Environmental Change, Water Scarcity and Farmers' Differentiated Adaptations: Evidence from the Three Gorges Dam*

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Abstract

Using the 2003 initial impoundment of the world's largest hydroelectric dam as a natural experiment, we assess how rural households with varying endowments adapt differently to the dam-induced water scarcity in the downstream area. In response to a 13% reduction in rice yields, those who are wealthier and more experienced in market transaction, and less constrained by access to credit, made up their income loss from agriculture by allocating 97 to 106 more labor days (equivalent to 97 to 106 days per year) to non-agricultural activities, whereas the disadvantaged ones expanded the acreage of rice cultivation. These differential strategies adopted by these households resulted in widening income inequality.

Keywords: Climatic and Environmental Change, the Three Gorges Dam, Adaptation, Agricultural Production, Non-agricultural Activities

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1 Introduction

The environmental sustainability of the mega-hydroelectric dams is increasingly drawing the public attention (Winemiller, et al., 2016; Zarfl et al., 2019; Barbarossa et al., 2020). In response to growing concerns, most developed countries have stopped building big dams and demolished thousands of them since the late 1960s.[1] Yet developing countries have been ramping up the construction of mega-hydroelectric dams in recent decades to meet increasing demand for energy. The new dams introduce climatic-environmental problems that have been identified before, including disrupting the river cycle, and changing the local climate and the ecology for fishing and agriculture, etc. More importantly, new problems arise when these changes threaten the livelihoods of millions of smallholder households near the river.

At the micro level, environmental changes generate new sources of inequality. For example, resourceful households may adapt more effectively by adopting new technologies, switching to non-agricultural jobs, and eventually becoming urbanized, while those without the means and resources to adapt suffer more economically. Therefore, any comprehensive evaluation of the socio-economic consequences and welfare impacts of the dam-induced climatic-environmental changes must account for household heterogeneity and focus on micro-level adaptation mechanisms (Barreca et al., 2016; Jessoe et al., 2018; Blakeslee et al., 2020).

In this paper, we utilize the sharp increase in water scarcity in the vast downstream Yangtze River basin induced by the construction of the world's largest hydroelectric dam—China's Three Gorges Dam (TGD)—as a natural experiment to empirically explore rural households' adaption to the dam-induced changes. Scientific studies have linked the persistent decrease in precipitation in the downstream areas to the dam's water impoundment cycle. We use this dam-induced change to explore three questions. First, we study whether farmers spontaneously adapt to the environmental changes by adopting different agricultural practices and technologies, and/or reallocating more labor from agricultural to non-agricultural activities. Second, we examine household-level heterogeneity in adaptation strategies and the factors that restrict their choices. Third, we evaluate the welfare consequences of these adaptation strategies, particularly whether they are effective enough to offset the negative impacts on rural households' family income.

The setting of the TGD provides us with an ideal quasi-laboratory environment with which to tackle two empirical challenges associated with identifying adaptations to climatic-environmental changes.[2] The first is related to the cognitive bias of environmental change

[1] See, e.g., `https://www.damremoval.eu/`.

[2] See Dell et al. (2014) for a detailed review of the empirical development of (and challenges in) the

awareness. If economic agents misjudge a permanent climatic-environmental change to be a short-term shock, they may fail to adapt (Burke and Emerick, 2016; Dell et al., 2014). Unlike droughts, floods and other climate disasters, the effects of which fade within a short period of time, the TGD's effect on the local climate is persistent. Moreover, the dam's climatic impacts have been widely covered by the international and domestic media, which should raise farmers' awareness of the need to adapt.[3]

The second empirical challenge pertains to identifying agents' heterogeneous responses. If agents with different endowments and information spontaneously adapt in different ways, it may be difficult to detect a significant, uniform adaptation behavior among the whole population.[4] As one of China's most important agricultural production areas, the water scarcity problem in the downstream Yangtze River basin potentially affects the livelihoods of more than 12 million smallholder farmers in the area. To make progress, we use large-scale, micro-level panel data on 40,000 rural households between 1995 and 2013 from the National Fixed Point Survey (NFPS) to explore within-village household heterogeneity in adaptation.

We use a difference-in-differences (DID) design to explore both the *spatial variation* in villages' proximity to the Yangtze River and the *temporal variation* in the dam's initial impoundment in June 2003. Using Gridded Monthly Time Series Precipitation Data from Willmott and Matsuura (2016), we first identify the spatial scope of the dam's climatic effect as within the 200 km band parallel to the river downstream of the dam. We then use this 0-200 km band as our spatial treatment group and compare it to the 200-400 km band (our control group). Our DID estimation confirms that the dam has generated a substantial 13% reduction in the crop yields of rice—the main grain crop grown in the area. The results are robust to the inclusion of multiple control variables, including agricultural inputs, climate variables, family characteristics, agricultural policies, village GDP per capita, and village-specific time trends. The dam's negative effect on crop yields persists for the entire post-treatment period of 2003 to 2013.

climate change literature.

[3]See, for instance, Erica Gies, "Heading Off Negative Impacts of Dam Projects," New York Times, December 8, 2015; Matt McGrath, "Large hydropower dams 'not sustainable' in the developing world," BBC, November 5, 2018; A special report by the people.com.cn—the official propaganda website of Chinese government, "Does the impoundment cycle of the Three Gorges Dam cause the severe drought along the Yangtze River?", 10 January of 2013.

[4]For example, Jessoe et al. (2018) argue that the costs of climate change could be particularly acute in developing countries, as households in these countries "do not have access to the portfolio of adaptation strategies available in more developed countries." Cattaneo and Peri (2016) find that higher temperatures in mid-income countries increased the rate of migration to urban areas and to other countries, while in poor countries temperature increases reduced migration. They conclude that the presence of severe liquidity constraints in poor countries could explain the different responses.

We find little evidence that farmers adopt a uniform adaptation strategy to mitigate the effect from long-term decrease in yields, though we do observe farmers in the affected areas increased the cultivation area of rice on average. Taking into consideration the household heterogeneity, we identify two types of adaptation strategies among farming households. Only those households that are more financially constrained (proxied by households' landholding or external debt) or have less market transaction experience (proxied by whether they sold their agricultural products on the market) enlarge their cropping area of rice by around 12-20%. The behavior of such disadvantaged households is similar to the subsistence farmers illustrated in Aragón et al. (2020), which find that Peruvian farmers with limited coping mechanisms adapt to decreasing agricultural productivity resulted from extreme heat by increasing the plantation area.[5] In contrast, households that are less financially constrained or that have more market transaction experience shift significantly more of their labor from agricultural to non-agricultural activities, for they spend 4.5 to 6 times ($e^{1.7} - 1$ to $e^2 - 1$) more labor days (equivalent to 97 to 106 days per year) working outside their home county in non-agricultural employment.

In addition to financial constraints and market experience, we also find some suggestive evidence on the role of information and climate awareness in shaping heterogeneous adaptation. Though households' average newspaper and magazine readership does not affect which adaptation strategy they pursue, the content of this media matters. In affected villages with more local newspaper coverage on climate change or water scarcity, households are more likely to migrate out for non-agricultural employment. In affected villages with less such coverage, households are more likely to increase their cropping area of rice.

As for the welfare consequences, we find that households that choose to engage in non-agricultural activities are able to completely offset the negative shock caused by the climatic-environmental change, as there is no significant difference in their total annual income compared to similar households in unaffected areas after 2003. By contrast, households that choose to cultivate more rice can rarely mitigate the loss: their total annual income is 10-13% lower than their counterparts in unaffected areas after 2003. The varying income effects generated by the different adaptation approaches increase within-village income inequality between the two types of households.

This paper contributes to three strands of literature. First, it joins a nascent literature dedicated to understanding how rural households adapt to long-term climatic-environmental

[5]They interpret this result using agricultural household models with incomplete markets, as in De Janvry et al., 1991; Taylor and Adelman, 2003). According to these models, production and consumption decisions are inextricably linked in farming households with low consumption levels. In order to maintain a subsistence level of consumption, such households may resort to the more intensive use of non-traded inputs such as land and labor to smooth the negative income shock.

change. Several papers have used low-frequency weather fluctuation over the last few decades to identify patterns of agricultural adaption in the United States (Lobell and Asner, 2003; Schlenker et al., 2005; Deschênes and Greenstone, 2007; Burke and Emerick, 2016), India (Taraz, 2017) and sub-Saharan Africa (Barrios et al., 2006; Henderson et al., 2017). Despite some evidence of adaptation in agricultural production and urbanization identified by Taraz (2017) and Barrios et al. (2006), most studies have not found that farmers make significant adaptations to long-term changes (Dell et al., 2014). A small number of papers have attempted to identify approaches to adaptation by examining the long-run effects of a permanent shock. Hornbeck (2012), for example, studies the impact of the dust bowl in the United States. Fishman et al. (2017) and Blakeslee et al. (2020) explore the impact of increasing underground water scarcity in India. These studies have found little proof of agricultural adaptation, but substantial evidence of migration and labor reallocation to off-farm activities. In contrast, Aragón et al. (2020) and Jagnani et al. (2020) find subsistence farmers from Peru and Kenya adjust agricultural inputs such as area planted, pesticides, and weeding labor usage to cope with the negative productivity shock from hot weather. Using the permanent shock from the TGD, we find evidence on both adaptation strategies—increasing agricultural input and reallocating labor—among different rural households from the downstream Yangtze River.

Our study further clarifies the constraints that determine which adaptation strategy households choose. In what ways farmers choose to adapt, previous studies have found that this decision depends on whether the farmers have the necessary skills, resources and information to take advantage of such adaptations (Munshi and Rosenzweig, 2016; Blakeslee et al., 2020). We find that wealth and market experience are important determinants of whether farming households choose reallocating labor to non-farm sector over increasing input—the former is empirically proven to be a more efficient way in compensating loss. In addition, our findings also reveal that information from mass media about climatic-environmental change is another crucial factor that influences households' choice of adaptation strategy.

Second, by identifying households' different approaches to adapting to climatic-environmental changes as a source of the increasing income inequality, we also contribute to an emerging literature on the distributional effect of infrastructure construction, particularly dams. For example, Duflo and Pande (2007) find that the construction of irrigation dams in India benefits downstream districts by increasing agricultural production and decreasing the poverty rate, but harms the upstream districts. Similarly, Chakravarty (2011) finds that irrigation dams in Africa benefit children born in households located immediately downstream from a dam by reducing infant mortality by 3.84-4.60%, but harm areas further downstream by increasing infant mortality by 2.18-1.36%. Instead of regional inequality, our study documents an additional source of *within-village* inequality among households based on the different strategies they employ to adapt to environmental changes.

Finally, we add to a large literature on the trade-offs between economic development and environmental conservation. While early studies focused on developing general economic models of this trade-off (Arrow et al., 1995; Dasgupta, 2007) or estimating the environmental Kuznets curve using macro-level data (Grossman and Krueger, 1995; Andreoni and Levinson, 2001), recent studies have empirically estimated the climatic-environmental costs of large infrastructure projects and studied the distribution of these costs using micro-level data. Examples include the development of transportation infrastructure and deforestation in India (Asher et al., 2020) and Mexico (Alix-Garcia et al., 2013), and the impact of developing an airport traffic and urban rail network on the intensification of air pollution (Chen and Whalley, 2012; Schlenker and Walker, 2016). Our paper identifies dam-induced climatic change as a new channel of the negative environmental effect of hydroelectricity projects on agricultural production.

