Irrigation Investments and Agricultural Productivity: Unveiling the Mechanisms and Impacts under Climate Change

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Abstract

Leveraging exogenous government irrigation investments and longitudinal household survey data over 15 years, we investigate how irrigation affects agricultural productivity under climate change. We find that the irrigation investment increased the share of irrigated farmland by 11.0%, which, in turn, increased per-area output by 14.9%, net agricultural income by 15.6%, agricultural TFP by 13.7%, and per-labor output by 36.2%. These effects are driven by four key mechanisms: increased use of high-productivity inputs, expanded cultivation area, labor reallocation from farm work to off-farm work, and mitigation of drought damage. The induced land expansion and labor reallocation explain the much larger increase in per-labor output. A cost-benefit analysis suggests a high rate of return to irrigation investment, with about half of the return stemming from labor reallocation that increased off-farm income. This study highlights the policy relevance of irrigation investments in improving agricultural productivity and accelerating rural transformation under climate change.

Keywords: irrigation investment, agricultural productivity, labor reallocation, climate change

JEL Codes: Q12, O15, Q54, O13, C23.

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1 Introduction

Irrigation has long been recognized as a critical determinant of agricultural productivity, especially in regions vulnerable to water scarcity and climate change (e.g., Huang et al., 2006; Bardhan et al., 2012; García Suárez et al., 2019; Blakeslee et al., 2023). As global agricultural systems face increasing climate variability, understanding the causal impact of irrigation on agricultural productivity has become even more pressing. However, estimating the true effect of irrigation is complicated by endogeneity issues, as investments in irrigation are often driven by factors that also influence agricultural outcomes, such as economic conditions and geographic characteristics. Furthermore, although irrigation is widely recognized as a way to increase crop yields, its long-term economic returns remain less well understood, particularly in the context of climate change, where extreme weather events like droughts pose escalating risks to agricultural sustainability. Additionally, few studies have systematically identified the mechanisms through which irrigation affects agricultural productivity, leaving a significant gap in our understanding of its broader economic benefits.

In this study, we leverage a unique dataset derived from five waves of longitudinal household surveys conducted across 88 villages in China over a 15-year period. We utilize the plausibly exogenous rollout of government irrigation investments in these villages to identify the causal effect of irrigation investment on agricultural productivity.[1] Importantly, we aim to uncover the mechanisms underlying this impact and estimate the rate of return to irrigation investment. Unlike previous research, which has primarily examined the effect of irrigation on agricultural output value, this study incorporates four distinct productivity measures—per-area output, per-labor output, net agricultural income, and agricultural Total Factor Productivity (TFP)—thereby providing a more comprehensive view of irrigation's effects across different dimensions. To enhance comparability, we focus on three major staple crops (rice, wheat, and corn), which account for over 90% of crop production in China. To guide our empirical analysis, we develop a conceptual framework to examine the major channels through which irrigation investment could influence agricultural productivity.

We find that the irrigation investment increased the share of irrigated farmland

1. We focus on government investments aimed at expanding irrigation areas and improving irrigation facilities to ensure a reliable water supply. Due to concerns about comparability, we exclude investments in water-saving irrigation technologies and facilities.

by 11.0%, which, in turn, substantially enhanced all four agricultural productivity measures. The estimates indicate that the irrigation investment led to a 14.9% increase in per-area output, a 15.6% rise in net agricultural income, and a 13.7% improvement in agricultural TFP. However, the irrigation investment had an even more pronounced effect on per-labor agricultural output, increasing it by 36.2%—more than twice the impact observed on the other productivity measures. We demonstrate that this significantly larger impact on per-labor output is attributable to irrigation's role in substantially reducing agricultural labor input while simultaneously expanding cultivated farmland.

We identified four major channels through which irrigation increases agricultural productivity. First, we find that the irrigation investment significantly increased the use of pesticide, fertilizer, and machinery by 14.05%, 6.16%, and 14.21%, respectively. The increased use of these high-productivity inputs could boost agricultural productivity (Tilman et al., 2002; Chambers et al., 2010; McArthur and McCord, 2017). Second, we find that the irrigation investment reduced the share of retired and idled farmland by 7.58% and increased the share of farmland rented out by 2.39%, leading to a net increase in cultivated farmland. This net increase in cultivated farmland contributes to the rise in per-labor output. Third, we show that the irrigation investment reduced an average household's agricultural working time by 16.14% and increased its off-farm working time by 8.72%. The reduction in agricultural labor input is another explanation for the significantly larger increase in per-labor output. Fourth, we demonstrate that the irrigation investment could offset more than half of the drought-induced damage to agricultural income. By addressing these channels, our study provides new insights into how irrigation investment can enhance agricultural productivity, particularly in the context of climate change and rural transformation.

We estimate the rate of return to irrigation investment in China under different climate change scenarios. We find a high rate of return even without accounting for the mitigating effect of irrigation on drought damage or its impact on off-farm income; the return over 10 years is sufficient to cover the total cost of the irrigation investment. Accounting for the mitigating effect of irrigation on drought damage under the climate change scenarios RCP4.5 and RCP8.5 would significantly increase the estimated rate of return. More importantly, the rate of return would double when additionally accounting for the effect of irrigation on off-farm income through labor reallocation. This finding highlights that saving agricultural labor is a critical channel through which irrigation investment improves the welfare of farmers.

This paper makes several key contributions to the literature on irrigation and agricultural productivity. First, it provides robust causal evidence of the impact of irrigation on agricultural productivity. Although many studies have examined the impact of irrigation on agricultural outcomes, the findings are mixed. Some studies find a large positive impact of irrigation on agricultural output (e.g., García Suárez et al., 2019; Huang et al., 2006), while others find insignificant or even negative impacts (e.g., Mazur, 2023; Fuglie et al., 2021). A potential explanation for the mixed findings is that irrigation investment is endogenous, and most existing studies did not adequately address the endogeneity bias. Appendix A.2 presents a review of 22 relevant articles published in mainstream economic journals. The literature review highlights the mixed findings and shows that only 4 of the 22 articles attempted to address the endogenous bias using standard causal-effect identification methods (Duflo and Pande, 2007; Jones et al., 2022; Bravo-Ureta et al., 2020; Dyer and Shapiro, 2023). Our study is most closely related to these causal-effect studies. The main difference is that our study is the only one to employ four different productivity measures (existing studies focus on the effect on agricultural income), to examine the mechanism of the effect, and to calculate the rate of return to the investment.

Second, our study offers a novel exploration of the mechanisms through which irrigation affects agricultural productivity, including the increased use of high-productivity inputs, labor reallocation, expansion of cultivated land, and mitigation of the damage from climatic shocks. These findings complement existing studies on how irrigation mitigates the damage from climatic shocks (e.g., Gatti et al., 2021; Wang et al., 2024) by extending the analysis to production inputs, land reallocation, and labor reallocation. To the best of our knowledge, our study is the first to systematically examine the mechanisms of the impact of irrigation on agricultural productivity based on household-level data. These analyses offer valuable insights for policymakers aiming to invest in irrigation infrastructure.

Finally, our study provides a comprehensive cost-benefit analysis that is critical for the development of irrigation investment policies. Our analysis takes into account not only the effect of irrigation investment on agricultural income but also the effect through mitigating the damage from drought under different climate change scenarios and the effect on off-farm income through reallocating labor from agricultural to off-farm work. These analyses complement existing studies that only account for the effect of irrigation on agricultural outcomes. We show that accounting for the mitigating effect of irrigation on the damage from drought could significantly increase the estimated gain from irrigation investment. More importantly, we illustrate that omitting the potential gain from labor reallocation could substantially underestimate the return to irrigation investment by more than half.

The remainder of this paper is organized as follows: Section 2 introduces the background of this study. Section 3 develops a conceptual framework to facilitate understanding the mechanisms of the impact of irrigation on agricultural productivity. Section 4 describes the data and identification strategy. Section 5 reports the estimation results. Section 6 concludes.

2 Background

Since the 1950s, significant investments in irrigation infrastructure from government resulted in a high-speed growth of irrigated land areas. By the end of the 1970s, nearly half of the cultivated land areas had access to irrigation (Wang et al., 2020). During this period, the irrigation investment was mainly targeted at exploiting surface water resources. Starting from the early 1970s, the government began to support tube well construction in response to the shortage of surface water. However, after the de-collectivization of agricultural production in the late 1970s, irrigation investments slowed. Since the late 1990s, the decline in irrigated area and stagnant agricultural performance led to a new round of irrigation investment from the government. The focus of this round of investment was upgrading existing irrigation facilities.

Entering the 21st century, continuous growth of irrigation investments led by the Chinese government has been observed in North China, evidenced by several government programs. China started an irrigation program in 2001 to invest in the irrigation expansion in 300 key counties. Starting from 2005, 400 key counties were chosen for an irrigation program that subsidized small-scale farmland irrigation and water conservancy projects. From 2009 to 2015, a total of 2706 counties were chosen to take part in a new round of irrigation programs. In addition to programs specifically focused on irrigation, government investment in irrigation system may also stem from broader agricultural support policies, such as Basic Farmland Construction Policy started in 2006 (Huang et al., 2024). Irrigation programs mostly targeted at counties in arid northern grain-producing areas, and a county could be subject to several programs. However, when it comes to individual villages, the chance of receiving multiple investments is low.

Irrigation investments fall into two categories based on purpose. The first category supports irrigation expansion and guarantees water supply through investment in water supply facilities such as tube wells, pumps, pumping houses, power systems, and channels that transfer water from rivers or reservoirs to fields. The second category involves investment in water-saving technologies, including canal lining, sprinklers, drip irrigation, and water-measuring devices. These investments can come from county and higher-level governments or local communities, such as farm households, village collectives, and water managers. According to our field survey data from 88 villages (Figure 1), the village-average annual irrigation investment from the government reached 3.23 million yuan (in 2015 constant value) but varied widely over the years from 2001 to 2015.

