0039)	(0.0039)
$RS_{ct}^{+1,2}$	0.0012	0.0050	0.0024	0.0029
	(0.0040)	(0.0042)	(0.0045)	(0.0045)
RS_{ct}^{+2}	-0.0089	-0.0117*	-0.0152**	-0.0147**
	(0.0062)	(0.0066)	(0.0067)	(0.0067)
L1. RS_{ct}^{-2}		0.0252	0.0395*	0.0454*
		(0.0220)	(0.0238)	(0.0250)
L1. $RS_{ct}^{-1,2}$		-0.0009	0.0041	0.0037
		(0.0034)	(0.0038)	(0.0040)
L1. $RS_{ct}^{+1,2}$		0.0195***	0.0229***	0.0238***
		(0.0043)	(0.0046)	(0.0049)
L1. RS_{ct}^{+2}		-0.0085	-0.0140	-0.0122
		(0.0107)	(0.0108)	(0.0108)
L2. RS_{ct}^{-2}			0.0149	0.0221
			(0.0235)	(0.0263)
L2. $RS_{ct}^{-1,2}$			0.0129***	0.0125***
			(0.0035)	(0.0038)
L2. $RS_{ct}^{+1,2}$			0.0097**	0.0099**
			(0.0044)	(0.0047)
L2. RS_{ct}^{+2}			-0.0303***	-0.0287***
			(0.0075)	(0.0080)
L3. RS_{ct}^{-2}				0.0269
				(0.0218)
L3. $RS_{ct}^{-1,2}$				-0.0016
				(0.0039)
L3. $RS_{ct}^{+1,2}$				0.0028
				(0.0048)
L3. RS_{ct}^{+2}				0.0047
				(0.0072)
Adj-R^2	0.7155	0.7155	0.7155	0.7155
#. of Obs.	1,819,904	1,819,904	1,819,904	1,819,904

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Firm-level TFP is estimated using the Olley & Pakes (1996) method, with the ACF correction. All specification control for firm-level covariates, weather variables firm FE, industry-by-year FE, province-by-year FE. See notes to Table 2 for detailed information.

Table A9: Alternative clustering strategies

	RS_{ct}^{-2}	$RS_{ct}^{-1,2}$	$RS_{ct}^{+1,2}$	RS_{ct}^{+2}
Estimated coefficients	**-0.0540**	**-0.0193**	**0.0012**	**-0.0089**
Baseline (firm level)	(0.0208)***	(0.0034)***	(0.0040)	(0.0062)
Firm & County-by-Year	(0.0325)*	(0.0093)**	(0.0075)	(0.0162)
Firm & Two-digit industry-by-year	(0.0222)**	(0.0051)***	(0.0048)	(0.0083)
Firm & Three-digit industry-by-year	(0.0225)**	(0.0044)***	(0.0048)	(0.0079)
Firm & province-by-two-digit industry	(0.0252)**	(0.0054)***	(0.0054)	(0.0096)
Firm & city-by-two-digit industry	(0.0260)***	(0.0052***	(0.0054)	(0.0099)
Firm & province-by-two-digit industry-by-year	(0.0300)***	(0.0051)***	(0.0052)	(0.0085)
County	(0.0408)	(0.0101)**	(0.0097)	(0.0231)

Note: ***p < 0.01, **p < 0.05, *p < 0.1. The dependent variable is firm-level TFP estimated using the Olley & Pakes (1996) method, with the ACF correction. The runoff variable is constructed from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. We use the full specification, which includes firm-level controls, all weather controls, firm fixed effects, industry-by-year fixed effects and province-by-year fixed effects.

Table A10: Spatial spillovers

	(1) Bordering	(2) IDW (50km)	(3) IDW (100km)	(4) IDW (200km)
RS_{ct}^{-2}	-0.0577**	-0.0492**	-0.0514**	-0.0479**
	(0.0271)	(0.0217)	(0.0213)	(0.0216)
$RS_{ct}^{-1,2}$	-0.0186***	-0.0196***	-0.0193***	-0.0191***
	(0.0035)	(0.0034)	(0.0035)	(0.0036)
$RS_{ct}^{+1,2}$	0.0010	-0.0037	-0.0055	0.0013
	(0.0040)	(0.0066)	(0.0064)	(0.0040)
RS_{ct}^{+2}	-0.0086	-0.0091	-0.0094	-0.0085
	(0.0063)	(0.0062)	(0.0063)	(0.0064)
$SP\_RS_{ct}^{-2}$	-0.4437	0.0233	0.0665	0.0701
	(0.3858)	(0.0209)	(0.0822)	(0.0464)
$SP\_RS_{ct}^{-1,2}$	0.0460	-0.0072*	0.0063	0.0040
	(0.0335)	(0.0044)	(0.0045)	(0.0073)
$SP\_RS_{ct}^{+1,2}$	-0.0047	0.0075	0.0112	0.0033
	(0.0379)	(0.0083)	(0.0094)	(0.0080)
$SP\_RS_{ct}^{+2}$	0.0313	-0.0027	-0.0168	0.0052
	(0.0391)	(0.0143)	(0.0104)	(0.0205)
Constant	5.3069**	5.1814**	5.1229**	5.0977**
	(2.1125)	(2.1107)	(2.1123)	(2.1121)
Adj-R^2	0.7155	0.7155	0.7155	0.7155
Firm-level controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes
# of Obs.	1,819,904	1,819,904	1,819,904	1,819,904

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Firm-level TFP is estimated using the Olley & Pakes (1996) method, with the ACF correction. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Firm-level controls are firm age, leverage ratio, intangible assets ratio, firm size captured by the log value of total assets, ownership dummies, export status, whether the firm has multiple plants and the total employment of the firms' 2-digit industry in the same county. Weather controls consist of fifty 3 ◦C wide bins (ranging from below -12 ◦C to above 30 ◦C, with the bin 15-18 ◦C omitted as the reference group), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed and the direction of maximum wind speed.