2 Climate Impacts of the Three Gorges Dam

2.1 The Construction of the Three Gorges Dam (TGD)

The TGD is the world's largest hydroelectric dam in terms of installed capacity (22,500 MW). It is located in Yichang, Hubei Province, and spans the Yangtze River (see Figure 1). The Yangtze runs from the west to the east of China, and the longitude of the dam is around 111 degrees, which we use to separate the river into upstream (<111 degrees longitude) and downstream (>111 degrees) regions. The whole reservoir area of the TGD includes 25 county-level districts, which has an area of 59,900 km^2 and a population of 16 million.

[Figure 1 about here]

Construction on the dam began in 1993. In June 2003 the reservoir began to fill (in what is known as the impoundment process): the reservoir's water level rose abruptly from 66m to 135m that month, the largest rise in the dam's history. The water level rose again in September 2006 to 156m at its completion.

The project soon brought real benefits to the region and the country. Each year the dam impounds and releases an average of 39.3 billion tons of water in (and from) the upstream reservoir area—generating around 88.2 billion kWh of electricity, enough for the needs of

22 million people in China (estimated at the per capita consumption at 3927.04 kWh for Chinese).[6]

Even though the dam fulfills its main objectives—to supply water for the largest hydroelectric plant in the world and to help control the devastating floods that plague the lowlands downstream—it has also generated negative social and environmental costs. The reservoir flooded more than 1,300 villages from 13 cities, causing the relocation of 1.2 million people, and hazardous waste dumps were created throughout the planning and implementation stages of the TGD (Brown et al., 2008). The TGD also increased seismicity from the loading of the water, landslides, changed ecosystems, accumulated pollution, increased the chances of waterborne diseases, and changed the salinity of the Yangtze estuary.[7]

2.2 Climate Impacts of the Three Gorges Dam: Hydrological and Climatological Evidence

The dam's construction has generated ongoing debates about its environmental (particularly climatic) impacts among the public as well as scientific communities. Scientific debates over whether the water impoundment cycle would permanently change the precipitation and temperature pattern along the Yangtze River heated up after two unprecedented droughts badly affected the river's downstream region in 2006 and 2011. Rainfall in the river basin was 40% below average during the 2011 drought (Qiu, 2011).

Hydrological studies have found evidence to link the TGD to the decreasing precipitation in the downstream areas. For example, using independent satellite rainfall data and numerical simulations from NASA's Tropical Rainfall Measuring Mission, Wu et al. (2006) confirm that the monthly precipitation level decreased in the downstream region but increased upstream after the dam's water level abruptly rose in June 2003. In a more recent study using detailed daily precipitation data, a group of researchers from the National Meteorological Center (Ma et al., 2010) confirms the decrease in precipitation and humidity downstream of the reservoir, especially in spring, and the increase in precipitation and humidity upstream.

Hydrologists have further identified the water impoundment cycle of the TGD as the likely cause of the decrease in precipitation downstream. Taking advantage of gravity and the water cycle, mega-hydroelectric dams harness the potential energy of moving water to generate electricity. To capture as much energy as possible, the TGD is designed to impound water during the flood season in the upstream area (between October and May) and release

[6]See more statistics about the TGD from the Chinese Wikipedia (`https://zh.wikipedia.org/wiki/Three_Gorges_Dam`).

[7]See more details from Mara Hvistendahl, "China's Three Gorges Dam: An Environmental Catastrophe?," Scientific American, March 25, 2008.

water in the upstream drought season (June to September) to generate electricity. This design has two advantages. First, during the impoundment period, the reservoir can capture the abundant water resources from the melting glaciers on the Tangula Mountains—the origin of the Yangtze River—in winter and spring. Second, the water release period between June and September corresponds to the peak season of electricity consumption in the summer, so more electricity can be generated to meet the increasing demand.

This water impoundment cycle inevitably changes the river's natural water cycle. For example, Li et al. (2013) confirm that the initial impoundment in 2003 significantly reduced the river runoff downstream in the spring, which accounts for the downstream aggravation of the hydrological drought. Similarly, a scientific report from Nature confirms a decreasing downstream sediment discharge during winter and spring (Yang et al., 2015). Wang et al. (2013) also find a significant decrease in the downstream river level after the dam's construction.

The impoundment cycle eventually leads to a seasonal water shortage in the downstream areas. Figure 2 illustrates the mechanism linking the dam's impoundment cycle (characterized by decreasing runoff and discharge, which reduce water evaporation) with the decrease in precipitation downstream.

[Figure 2 about here]

Many hydrological and climatological studies have found evidence that the TGD has caused a downstream water supply problem. Other studies have documented changes in the air temperature, especially in the reservoir area. However, the literature has not yet reached a consensus on the geographic scale of the impacts. Previous studies mainly focus on relatively small geographic areas, such as the area immediately downstream of the dam or near lakes connected to the river. For example, when studying the effects on precipitation, Ma et al. (2010) only simulate the effects in upstream regions of the dam. Similarly, when addressing temperature effects, Deng et al. (2012) find a warming trend only within the reservoir area of the dam. The overall geographic scale of the dam's climate effects in the vast downstream Yangtze River basin is unclear. Before we further explore the agricultural impacts of the water shortage, the next section assesses the scale of the dam's climate impacts.

2.3 Climate Impacts of the Three Gorge Dam: A Difference-in-Differences Analysis

This section systematically analyzes the TGD's climate impacts in the downstream area using a DID approach and monthly precipitation data. The precipitation data are taken from the Terrestrial Air Temperature and Precipitation 1900-2014 Gridded Monthly Time Series.[8] According to Dell et al. (2014), this dataset is the most frequently used gridded weather data by economists. We use data between 1990 and 2013 to construct a relatively balanced panel before and after the dam's construction.[9]

Our DID design draws on (1) regional variation by comparing regions that are closer to the river with those farther away and (2) temporal variation by comparing the years before and after the initial impoundment of the dam in June 2003. The design assumes that regions close to the river are more likely to be affected by the dam's water impoundment cycle after 2003. However, since we lack priori knowledge on the geographic scale of the dam's climatic impact, we try different specifications by comparing eight different 50km distance bands along the Yangtze River (Figure 1).

In order to determine the geographic scale of the dam's climate impact, we estimate a DID model with the following specification:

$$Y_{it} = \beta_0 + \sum_{k \in K} \beta_k \cdot (0,1) Dist_{i,k} \cdot P_{t,2003June} + \delta_i + \mu_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} denotes the total precipitation in grid i at year-month t; the set K contains the seven distance bands parallel to the Yangtze River (regions from the band that is 350-400 km away is the reference group), the dummy variable $Dist_{i,k}$ denotes whether grid i is located in band k in the downstream area; and δ_i and μ_t are grid and year-month fixed effects, respectively. We cluster standard errors at the grid level.

Our DID estimates β_k are the coefficients of each band dummy interacting with the post-June 2003 dummy variable, which captures the differences in precipitation between each of the seven bands and the reference group before and after June 2003. The model is estimated using a sample of all grids that are within 400 km of the river covering the entire downstream river basin.

We restrict our analysis on precipitation to the impoundment period (October to May). As discussed in Section 2.1, the downstream water supply problem is likely the result of the dam's impoundment cycle, as evident in Figure 3, which plots the average monthly changes

[8] We use Version 4.01 provided by Matsuura and Willmott from `http://climate.geog.udel.edu/~climate/html_pages/Global2014/README.GlobalTsP2014.html`. This dataset provides global (terrestrial) monthly average temperature and precipitation at a 0.5*0.5 degree resolution (approximately 56*56 km at the equator). Climate scientists use a combination of three spatial interpolation models to interpolate values for each grid from an average of 20 nearby ground weather stations for the whole terrestrial surface of the earth, adjusting for elevation.

[9] Gridded interpolated datasets are a good source of information on temperature and precipitation for economic analysis, as they provide a balanced panel that adjusts for issues like missing ground station data. We use daily weather data from 2,308 ground observatory stations in China between 1990 and 2013 to confirm the robustness of our estimates.

in river runoff at four downstream hydrological stations after the initial impoundment in 2003.[10] The figure shows that the downstream runoff indeed significantly decreases between November and April, and significantly increase between June and September when the dam normally releases water. Appendix Table A1 reports the summary statistics of the monthly precipitation by each distance band.

[Figure 3 about here]

Figure 4 shows that bands closer to the river have significantly lower precipitation after the initial impoundment, up to 200 km away from the river. Figure 4 plots the DID coefficients estimated for each of the seven bands compared to the reference 350-400km band using equation (1). We find that the coefficients on the 0-50 km, 50-100 km, 100-150 km, and 150-200 km bands are all negative and statistically significant. This finding indicates that the construction of the TGD reduced precipitation within a 200km band along the river in the downstream area. The coefficients on the 200-250km, 250-300km, and 300-350km bands are all statistically insignificant and close to zero, indicating that dam does not have an effect beyond the 200km range. Appendix Table A2 reports detailed estimated coefficients.

[Figure 4 about here]

The following analysis of the dam's impact on agricultural production and farmers' adaptation uses a simplified specification to compare a larger 0-200 km band with a 200-400 km band of the river downstream:

$$Y_{it} = \beta_0 + \beta_1 \cdot (0,1)Dist_{i,200} \cdot P_{t,2003June} + \delta_i + \mu_t + \varepsilon_{it}. \tag{2}$$

Finally, we find that the TGD's negative precipitation effect is not restricted to the area immediately downstream of the dam; it also extends to the entire downstream region. Figure 5 plots the DID coefficients estimated for each longitude degree following equation (2). We find that most of the coefficients in the downstream areas are negative and even larger in magnitude in regions that are far from the dam. This finding implies that regions that are far from the dam but close to the river can still be affected by the TGD. The geographical scale of the climate shock we identify is larger than that detailed in previous hydrological studies, which indicates that more downstream households will be at risk.

[Figure 5 about here]

[10]The river runoff data is obtained from the *Annual Report National Hydrology (1999-2014)*.

3 Effects of the Dam on Agricultural Production

In this section, we evaluate how the water scarcity caused by the TGD affects the yields of major agricultural crops in the vast downstream areas.

3.1 National Fixed-Point Household Survey (NFPS) on Agriculture

We use household-level data on agricultural production and household behaviors from the NFPS for this analysis (Benjamin et al., 2005). This survey, conducted by the Chinese Ministry of Agriculture since 1986, tracks a nationally representative sample of about 20,000 rural households in approximately 300 villages, covering all 31 continental Chinese provinces. The NFPS administers both village- and household-level questionnaires. NFPS villages were selected for representativeness based on region, income, cropping patterns, population, and non-farm activities. The village questionnaire contains rich information on the socio-economic conditions of the village. Of the 300 villages, 94 are located within the 400 km band downstream of the dam. These 94 villages constitute our main sample of analysis (see Figure 1 for the geographic locations of these villages).

Within each sampled village, households are randomly selected to complete the household and individual (for each adult member of the household) questionnaires. Thus, the household sample analyzed in this paper consists of a panel of about 7,000 households across 94 villages in 10 provinces for the period 1995-2013. The household questionnaire contains detailed information on household agricultural production by crop, non-agricultural activities, household consumption, asset accumulation, employment, and income. Benjamin et al. (2005) provide a detailed description of the data and present evidence that the data are of good quality. The long time span panel structure of the data and the detailed information on household economic activities are an ideal and unique fit for our empirical purpose.

Table 1 presents the summary statistics of the main variables we use for the empirical analysis. The area we study has an average temperature of 16 degrees Celsius and 110 mm of precipitation per month. Rice is the most important grain crop grown downstream: around 58% of households grow rice, while only 33 and 24%, respectively, grow wheat and corn. Of all grain crops, around 64% of the land is used for rice cultivation, 26% for wheat cultivation, and less than 10% for corn. To measure adaptation in other margins, we also construct measures on the time (or share of time) spent on local non-agricultural activities within and outside one's home county (out-migration), measured as the number of days of labor. Share of time is measured as the number of days of labor spent on a specific activity over days of labor spent on all activities. In our data, around 17% of the labor days are spent on local non-agricultural work and 19% on out-migration non-agricultural work.