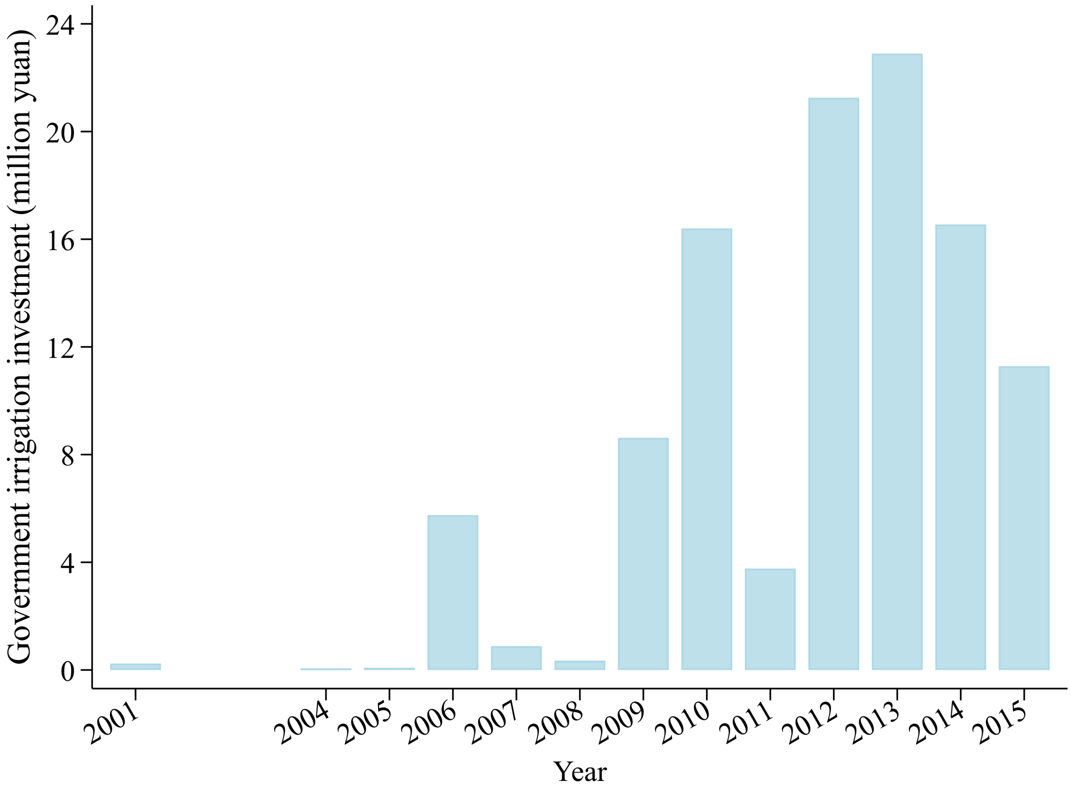

FIGURE 1 Village-average government annual investments in irrigation

Notes: This figure is made based on the field survey data detailed in subsection 4.1. The irrigation investments have been adjusted to constant 2015 yuan.

3 Conceptual Framework

This study focuses on examining the effect of government irrigation investment in expanding the irrigation area and improving irrigation facilities to guarantee the irrigation water supply. Due to concerns about endogeneity and comparability, our analysis excludes non-government investments and government investments in water-saving irrigation technologies and facilities. For brevity, we refer to government irrigation investment in expanding the irrigation area and improving irrigation facilities to guarantee the irrigation water supply as government irrigation investment in the following analysis.

Besides the direct effect through increasing the use of irrigation water, we expect that irrigation investment will indirectly affect agricultural productivity through adjusting the use of labor, farmland, and other high-productivity inputs, and offsetting the damage from climatic shocks. To fully capture the effects of agricultural productivity, our study adopts four different productivity measures: per-area output, per-labor output, agricultural TFP, and net agricultural income. Figure 2 illustrates the potential effect of irrigation investment on agricultural productivity through each of the channels that will be detailed in the following.

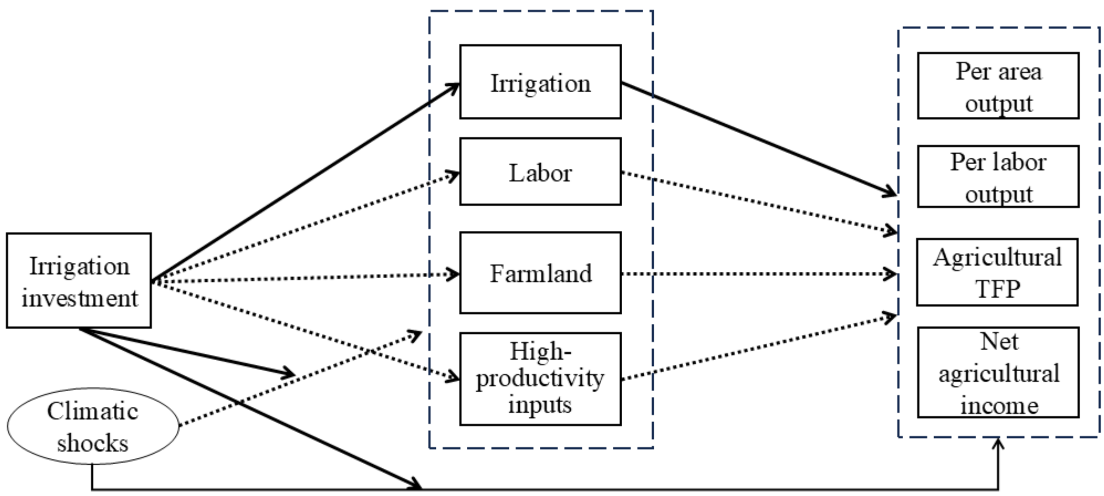

FIGURE 2 Potential impacts of irrigation investment on agricultural productivity through different channels

Notes: The solid arrows represent certain effects, while the dashed arrows indicate uncertain effects.

Direct effect of more irrigation. Irrigation investment naturally increases irrigation area and reliability. Given all other production inputs, more irrigation and higher irrigation reliability could increase per-area output and per-labor output. The effect on agricultural TFP depends on whether output increases more than proportionally to the increase in irrigation costs. Irrigation investment could lead farmers to adjust other inputs and thus generate the following indirect effects on agricultural productivity.

Effect through the adjustment of labor. The effect of irrigation investment on agricultural productivity through labor adjustment is uncertain. Irrigation is labor intensive (Schuenemann et al., 2018). If irrigation facilities are not well-operating, farmers may spend a great deal of time ensuring water sources and maintaining irrigation channels. As such, irrigation investment has the potential to reduce the time allocated to irrigation. However, irrigation investment could also increase farmers' time allocated to irrigation if the investment expands the irrigation area. Changes in labor input have different effects on different productivity measures. For example, a reduction in labor input could increase per-labor output but not directly affect agricultural TFP.

Effect through the adjustment of cultivated area. The effect of irrigation investment on the area of farmland managed is also uncertain. Irrigation investment may lead farmers to convert forests and idle lands into cropland. Better irrigation conditions may also make land leasing more profitable, thus promoting the transfer of land out. Changes in farmland have different effects on different productivity measures. For example, an increase in land area could increase per-labor output but may not directly affect per-area output and agricultural TFP.

Effect through the adjustment of high-productivity inputs. If irrigation complements other high-productivity inputs (e.g., fertilizer, pesticide, and machinery), irrigation investment could increase the use of other high-productivity inputs and thus increase agricultural productivity (Cai et al., 2008). The effect on agricultural TFP depends on how these high-productivity inputs disproportionately increase agricultural output. However, if irrigation substitutes other high-productivity inputs, agricultural productivity could decline.

Effect through mitigating the damage from climatic shocks. Existing studies suggest that irrigation investment could offset the yield damage from drought (Kuwayama et al., 2019; Mukherjee and Schwabe, 2015) and extreme heat (Thiery et al., 2020; Wang et al., 2024) and thus increase agricultural productivity. This study shows that irrigation mitigates the damage from climatic shocks by leading farmers to adjust the use of other inputs. Therefore, irrigation also indirectly affects agricultural productivity under climatic shocks through the adjustment of other inputs.

4 Data and Method

4.1 Data

4.1.1 Field survey data

The household-level data were sourced from the Institution and Management of Water Resources in China surveys, conducted by the China Center for Agricultural Policy at Peking University. The surveyed regions are located in Ningxia and Henan provinces in the upstream and downstream of the Yellow River Basin, and Hebei Province in the Haihe River Basin. These three provinces were selected for the survey because they represent different levels of water shortage and irrigation patterns in China.[2] This multi-round, follow-up survey tracked fixed samples over time in these three provinces. After the initial survey in 2001, researchers revisited the same villages every 3–4 years to interview the same households. In total, five survey rounds were conducted between 2001 and 2016, specifically in the years 2001, 2004, 2008, 2012, and 2016.

The sample households were selected using a stratified random sampling method that reflects variations in water scarcity and irrigation conditions. In Hebei province, one county was randomly selected from the coastal region, one from the mountainous region, and one from the central region. Five counties in Ningxia and six counties in Henan were selected based on their varying distances from the Yellow River. In each county, 2 to 4 townships were randomly chosen, followed by 2 villages randomly chosen from each township, and 4 farmers randomly chosen from each village (with 5 or 6 farmers selected in a few larger villages). Based on this sampling method, the first survey round in 2001 included 338 farmers from 78 villages across 14 counties in 3 provinces.

Subsequent surveys aimed to track the same farmers from the previous rounds. However, over time, sample attrition became unavoidable. During each round, investigators first attempted to re-interview the farmers surveyed previously in each

2. Hebei faces a severe water shortage, with agricultural production heavily reliant on groundwater irrigation. In contrast, Henan is a typical province where both groundwater and surface water are used for irrigation. Meanwhile, in Ningxia, agricultural irrigation depends primarily on water from the Yellow River, with minimal reliance on groundwater.