Table A11: Firm attrition

Runoff shocks		
	(1)	(2)
RS_{ct}^{-2}	-0.0051**	-0.0060***
	(0.0020)	(0.0020)
$RS_{ct}^{-1,2}$	-0.0011***	-0.0008*
	(0.0004)	(0.0004)
$RS_{ct}^{+1,2}$	-0.0015***	-0.0013
	(0.0006)	(0.0016)
RS_{ct}^{+2}	0.0006	0.0009
	(0.0008)	(0.0008)
Constant	0.8556***	1.8184***
	(0.0001)	(0.3479)
Adj-R^2	0.8749	0.8750
Firm FE	Yes	Yes
Weather controls	No	Yes
Province-by-Year FE	Yes	Yes
Industry-by-Year FE	Yes	Yes
# of Obs.	2,153,511	2,153,511

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. The dependent variable is a dummy indicating whether the firm is present on an annual basis. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Weather controls consist of fifty 3 ◦C wide bins (ranging from below -12 ◦C to above 30 ◦C, with the bin 15-18 ◦C omitted as the reference group), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

Table A12: Increasingly balanced samples

Runoff shocks	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RS_{ct}^{-2}	-0.0583***	-0.0583***	-0.0531**	-0.0569**	-0.0628**	-0.0660**	-0.0748**	-0.0894**	-0.0710*	-0.0595
	(0.0210)	(0.0210)	(0.0218)	(0.0239)	(0.0265)	(0.0295)	(0.0329)	(0.0359)	(0.0383)	(0.0412)
$RS_{ct}^{-1,2}$	-0.0192***	-0.0192***	-0.0193***	-0.0207***	-0.0208***	-0.0148***	-0.0096**	-0.0077	-0.0027	-0.0027
	(0.0035)	(0.0035)	(0.0035)	(0.0037)	(0.0041)	(0.0043)	(0.0046)	(0.0050)	(0.0054)	(0.0058)
$RS_{ct}^{+1,2}$	0.0013	0.0013	0.0022	0.0035	0.0073	0.0070	0.0079	0.0139**	0.0148**	0.0071
	(0.0040)	(0.0040)	(0.0041)	(0.0043)	(0.0048)	(0.0050)	(0.0054)	(0.0059)	(0.0063)	(0.0068)
RS_{ct}^{+2}	-0.0099	-0.0099	-0.0091	-0.0060	0.0021	0.0030	0.0026	0.0132	0.0076	0.0094
	(0.0063)	(0.0063)	(0.0066)	(0.0071)	(0.0078)	(0.0085)	(0.0094)	(0.0109)	(0.0120)	(0.0128)
Constant	5.3079**	5.3174**	6.1566***	6.7032***	4.8026**	5.8173**	7.3156***	6.6300**	7.6062***	8.6751***
	(2.1416)	(2.1417)	(2.1841)	(2.2798)	(2.3555)	(2.3706)	(2.4344)	(2.6055)	(2.7637)	(3.0361)
Adj-R^2	0.7188	0.7180	0.7186	0.7186	0.7165	0.7181	0.7261	0.7257	0.7303	0.7350
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	1,746,328	1,643,294	1,485,015	1,303,592	1,027,618	868,460	703,853	556,891	470,236	386,398

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Firm-level TFP is estimated using the Olley & Pakes (1996) method, with the ACF correction. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Firm-level controls are firm age, leverage ratio, intangible assets ratio, firm size captured by the log value of total assets, ownership dummies, export status, whether the firm has multiple plants and the total employment of the firms' 2-digit industry in the same county. Weather controls are consisted of fifty 3 ◦C wide bins (ranging from below -12 ◦C to above 30 ◦C, with the bin 15-18 ◦C omitted as the reference group), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

Table A13: Runoff shock effects by four quantiles of industrial-level water intensity

Runoff shocks	Our estimates of industrial-level water intensity				US industrial-level water intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	0-25%	26%-50%	51%-75%	76%-100%	0-25%	26%-50%	51%-75%	76%-100%
RS_{ct}^{-2}	-0.0791	-0.0392	-0.1024**	-0.0273	-0.0504	-0.0222	-0.1021**	-0.0554
	(0.0485)	(0.0350)	(0.0430)	(0.0426)	(0.0476)	(0.0416)	(0.0465)	(0.0342)
$RS_{ct}^{-1,2}$	-0.0128	-0.0175***	-0.0241***	-0.0088	-0.0122	-0.0383***	-0.0165**	0.0030
	(0.0082)	(0.0061)	(0.0059)	(0.0086)	(0.0075)	(0.0066)	(0.0067)	(0.0069)
$RS_{ct}^{+1,2}$	-0.0282***	0.0001	0.0085	0.0175*	0.0039	-0.0074	-0.0033	0.0125
	(0.0095)	(0.0070)	(0.0070)	(0.0092)	(0.0084)	(0.0079)	(0.0078)	(0.0078)
RS_{ct}^{+2}	-0.0284*	0.0109	-0.0142	-0.0202	-0.0377***	-0.0044	-0.0256**	0.0126
	(0.0149)	(0.0110)	(0.0111)	(0.0149)	(0.0136)	(0.0125)	(0.0124)	(0.0117)
Constant	9.3030*	9.3392**	-3.0832	8.3993**	8.2908	12.0414***	7.3901	-1.1021
	(5.4737)	(3.8971)	(4.2896)	(3.9987)	(5.2345)	(4.4489)	(4.9018)	(3.1285)
Adj-R^2	0.6429	0.7598	0.7061	0.6580	0.7569	0.6676	0.7035	0.6808
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	319,285	641,594	604,181	254,844	413,704	567,940	475,202	363,058

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Firm-level TFP is estimated using the Olley & Pakes (1996) method, with the ACF correction. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Firm-level controls are firm age, leverage ratio, intangible assets ratio, firm size captured by the log value of total assets, ownership dummies, export status, whether the firm has multiple plants and the total employment of the firms' 2-digit industry in the same county. Weather controls consist of fifty 3 ◦C wide bins (ranging from below -12 ◦C to above 30 ◦C, with the bin 15-18 ◦C omitted as the reference group), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