Following Burke and Emerick (2016), we measure crop yields as the logarithm of output divided by total sowing area. Agricultural inputs—such as labor, fertilizer, pesticide, agricultural films and seed—are also measured as the logarithm of input per area. We also take the logarithm for non-agricultural labor days, migration labor days, total income, and income per capita.

[Table 1 about here]

3.2 Effects of the Three Gorges Dam on Crop Yields

We use a DID specification similar to equation (2) to estimate the dam's effects on crop yields in regions that have experienced an unexpected decrease in total precipitation. The empirical model is estimated at the household level and is specified as follows:

$$Y^k_{mnt} = \sigma_0 + \sigma_1 \cdot (0,1) Dist_{n,200} \cdot P_{t,2003June} + \sigma_2 lnarea^k_{mnt} + \sigma_3 lnlabor^k_{mnt} + \theta_m + \mu_t + \omega_{mnt}, \quad (3)$$

where Y^k_{mnt}, the outcome variable denotes the yield of crop k (among either type including rice, wheat, corn, soybean, cotton, and vegetable) produced by household m in village n in year t. $Dist_{n,200}$ indicates that village n is within the 0-200 km band parallel to the Yangtze River. Model (3) is estimated using the sample of 94 villages within 400km of the river downstream of the dam. To control for the effects of economies of scale, we include the logarithm of total farming area of each crop $lnarea^k_{mnt}$ as the control variable in all models. We also control for crop-specific days of labor per mu $lnlabor^k_{mnt}$ to measure the labor input. We include household fixed effects θ_m and year fixed effects μ_t in all model specifications at the household level and cluster all standard errors at the village level.

Table 2 reports the results. Panel A shows the impacts of the TGD on three main grain crops—rice, wheat, and corn. Panel B shows the impacts on other crops, including soybeans, cotton, and vegetables. For each type of crop, we first estimate a model without adding any control variables in the first column. The second column includes input control variables, including land and labor.[11]

[Table 2 about here]

[11] When estimating the effects on crop yields, we only include households that grow the specific type of crop in the sample. Therefore, the sample sizes are different for each crops.

We find that rice yields decreased significantly by around 13% in areas where the TGD unexpectedly reduced the total precipitation. This result is robust to controlling for different agricultural inputs (column (2)), the coefficient of which only slightly decreases to 12%. The negative impact on rice yields is consistent with our earlier finding that the TGD mainly reduced precipitation in the spring, because this is the primary growing season for rice in affected areas. Rice is also the crop that requires the most water during the growing season. We find no statistically significant effects on other types of crops after controlling for inputs.

Even though we only identify a significant negative effect on rice, the overall effect is still economically important. Crops other than rice are not grown by every household in the region. Therefore, either the drop in precipitation has no significant effect on the other five types of crops, or our sample size is too small to identify any significant effects. Nevertheless, the overall effect is economically significant, since rice accounts for around 64% of the total cropping area of grain crops in the region.

We then test the parallel time trend assumption of the DID analysis by estimating the TGD's effects on crop yields for each year since 1995 using the following equation:

$$Y_{it} = \varphi_0 + \sum_{k=1995}^{2013} \varphi_k \cdot (0,1)Dist_{i,200} \cdot P_{t=k} + \delta_i + \mu_t + \varepsilon_{it}. \tag{4}$$

Figure 6 plots the coefficients on rice yields; it shows that the differences between the treatment and control villages do not exhibit significant pre-trends before 2003. However, the differences between the groups decrease sharply after 2003, indicating that the changes in rice yields were indeed caused by the sharp decline in the water supply downstream generated by the dam's initial impoundment that year. Moreover, instead of a temporal shock, the dam induced a persistent decrease in rice yields during our study period. The most serious adverse effect happened between 2011 and 2013 when an extreme drought hit the downstream area. Appendix Figure A1 reports the figures for other types of crops, which show no significant changes over time.

[Figure 6 about here]

3.3 Robustness Checks

3.3.1 More Controls on the Crop Yield Effect

To check the robustness of our findings on rice yields, we add additional control variables one by one in the regressions and report the results in Table 3.[12] First, we add proxies

[12] The full results are reported in Appendix Table A3.

for village- and county-level GDP as well as village-specific linear time trends in column (1). Village- and county-level GDP, documented in village-level surveys or approximated by measures derived from nighttime satellite images, control for the changing opportunities for non-agricultural employment. Village-specific linear time trends control for differences in other unobservable time trends, if any, between the treatment and control villages. Second, we add controls for land and labor inputs in column (2).

[Table 3 about here]

Third, since crop yields can also be affected by various agricultural policies and reforms, some of which also occurred around 2003, we take into consideration three main agricultural reforms during this period: the agricultural tax reform (2001-2006), the property rights reform (2004-2013), and the "return farmland to forest" policy (1999-2008). For each of these policies, different provinces or counties enrolled into the program at different time points. We use information on the location and timing of the implementation of the reforms to construct the controls.[13] We generate three measures to denote whether a village in a specific year was within the province or county that has implemented the policy, respectively. We control for these measures of policy implementation as additional control variables in column (3) and find no significant change in our result.

Fourth, in column (4), we add controls for other climate variables that previous studies have demonstrated have significant impacts on crop yields, including temperature, the square of temperature, humidity, and atmospheric pressure (Schlenker and Roberts 2009; Zhang et al., 2017). Fifth, in column (5), we control for additional agricultural input variables, including the amount of fertilizer, the amount of agricultural chemicals applied for each type of crop (pesticide), and yearly household expenditure on agricultural films. We also control for household characteristics that may affect crop yields, including the number of agricultural laborers and their average education level. Due to the missing data for these variables, the number of observations drops significantly. Nevertheless, we find that adding additional control variables barely changes the magnitude of the dam's effect on rice yields.

Finally, in order to study the adaptation behaviors of rice farmers, we restricted the household sample to those who grew rice prior to the dam (in 2002) in columns (6) and (7). Column (6) includes all control variables, while column (7) only includes village- and county-level GDP and village-specific linear time trends. We find that restricting to this

[13]We collect county-level information on the implementation years for the agricultural tax reform from the Fiscal Statistical Compendium for All Prefectures and Counties (1999-2007). The provincial-level timetable for the property rights reform is from Chari et al. (2020), and the provincial-level information on the implementation year for the return farmland to forest policy is from the China Forestry Statistical Yearbooks (1999-2015).

subsample has little effect on the results. Therefore, our empirical findings are quite robust to both additional control variables and using a restricted sample, which implies that our DID empirical strategy is unlikely to be contaminated by unobservable different time trends between the treatment and control groups. Since adding additional control variables does not significantly change the results on yields, in order to maintain the size of the analytical sample we use the specification in column (7) as the main specification to analyze adaptation in the rest of the paper.

3.3.2 Effects of State Intervention

The central government spent an estimated 85.6 billion resettling households affected by the construction of the TGD (National Audit Office, 2013).[14] Those located near the reservoir received substantial compensation to cover the environmental costs. Yet the central government did not create guidelines to provide climatic compensation to farmers residing downstream of the dam. In fact, it only very recently acknowledged that the project had any impacts.[15] Given its skepticism regarding such an impact, the government is unlikely to provide fiscal subsidies to farmers residing in the downstream areas. Nevertheless, we utilize detailed annual village-level data on fiscal revenues and expenditures to formally test whether villages receive fiscal transfers from the central government. Table 4 reports the results by estimating the dam's effects on various types of fiscal revenues and expenditures at the village level using the DID model in equation (2). We find no significant increase in revenue transferred from the central government to local governments. Nor do we find any significant increase in total expenditure, subsidies for irrigation, subsidies for other agricultural inputs, or expenditures on general public goods provision. The coefficients on subsidies for other agricultural inputs and expenditures on public goods are even negative. These results suggest that no government subsidies have been provided to downstream villages to compensate for the dam's economic impact.

[Table 4 about here]

[14]For more detail, see "Audit results of the financial accounts for the completion of the Three Gorges Dam Project," June 7, 2013, (http://www.gov.cn/gzdt/2013-06/07/content_2421795.htm).

[15]For more detail, see International Rivers Organization, "Chinese Government Acknowledges Problems of Three Gorges Dam," May 19, 2011, (https://www.internationalrivers.org/blogs/227/chinese-government-acknowledges-problems-of-three-gorges-dam).

4 Adaptation by Farmers

In the previous section, we confirmed that the construction of the TGD generated a substantial, persistent negative impact on the yields of rice—the most important agricultural crop in the area—for households downstream. In this section, we explore whether farmers in these areas have actively adapted to this negative climate shock, for example by changing their cropping patterns, agricultural inputs, distribution of labor days between local agricultural and non-agricultural activities, or out-migration decisions.

4.1 Farmer Households' Adaptations

In response to a persistent decrease in precipitation, farmer households can adopt different strategies to mitigate the negative effects on crop yields. One direct adaptation strategy is to switch to crops that are less affected by aridness, such as corn. We test whether this is the case by determining whether the inputs in terms of land and labor days for the six main grain and cash crops change in the areas affected by the dam in Table 5. We use similar specifications in equation (3), changing only the dependent variables and restrict the sample to rice-growing households in 2002. The model specification is the same as Table 3, column (7). Panel A reports the results on the area and labor of rice and other grain crops. Appendix Table A4 reports the results for all six main crops.

[Table 5 about here]

We find that farmers do not increase the amount of land or labor devoted to other grain crops. They instead significantly increase the total cropping area of rice after the shock. While this does not seem to be an economically efficient way to compensate for the loss, it may help farmers maintain their total level of output. Section 5.3 examines in more detail whether such an adaptation strategy can effectively mitigate the income shock from decreased precipitation.

Farmers can also adapt to water scarcity by increasing other inputs such as fertilizer, pesticides, agricultural film or spending more on better seeds to boost the yields. But the results from Panel B of Table 5 show no significant increase in these four types of additional inputs.

One potential margin of adaptation to the persistent decrease of precipitation is to increase investment in irrigation for the affected households (Taraz, 2017). However, due to the data limitation that the NFPS only provide information on household level irrigation expenditure after 2003, we cannot explore the same difference-in-differences analysis to examine the effect on it. We do compare the time trends of households' irrigation expenditure in the affected areas with those in the unaffected areas and find no clear divergence of irrigation investment between the two areas after 2003. However, a more rigorous test on irrigation investment requires more detailed and completed data.

Finally, we also want to check whether the farmers affected by the dam increase their non-agricultural activities, such as finding part-time non-agricultural employment in the village or migrate out to seek more non-agricultural employment opportunities.[16] We replace the dependent variables with the total labor days that farmers spent on local non-agricultural job in column (9) and on out-migration in column (11) and use the share of labor days on these two types of non-agricultural jobs in columns (10) and (12) in Panel C of Table 5. We still do not find significant changes in the amount or share of time farmers spend on local or out-migration non-agricultural activities.

Other than increasing the cropping area of rice, the lack of evidence that the average household is adequately adapting in other ways implies that farmers in affected regions are facing certain constraints. For example, those with limited access to information may not be aware of the extent and persistence of the climate shock induced by the dam. Even if they are aware of the problem, farmers with financial constraints may not have the necessary resources to change their cropping patterns or to switch to non-agricultural activities locally or migrate to other places. To verify if this is the case, we examine whether there are differentiated patterns of adaptation by households facing different constraints in the next section.