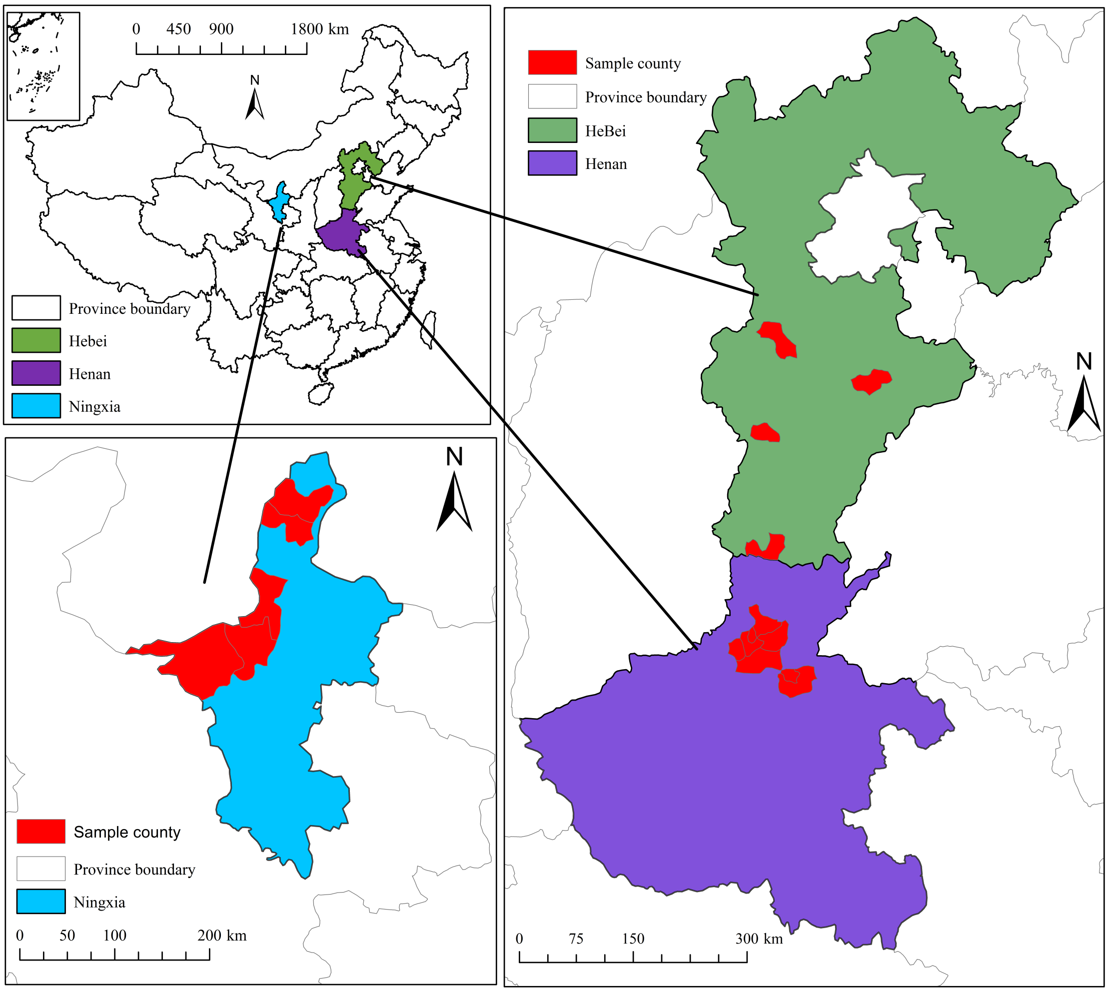

FIGURE 3 Sample counties

Notes: This figure presents the location of sample counties (marked in red) in each province.

village. A new household would be randomly selected from the same village to replace the household from the last survey that could not be tracked. Since the third survey round, recognizing the heavy reliance on groundwater irrigation in Hebei Province, the survey added one more county in Hebei, randomly selecting 4 townships, 8 villages, and 4 farmers from each village, resulting in 32 new farmers. Ultimately, across all five survey rounds, the study involved a total of 571 households from 88 villages in 15 counties. The location of the sample counties is displayed in Figure 3.

The survey included both village and household questionnaires. The household questionnaire gathered detailed information on household demographics, labor allocation of each family member, land use and irrigation practices for individual plots, as well as agricultural production inputs and outputs for each plot. The village questionnaire collected the village's social and economic characteristics and irrigation investments. The sources of investments were classified into government funding (including central and local levels) and community contributions (comprising farm households, village collectives, and water managers). In the first four survey rounds, irrigation investment data were collected for the years 2001, 2004, 2007, and 2011. In the fifth round, detailed annual irrigation investment data were recalled for the years from 2005 to 2015. By combining data from these rounds, a near-continuous dataset during 2001 to 2015 was created, with the exception of gaps for the years 2002 and 2003.

4.1.2 Climate data

Daily precipitation and temperature data are derived from the latest state-of-the-art global reanalysis dataset, the Enhanced Global Dataset for the Land Component of the Fifth Generation of European ReAnalysis (ERA5-Land).[3] The dataset spans from 1981 to the present and has a resolution of 9 km $\times$ 9 km. Based on the location information of our sample villages, we use ArcGIS to construct village-level daily mean temperature and daily total precipitation from 2001 to 2016 (the period covered by our survey data); we use the data from the climatic grid closest to the village center as the climatic data for the village.

Measuring drought by PDSIs. Based on the climatic data, we construct the widely used Palmer Drought Severity Index (PDSI) to measure the dryness of the sample village (e.g., Seneviratne, 2012; Sheffield et al., 2012). We calculate the village-level drought measure in each year in two steps. First, following the method of Liu et al. (2004), we combine the village-level precipitation and temperature with county-level soil data derived from the Institute of Soil Science at the Chinese Academy of Sciences to calculate the monthly PDSI values for each village.[4] The monthly PDSI ranges from -10 to 10, with smaller values indicating drier conditions, although most values typically fall within the range of -4 to 4. The PDSI does not account for human activities such as irrigation or the cultivation of drought-tolerant crops and thus reflects agricultural drought only under natural conditions (Wu et

3. Details of ERA5-Land can be found in Muñoz-Sabater et al. (2021).

4. The original calculation of PDSI uses precipitation, temperature, and soil moisture data along with the Thornthwaite method for calculating evapotranspiration. The revised PDSI calculation developed by Liu et al. (2004) improves accuracy by adopting the Penman-Monteith formula, expanding station coverage, refining soil moisture parameters with region-specific capacities, and recalculating climate constants and weighting factors. These adjustments enhance spatial comparability and better capture extreme droughts, making the model more suitable for China's diverse climate and agriculture.

al., 2022).

Second, we measure the annual drought level (named as PDSIs) as the number of months in each cropping year (from October of the last year to September of this year) with a monthly PDSI below -3. We use the annual measure of PDSIs instead of the monthly average PDSI since PDSIs better capture the duration of extreme drought. We do not use the drought measure for the calendar year (January to December) or a single growing season because our sample areas primarily practice the double-cropping of winter wheat and summer maize in a cropping year.[5] We present robustness checks to show that the estimates are robust to defining drought differently based on the calendar-year or the major growing season from April to September (Appendix Table A.2). Since a PDSI of -3 or lower is regarded in the literature as indicating severe drought or more extreme conditions (e.g., Zhao et al., 2017), we adopt -3 of PDSI as the threshold here; we show that the main results are robust to alternative thresholds (Figure 7).

Measuring extreme heat by HDDs. We also follow the literature (Jones et al., 2010; Burke and Emerick, 2016) to construct the widely used temperature measures of Growing Season Degree-Days (GDDs) and Harmful Degree-Days (HDDs) based on the daily temperature. GDDs represent the cumulative heat exposure between a lower threshold of 8°C and an upper threshold of 32°C over a cropping year. HDDs measure cumulative exposure to temperatures that exceed the harmful threshold of 32°C during the same period. These two variables are commonly used together to capture the non-linear effects of temperature on crop growth. Among them, HDDs specifically capture the harmful impacts of extremely high temperatures, as crop yields decline sharply once temperatures exceed a critical threshold (Burke et al., 2015).

To calculate GDDs and HDDs, we first determine the temperature exposure within the temperature bounds for each day, and then sum over daily exposures to obtain annual GDDs and HDDs. For each day, the within-day temperature distribution is approximated using a sinusoidal curve based on the daily minimum and maximum temperatures (Schlenker and Roberts, 2009). This approximation estimates the time that each village is exposed to each 1°C temperature interval within a day and converts this exposure into degree-days. For GDDs, time exposed to temperatures below 8°C contributes 0 GDDs, while temperatures between 8°C

5. The growing season of winter wheat is usually from October of the last year to May of this year, and the growing season of summer maize is usually from May of this year to September of the same year.

and 32°C contribute $z - 8$ GDDs, and temperatures above 32°C contribute 24 GDDs. For HDDs, time exposed to temperatures above 32°C contributes $z - 32$ HDDs; otherwise, it contributes 0 HDDs. Finally, annual GDDs and HDDs are calculated by summing HDDs and GDDs for all days over a cropping year.

4.1.3 Summary statistics

Table 1 presents the summary statistics of key variables. The data reveal that 85% of farmlands are irrigated, with a standard deviation of 29%. Household average net agricultural income is 8,000 yuan (in 2015 constant yuan, approximately 1,200 USD). Per-area agricultural output is 422 kg/mu, and per-labor agricultural output is 2,680 kg.[6] The average PDSIs is 0.93, implying that an average village experienced roughly one month of drought with PDSI below -3 each year. The average HDDs is 11, implying that an average village experienced 11 accumulated days with temperatures above 32°C.

6. Per-labor agricultural output is calculated as output per agricultural labor. Agricultural labor refers to household members involved in agricultural work, weighted by the proportion of time spent on three major staple crops.

TABLE 1 Summary statistics of key variables

Variable	Definition	Mean	SD
Household-year outcome variables:			
Share of irrigated farmland	Share of farmland irrigated	0.85	0.29
Per-area output (kg/mu)	Output per mu	422	128
Per-labor output (kg)	Output per agricultural labor	2680	2871
Agricultural TFP	See the main text	0.77	0.24
Net agricultural income (1,000 yuan)	Net agricultural income	8	10
Farm work (days)	Agricultural labor time	114	133
Off-farm work (days)	Non-agricultural labor time	229	255
Pesticides (yuan/mu)	Costs of pesticides per mu	29	28
Fertilizers (yuan/mu)	Costs of fertilizers per mu	127	73
Machinery (yuan/mu)	Costs of machinery per mu	64	57
Village-year control variables:			
PDSIs (months)	Months with PDSI below -3	0.93	1.63
HDDs (degree days)	Harmful degree-days	11	10
GDDs (100 degree days)	Growing degree-days	73	33
Precipitation (100 mm)	Annual total precipitation	5.44	1.96
Temperature (°C)	Annual mean temperature	12.57	2.48

Notes: The number of observations for these variables is 1,685. All monetary values have been adjusted to constant 2015 yuan. All household-level measures are calculated for the three major staple crops (rice, wheat, and corn). See data sources from the main text.