Table A14: Runoff shock effects on wastewater related variables

	# wastewater treatment devices			Volume of wastewater treatment			Volume of wastewater discharged		
Runoff shocks	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
RS_{ct}^{-2}	0.0010	-0.0006	-0.0002	-0.5437*	-0.5142*	-0.4600	-0.0801	-0.0911	-0.0865
	(0.0131)	(0.0132)	(0.0132)	(0.3077)	(0.3113)	(0.3130)	(0.0915)	(0.0915)	(0.0915)
$RS_{ct}^{-1,2}$	0.00400*	0.00450*	0.00450*	0.1610***	0.1625***	0.1573***	-0.0321*	-0.0263	-0.0232
	(0.0024)	(0.0024)	(0.0025)	(0.0462)	(0.0462)	(0.0466)	(0.0192)	(0.0192)	(0.0195)
$RS_{ct}^{+1,2}$	0.0011	0.0012	0.0014	-0.1144**	-0.1179**	-0.1122**	0.0219	0.0184	0.0173
	(0.0029)	(0.0029)	(0.0029)	(0.0470)	(0.0471)	(0.0477)	(0.0219)	(0.0218)	(0.0219)
RS_{ct}^{+2}	0.0010	0.0009	0.0005	0.0471	0.0324	0.0522	0.0110	0.0041	0.0058
	(0.0050)	(0.0050)	(0.0050)	(0.0812)	(0.0810)	(0.0808)	(0.0329)	(0.0329)	(0.0333)
Constant	0.5557***	0.2035***	-1.4950	7.3244***	2.9383***	9.1834	9.2105***	6.0896***	-3.2030
	(0.0004)	(0.0253)	(1.4001)	(0.0055)	(0.4203)	(27.0748)	(0.0031)	(0.1727)	(7.8429)
Adj-R^2	0.7493	0.7497	0.7498	0.7717	0.7722	0.7725	0.7453	0.7462	0.7463
Firm-level controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Weather controls	No	No	Yes	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Year FI	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	305,836	304,367	304,367	137,554	136,814	136,814	321,912	320,390	320,390

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the firm level. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Firm-level controls are firm age, leverage ratio, intangible assets ratio, firm size captured by the log value of total assets, ownership dummies, export status, whether the firm has multiple plants and the total employment of the firms' 2-digit industry in the same county. Weather controls consist of fifty 3 ◦C wide bins (ranging from below -12 ◦C to above 30 ◦C, with the bin 15-18 ◦C omitted as the reference group), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

Table A15: Effect of runoff shocks on county-level industrial water withdrawals

Runoff shocks	(1)	(2)	(3)
RS_{ct}^{-2}	-0.4235**	-1.7667**	-0.0166
	(0.1822)	(0.8649)	(0.1904)
$RS_{ct}^{-1,2}$	-1.0030***	-0.4741**	-0.8266*
	(0.3863)	(0.2377)	(0.4830)
$RS_{ct}^{+1,2}$	0.8354	0.5861	0.2713
	(0.5718)	(0.4383)	(0.2617)
RS_{ct}^{+2}	-0.9567*	-0.4743	1.3974**
	(0.5263)	(0.4490)	(0.7045)
Constant	16.0073***	749.6508	1300.64
	(0.0293)	(625.6476)	(864.6903)
Adj-R^2	0.9687	0.9689	0.9695
Weather controls	No	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Province-by-Year FE	No	No	Yes
# of Obs.	27,350	27,350	27,350

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the county level. Dependent variable is the county-level total industrial withdrawal index. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Weather controls consist of fifty 3 ◦C wide bins (ranging from below -12 ◦C to above 30 ◦C, with the bin 15-18 ◦C omitted as the reference group), third-order polynomials in cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

Table A16: The role of water source and cooling technology

Runoff shocks	(1) Surface water (Yes=1)	(2) Once-through cooling (Yes=1)
RS_{ct}^{-2}	N.A.	N.A.
	(N.A.)	(N.A.)
$RS_{ct}^{-2} * Dummy$	N.A.	N.A.
	(N.A.)	(N.A.)
$RS_{ct}^{-1,2}$	-0.1069	-0.3510
	(0.4234)	(0.3697)
$RS_{ct}^{-1,2} * Dummy$	-1.1837**	-0.9138^{+}
	(0.5807)	(0.6301)
$RS_{ct}^{+1,2}$	0.3647	-0.0182
	(0.3287)	(0.2545)
$RS_{ct}^{+1,2} * Dummy$	0.7888**	-0.2172
	(0.3549)	(0.2907)
RS_{ct}^{+2}	-0.3886	-0.0302
	(0.3228)	(0.1658)
$RS_{ct}^{+2} * Dummy$	0.2185	-0.0164
	(0.3229)	(0.1537)
Constant	8.9736***	8.9506***
	(0.0468)	(0.0479)
Adj-R^2	0.4335	0.3882
Power plant FE	Yes	Yes
Province-by-Year FE	Yes	Yes
# of power plants	60	60
# of Obs.	305	305

Note: ***p < 0.01, **p < 0.05, *p < 0.1., $^{+}$< 0.20. Robust standard errors in parenthesis are clustered at the power plant level. The dependent variable is the annual amount of electricity generated in logarithm form. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county.

Table A17: Moderating effects of other water sources and cooling technologies

Runoff shocks	(1) seawater=1	(2) groundwater=1	(3) reclaimed water=1	(4) air cooling=1	(5) Closed-loop=1
RS_{ct}^{-2}	N.A.	N.A.	N.A.	N.A.	N.A.
	(N.A.)	(N.A.)	(N.A.)	(N.A.)	(N.A.)
$RS_{ct}^{-2} * Dummy$	N.A.	N.A.	N.A.	N.A.	N.A.
	(N.A.)	(N.A.)	(N.A.)	(N.A.)	(N.A.)
$RS_{ct}^{-1,2}$	-0.7379	-1.1732**	-0.8022*	-0.7939*	-1.3179**
	(0.4595)	(0.4425)	(0.4017)	(0.4021)	(0.5478)
$RS_{ct}^{-1,2} * Dummy$	-0.6046	1.1533*	N.A.	N.A.	0.9066
	(0.8339)	(0.6009)	(N.A.)	(N.A.)	(0.6257)
$RS_{ct}^{+1,2}$	-0.1858	-0.2208	-0.3495	-0.2593	-0.0374
	(0.2382)	(0.2097)	(0.2159)	(0.1984)	(0.2942)
$RS_{ct}^{+1,2} * Dummy$	0.0789	0.4359	0.7645*	1.2327**	-0.2003
	(0.3522)	(0.2657)	(0.4076)	(0.5720)	(0.4293)
RS_{ct}^{+2}	-0.1767	-0.0592	N.A.	-0.1295	0.0478
	(0.1719)	(0.2023)	(N.A.)	(0.1625)	(0.2244)
$RS_{ct}^{+2} * Dummy$	0.2461	-0.2544	-0.1215	N.A.	-0.0857
	(0.1621)	(0.2755)	(0.1708)	(N.A.)	(0.2057)
Constant	8.9620***	8.9675***	8.9721***	8.9577***	8.9557***
	(0.0557)	(0.0470)	(0.0519)	(0.0520)	(0.0491)
Adj-R^2	0.3607	0.4335	0.3976	0.3882	0.3880
Power plant FE	Yes	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes	Yes
# of power plants	60	60	60	60	60
# of Obs.	305	305	305	305	305

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the power plant level. The dependent variable is the annual amount of electricity generated in logarithm form. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county.