4.2 Differentiated Adaptations by Households with Different Constrains

This section explores the effects of household heterogeneity on patterns of adaptation to the dam's local climate shock.

4.2.1 Financial Constraints

Farmers may lack the financial resources to adopt any active strategies other than simply increasing the area cultivated with rice. For example, Dustmann and Okatenko (2014) find that migration intentions correspond to individual wealth. Similarly, Bazzi (2017) finds that households' level of wealth affects their intention to migrate in response to persistent income

[16]Constrained by China's *hukou* registration system, farmers seldom move. Since the economic reform in 1978 they have been allowed to temporarily move to find jobs in other areas. Farmers often exploit such opportunities to find non-agricultural jobs in urban areas to obtain higher wages. Normally, these migrant farmers return home at least once a year.

shocks. Angelucci (2015) discovers that financial constraints on international migration are binding only for low-income Mexican households. Given the significant effects of financial constraints, Cai (2020) confirms the positive impact of credit access on farmers' migration decisions. We thus use the amount of land owned by the household as a measure of wealth, and the size of its external debt as a measure of access to credit to examine the heterogeneous patterns of adaptation depending on financial constraints. For the wealth channel, we divide the sampled households into "high" and "low" groups based on whether their land holdings are above or below the median level in 2002.[17] For the credit channel, given that only about 18% of households owed money in 2002, we divide the households into "high" and "low" groups based on whether they had debts at the end of 2002.[18] We then run the following regression separately for the "high" and the "low" groups of households:

$$Y^H_{mnt} = \gamma_0 + \gamma_1 \cdot (0,1)Dist_{n,200} \cdot P_{t,2003June} + X^H_{mnt} \cdot \beta_i + \theta^H_m + \mu_t + \sum_{j=n}^{J} J \cdot T + \omega_{mnt}, \quad (5)$$

where the superscript H denote whether the sample is from "high" or "low" group, $(0,1)Dist_{n,200}$ is our key explanatory variable, namely the village's distance to Yangtze River, X^H_{mnt} stands for control variables, $\sum_{j=n}^{J} J \cdot T$ stands for village specific time trends.

Panel A of Table 6 shows that households' wealth significantly affects their adaptation patterns: those with less land grow more rice, while those with more land spend more time on out-migration non-agricultural activities. Panel A of Table 6 uses household-level farm size to measure financial constraints. Panel A1 reports the results for the "high" households and A2 for the "low" households. Panel A shows that rice yields significantly decreased due to the impacts of the dam for both types of households. However, only households with below-median farm sizes increased their cropping areas of rice by 19%. Those with above-average-sized farms significantly increased their total labor days on out-migration, suggesting that the two types of families indeed used different strategies to cope with the climate shock of the dam. According to our estimation, families affected by the shock with larger farms spend 4.5 times ($e^{1.7} - 1$) more labor days (equivalent to 97 days per year [19]) than those unaffected by the shock as migrant workers in non-agricultural sectors outside their home

[17] Given the practical difficulties of converting rural households' assets into monetary value, the NFPS does not provide information on family wealth. We thus use the quantity of the most important asset for rural households—size of arable land—to proxy for family wealth.

[18] These debts include formal bank loans, loans from rural credit cooperatives, and money borrowed from relatives and friends.

[19] We calculate this magnitude by using labor days rather than the logarithm of labor days as the dependent variable in the same regression

county. The coefficients on local non-agricultural activities are also different between the two groups: the pertinent coefficient for large households is positive and marginally significant, while the corresponding coefficient for small households is negative.

[Table 6 about here]

We find similar empirical results for the credit access channel. Panel B of Table 6 shows that "low" debt households (those with no debt) significantly increase the number of acres cultivated with rice, while "high" households (those with some debt) significantly increase the number of days of labor devoted to out-migration non-agricultural activities. However, given that the magnitude of the coefficients for the two groups is very similar, the significance level is only due to smaller standard errors, which suggests the evidence provided by the credit access channel is still weak.[20]

In sum, we find that farming households adopt different adaptation strategies according to the level of family wealth, approximated by the size of their land holdings. Poorer households adapt by cultivating more rice, while richer households choose a more efficient way to engage in non-agricultural activities—working outside the home county.

4.2.2 Market Experience

The extent to which humans adapt to climate change partially depends on the information they receive. The market is an important channel for such information, for instance through price signals (Anderson and Kirwin, 2018). Therefore, the second constraint on farmers' adaptation that we explore is market experience constraints. Farmers may be constrained by a lack of access to information on outside economic opportunities, which they need in order to choose more efficient adaptation strategies such as non-agricultural activities.

We test this channel by looking at farmers' past market experience at the household level. We divide households into the "high" market experience group if they sold an above-median share of their agricultural products (rice) in the market in 2002, and the opposite for the "low" group.

Table 7 reports the regression results divided by degree of market experience. The results suggest that the dam reduced rice yields for both types of households (columns (1) and (8)). However, similar to wealth, market experience also sorts households into two groups that adopt different adaptation strategies. Households with "low" market experience increase the amount of land cultivated with rice by 20% after the shock of the dam, while those with

[20] Because the number of households with any debt is relatively small (only 8,576 observations), the comparison between "high" and "low" households in Table 6 is very unbalanced, which may explain why we find a relatively weak result.

"high" experience significantly spend 6 times ($e^2 - 1$) more the number of days (equivalent to 106 days per year) as migrant workers outside their home county. The pertinent coefficient for local non-agricultural activities is also positive with large magnitude of the effect and very close to the level of statistical significance. The two groups of households have no significant differences on other margins.

[Table 7 about here]

4.2.3 Media Coverage

Finally, agents' awareness of climate change, which is crucial for determining the pattern of adaption behavior (Dell et al., 2014; Burke and Emerick, 2016), can also be shaped by media coverage (Schmidt et al., 2013; Brulle et al., 2012). Therefore, the third constraint we study is access to information on climate change through local media. Since we do not have good measures on household-level media access, we study media coverage at the village level.

First, we construct a measure of village-level media access by counting the number of local newspapers and magazines. We classify villages as having "high" levels of media access if they had an above-median (n = 30) number of newspapers and magazines in 2002, and the opposite for the "low" group. Table 8 shows that while households in low-access villages adapt to the climate shock by increasing the cultivation area of rice, those high-access villages are only marginally more likely to engage in out-migration activities (the coefficient is positive but not significant at the 10% level).

[Table 8 about here]

Accessibility to information is also determined by media content. To improve our measure of information, we therefore construct a measure of whether local newspapers report on climate change and/or water scarcity. We use the digital archives of 177 general-interest newspapers published in mainland China from Wisenews, a Hong Kong-based data vendor of newspaper content, from which we obtained all news articles containing the keywords "climate change" (*qihou bianhua*, *qihou bianqian*) and "water scarcity" (*queshui*, *hanzai*, *hanqing*, and *ganhan*). We then count the number of reports related to climate change and water scarcity by prefecture and year. We then merge the prefecture-level variable with the villages and separate the sampled villages into a "high" media coverage group (some coverage on climate change) and "low" coverage group no such reporting.

Table 9 shows that households' adaptation behaviors differ across villages that receive different levels of climate change-related media coverage. Panel E2 shows that villages that receive no coverage choose the less efficient adaptation method by increasing the cultivation area of rice by around 21%. Villages with such coverage choose the more efficient way of adaptation through out-migration: farmers in these villages spend around 2 times ($e^{1.13} - 1$) more time (equivalent to 73 days per year) on non-agricultural activities outside their home county. These findings suggest that information related to climate change provided by local media can facilitate economically more efficient adaptation to local climate shocks.

[Table 9 about here]

4.3 Discussions about Constraints on Adaptation

Table A5 in the Appendix provides the summary statistics comparing the different characteristics of the "high" versus "low" types of households. These comparisons show that the "high" type of households in terms of wealth (land holdings) also have more access to credit and market experience, while the "low" type is deprived in all dimensions. The finding that only the "low" type of households choose to increase land input—a seemingly less economically efficient way than taking non-agricultural jobs—to adapt proves that endowments in wealth, financial resource, and knowledge indeed constrain farmers' choices of adaption. The behaviors of the "low" type households in the downstream Yangtze regions resemble those of the Peruvian farmers described in Aragón et al. (2020), where the authors find that farmers with limited coping mechanisms to the extreme heat choose to adapt by increasing the area planted. Similar to Aragón et al. (2020), we can also explain the behavior of the "low" type household following the standard agricultural producer-consumer household models as in De Janvry et al. (1991) or Taylor and Adelman (2003). In these models, the farming households are on the edge of subsistence. Therefore, they typically make simultaneous, interrelated consumption and production decisions. When negative productivity shock hits, they may have no choice but to resort to more intensive use of non-traded inputs such as land and labor so as to subsist. In their models, the subsistence farmers are often constrained by the imperfections in input markets such that they can't choose a different adaptation strategy. We find that they are also constrained by endowments. The "low" type households cannot afford strategies such as migrating-out for non-farm jobs, adopting new farming technology, and etc.,which require some inputs and/or knowledge as fixed costs.

5 Welfare Consequences of the Climate Shock

In this section, we explore the welfare consequences of these differentiated adaptations by different types of households. Specifically, we want to understand whether more economically efficient adaptive measures help some households mitigate the negative income shocks.

Households' different degrees of ability to mitigate shocks may increase income inequality due to climate change.

To estimate the overall welfare effects of the dam-induced climate shock, we compare the differences in either total household income or income per capita between households located within the 0-200 km band vs. the 200-400 km band downstream of the Yangtze River over time. Panel A of Table 10 reports the results using total income as the dependent variable, while Panel B reports the results using income per capita as the dependent variable. We find that the climate shock negatively affects the income level of the average household. Affected households have an 8.3% lower household income (significant at the 10% level, column (1)), and 6.3% lower per capita income (barely significant, column (5) in Panel B).

[Table 10 about here]

To further quantify the increase in inequality due to farmers' differentiated adaptations, we add the interaction terms between the DID variable (After 2003 × within 200 km) and a dummy variable indicating the "high" group categorized by each household-level factor affecting the pattern of differentiated adaption from Tables 6 to 7—family wealth, credit access, and market experience. The empirical model is specified as follows:

$$Welfare^{H}_{mnt} = \varphi_0 + \gamma_1 \cdot (0,1)Dist_{n,200} \cdot P_{t,2003June} + \gamma_2 \cdot (0,1)Dist_{n,200} \cdot P_{t,2003June} \cdot High_{mn} + X^{H}_{mnt} \cdot \beta_i + \theta^{H}_{m} + \mu_t + \sum_{j=n}^{J} J \cdot T + \omega_{mnt}, \quad (6)$$

where $High_{mn}$ is a dummy variable indicating whether household m is from the "high" group. After adding interaction terms between $High_{mn}$ and $(0,1)Dist_{n,200} \cdot P_{t,2003June}$, coefficient γ_1 captures the main effect of $(0,1)Dist_{n,200} \cdot P_{t,2003June}$, which depicts the across-region income gaps of the "low" group households from the affected vs. unaffected areas. Coefficient γ_2 of the three-way interaction terms measures the within-region income gaps between the "high" and "low" groups from the affected areas.

The estimation results are shown in columns (2)-(5) and columns (6)-(8) in Table 10. The results of the main effects (Panel A) show that the climate shock caused by the construction of the TGD significantly reduced the total income of households with smaller land, less credit access and less market experience by 12.5%, 9.7% and 10%, respectively. For the within-region comparison, we find that households with more land and more credit access are able to mitigate the negative climate impacts on total income. The coefficients on the three-way interaction term for these two groups are positive, and the overall effects ($\gamma_1 + \gamma_2$) are close to zero. These findings suggest that the negative impacts on total household income are mainly driven by households that took economically inefficient adaptation measures (increasing the cultivation area of rice). Households with more land and access to credit can adapt to the shock more efficiently (increasing participation in out-migration non-agricultural activities) and therefore successfully mitigate the negative impacts.