Figure 4 (blue dots) presents the village-level accumulated distribution of the starting year of government-funded irrigation investments. Note that we only include data for government investments in expanding the irrigation area and guaranteeing the irrigation water supply; we exclude non-government investments and government investments in water-saving irrigation technologies and facilities. We find that over our sample period, 16% of villages began receiving government irrigation investments in 2001, and the percentage of sample villages receiving the investments gradually increased over time, reaching 89% by 2015.[7] For comparison, the figure also presents the timing of county-level irrigation investments (green dots), which was collected from official websites for the different rounds of national irrigation investments introduced in section 2. We observe a very similar trend for the county-level irrigation investments, suggesting that the village-level investment is driven by the county-level investment.

7. This does not imply that the figure represents the first round of investment in the village, as some villages may have received investments earlier. However, the observed starting year of the "new" investment provides a valid exogenous shock for our identification strategy introduced in the next subsection.

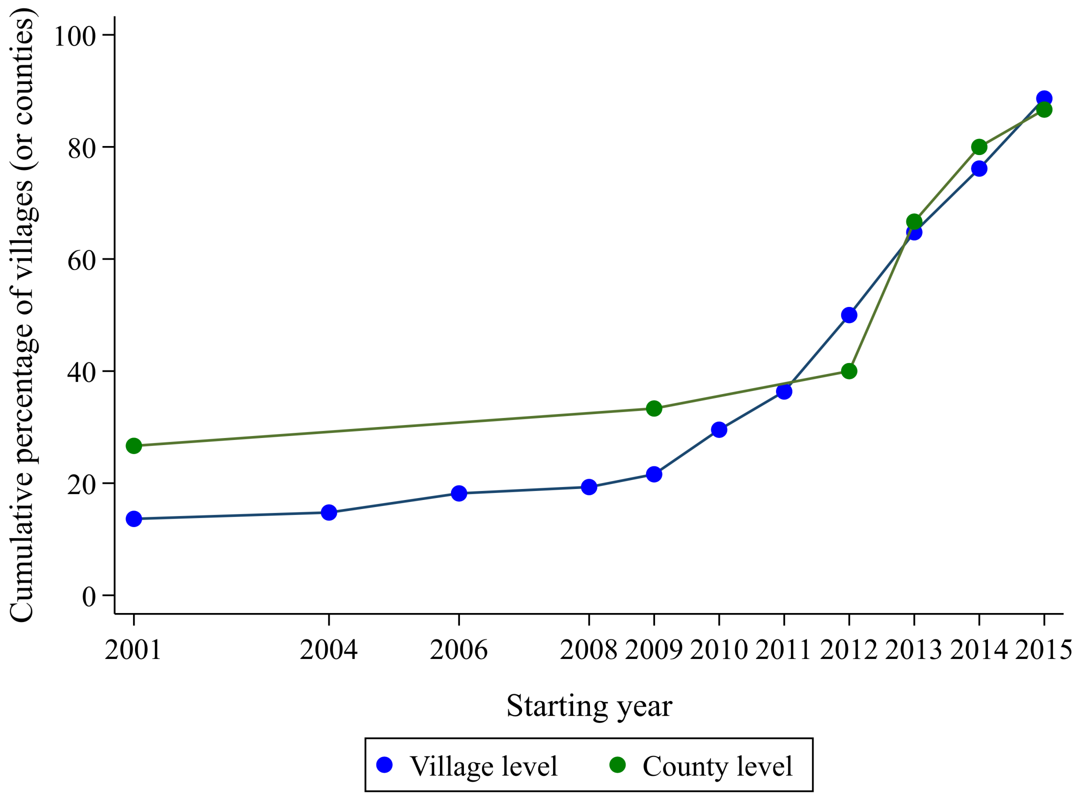

FIGURE 4 Starting year of the government-funded irrigation investments

Notes: This figure presents the distribution of the village-level (blue dots) and county-level (green dots) years of government irrigation investments. Village-level data are derived from the survey, and county-level data are from were collected from official websites.

Figure 5 presents the village-level association between the share of irrigated farmland and different agricultural productivity measures: per-area output, per-labor output, net agricultural income, and agricultural TFP. We first calculate the village-average productivity measures and share of irrigated farmland over the sample years for each of the 88 sample villages. We then plot the association between these two village-level variables. It shows a significantly positive association between each of the four productivity measures and the share of irrigated farmland. The simple association suggest that, for example, a 10 percentage point raise in the irrigated area would increase crop output per area by 6%.

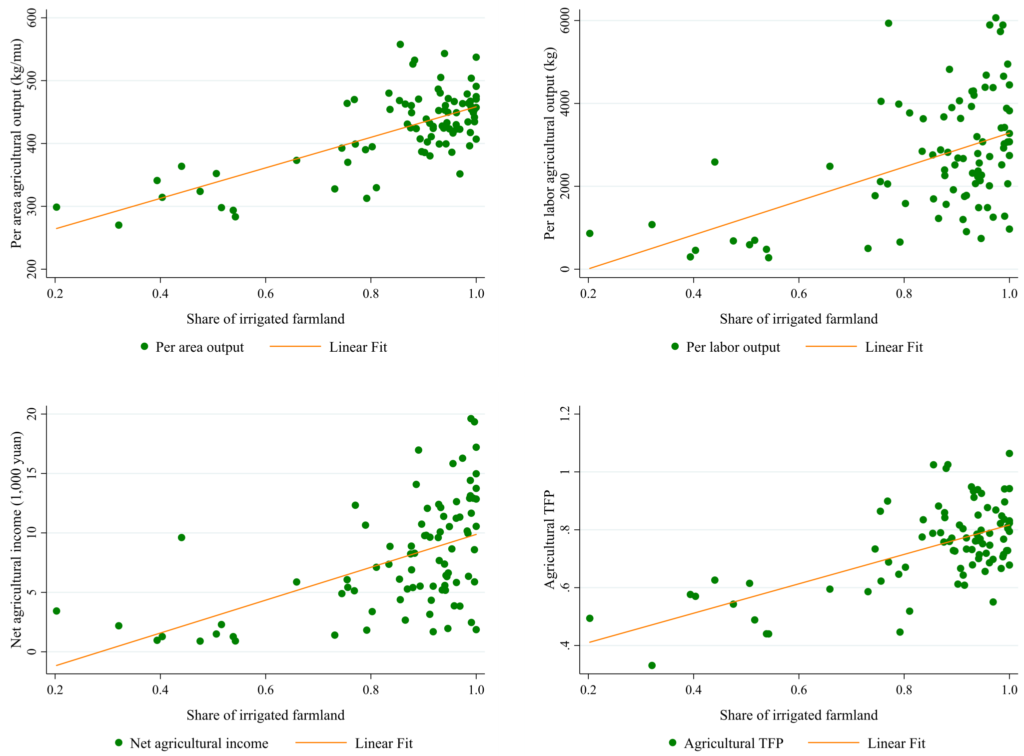

FIGURE 5 Association between the share of irrigated farmland and different agricultural productivity measures at the village level

Notes: The village-level values are calculated as the average for all sample households in the village over all sample years. The data come from the survey.

4.2 Empirical strategy

4.2.1 The baseline model

We employ a staggered Difference-in-Differences (DID) model to estimate the effect of irrigation on agricultural productivity:

$$y_{ijt} = \alpha_0 + \alpha_1 Post_{jt} + X_{ijt}\lambda + \mu_i + \tau_t + \varepsilon_{ijt} \ , \tag{1}$$

where y_{ijt} represents the outcome variables for household i in village j and year t. The key outcome variables are the share of irrigated farmland and different measures of agricultural productivity. We adopt four productivity measures: per-area output, per-labor output, agricultural TFP, and net agricultural income. All productivity measures are calculated for the three major staple crops (rice, wheat, and corn) which account for more than 90% of crop production in China.

The key explanatory variable $Post_{jt}$ is a dummy variable that equals 1 for years after the irrigation investment in village j and 0 otherwise. The investment here refers to the irrigation investment from government at the county level and above; we exclude the investment from farm households, village collectives, and water managers to avoid the endogeneity issues. Our baseline estimation uses the first year of investment as the policy starting year. Considering that investment could last for several years, in robustness checks we also use the last investment year as the policy starting year (Appendix Table A.3). The key coefficient of interest α_1 is thus estimated based on comparing villages that received government investment early and later. As presented in Figure 4, not all villages received government investment during our sample years. Those that did not receive government investment are served as pure control group, which is important for avoiding the potential bias in a staggered DID estimation (Borusyak et al., 2021).

The model includes the household-fixed effects (μ_i) to account for household-specific time-invariant factors and year-fixed effects (τ_t) to account for annual shocks common to all households. The model also controls for a vector of control variables (X_{ijt}), including climate variables (PDSIs, HDDs, GDDs) and the interaction between initial village features (per capita farmland, per capita income, the share of migrant workers, water shortage conditions) and a full set of year dummies. These village-level variables are also derived from our survey data. Finally, the error term is denoted by ε_{ijt}. Standard errors are clustered at the village level to address spatial correlation across households within a village.

4.2.2 Addressing the endogeneity concern

The major concern of the above identification strategy is that the timing of irrigation investment could be endogenous. For example, the timing of irrigation investment could be determined by village features such as economic conditions, irrigation potential, and damage from drought. If these determinants of irrigation investment were correlated with agricultural productivity, the estimate of α_1 could be biased. We adopt the following five methods to address the endogeneity concern.

First, we control for household-fixed effects to account for all time-invariant local factors that could be correlated with the irrigation investment, such as groundwater endowment and various geographic factors affecting the cost of irrigation investment. In addition, we control for the interactions between the initial values of five key determinants of irrigation investment (i.e., per capita farmland, per capita income, the share of migrant workers, water shortage conditions, and the distance to the county center) and a full set of year dummies. These control variables further account for the potential confounding effects of differences across villages.

Second, we show that there is no significant correlation between potential determinants of irrigation and the timing of government irrigation investment. As presented in Appendix Table A.4, we examined the correlation between the initial values of eight potential determinants of irrigation (i.e., per capita farmland, per capita income, the share of migrant workers, water shortage conditions, the distance to the county center, population size, annual total precipitation, and annual mean temperature) and the timing of government irrigation investment. We find no significant correlation for each of these variables or joint significance of these variables. This finding suggests the exogeneity of the timing of government irrigation investment.