Table A18: Runoff shocks and water pollution

Runoff shocks	Without weather controls				With weather controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	COD	DO	NH_4N	pH	COD	DO	NH_4N	pH
RS_{ct}^{-2}	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.
	(N.A.)	(N.A.)	(N.A.)	(N.A.)	(N.A.)	(N.A.)	(N.A.)	(N.A.)
$RS_{ct}^{-1,2}$	0.2712**	-0.0448	0.4589*	0.0648***	0.2695**	-0.0402	0.4505	0.0647***
	(0.1399)	(0.1182)	(0.2768)	(0.0238)	(0.1332)	(0.1182)	(0.2803)	(0.0230)
$RS_{ct}^{+1,2}$	-0.0509	0.1416	-0.0997	-0.0133	-0.1110	0.1505*	-0.1004	-0.0191
	(0.1682)	(0.0859)	(0.1067)	(0.0209)	(0.1361)	(0.0875)	(0.1075)	(0.0200)
RS_{ct}^{+2}	-0.4118	0.0914	-0.1315	-0.0068	-0.5759	0.1029	-0.1306	0.0007
	(0.4297)	(0.1362)	(0.1304)	(0.0342)	(0.4222)	(0.1373)	(0.1482)	(0.0355)
Constant	4.7198***	7.6946***	0.7824***	7.6653***	867.8569	242.2432	-2.0e+02*	47.9165
	(0.0218)	(0.0160)	(0.0329)	(0.0032)	(597.8570)	(175.0863)	(117.2903)	(30.0268)
Adj-R^2	0.6269	0.5886	0.0844	0.5150	0.6550	0.5958	0.0907	0.5132
Weather controls	No	No	No	No	Yes	Yes	Yes	Yes
Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-by-Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	9,828	9,828	9,828	9,828	9,705	9,705	9,705	9,705

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the monitoring station level. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Weather controls consist of third-order polynomials in mean temperature, cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

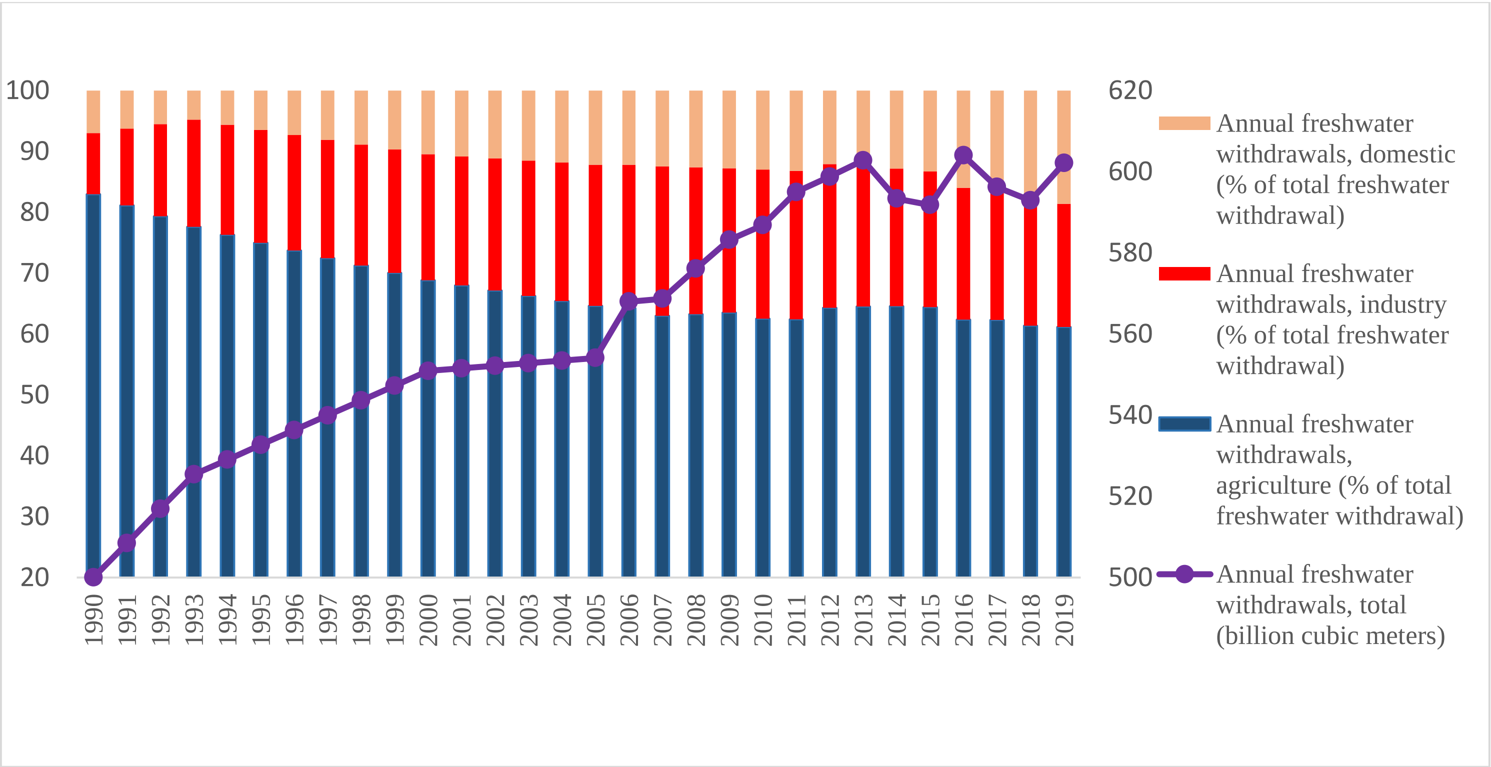
Table A19: Runoff shock, TFP and local economic growth