Although the level of statistical significance is lower for the results on per capita income than for total income, the sign and magnitude of the coefficients are still similar. Panel B of Table 10 shows that only small farms have significantly lower per capita income after the climate shock, but the coefficients estimated using other criteria are also negative and close to the 10% level of significance. For the within-region comparison, similar to the results on total income, households with more land and access to credit are able to mitigate the initial negative shock and maintain a stable per capita income level due to their more efficient adaptation strategy.

In sum, we find that adaptation through out-migration or engaging in non-agricultural activities helped the "high" group mitigate the income shock caused by the change in precipitation. By contrast, the "low" group's adaptation strategy—cultivating more land with rice—barely mitigates the income shock. In addition to cross-region income differences, the dam also exacerbates income inequality between different types of households in the affected areas.

6 Conclusion

This paper provides some of the first evidence on the medium- to long-term impacts of large-scale, climatic and environmental shocks on rural populations in developing country. When the construction of a mega energy project induces such shocks and permanently changes the local climate and environment, small household farmers who rely on labor-intensive, family-farming agriculture in these countries are particularly vulnerable to these changes.

Using the construction of the world's largest hydroelectric project (the TGD) as a case study, we first confirm that downstream areas experienced a substantial loss of precipitation—a critical source of irrigation water for farming—after the initial impoundment of the dam in June 2003, which caused a substantial 13% decrease in rice yields in villages close to the river compared to those further away. More importantly, this adverse effect does not seem to attenuate over time, raising concerns about the long-term impacts on farmers' livelihoods.

However, households react differently to resource constraints, and adapt in different ways. Those with abundant wealth, access to credit, and market experience seem to be relatively successful at offsetting the agricultural income losses by reallocating labor to off-farm employment locally, or migrating out for better economic opportunities, which leaves their total income relatively unaffected. Disadvantaged households adapt by increasing the total cropping area of rice, which barely compensates for the income loss associated with the reduction in yield. Over time, these different approaches to adaptation widen the within-village income disparity between these households.

These results suggest that disadvantaged households in developing countries are more vulnerable to long-term climate impacts because resource constraints limit their adaptation strategies. Although the adverse impacts on income caused by the climate-change-induced loss of agricultural production can be mitigated by developing the local non-agricultural economy and out-migration opportunities, we find that such opportunities are usually not available to households characterized by less wealth, access to credit, and market experience. Therefore, differentiated adaptation strategies widen the income gap, which could be another social problem induced by agro-climatic and environmental changes that calls for government and social intervention.

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Tables and Figures

Figure 1. Location of TGD and Survey Villages Downstream of the Yangtze River

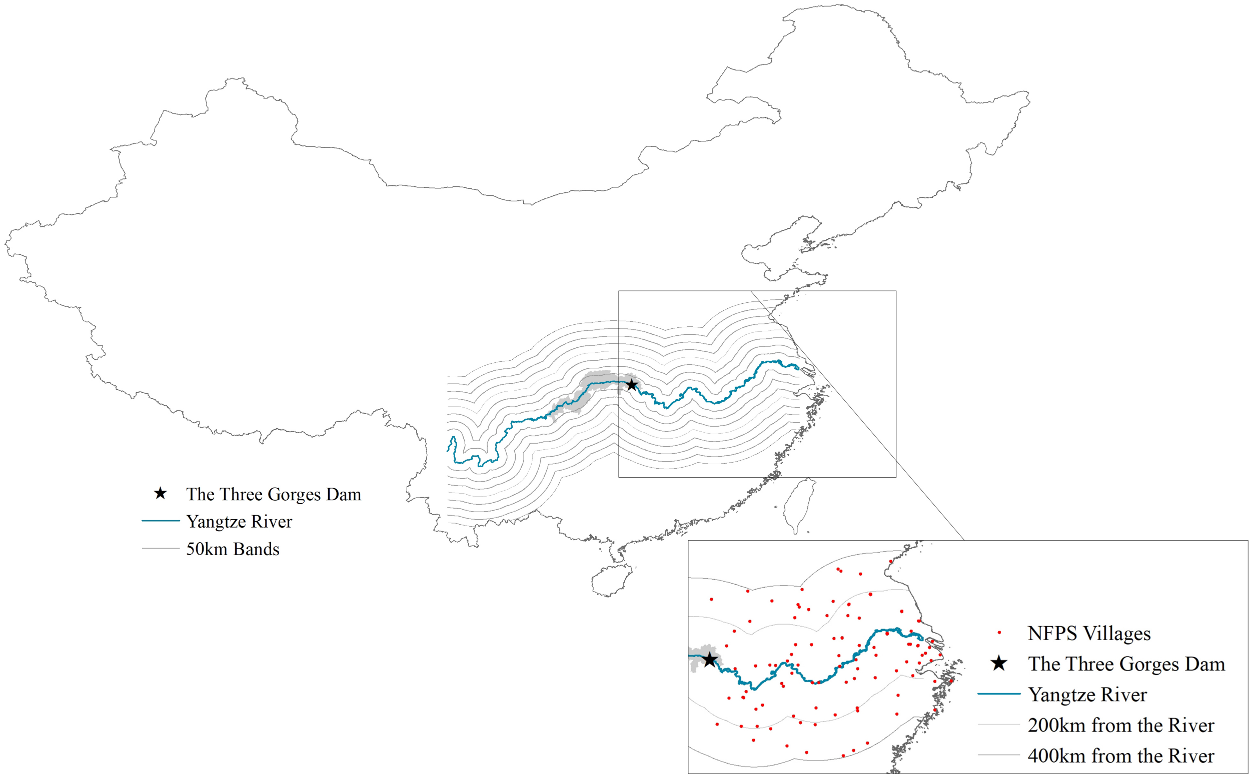


Figure 2. Illustration of the Climatic Effect from the Water Impoundment Cycle of the TGD

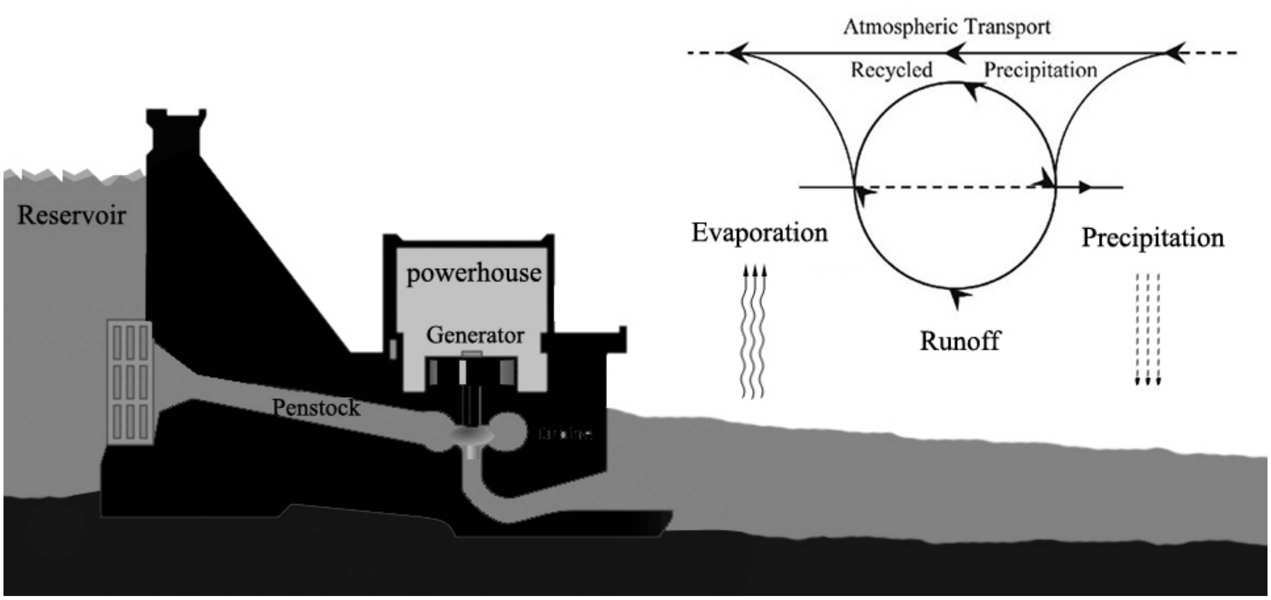
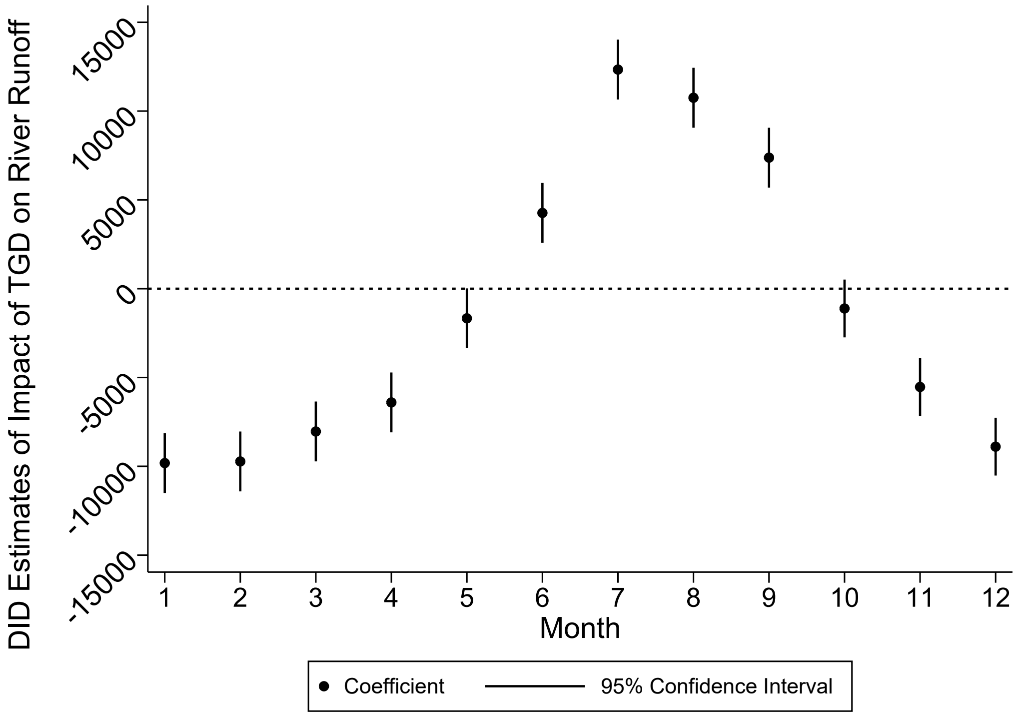
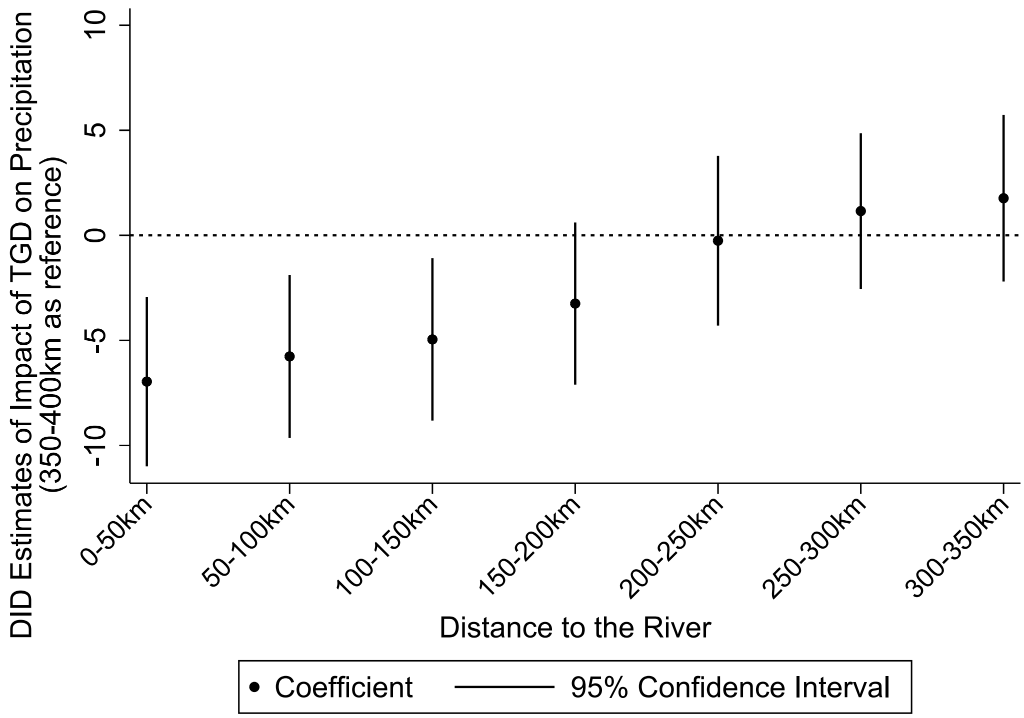