Third, we exclude the irrigation investment from non-government sources (i.e., households, village collectives, and water managers). Our survey data contain detailed information on the funding source of the irrigation investment. Most of the irrigation investment comes from governments at the county level and above, but a significant number of villages also invest in their own irrigation system based on the funding from the village committee, water managers, or farmers. To avoid the concern that the local funding could be endogenous, our analysis is based only on the plausibly exogenous investment from higher-level governments.

Fourth, we further address the endogeneity concern by adopting the timing of the county-level irrigation investment from national programs as the proxy for the timing of village-level irrigation investment. As detailed in subsection **??**, China implemented multiple irrigation investment programs in different counties during our sample period. We collect the program information from government websites for our sample counties. As presented in Figure 4, the distribution of national irrigation investment programs at the county level closely resembles that of the village-level irrigation investment. As presented in Appendix Table A.5, the resulting estimates are comparable.

Finally, we adopt an event-study estimation to support the parallel-trends assumption:

$$Irr_{ijt} = \beta_0 + \sum_{g=2}^{G} \beta_g Lag_{jt}^g + \sum_{d=0}^{D} \beta_d Lead_{jt}^d + X_{ijt}\lambda + \mu_i + \tau_t + \epsilon_{ijt} \;, \qquad (2)$$

where Irr_{ijt} is the share of irrigated farmland for household i ,village j, and year t,

Lag_{jt}^{g} is a dummy variable indicating that year t is g periods before the irrigation investment in village j, and $Lead_{jt}^{d}$ is a dummy variable indicating that year t is d periods after the irrigation investment in village j. We omit the first lag indicator due to perfect collinearity. All other variables are the same as those defined in model (1).

As presented in Figure 6, all estimates of β_g are statistically insignificant and close to zero, supporting the parallel-trends assumption that villages with irrigation investment early and later have the same preexisting trends. The estimates of β_d are all positive and statistically significant, confirming that the investment substantially increased the share of irrigated farmland. The figure also shows that the estimates are robust to excluding the village-level control variables and excluding the climatic control variables from the baseline regression, respectively. In addition, we show that the estimates are robust to heterogeneous treatment effects by constructing the stacked regression estimator following the method of Cengiz et al. (2019).

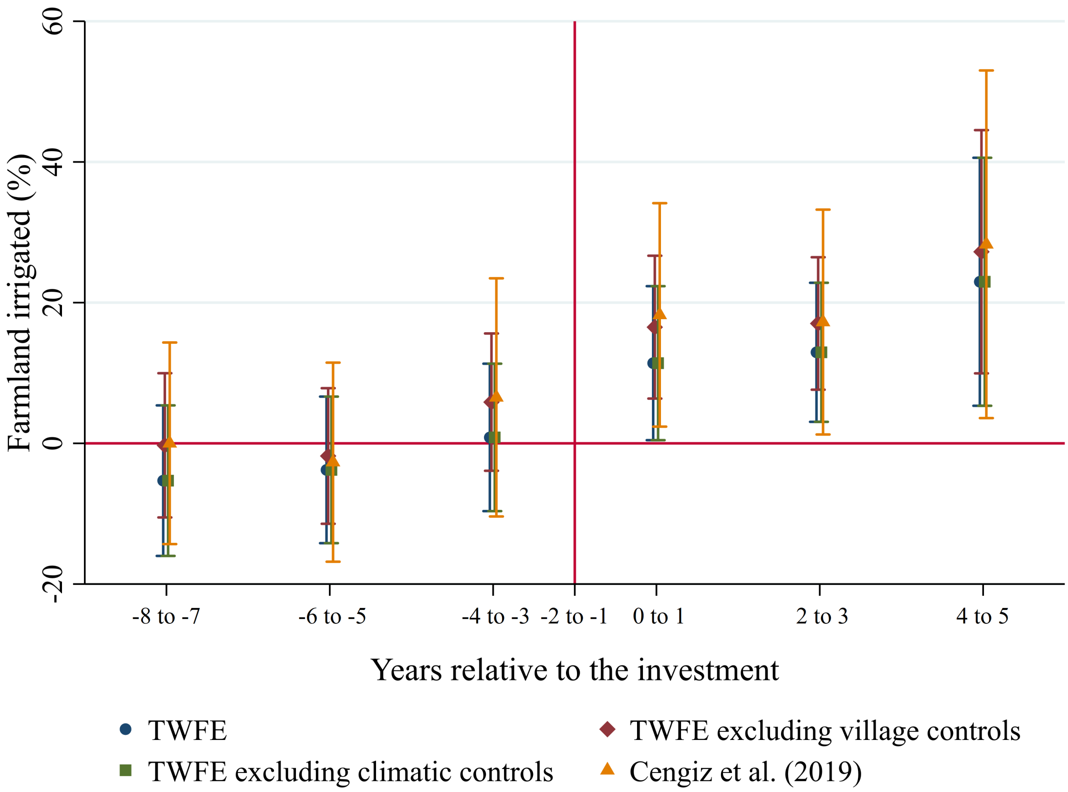

FIGURE 6 Event-study estimates of the effect of government irrigation investment on the share of irrigated farmland

Notes: This figure presents the event-study estimates based on model (2). Besides the baseline estimate (TWFE), the figure also examines the robustness to excluding the village-level controls and climatic controls, as well as adopting the heterogeneous treatment effect estimate of Cengiz et al. (2019). The dependent variable is the percentage of farmland irrigated (%). The omitted base period is 1-2 year prior to the irrigation investment, indicated by the dashed vertical line. Capped spikes indicate the 95% confidence intervals, calculated based on standard errors clustered at the village level.

4.2.3 Mitigating the damage from climatic shocks

We extend the baseline DID model (1) to investigate the mitigating effect of irrigation investment on the damage from climatic shocks:

$$y_{ijt} = \delta_0 + \delta_1 C_{jt} + \delta_2 C_{jt} * Post_{jt} + \delta_3 Post_{jt} + X_{ijt}\lambda + \mu_i + \tau_t + \epsilon_{ijt} \tag{3}$$

where C_{jt} is a climatic shock measure (i.e., of PDSIs and HDDs, see subsection 4.1.2 for the definition) in village j and year t, and all other variables are the same as defined before. The climatic shock measure C_{jt} is demeaned to facilitate the interpretation of the estimates. The coefficient δ_1 captures the effect of the climate shock in the case of no irrigation investment, the coefficient δ_3 captures the effect of irrigation, and the coefficient δ_2 captures the mitigating effect of irrigation on the impact of climatic shock. If climatic shock is harmful, we expect to see a negative estimate of δ_1. If irrigation investment offsets the negative impact of the climatic shock, we expect to see a positive estimate of δ_2. By comparing δ_2 and δ_1, we are able to know how much of the damage from the climatic shock can be offset by the irrigation investment.

4.2.4 Measuring agricultural TFP

Our baseline analysis uses the household-level agricultural TFP calculated based on the Error Components Frontier approach proposed by Battese and Coelli (1992), which has been widely used in literature (Sherlund et al., 2002; Gong, 2020; Chen and Gong, 2021). In this approach, a Cobb-Douglas stochastic frontier model is expressed as:

$$\begin{aligned} y_{it} = \alpha &+ \beta_l l_{it} + \beta_w w_{it} + \beta_p p_{it} \\ &+ \beta_f f_{it} + \beta_m m_{it} \\ &+ \lambda_t - u_{it} + v_{it} \ , \end{aligned} \tag{4}$$

where y_{it} is the per-area output of the three major staple crops (rice, wheat, and corn) of household i in year t. l_{it} is the labor-day inputs per area, w_{it}, p_{it}, f_{it}, and m_{it} represent the costs of irrigation, pesticides, fertilizers, and machinery per area in the crop production, respectively. β_l, β_w, β_p, β_f, and β_m are the coefficients that capture the elasticity of the output with respect to each input. TFP is calculated as $A_{it} = exp(\alpha + \lambda_t - u_{it})$, where α is the intercept, λ_t measures year-fixed effects, and u_{it} accounts for technical inefficiency.[8]

We adopt three alternative TFP measures in robustness checks. First, we adopt the traditional production approach, assuming a fixed input-output relationship without accounting for technology and efficiency changes (Chari et al., 2021). Second, we adopt a crop-level Error Components Frontier approach that estimates the Cobb-Douglas stochastic frontier model (4) separately for wheat, maize, and rice. The household-level TFP is then calculated as the average across crops. Third, we adopt the Error Components Frontier approach based on the Transcendental Logarithmic stochastic frontier model instead of the Cobb-Douglas stochastic frontier

8. The technical inefficiency measure is calculated as $u_{it} = \exp(-\eta(t-T))u_i$, where u_i is an i.i.d. nonnegative truncation of the $N(\lambda, \theta^2)$ distribution with mean λ and variance θ^2 , η is a scalar parameter, T is the length of the sample period.

model (Gong, 2018):

$$
\begin{aligned}
y_{it} = {} & \alpha + \beta_1 l_{it} + \beta_2 w_{it} + \beta_3 p_{it} + \beta_4 f_{it} + \beta_5 m_{it} + \beta_6 l_{it}^2 + \beta_7 w_{it}^2 + \beta_8 p_{it}^2 + \beta_9 f_{it}^2 + \beta_{10} m_{it}^2 \\
& + \beta_{11} l_{it} w_{it} + \beta_{12} l_{it} p_{it} + \beta_{13} l_{it} f_{it} + \beta_{14} l_{it} m_{it} \\
& + \beta_{15} w_{it} p_{it} + \beta_{16} w_{it} f_{it} + \beta_{17} w_{it} m_{it} + \beta_{18} p_{it} f_{it} + \beta_{19} p_{it} m_{it} + \beta_{20} f_{it} m_{it} \\
& + \lambda_t - u_{it} + v_{it} \ ,
\end{aligned}
\tag{5}
$$

where the only difference from model (4) is that here we include the squares and the interaction of all production inputs. As presented in Appendix Table A.6, the estimated effects are robust to these different TFP measures.