	(1)	(2)	(3)	(4)
RS_{ct}^{-2}	-0.0522***	-0.0479**	-0.0387*	-0.0324
	(0.0191)	(0.0192)	(0.0202)	(0.0203)
$RS_{ct}^{-1,2}$	-0.0115**	-0.0134***	-0.0068	-0.0082
	(0.0045)	(0.0045)	(0.0050)	(0.0051)
$RS_{ct}^{+1,2}$	-0.0082	-0.0087*	-0.0082	-0.0087*
	(0.0052)	(0.0052)	(0.0052)	(0.0052)
RS_{ct}^{+2}	-0.0038	-0.0040	-0.0032	-0.0037
	(0.0079)	(0.0081)	(0.0079)	(0.0080)
Manufacturing TFP			0.0802*	0.0908**
			(0.0425)	(0.0419)
Constant	5.4254***	-27.5285	5.3909***	-28.2690
	(0.0008)	(21.1755)	(0.0183)	(21.1489)
Adj-R^2	0.9911	0.9912	0.9911	0.9912
Weather controls	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Province-by-Year FE	Yes	Yes	Yes	Yes
# of Obs.	26,110	26,110	26,110	26,110

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parenthesis are clustered at the monitoring station level. Runoff data is from the GISS climate model and is calculated for each county based on the spatially weighted average of gridcells falling into that county. Weather controls consist of third-order polynomials in mean temperature, cumulative precipitation, mean air pressure, relative humidity, sunshine duration, wind speed, and the direction of maximum wind speed.

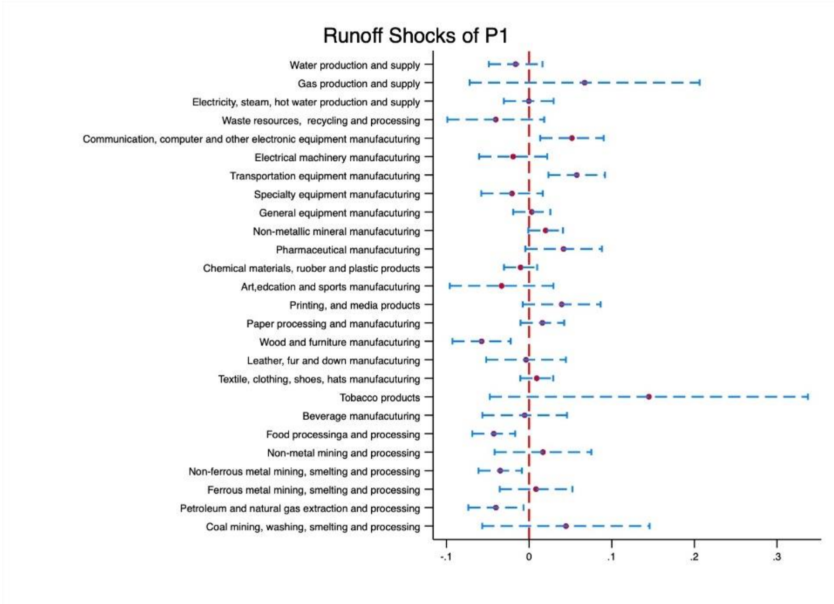
Appendix Figures

Figure A1: Annual freshwater withdrawals and share by different sectors

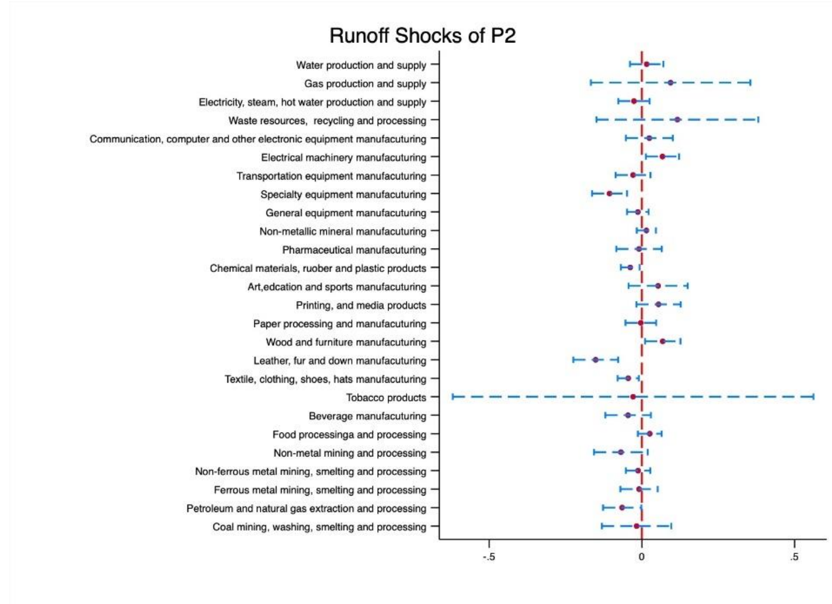


Source: World Bank Development Indicator Database.