Figure 3. Differences in Runoff from Yangtze River over Months



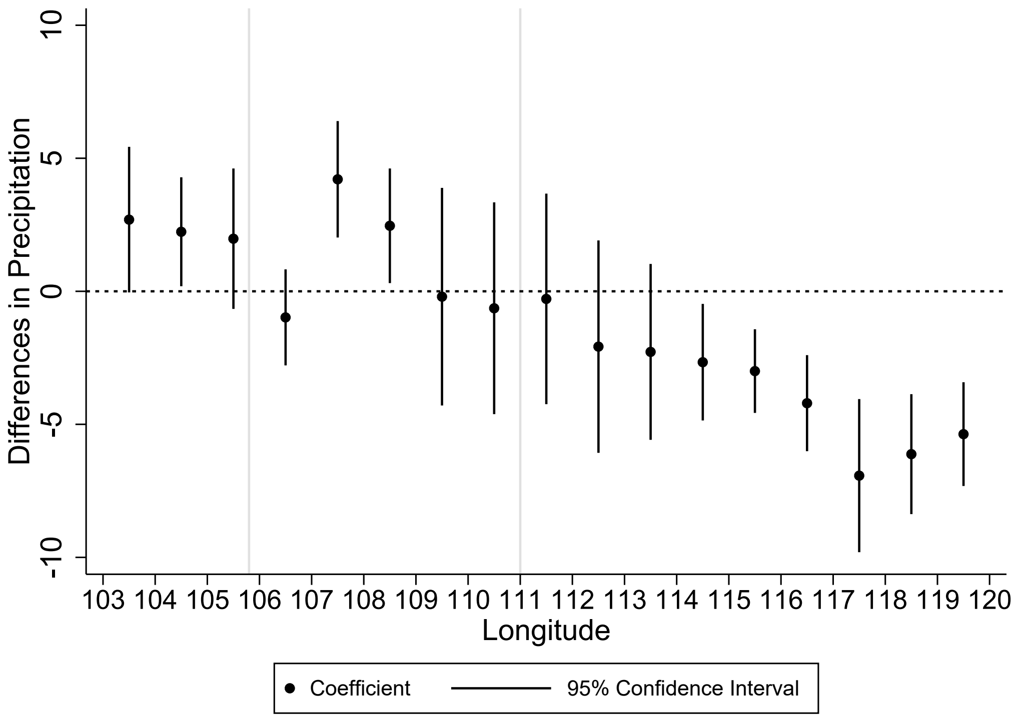
Notes: This figure shows the differences in river runoff in downstream Yangtze before and after the construction of the TGD. The horizontal axis denotes the months. The vertical axis shows the differences in river runoff before and after June 2003.

Figure 4. Effect of TGD on Total Precipitation, by Distance Bands to the Yangtze River



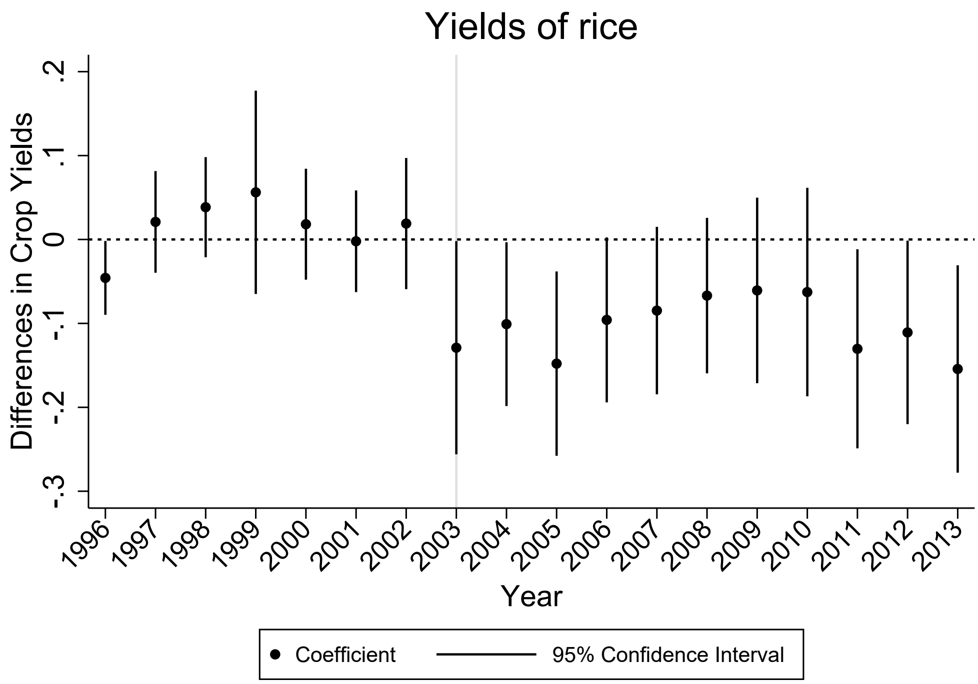
Notes: This figure shows the effects of the TGD on the total precipitation in the downstream Yangtze River by the distance bands paralleled to the river. The horizontal axis denotes the distance of each band to the river. The vertical axis shows the coefficients from the DID empirical model specified in equation (1) estimated using the gridded precipitation data.

Figure 5. Effect of TGD on Total Precipitation, by Longitude



Notes: This figure shows the effects of the TGD on total precipitation along the Yangtze River. The horizontal axis denotes the longitudinal degree of the grids. The vertical axis shows the coefficients from the DID empirical model (equation (2)) estimated using data from each longitudinal degree. Regions within the vertical lines denote the reservoir of the TGD.

Figure 6. Effect of Dam on Crop Yields of Rice, by Year



Notes: This figure shows the effects of the TGD on the yields of rice over time. The figure shows the point estimates of coefficients and 95% confidence intervals estimated using equation (4). The vertical line indicates the year 2003.

Table 1. Summary Statistics

	(1) Mean	(2) Standard Deviation	(3) Min	(4) Max	(5) Number of Obs.
Panel A			Climate		
Precipitation	110.426	97.535	0	1043.3	194,700
Temperature	16.086	8.594	-9.5	33.5	194,700
Panel B			Crop Yields ln(output/area)		
Rice	6.083	0.313	4.946	6.861	63,472
Wheat	5.628	0.434	4.094	6.397	36,164
Corn	5.684	0.554	3.576	6.908	25,331
Soybean	4.806	0.565	2.996	6.215	25,747
Cotton	4.528	0.681	2.526	5.991	16,166
Vegetable	7.472	0.776	5.098	9.262	66,861
Panel C			Area of Crops ln(area)		
Rice	1.615	0.661	0.095	3.135	45,983
Wheat	0.435	0.660	0	2.485	45,983
Corn	0.099	0.262	0	1.946	45,983
Soybean	0.116	0.253	0	1.946	45,983
Cotton	0.146	0.413	0	2.079	45,983
Vegetable	0.292	0.307	0	2.197	45,983
Panel D			Other Inputs ln(Input/area)		
Labor (Rice)	3.374	0.809	1.558	5.647	45,983
Labor (other grain crops)	4.590	1.017	0	6.531	45,983
Fertilizer (Rice)	2.479	2.148	0	5.525	45,983
Pesticides (Rice)	0.417	0.475	0	1.904	45,977
Agricultural Film (Rice)	0.071	0.180	0	0.981	45,950
Seed Expenditure (Rice)	3.942	0.965	1.099	5.978	31,121
Panel E			Other Margins of Adaptation		
Non-Agriculture (day)	1.945	2.310	0	6.524	45,983
Non-Agriculture (share)	0.130	0.218	0	0.905	45,962
Migration (day)	1.475	2.393	0	6.399	45,983
Migration (share)	0.134	0.262	0	1	44,489
Income (total)	9.740	0.727	7.929	11.662	45,965
Income per capita	8.442	0.710	6.996	10.430	45,802

Notes: This table shows the summary statistics of major variables. All input variables are in logarithm and are shown as input per area.

Table 2. Effects of the TGD on Crop Yields

	Crop Yields of:					
Panel A	Rice		Wheat		Corn	
	(1)	(2)	(3)	(4)	(5)	(6)
0-200km*Post-2003	-0.132***	-0.118***	-0.045	-0.024	-0.105	-0.118
	(0.046)	(0.038)	(0.059)	(0.060)	(0.111)	(0.111)
Number of Villages	80	80	61	60	55	53
Number of Households	5148	5128	3515	3502	2476	2452
Number of Obs.	63472	61628	36164	34520	25331	24175
Within R-squared	0.013	0.085	0.001	0.015	0.003	0.030
Panel B	Soybean		Cotton		Vegetable	
	(7)	(8)	(9)	(10)	(11)	(12)
0-200km*Post-2003	-0.017	-0.067	-0.103	-0.149	0.014	0.039
	(0.091)	(0.087)	(0.259)	(0.262)	(0.119)	(0.133)
Number of Villages	71	71	54	53	89	89
Number of Households	3057	3016	2110	2059	5708	5669
Number of Obs.	25747	24574	16166	15278	66861	62933
Within R-squared	0.0001	0.044	0.001	0.005	0.000	0.133
Controlling for Land & Labor Inputs	No	Yes	No	Yes	No	Yes
Household and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the dam's effects on the yields of various crops. All models are estimated by the DID model specified in equation (3). The full sample includes households from villages within 400 km of the Yangtze River. The coefficients on the interaction term between after 2003 and within 200 km of the Yangtze River are shown in the table. All models include household and year fixed effects. For each type of crop, the first column includes no additional control variables, while the second column includes labor and land inputs as control variables. Robust standard errors clustered at the village level are shown in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 3. Effects of the TGD on Crop Yields, Additional Controls