5 Results

5.1 Effect of irrigation on agricultural productivity

Table 2 presents the DID estimates of model (1). Column 1 shows that the irrigation investment increased the irrigated farmland ratio by 11.0%. The effect on the share of irrigated farmland is not very large, presumably because the irrigated farmland ratio was already high before the investment. In addition, expanding the irrigated farmland area is not the only effect of the irrigation investment. The investment also tends to increase the reliability of irrigation, which could further benefit agricultural productivity. Due to data limitations, we are unable to estimate the effect of the irrigation investment on irrigation reliability. However, this limitation does not bias the following estimations of the effect on agricultural productivity, the mechanisms of the effect, and the rate of return to irrigation investment.[9]

Columns 2–5 present the effect on agricultural productivity, measured by per-area output (kg), per-labor output (kg), agricultural TFP (calculated based on equation (4)), and net agricultural income (1,000 yuan). We find that the irrigation investment increased per-area output by 14.9%, per-labor output by 36.2%, agricultural TFP by 13.7%, and net agricultural income by 1.28 thousand yuan (or 15.6% of the mean). The effect on per-labor output is much larger as irrigation significantly reduced agricultural labor input and increased the farmland managed, which will be shown later. Appendix Table A.7 shows that the estimates are robust

9. The only limitation is that we cannot infer the marginal effect of the share of irrigated farmland on agricultural productivity by combining the estimated effect on the share of irrigated farmland with the effect of the investment on agricultural productivity, as the latter also incorporates the effect of increasing irrigation reliability.

to excluding all the control variables. Appendix Table A.6 adopts three alternative TFP measures and finds similar results.

TABLE 2 Effect of irrigation on agricultural productivity

	(1) Share of irrigated farmland	(2) Log per-area output (kg)	(3) Log per-labor output (kg)	(4) Log agricultural TFP	(5) Net agricultural income (1,000 yuan)
$Post_{jt}$	0.110**	0.149**	0.362***	0.137**	1.281***
	(0.05)	(0.06)	(0.13)	(0.06)	(0.34)
Control variables	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1685	1685	1685	1685	1685

Notes: This table presents the estimates of model (1). The dependent variables are the share of irrigated farmland (column 1), log per-area output (column 2), log per-labor output (column 3), log agricultural TFP (column 4), and net agricultural income (column 5). The outcome variables in column 2–4 are for the three major staple crops (rice, wheat, and corn). All regressions include the full set of control variables, year-fixed effects, and household-fixed effects. Standard errors are reported in parentheses. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.2 Mechanisms of the effect

5.2.1 More use of high-productivity inputs

As presented in columns 1–3 of Table 3, we find that the irrigation investment significantly increased the use of pesticide, fertilizers, and machinery by 4.03, 7.81, and 9.09 yuan per mu, respectively (or 14.05%, 6.16%, and 14.21%, respectively, relative to the mean). The increase in the use of these inputs suggests that irrigation complements them (Rosegrant et al., 2002; Cai et al., 2008). Existing studies have found that pesticide, fertilizer, and machinery are high-productivity inputs that could enhance agricultural productivity (Tilman et al., 2002; Chambers et al., 2010; McArthur and McCord, 2017). More use of high-productivity inputs could increase all the three productivity measures of per-area output, per-labor output, and TFP. Therefore, one reason for the substantial positive impact of irrigation on agricultural productivity is that irrigation increased the use of high-productivity inputs.

TABLE 3 Effect of irrigation on agricultural inputs

	(1) Pesticides (yuan/mu)	(2) Fertilizers (yuan/mu)	(3) Machinery (yuan/mu)	(4) Farmland change (%)	(5) Farmland rent-out (%)
$Post_{jt}$	4.03***	7.81***	9.09***	-7.58***	2.39***
	(0.60)	(1.27)	(0.86)	(0.36)	(0.35)
Dep. var. mean	28.68	126.82	63.65	4.29	7.94
Control variables	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1685	1685	1685	1685	1685

Notes: This table presents the effect of irrigation on agricultural production inputs, estimated based on model (1). The dependent variables are per-area pesticide costs (column 1), fertilizer costs (column 2), machinery costs (column 3), the share of retired and idled farmland (column 4), and the share of farmland rented out (column 5). Standard errors are reported in parentheses. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.2.2 Farmland use adjustment

As presented in column 4 of Table 3, we find that the irrigation investment reduced the share of retired and idled farmland in the total farmland by 7.58% (column 4). The share of retired and idled farmland is calculated as the ratio between the retired and idled farmland of the household and the total farmland owned by the household. This finding suggests that irrigation improvement leads farmers to reclaim the retired or idle farmland. More farmland input could increase per-labor output but may reduce per-area output and TFP as these originally retired and idled farmland tend to have lower productivity. This finding could explain why the positive impact on output per labor is much larger than the impact on other productivity measures (Table 2). Column 5 shows that irrigation investment increases the share of farmland rented out by 2.39%, which is much smaller than the impact on the reclamation of retired or idle farmlands, suggesting a net positive effect on the farmland managed.

5.2.3 Labor reallocation

Table 4 shows that irrigation investment significantly shifts labor from agricultural work to off-farm employment. The irrigation investment reduced an average household's agricultural working time by 18.40 days (or 16.14%, column 1) and increased its off-farm working time by 19.97 days (or 8.72%, column 2). These findings are confirmed by the village-level estimates presented in columns 3 and 4, which suggest that irrigation investment reduced the village-level share of labor in agriculture by 9% and increased the share of migrant labor by 6%.[10] The labor reallocation is consistent with the fact that improved irrigation system reduces the time required for irrigation (Uysal and Atış, 2010; Moyo et al., 2024; Chaurey and Le, 2022). Lower agricultural labor input could increase per-labor output, but may have a negative effect on per-area output and an uncertain effect on TFP.

TABLE 4 Effects of irrigation on labor allocation

	Household-level estimates		Village-level estimates	
	(1) Farm work (days)	(2) Off-farm work (days)	(3) Share of agricultural labor	(4) Share of migrant labor
$Post_{jt}$	-18.40***	19.97***	-0.09**	0.06**
	(1.68)	(1.70)	(0.04)	(0.02)
Dep. var. mean	114	229	0.74	0.18
Control variables	Yes	Yes	No	No
Time FE	Yes	Yes	Yes	Yes
Observations	1685	1685	264	1685

Notes: This table presents the effect of irrigation investment on labor allocation, estimated based on model (1). The dependent variables are household-level farm working time (column 1), household-level off-farm working time (column 2), village-level share of labor in agriculture (column 3), and village-level share of migrant labor (column 4). Standard errors are reported in parentheses. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.2.4 Mitigating the damage from drought

We examine how irrigation investment could mitigate the damage from drought by estimating model (3). Considering that the mitigating effect may work through input adjustments, here we focus on the effect on net agricultural income; other productivity measures are less able to account for input adjustments. Our main analysis focuses on the effect of drought, which is most relevant for irrigation investment. Appendix Table A.8 presents the corresponding estimates for extreme heat measured by HDD; we find no significant mitigating effect of irrigation investment on the damage from extreme heat.

As presented in column 1 of Table 5, the coefficient of PDSIs suggests that a one-unit increase in PDSIs (i.e., one additional month with PDSI below -3) could

10. The smaller effect estimated based on the village-level data is presumably because the village-level employment data do not fully account for part-time off-farm work.

reduce the agricultural income of an average household by 0.47 thousand yuan. The coefficient of the interaction term between irrigation investment and PDSIs suggests that irrigation investment could offset 0.26 thousand yuan (or 55.3%) of this damage. Columns 2–5 of the table suggest that irrigation mitigates the damage from drought by affecting production inputs. We also estimate the effect on each production input based on model (3). We find that PDSIs significantly reduces the input of labor (column 2) and increases the expenditures on pesticide (columns 3) and machinery (column 5).[11] The estimate of the interaction term between irrigation investment and PDSIs suggests that irrigation investment can partly offset the effect on pesticide and machinery costs and reverse the effect on labor input.

TABLE 5 Mitigating the damage from drought by irrigation investment

	(1) Net agricultural income (1,000 yuan)	(2) Farm work (days)	(3) Pesticides (yuan/mu)	(4) Fertilizers (yuan/mu)	(5) Machinery (yuan/mu)
PDSIs	-0.47***	-4.54***	10.80***	-4.71	24.20***
	(0.10)	(0.47)	(4.14)	(8.32)	(6.66)
$PDSIs \times Post_{jt}$	0.26**	9.18***	-1.37***	-2.45***	-3.48***
	(0.12)	(0.58)	(0.43)	(0.82)	(0.50)
$Post_{jt}$	1.22***	-18.65***	5.37***	25.80***	9.92***
	(0.34)	(1.69)	(1.35)	(2.93)	(2.04)
Household FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1685	1685	1685	1685	1685

Notes: This table presents the interaction effect between irrigation investment and PDSIs, estimated based on model (3). The dependent variables are household net agricultural income (column 1), time allocated to farm work (column 2), per-area cost of pesticides (column 3), fertilizers (column 4), and machinery (column 5). The PDSIs is demeaned. Standard errors are reported in parentheses. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Figure 7 examines the robustness of the finding to different levels of drought. Our baseline analysis defines months with a PDSI below -3 as drought. Recall that PDSI is an index typically falling within the range of -4 to 4, with smaller values indicating drier conditions. To examine the robustness to different drought thresholds, we adopt eight alternative thresholds ranging from -4 to 0, with an

11. These effects reflect farmers' adaption to drought through adjusting these inputs (Huang et al., 2020; Tambet and Stopnitzky, 2021; Chen and Gong, 2021).

interval of 0.5. Figure 7 presents the marginal effect of drought and the offsetting effect of irrigation investment, estimated under each of these alternative thresholds. We find that the effects are small and mostly insignificant for thresholds above -2.5, and the effects increase substantially for thresholds below -3. Consistent with our baseline finding, the estimates suggest that irrigation investment could offset about half of the damage from drought for thresholds below -3.