Figure A2: Heterogeneous positive runoff effects across two-digit industries



Aa: Positive moderate runoff shock effects across industries



Ab: Positive large runoff shock effects across industries

Figure A3: Granular runoff shocks

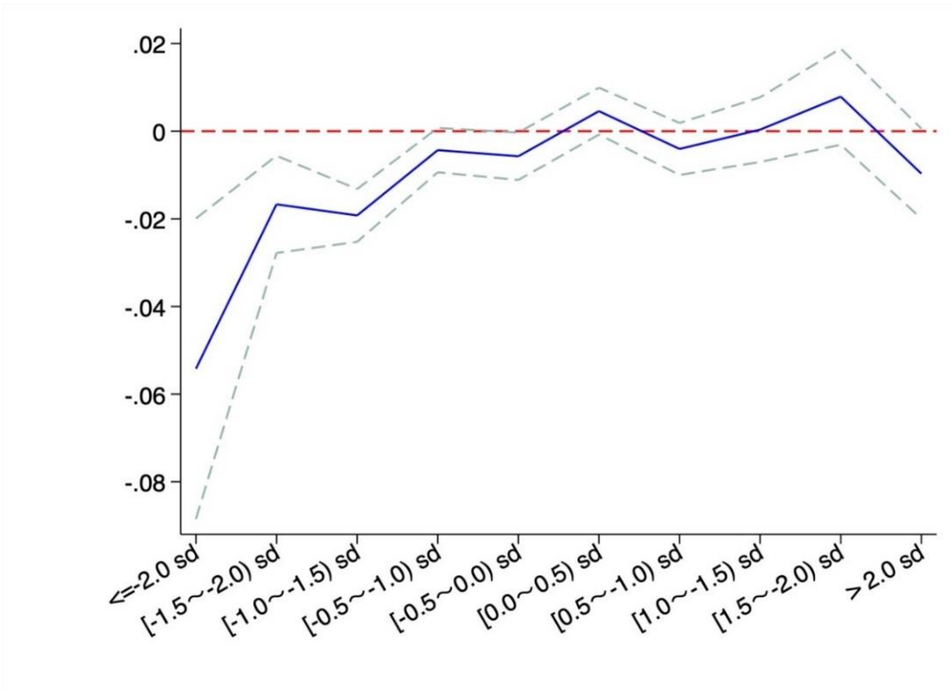
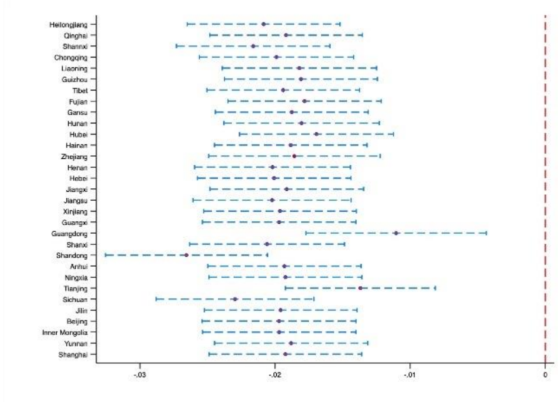
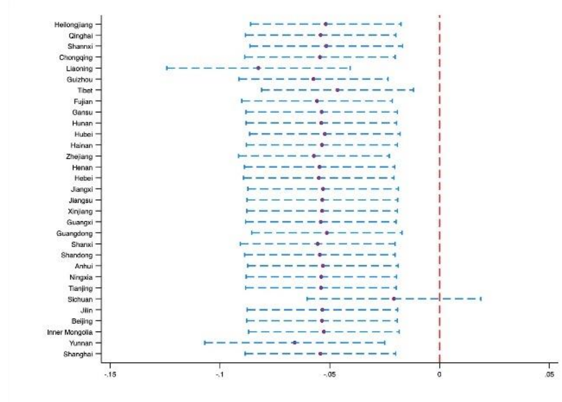


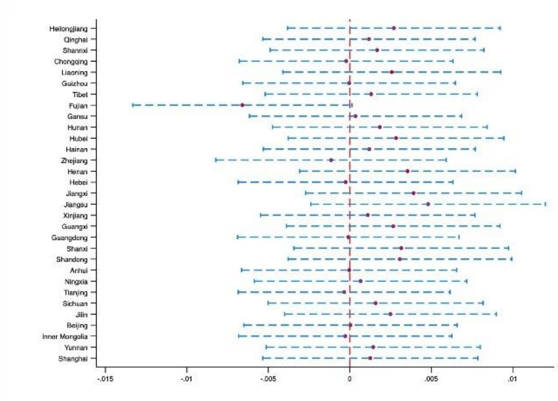
Figure A4: Excluding one province (municipality) in each regression



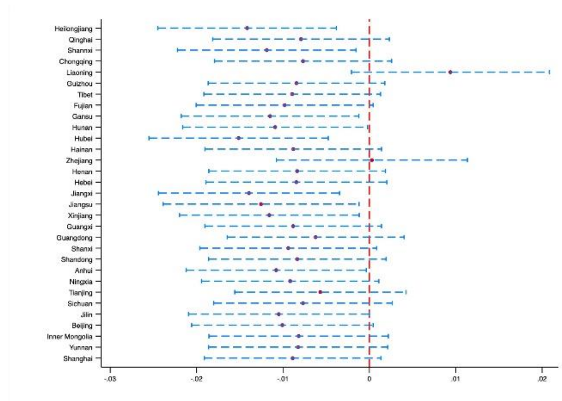
OA2a: negative moderate runoff shocks



OA2a: negative large runoff shocks

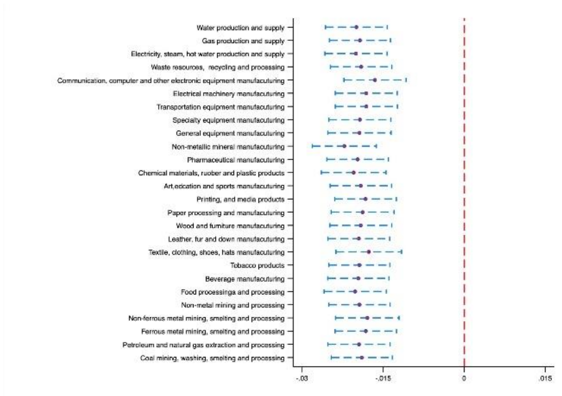


OA2c: positive moderate runoff shocks

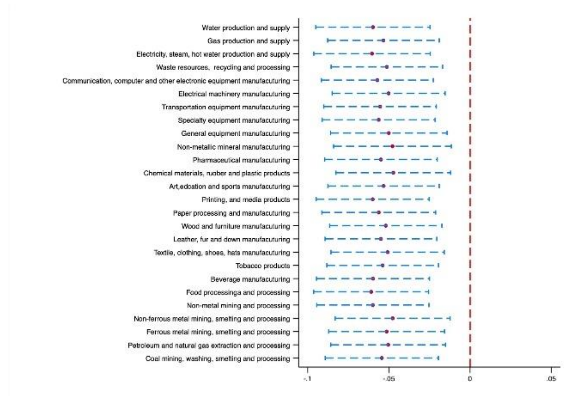


OA2d: positive large runoff shocks

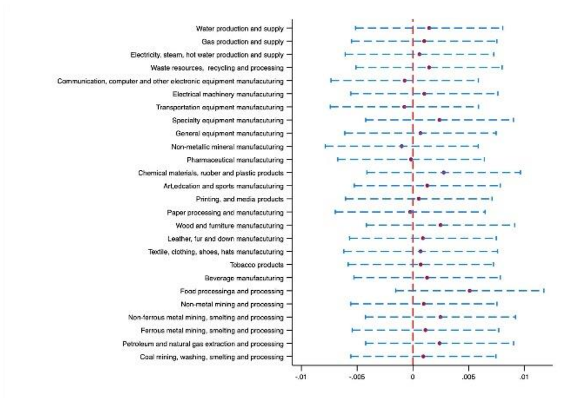
Figure A5: Excluding one industrial sector in each regression