	Rice Yields						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0-200km*Post-2003	-0.176***	-0.167***	-0.165***	-0.157***	-0.185***	-0.190***	-0.187***
	(0.056)	(0.050)	(0.051)	(0.050)	(0.059)	(0.060)	(0.058)
County and Village GDP	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village Specific Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Land & Labor Inputs	No	Yes	Yes	Yes	Yes	Yes	No
Three Policy Programs	No	No	Yes	Yes	Yes	Yes	No
Temperature (Non-linear) and Other Climate Variables	No	No	No	Yes	Yes	Yes	No
Additional Inputs	No	No	No	No	Yes	Yes	No
Household Labor and Education	No	No	No	No	Yes	Yes	No
Restricted to Rice-Growing Households in 2002	No	No	No	No	No	Yes	Yes
Household and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Villages	72	72	72	72	70	66	66
Number of Households	4803	4784	4784	4784	4708	3575	3588
Number of Obs.	55864	54315	54315	54315	43453	37368	47893
Within R-squared	0.008	0.080	0.081	0.087	0.116	0.120	0.009

Notes: This table shows the dam's effects on rice yields by adding additional control variables to check the robustness of the baseline models. Column (1) includes control variables for county and village GDP, as well as village-specific linear time trends. Column (2) adds labor and land inputs as additional controls. Column (3) additionally controls for three economic policies that may affect the main results: agricultural tax reform, property rights reform (Chari et al., 2020), and the policy designed to return farmland to forest. In column (4), we control for average temperature, square of average temperature, and other climate variables such as humidity and atmospheric pressure. In column (5) we add controls for additional inputs, including fertilizer, pesticide, and agricultural films. We also add household-level control variables, including the average education level of household farm labor and the ratio of household labor over the total household population. In columns (6) and (7), we estimate the baseline model using a subsample of households that cultivated rice in 2002. This is the sample we use to study the adaptive behaviors of farmers. Column (6) adds all control variables. Column (7) uses the same control variables as Column (1). Robust standard errors clustered at the village level are shown in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 4. Effects of the TGD on Village-Level Fiscal Revenue and Expenditure

	Revenue from Upper-level Government Transfer	Total Expenditure	Expenditure on Irrigation	Expenditure on Other Agricultural inputs	Expenditure on Public Goods
	(1)	(2)	(3)	(4)	(5)
0-200km*Post-2003	0.448	0.061	0.768	-0.073	-0.142
	(0.437)	(0.232)	(0477)	(0.451)	(0.279)
Village and Year FE	Yes	Yes	Yes	Yes	Yes
Number of Villages	80	80	80	80	80
Number of Obs.	1219	1337	1357	1357	1269
Within R-squared	0.003	0.0002	0.005	0.0001	0.0004

Notes: This table shows the effects of the TGD on fiscal revenue and expenditure at the village level. All models are estimated using the DID model at the village level. The results reveal no statistically significant effects on revenue from upper-level government transfers, total expenditure, expenditure on agriculture, and expenditure on public goods. Robust standard errors clustered at the village level are shown in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 5. Effects of the TGD on Adaptation

Panel A	Area of Rice	Area of Other Crops	Labor Input of Rice	Labor Input of Other Crops
	(1)	(2)	(3)	(4)
0-200km*Post-2003	0.128**	-0.027	0.135	-0.092
	(0.057)	(0.052)	(0.136)	(0.282)
Number of Obs.	45983	45983	45983	44083
Within R-squared	0.003	0.0003	0.002	0.0003
Panel B	Fertilizer (Rice)	Pesticides (Rice)	Agricultural Film (Rice)	Seed Expenditure (Rice)
	(5)	(6)	(7)	(8)
0-200km*Post-2003	0.125	-0.082	0.055	0.314
	(0.240)	(0.095)	(0.049)	(0.262)
Number of Obs.	45983	45977	45950	31121
Within R-squared	0.002	0.001	0.002	0.004
Panel C	Non-Agriculture (share)	Non-Agriculture (day)	Out-Migration (share)	Out-Migration (day)
	(9)	(10)	(11)	(12)
0-200km*Post-2003	-0.026	-0.049	0.779	0.055
	(0.216)	(0.031)	(0.539)	(0.063)
Number of Obs.	45983	45962	45983	44489
Within R-squared	0.0002	0.002	0.002	0.001
County and Village GDP	Yes	Yes	Yes	Yes
Village Specific Time Trends	Yes	Yes	Yes	Yes
Household and Year FE	Yes	Yes	Yes	Yes

Notes: This table shows the dam's effects on households' adaptation. Panel A shows the effects on land and labor inputs. Panel B shows the effects on other inputs into rice cultivation. Panel C shows the effects on other margins of adaptation, including non-agricultural activities and migration. All models are estimated by the DID model specified in equation (3). The analytical sample only includes households that cultivated rice in 2002. For all specifications, we control for village and county GDP, village-specific time trends, and household and year fixed effects. Robust standard errors clustered at the village level are shown in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 6. Heterogenous Adaptation by Proxies for Financial Constraints

	Yields of Rice	Area of Rice	Area of Other Crops	Labor Input of Rice	Labor Input of Other Crops	Nonagri-culture (day)	Out-Migration (day)
	By Household Family Wealth						
Panel A1	High (Farm Size in 2002 >=Median(6.8mu))						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0-200km*Post-2003	-0.135*	0.031	-0.018	0.068	-0.116	0.371*	1.736***
	(0.077)	(0.041)	(0.074)	(0.087)	(0.345)	(0.203)	(0.392)
Number of Obs.	23337	23337	23337	23337	22870	23337	23337
Within R-squared	0.005	0.001	0.001	0.001	0.001	0.001	0.008
Panel A2	Low (Farm Size in 2002 <Median(6.8mu))						
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
0-200km*Post-2003	-0.243***	0.187***	-0.063	0.193	-0.111	-0.425	-0.074
	(0.051)	(0.065)	(0.053)	(0.163)	(0.348)	(0.302)	(0.553)
Number of Obs.	22646	22646	22646	22646	21213	22646	22646
Within R-squared	0.014	0.007	0.001	0.006	0.001	0.001	0.001
	By Household Credit Access in 2002						
Panel B1	High (Household Debt in 2002>0)						
	(15)	(16)	(17)	(18)	(19)	(20)	(21)
0-200km*Post-2003	-0.222***	0.128	-0.018	0.064	-0.346	0.094	0.894*
	(0.073)	(0.079)	(0.066)	(0.143)	(0.276)	(0.279)	(0.478)
Number of Obs.	8576	8576	8576	8576	8342	8576	8576
Within R-squared	0.006	0.003	0.0001	0.001	0.003	0.001	0.003
Panel B2	Low (Household Debt in 2002=0)						
	(22)	(23)	(24)	(25)	(26)	(27)	(28)
0-200km*Post-2003	-0.189***	0.126**	-0.030	0.148	-0.049	-0.043	0.775
	(0.051)	(0.055)	(0.053)	(0.141)	(0.287)	(0.229)	(0.567)
Number of Obs.	37321	37321	37321	37321	35660	37321	37321
Within R-squared	0.009	0.003	0.0005	0.003	0.0001	0.0003	0.003

Notes: This table shows the heterogeneous effects of the TGD on households' adaptation by households facing different financial constraints. Panel A shows the results for "high" or "low" wealth households and Panel B for households with "high" or "low" credit access. All models are estimated using the DID model specified in equation (5). For all specifications, we control for village and county GDP, village-specific time trends, and household and year fixed effects. Robust standard errors clustered at the village level are shown in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 7. Heterogenous Adaptation by Market Experience

	Yields of Rice	Area of Rice	Area of Other Crops	Labor Input of Rice	Labor Input of Other Crops	Nonagri-culture (day)	Out-Migration (day)
	By Household Market Experience						
Panel C1	High (Proportion of Rice Sold in the Market in 2002>= Median)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0-200km*Post-2003	-0.159**	0.033	-0.010	0.128	-0.204	0.299	2.002***
	(0.065)	(0.046)	(0.078)	(0.105)	(0.333)	(0.252)	(0.488)
Number of Obs.	22996	22996	22996	22996	22996	22996	22996
Within R-squared	0.010	0.0004	0.0007	0.003	0.003	0.001	0.011
	Low (Proportion of Rice Sold in the Market in 2002<Median)						
Panel C2	(8)	(9)	(10)	(11)	(12)	(13)	(14)
0-200km*Post-2003	-0.205***	0.198***	-0.044	0.085	-0.055	-0.327	-0.227
	(0.059)	(0.060)	(0.045)	(0.163)	(0.298)	(0.276)	(0.592)
Number of Obs.	22987	22987	22987	22987	21797	22987	22987
Within R-squared	0.009	0.008	0.0008	0.006	0.0008	0.001	0.002

Notes: This table shows the heterogeneous effects of the TGD on households' adaptation by market experience, which is measured as the proportion of its rice the household sold in the market in 2002. Panel C1 shows the results for "high" market experience households. Panel C2 shows the results for "low" market experience households. All models are estimated using the DID model specified in equation (5). For all specifications, we control for village and county GDP, village-specific time trends, and household and year fixed effects. Robust standard errors clustered at the village level are shown in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 8. Heterogenous Effects of TGD on Agriculture, by Newspaper and Magazine

	Yields of Rice	Area of Rice	Area of Other Crops	Labor Input of Rice	Labor Input of Other Crops	Nonagri-culture (day)	Out-Migration (day)
			By Village Access to Media				
Panel D1		High (Number of Newspapers and Magazines >30)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0-200km*Post-2003	-0.154**	0.128	-0.088	0.107	-0.214	-0.112	1.060
	(0.071)	(0.080)	(0.070)	(0.183)	(0.405)	(0.315)	(0.724)
Number of Obs.	21962	21962	21962	21962	20514	21962	21962
Within R-squared	0.009	0.008	0.001	0.002	0.002	0.002	0.006
Panel D2		Low (Number of Newspapers and Magazines <=30)					
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
0-200km*Post-2003	-0.238***	0.110**	0.037	0.093	-0.056	0.057	0.498
	(0.069)	(0.053)	(0.081)	(0.171)	(0.352)	(0.337)	(0.816)
Number of Obs.	24021	24021	24021	24021	23569	24021	24021
Within R-squared	0.011	0.002	0.0003	0.001	0.0001	0.0001	0.002

Notes: This table shows the heterogeneous effects of the TGD on households' adaptation according to the number of newspapers and magazines at the village level. Panel D1 shows the results for households from villages that have more newspapers and magazines than the median (30). Panel D2 shows the results for households from villages that have less newspapers and magazines. All models are estimated using the DID model specified in equation (5). For all specifications, we control for village and county GDP, village-specific time trends, and household and year fixed effects. Robust standard errors clustered at the village level are shown in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 9. Heterogenous Effects of TGD on Agriculture, by News Coverage

	Yields of Rice	Area of Rice	Area of Other Crops	Labor Input of Rice	Labor Input of Other Crops	Nonagri-culture (day)	Out-Migration (day)
			By Prefecture News Coverage				
Panel E1			High (Any News Coverage)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0-200km*Post-2003	-0.183**	0.053	0.031	0.092	-0.203	0.062	1.127*
	(0.075)	(0.045)	(0.060)	(0.165)	(0.266)	(0.315)	(0.660)
Number of Obs.	29480	29480	29480	29480	28029	29480	29480
Within R-squared	0.009	0.001	0.0004	0.001	0.001	0.0003	0.004
Panel E2			Low (No News Coverage)				
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
0-200km*Post-2003	-0.187**	0.212**	-0.112	0.180	0.578	-0.133	0.182
	(0.078)	(0.093)	(0.088)	(0.206)	(0.459)	(0.269)	(0.839)
Number of Obs.	16503	16503	16503	16503	16054	16503	16503
Within R-squared	0.009	0.009	0.004	0.007	0.006	0.0001	0.001