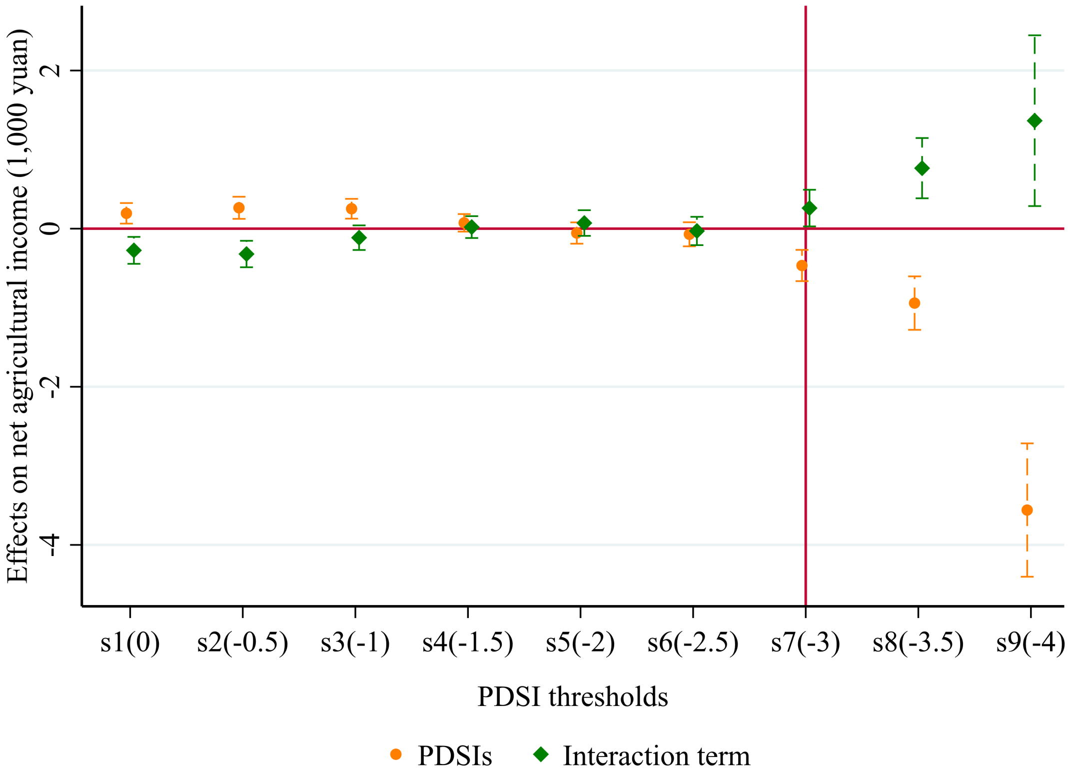

FIGURE 7 Mitigating effect of irrigation under different levels of drought

Notes: The figure shows the marginal effects of PDSIs (orange circle) and the interaction term $PDSIs * Post_{jt}$ (green diamond) on net agricultural income under different thresholds of drought, estimated based on model (3). We adopt eight alternative thresholds ranging from -4 to 0, with an interval of 0.5. The red solid vertical line corresponds to the baseline threshold of -3 (s7). Capped spikes indicate the 95% confidence intervals.

5.3 Return to irrigation investment under climate change

We conduct a cost-benefit analysis of government irrigation investment based on the estimated effects. We take into account the effect of irrigation investment on agricultural income, off-farm income (through increasing off-farm work), and the mitigating effect on the damage from drought under different climate change scenarios. The rate of return to government irrigation investment is calculated based on:

$$_{s}=\frac{\sum_{t=1}^{N}\frac{a_{s,t}}{(1+r)^{t-1}}}{Y}\times 100\ , \tag{6}$$

where $a_{s,t}$ represents the gain from the investment in year t under climate change scenario s, N is the assumed service years of the irrigation facilities, Y is the total irrigation investment, and r is the annual discount rate, which is set at 0.05 following the literature (Heumesser et al., 2012; You et al., 2011).

As presented in Figure 8, we calculate the rate of return at the village level over the time horizons N of 5, 10, 15, and 20 years, respectively. We calculate the rate of return under each of the five scenarios: (1) only accounting for the effect on agricultural income, not considering the mitigating effect and climate change (S1); (2) accounting for the effect on agricultural income, considering the mitigating effect but not climate change (S2); (3) accounting for the effect on agricultural income, considering both the mitigating effect and climate change under scenario RCP4.5 (S3); (4) accounting for the effect on agricultural income, considering both the mitigating effect and climate change under RCP8.5 (S4); (5) accounting for the effects on both agricultural and off-farm income, considering both the mitigating effect and climate change under RCP8.5.

Annual gains from irrigation investment (i.e., $a_{s,t}$) are calculated based on the following parameters: (1) village-average total investment of 3.23 million yuan (in 2015 constant value); (2) village-average household number of 468; (3) irrigation investment increases annual household-average agricultural income by 1.28 thousand yuan (column 5 of Table 2); (4) irrigation investment increases annual household-average off-farm income by 1.41, calculated based on the estimated effect on off-farm working time of 19.97 days (column 2 of Table 3) and average off-farm wage of 71 yuan per day; (5) irrigation investment offsets the marginal damage from PDSIs on agricultural income by 0.26 thousand yuan per year (column 1 of Table 5); (6) the baseline mean value of PDSIs of 0.93 per year; (7) climate change increases PDSIs by 0.007 per year and 0.029 per year, respectively, under climate change scenarios RCP4.5 and RCP8.5 Liang et al. (2018). We sum up the household-level gains to obtain village-level gains.

We find a high rate of return to the government irrigation investment. Even under the scenario with the lowest gain (S1), the return over 10 years is sufficient to cover the total cost of investment. Specifically, the rate of return under S1 is 0.7, 1.2, 1.6, and 1.9 over 5, 10, 15, and 20 years, respectively. The rate of return increases significantly when additionally taking into account the mitigating effect of irrigation on the damage from drought (S2), with a rate of return rising to 2.4 over 20 years. Further accounting for the effect of climate change under scenarios RCP4.5 (S3) and RCP8.5 (S4) increases the rate of return over 20 years to 2.5 and 2.7, respectively. Finally, further accounting for the effect on off-farm income doubles the rate of return over 20 years to 5.4 under RCP8.5. Therefore, ignoring the positive impact of irrigation investment on off-farm income tends to substantially underestimate the rate of return.

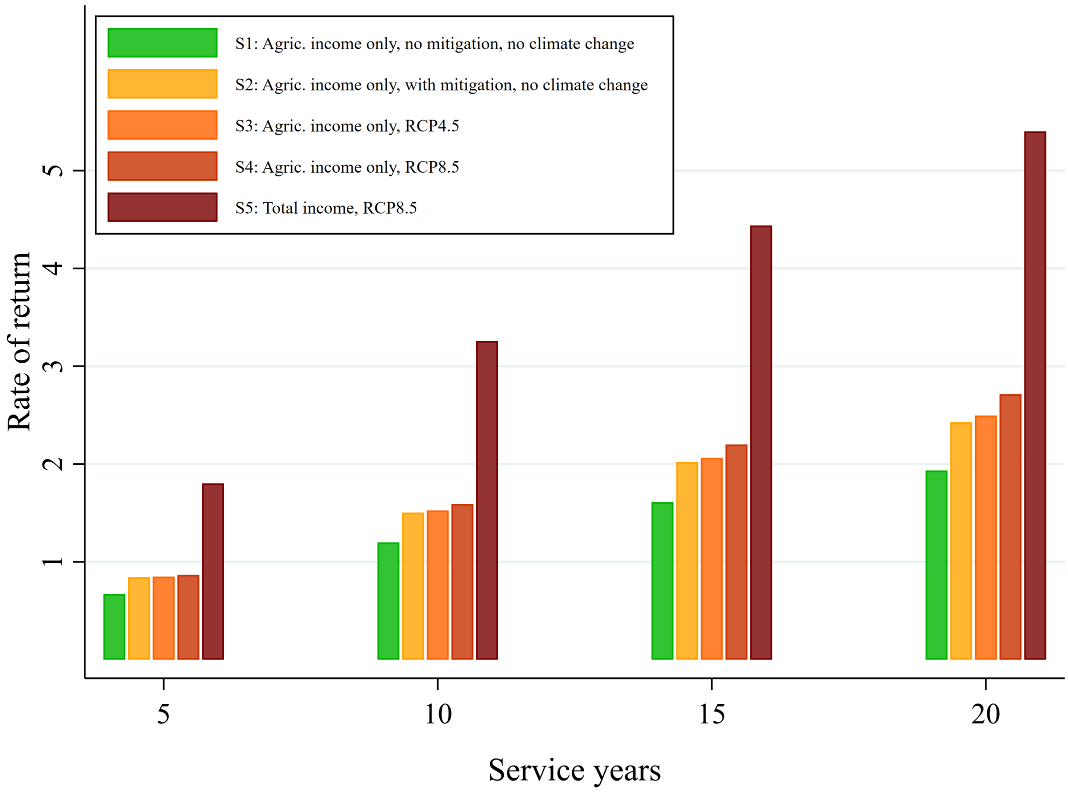

FIGURE 8 Rate of return to government irrigation investment

Notes: This figure presented the estimated rate of return to government agricultural investment under different scenarios and time horizons. See details of each scenario from the main text.

6 Concluding remarks

Irrigation is widely recognized as a key driver of agricultural productivity and rural economic development. However, estimating its true impact remains challenging due to the endogenous nature of irrigation investments. This study leverages plausibly exogenous government irrigation investments across 88 Chinese villages to identify the causal effects of irrigation on multiple agricultural productivity measures. We find that irrigation investment increased per-area output by 14.9%, net agricultural income by 15.6%, agricultural TFP by 13.7%, and per-labor output by 36.2%. Importantly, irrigation contributes to productivity gains not only by increasing the use of high-productivity inputs—such as pesticides, fertilizers, and machinery—but also by facilitating labor reallocation to off-farm employment, expanding cultivated land, and mitigating the adverse effects of drought. These results provide strong evidence that irrigation investment plays a central role in agricultural development, while its benefits extend beyond the farm by influencing labor markets and improving economic resilience to climate shocks.

Our findings have several important policy implications. First, given the high returns to irrigation investment, policymakers should prioritize targeted irrigation expansion in regions prone to water scarcity. Second, the substantial increase in the use of high-productivity inputs suggests that irrigation works best when combined with policies that ensure access to fertilizers, pesticides, and mechanization. Subsidies or credit support for these inputs may maximize the benefits of irrigation investments, leading to further improvements in productivity. Third, the observed labor reallocation effects indicate that irrigation can contribute to structural transformation by reducing the use of agricultural labor. Policies that facilitate skill development and job creation in non-agricultural sectors may enhance the welfare gains from irrigation investment. Finally, our findings highlight that irrigation plays a significant role in mitigating the economic damage from drought. In light of increasing climate variability, governments should integrate irrigation investment into broader climate adaptation strategies.