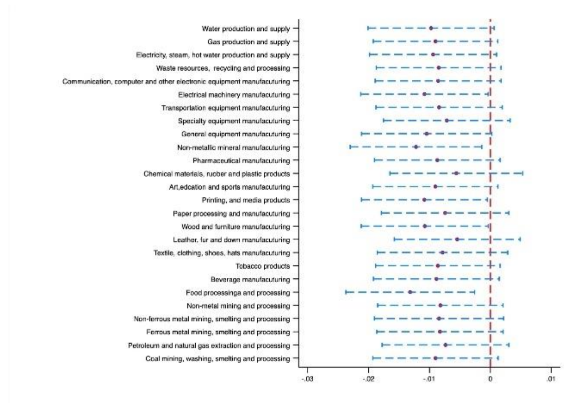
OA3a: negative moderate runoff shocks



OA3a: negative large runoff shocks

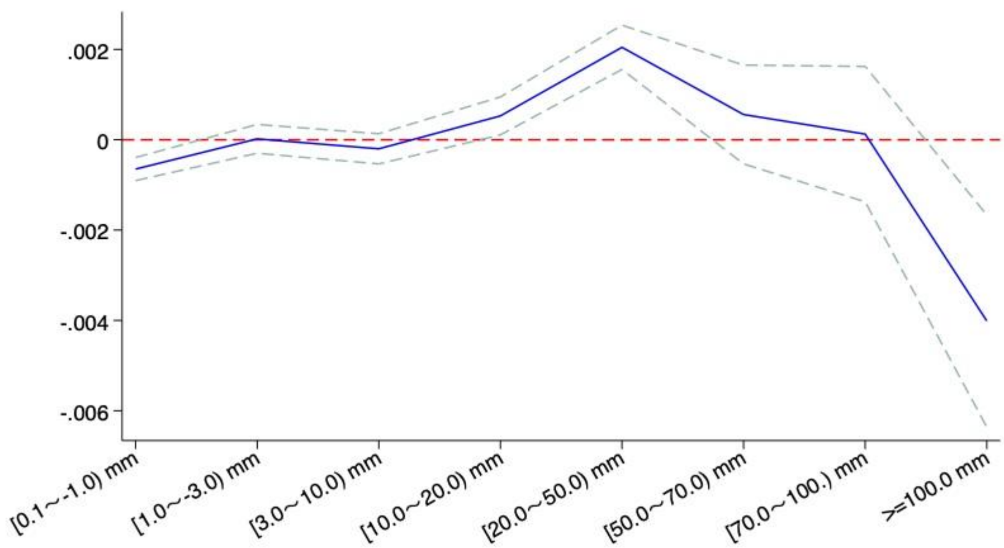


OA3c: positive moderate runoff shocks



OA3d: positive large runoff shocks

Figure A6: The estimated coefficients of different rainfall bins



Supplementary Information

S1 Geographical features

S1.1 The accessibility of groundwater

We use two datasets to capture the accessibility of county-level groundwater. The first is *Groundwater Resources of the World*, which maps the existence of underground water at the local level. The second is *Global Patterns of Groundwater Table Depth* provided by *Aquaknow*, which contains information on how complex or difficult it is to access available groundwater based on local geological characteristics. We define Chinese counties as having a high degree of groundwater accessibility if they are above the median in terms of the volume of groundwater that they have and below the median in complex value in the groundwater table. All other counties are categorized as having a low degree of groundwater accessibility.

S1.2 River density

We divide the cumulative river length within each county by its administrative area to obtain river density. The shape files of the river network in each county are obtained from the *United States Geological Survey*. We then merge the river network with the county map to obtain the cumulative river length within each county. The administrative area of each county is obtained from the *Ministry of Civil Affairs of the People's Republic of China*.

S1.3 Irrigated and rainfed cropland

The *International Water Management Institute* produced a map of global irrigated and rainfed croplands for 2000 using satellite images. The map shows irrigated and rainfed cropland areas for the globe at a 10 km × 10 km resolution level. We merge the irrigated and rainfed cropland areas with Chinese counties and extract the spatially averaged areas for each county. We scale irrigation and rainfed cropland areas by the administrative area of each county.

S2 Grid-level industrial water withdrawals (IWW)

Developed by Hou et al. (2023), the industrial water withdrawals (IWW) dataset is at a spatial resolution of 0.1° × 0.1° and is available monthly from 1965 to 2020 for mainland China. There are three steps involved in constructing this dataset: 1) spatial mapping of provincial level IWWs to grid-level IWWs; 2) seasonal allocation of annual IWWs to monthly IWWs; 3) constructing a grid-level panel dataset of IWWs. During these steps, various datasets, including industrial censuses, and many provincial and industrial statistic yearbooks, are used to feed the runoff construction process. Compared to similar datasets, this dataset has three major advantages. First, Hou et al. (2023) use firm-level information to map IWWs, instead of using indirect proxies like population density, which improves the accuracy of the mapping process. Second, this dataset takes seasonality into account. Finally, it has the highest level of spatial resolution to date. We calculate count-level IWWs by using the same spatially weighted technique as for runoff shocks.