While this study provides robust evidence on the benefits of irrigation, several areas warrant further investigation. First, our analysis focuses on northern China, where irrigation infrastructure is relatively well-developed; future research could assess whether similar effects hold in regions with less advanced irrigation systems. Second, a general equilibrium approach accounting for price adjustments in input and output markets could provide a more comprehensive evaluation of irrigation's economic impact. Third, more detailed data on off-farm employment outcomes could refine our understanding of the broader welfare effects of irrigation investment. Finally, this study focuses on irrigation investments aimed at expanding the irrigation area and increasing irrigation reliability, and future research could further guide policymakers in designing effective irrigation policies by extending the study to investments in water-saving technologies.

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A Appendix for Online Publication

A.1 A systematic review of the irrigation literature

We provide a systematic review of the economic literature on the impact of irrigation on agricultural outcomes. We search mainstream economic journals to retrieve all the econometrical-based articles on the impact of irrigation on agricultural outcomes. Table A.1 summarizes the 22 articles obtained. Our review excludes studies focusing on examining the effect of irrigation on local economic outcomes instead of agricultural outcomes (e.g., Marbler, 2024; Blakeslee et al., 2023), focusing on comparing the efficiency of different irrigation technologies (e.g., Rejesus et al., 2011; Mullally and Chakravarty, 2018), or focusing on capturing the offsetting effect of irrigation on the damage from climate change (e.g., Wang et al., 2024; Gatti et al., 2021).

We draw four major conclusions from these articles. First, the estimated effect of irrigation on agricultural outcomes varies widely across the 22 studies reviewed, ranging from no effect to a huge effect. Second, among the 22 articles reviewed, only 4 (marked in red) attempted to address the endogenous bias by standard causal-effect identification methods (i.e., RCT, RDD, IV, and PSM). Third, the 4 articles adopted causal-effect identification methods only examined the effect on agricultural output value; other productivity measures (per-area output, per-capita output, and TFP) are not adopted by these studies. Finally, and most importantly, while more than half of these articles (marked in orange) adopted micro data (at the farm or plot level), none of them examined the mechanisms of the impact of irrigation on agricultural productivity.

TABLE A.1 A systematic review of the irrigation literature

Citation	Estimated effect	Identification	Level
(Dizon et al., 2024)	Drop in irrigation constraints (10%) increases paddy yield by 16.9–40 kg/acre	FE	Farm
(Dyer and Shapiro, 2023)	Irrigation pumps increase net farm income by 13%	RCT	Farm
(Mazur, 2023)	Irrigation capital doesn't significantly improve productivity	No	Village
(Jones et al., 2022)	Irrigation increases yields by 43%-63% of annual agricultural production value	RDD	Plot
(Xiao et al., 2022)	Irrigated land area (10%) increase agricultural income by 8.38- 8.51%	FE	Farm
(Chatzimichael et al., 2020)	Output elasticities of irrigation water is 0.1462	No	Farm
(Bravo-Ureta et al., 2020)	Canal irrigation project increase the frontier output by 17.6-25.9%	PSM	Plot
(Fuglie et al., 2021)	The contribution of irrigated area to productivity growth is not significant	No	Country
(García Suárez et al., 2019)	Irrigation (acre) increases biomass yield by 51%	FE	County
(Huang et al., 2017)	Water-saving technologies rises wheat yield per unit of water by 17.6-116.4%	FE	Plot
(Rada, 2016)	Irrigation investments account for 18% of India annual input growth rate	No	State
(Birthal et al., 2015)	Irrigated area (%) increases rice yield by 0.132%	FE	District
(Weligamage et al., 2014)	Irrigation water (%) increase rice yield by 16-40%	No	Farm
(Wokker et al., 2014)	Water inputs elasticity of rice output is 0.057-0.069	No	Plot
(Burney et al., 2010)	Drip irrigation increase supply of vegetables by 1.9 t per month	FE	Farm
(Conradie et al., 2009)	Water availability (%) leads to a 0.325% growth in TFP	No	District
(Fleischer et al., 2008)	Higher quota(m^3) increase profits by \$1500	No	Farm
(Duflo and Pande, 2007)	Dam construction increases downstream crop output value by 0.34%	IV	District
(Huang et al., 2006)	Irrigation increases the yields of wheat by 17.7%, those of maize by 29.4%	FE	Plot
(Huang et al., 2005)	Irrigated land (ha per capita) increases household income per capita by 2628 yuan	FE	Farm
(Fan et al., 2000)	Irrigated cropped area (%) boosts TFP growth by 0.215	No	State
(Rosegrant et al., 1998)	Irrigation stock elasticity of yield is 0.17 for rice, 0.06 for maize	No	District

Notes: This table summarizes 22 econometrical-based articles on the impact of irrigation on agricultural outcomes, retrieved from mainstream economic journals. We use red in column 3 to highlight articles that employed a causal-effect identification method, and orange in column 4 to highlight articles that used micro data.

A.2 Result appendix

TABLE A.2 Robustness of the mitigating effect to alternative definitions of the growing season

	Net agricultural income (1,000 yuan)	
	(1) Using the calendar year	(2) Using the growing season
PDSIs	-0.56***	-0.51***
	(0.09)	(0.13)
$PDSIs \times Post_{jt}$	0.28***	0.28*
	(0.10)	(0.16)
$Post_{jt}$	1.15***	1.32***
	(0.34)	(0.34)
Control variables	Yes	Yes
Household FE	Yes	Yes
Time FE	Yes	Yes
Observations	1685	1685

Notes: This table examines the robustness of the estimates presented in column 1 of Table 5 to alternative definitions of the growing season, for which PDSIs is calculated. Column 1 defines the growing season as a calendar year (January–December), and column 2 defines the growing season as from April to September within a year. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE A.3 Robustness to the starting year of irrigation investment

	(1) Share of irrigated farmland	(2) Log per-area output (kg)	(3) Log per-labor output (kg)	(4) Log agricultural TFP	(5) Net agricultural income (1,000 yuan)
$Post_{jt}$	0.12**	0.17*	0.50***	0.16*	1.29***
	(0.05)	(0.10)	(0.16)	(0.09)	(0.40)
Control variables	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1685	1685	1685	1685	1685

Notes: This table provides a robustness check for the baseline estimates presented in Table 2. The only difference from the baseline estimation is that here we use the last investment year as the policy starting year. Standard errors are reported in parentheses. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE A.4 Determinants of the timing of irrigation investment

	(1) Baseline	(2) Including county-fixed effects	(3) Including climate controls
Per capita farmland (mu)	0.11	-0.66	-0.40
	(0.62)	(0.89)	(0.91)
Per capita income (1,000 yuan)	-0.08	-0.67	-0.40
	(0.40)	(0.64)	(0.66)
Share of migrant workers	0.81	-2.88	-3.02
	(4.49)	(5.69)	(5.68)
Water shortage	0.51	1.34	1.18
	(1.03)	(1.31)	(1.32)
Distance to county center (km)	0.01	0.00	0.00
	(0.06)	(0.07)	(0.07)
Population	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Precipitation (100 mm)			-4.57
			(3.19)
Temperature (ºC)			-7.74
			(4.90)
County FE	No	Yes	Yes
Observations	88	88	88

Notes: This table presents the OLS estimates of factors potentially influencing the starting year of irrigation investment. Water shortage is self-reported water scarcity level by village leaders, ranging from 1 to 4, with higher values indicating greater water shortage. The values of these independent variables here represent the averages across the five sample years. Columns 2 and 3 include county fixed effects. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE A.5 Effect of national irrigation investment programs

	(1) Share of irrigated farmland	(2) Log per-area output (kg)	(3) Log per-labor output (kg)	(4) Log agricultural TFP	(5) Net agricultural income (1,000 yuan)
$Post_{jt}$	0.20***	0.12**	0.92***	0.14**	4.67***
	(0.06)	(0.06)	(0.30)	(0.07)	(0.91)
Control variables	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1685	1685	1685	1685	1685

Notes: This table provides a robustness check for the baseline estimates presented in Table 2. The only difference from the baseline estimation is that here we use the timing of county-level irrigation investment as the key explanatory variable. Standard errors are reported in parentheses. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE A.6 Robustness to alternative TFP measures

	Log agricultural TFP		
	(1) Traditional approach	(2) Crop-specific frontier	(3) Translog frontier
$Post_{jt}$	0.14***	0.17***	0.13***
	(0.05)	(0.06)	(0.05)
Control variables	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1685	1685	1685

Notes: This table examines the robustness of the baseline estimates presented in column 4 of Table 2 to three alternative TFP measured introduced in subsection 4.2.4. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE A.7 Robustness to control variables

	(1) Share of irrigated farmland	(2) Log per-area output (kg)	(3) Log per-labor output (kg)	(4) Log agricultural TFP	(5) Net agricultural income (1,000 yuan)
$Post_{jt}$	0.12***	0.14**	0.28*	0.13**	1.39*
	(0.04)	(0.07)	(0.14)	(0.06)	(0.73)
Control variables	No	No	No	No	No
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1685	1685	1685	1685	1685

Notes: This table examines the robustness of the baseline estimates presented in Table 2 by excluding all control variables. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE A.8 Mitigating the damage from extreme heat by irrigation investment

	(1) Net agricultural income (1,000 yuan)	(2) Farm work (days)	(3) Pesticides (yuan/mu)	(4) Fertilizers (yuan/mu)	(5) Machinery (yuan/mu)
HDDs	-0.10***	0.72***	12.33***	19.26**	48.29***
	(0.02)	(0.08)	(4.58)	(9.61)	(6.94)
$HDDs \times Post_{jt}$	0.01	-0.27***	1.07***	-1.96***	-0.30
	(0.02)	(0.09)	(0.23)	(0.46)	(0.29)
$Post_{jt}$	1.25***	-17.20***	4.07***	23.49***	7.04***
	(0.34)	(1.73)	(1.30)	(2.77)	(1.85)
	(0.34)	(1.73)	(1.30)	(2.77)	(1.84)
Control variables	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	1685	1685	1685	1685	1685

Notes: This table presents the interaction effect between irrigation investment and HDDs, estimated based on model (3). The dependent variables are household net agricultural income (column 1), time allocated to farm work (column 2), per-area cost of pesticide (column 3), fertilizer (column 4), and machinery (column 5). The PDSIs is demeaned. Standard errors are reported in parentheses. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.