S3 Data on power plants

We manually collect the data on all power plants from *China Compendium of Statistical Materials of Electric Power Industry*, over the period 1999 – 2011. In each year, the *Compendium* reported installed capacity, utility hours, composition of generators, and amount of electricity generated, consistently for large power plants with installed capacity of at least one gigawatt (GW). For smaller power plants, defined as having installed capacity of 6000 kW and above, it also reports variables including auxiliary power ratio, power supply of coal consumption and, coal consumption for power generation and total coal consumption. Unfortunately, the *Compendium* only provides the provincial location of each power plant. We first manually searched online for the address of each power plant. These addresses were then cross checked with the *Global Database of Power Plants* maintained by the *World Resources Institute* and the *Global Coal Plant Tracker* maintained by *Global Energy Monitor*, which provide the longitude and latitude of major power plants in China, in order to get the exact location of each power plant.

To further assess the sensitivity of each coal power plant to water stress, we collect their water sources and cooling technologies from the *Materials of National Energy Efficiency Benchmarking Competition for Thermal Power Units 2012*.

S4 World Bank Enterprise Survey

The *World Bank Enterprise Survey (WBES)* dataset is collected through interviewing owners/senior managers of registered companies in both the manufacturing and service sectors. We focus on three waves carried out in 2002, 2005 and 2012, and manufacturing firms only.

We focus on three questions that are answered by the owner or senior manager of the surveyed firm: 1) Did this establishment experience power outages? 2) Did this establishment experience any production loss due to power outage; 3) Is power outage is a major obstacle to the current operations of this establishment? The original questions are provided below:

1. *Over fiscal year XXXX [e.g., 2012], did this establishment experience power outages?*
   - *A. Yes*
   - *B. No*

2. *Please estimate the losses that resulted from power outages either as a percentage of total annual sales or as total annual losses.*

A. *Loss as percentage of total annual sales due to power outages ___%*
B. *None*

3. *To what degree is electricity an obstacle to the current operations of this establishment?*

No obstacle	*Minor obstacle*	*Moderate obstacle*	*Major obstacle*	*Very Severe Obstacle*
0	*1*	*2*	*3*	*4*

We convert questions 2 and 3 into dummies. If firms reported production losses due to power outages, we create a dummy and set it equal to one. For question 3, we put firms selecting *Major obstacle* or *Very Severe Obstacle* into a group and label them as one.

Summary statistics for the responses are provided below.

Table S1 Summary statistics for dependent variables

	No. of Obs.	Mean	Std. Dev.	Min.	Max.
Any power outage (Yes=1)	15,418	0.740239	0.438518	0	1
Any production loss (Yes=1)	15,418	0.453496	0.497849	0	1
Power disruption is a major obstacle (Yes=1)	9,121	0.382853	0.48611	0	1

Note: These numbers are calculated from WBES2003, 2005 and 2012.

Note that the WBES just provides the city address of each firm. We thus aggregate county-level water runoff shocks to the city-level using the same spatially weighting method.

S5 Station-level water pollution dataset

We manually compiled a station – week level panel of waterborne pollutants from the National Automatic Monitoring System of Surface Water Quality (NAMS) maintained by China's National Environmental Monitoring Center (CNEMC). The NAMS was established in the late 1990s and is now contains 148 centrally controlled, automatic water quality monitoring stations. Unlike manual water quality monitoring stations under local management, automatic monitoring stations directly transmit data to the central MEE, which mitigates data manipulation (Hu et al, 2023). The water quality monitoring network was built for scientific purposes rather than regulatory purposes, mitigating the problem of endogenous location choice (He et al., 2020; Lin et al., 2024). The monitoring sites are determined by hydrological features of river basins, including water depth, speed and the soil characteristics of the riverbank (Lin et al., 2024). Many monitoring stations are deployed where major tributaries of lakes flow into their main streams to monitor the fluctuation of water quality caused by the tributary inflows.

The automatic water quality monitoring stations collect four indicators of water quality: chemical oxygen demand (COD), dissolved oxygen (DO), ammonia nitrogen (NH_4), and pH. COD measures the oxygen consumed by chemical breakdown of organic and inorganic matter in water. It is used to detect the volume of organic compounds in water, which may have negative impacts on aquaculture production, human health, and ecosystem services. Dissolved oxygen (DO) measures the concentration of oxygen in water. A higher value of DO indicates better water quality. NH_4 is a common toxicant derived from waste and fertilizers. pH measures the acidity of water, with higher acidic levels in the water regarded as being more toxic to users.

S6 China Health and Nutrition Survey

China Health and Nutrition Survey (CHNS) is jointly administered by the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute for Nutrition and Health at the Chinese Center for Disease Control and Prevention. We use five waves administered in 1997, 2000, 2004, 2006 and 2009, which coincide with the ASIF sample.

In these waves, two sets of health-related questions are compiled. The first set concerned self-reported health status and illness induced work absence. The original questions were:

1. Right now, how would you describe your health compared to that of other people your age?

- *A. Excellent*
- *B. Good*
- *C. Fair*
- *D. Poor*
- *E. Unknown*

We categorized respondents who selected *Excellent* and *Good* into the good heath group (Yes=1) and the rest into the unhealthy group (No=0)

2. During the past 3 months have you had any difficulty carrying out your daily activities and work or studies due to illness?

- *A. No*
- *B. Yes*
- *C. Unknown*

The second set of questions asked whether the respondents have suffered specific symptoms in the previous four weeks. These questions are:

1. Did you have any of these symptoms during the past 4 weeks (including today)?

- *A. Fever, sore throat, cough*
- *B. Diarrhea, stomachache*
- *C. Headache, dizziness*
- *D. Joint pain, muscle pain*
- *E. Rash, dermatitis*
- *F. Eye/ear disease*
- *G. Heart disease/chest pain*
- *H. Other infectious disease (specify: ___________)*
- *I. Other noncommunicable disease (specify: ___________)*

Summary statistics for the responses are provided below:

Table S2 Summary statistics for dependent variables

	No. of Obs.	Mean	Std. Dev.	Min.	Max.
Unhealthy (Yes=1)	38,859	0.0626	0.2422	0	1
Work absence due to illness (Yes=1)	48,382	0.0634	0.2436	0	1
Diarrhea and stomachache (Yes=1)	54,059	0.0307	0.1724	0	1
Eye/ear disease (Yes=1)	54,052	0.0099	0.0989	0	1
Rash, dermatitis (Yes=1)	54,053	0.0069	0.0828	0	1

Note: These numbers are calculated from CHNS 1997, 2000, 2004, 2006 and 2009.

References for Appendix

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