Notes: This table shows the heterogeneous effects of the TGD on households' adaptation according to whether there was local news coverage on climate-related issues. Panel E1 shows the results for households from villages that received some news coverage. Panel E2 shows the results for households from villages that did not receive any coverage. All models are estimated using the DID model specified in equation (5). For all specifications, we control for village and county GDP, village-specific time trends, and household and year fixed effects. Robust standard errors clustered at the village level are shown in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

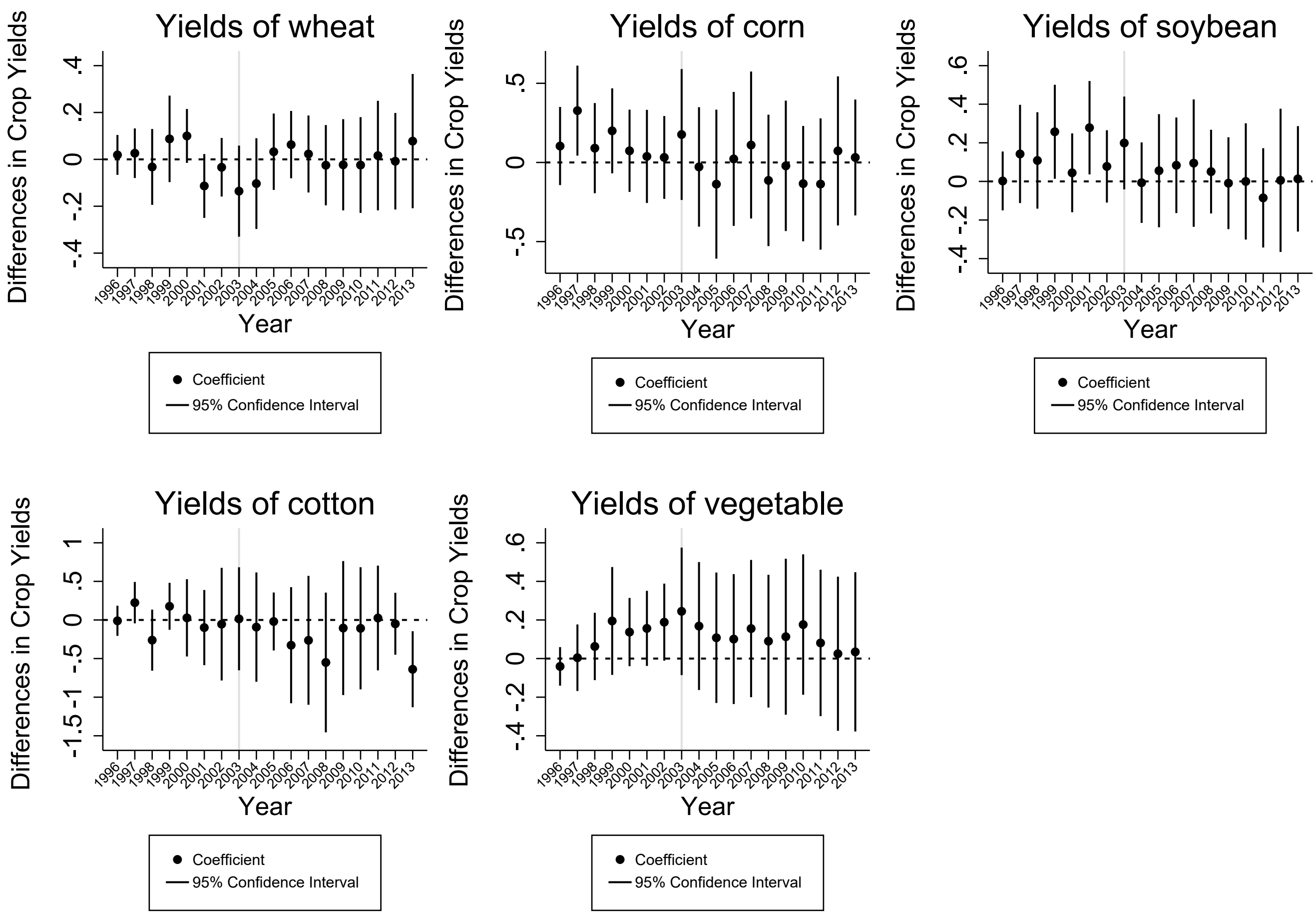
Table 10. Welfare Effects of TGD on Household Income

	All	By Farm Size	By Credit Access	By Market Experience
Panel A		Total Household Income		
	(1)	(2)	(3)	(4)
0-200km*Post-2003	-0.083*	-0.125**	-0.097**	-0.100*
	(0.047)	(0.49)	(0.047)	(0.050)
0-200km*Post-2003*High		0.082***	0.073***	0.032
		(0.025)	(0.019)	(0.024)
$\gamma + \gamma_{High}$		-0.043	-0.24	-0.068
		(0.048)	(0.051)	(0.047)
Number of Obs.	45965	45965	45965	45965
Within R-squared	0.002	0.004	0.003	0.003
Panel B		Household Income Per Capita		
	(5)	(6)	(7)	(8)
0-200km*Post-2003	-0.063	-0.119**	-0.071	-0.084
	(0.059)	(0.059)	(0.059)	(0.061)
0-200km*Post-2003*High		0.107***	0.040**	0.039
		(0.027)	(0.016)	(0.033)
$\gamma + \gamma_{High}$		-0.011	-0.031	-0.045
		(0.061)	(0.062)	(0.061)
Number of Obs.	45802	45802	45802	45802
Within R-squared	0.002	0.005	0.002	0.002

Notes: This table shows the effects of the TGD on total household income and per capita income for households facing different constraints. Panel A uses total household income as the dependent variable, while Panel B uses per capita income. All models are estimated using the DID model specified in equation (6). For all specifications, we control for village and county GDP, village-specific time trends, and household and year fixed effects. Robust standard errors clustered at the village level are shown in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Appendix: For Online Publication

Figure A1. Dam's Effect on (Non-Rice) Crop Yields, by Year



Notes: This figure shows the dam's effects on the yields of different crops over time. It shows the point estimates of coefficients and 95% confidence intervals estimated using equation (4). The vertical line indicates the year 2003.

Table A1. Monthly Total Precipitation and Average Temperature in Each Distance Band

	Downstream			Upstream		
	Pre-Impoundment	Post-Impoundment	Difference	Pre-Impoundment	Post-Impoundment	Difference
			Monthly Total Precipitation			
0-50km	89.882	77.729	-12.153	61.192	67.059	5.867
50-100km	93.691	81.082	-12.609	58.364	67.543	9.178
100-150km	90.486	75.847	-14.639	50.282	60.020	9.737
150-200km	89.666	76.443	-13.223	48.978	59.575	10.597
200-250km	88.607	77.146	-11.461	46.007	58.075	12.068
250-300km	85.784	74.140	-11.644	45.639	55.158	9.519
300-350km	84.335	72.617	-11.718	43.228	52.763	9.535
350-400km	78.557	66.470	-12.087	42.031	49.648	7.617
			Average Temperature			
0-50km	10.969	11.143	0.174	11.213	11.251	0.038
50-100km	10.688	10.545	-0.143	9.323	9.867	0.544
100-150km	10.472	10.432	-0.039	9.949	10.146	0.197
150-200km	10.499	10.596	0.097	10.774	10.708	-0.066
200-250km	10.614	10.352	-0.262	9.471	9.780	0.309
250-300km	10.095	9.812	-0.283	8.954	9.263	0.310
300-350km	9.872	8.849	-1.023	6.128	7.098	0.970
350-400km	10.389	9.307	-1.083	6.811	7.673	0.862

Note: Each cell of the table denotes the monthly total precipitation and average temperature in each distance band with the 0-400 km radius of the Yangtze River by down/upstream and by pre/post-impoundment in June 2003.

Table A2. Effects of the TGD on Downstream Precipitation and Temperature, by Distance to the River

	0-50km vs.						
	50-100km	100-150km	150-200km	200-250km	250-300km	300-350km	350-400km
	Panel A: Precipitation						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0-50km*Post-2003	-0.900	-1.162*	-1.807***	-3.937***	-4.863***	-5.825***	-4.237***
	(0.477)	(0.490)	(0.462)	(0.668)	(0.837)	(1.021)	(1.161)
50-100km*Post-2003		-0.263	-0.907	-3.037***	-3.963***	-4.925***	-3.338**
		(0.533)	(0.507)	(0.699)	(0.862)	(1.042)	(1.179)
100-150km*Post-2003			-0.645	-2.774***	-3.701***	-4.662***	-3.075**
			(0.521)	(0.709)	(0.870)	(1.049)	(1.185)
150-200km*Post-2003				-2.130**	-3.056***	-4.018***	-2.430*
				(0.691)	(0.855)	(1.037)	(1.174)
200-250km*Post-2003					-0.927	-1.888	-0.301
					(0.982)	(1.143)	(1.269)
250-300km*Post-2003						-0.962	0.626
						(1.250)	(1.366)
300-350km*Post-2003							1.587
							(1.486)
Number of Obs.	20200	29000	37400	45600	53600	61000	68800
Adjusted R-squared	0.747	0.727	0.710	0.691	0.677	0.668	0.663
	Panel B: Average Temperature						
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
0-50km*Post-2003	-0.010	-0.004	0.049	0.057	0.051	0.063	0.107**
	(0.023)	(0.031)	(0.035)	(0.035)	(0.038)	(0.042)	(0.040)
50-100km*Post-2003		0.006	0.059	0.067*	0.061	0.074	0.117**
		(0.030)	(0.034)	(0.034)	(0.037)	(0.042)	(0.039)
100-150km*Post-2003			0.053	0.061	0.055	0.068	0.111*
			(0.039)	(0.039)	(0.043)	(0.046)	(0.044)
150-200km*Post-2003				0.008	0.002	0.014	0.058
				(0.042)	(0.045)	(0.049)	(0.047)
200-250km*Post-2003					-0.006	0.006	0.050
					(0.045)	(0.049)	(0.047)
250-300km*Post-2003						0.013	0.056
						(0.051)	(0.049)
300-350km*Post-2003							0.043
							(0.053)
Number of Obs.	20200	29000	37400	45600	53600	61000	68800
Adjusted R-squared	0.989	0.988	0.988	0.986	0.985	0.983	0.981

Notes: This table shows the dam's effects on total precipitation and average temperature in the downstream area during the impoundment period by comparing different bands parallel to the Yangtze River. Each row shows the coefficient of a band dummy interacting with the post-impoundment dummy using the specification in equation (1). Robust standard errors clustered at the grid level are in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table A3. Full Table of Table 3

	Rice Yields						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0-200km*Post-2003	-0.176***	-0.167***	-0.165***	-0.157***	-0.185***	-0.190***	-0.187***
	(0.056)	(0.050)	(0.051)	(0.050)	(0.059)	(0.060)	(0.058)
County and Village GDP							
Village GDP per capita	0.000	0.005	0.005	0.008	0.009	0.009	-0.001
	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)
County GDP per capita	-0.032	-0.011	-0.016	-0.012	-0.015	-0.012	-0.033
	(0.037)	(0.035)	(0.034)	(0.034)	(0.052)	(0.053)	(0.037)
Land & Labor Inputs							
Area		-0.202***	-0.202***	-0.202***	-0.215***	-0.221***	
		(0.032)	(0.032)	(0.032)	(0.037)	(0.037)	
Labor Hour per area		0.031**	0.031**	0.033**	0.016	0.015	
		(0.014)	(0.014)	(0.014)	(0.010)	(0.009)	
Three Policy Programs							
"Return Farmland to Forest" Policy			0.006	0.012	0.012	0.007	
			(0.021)	(0.021)	(0.021)	(0.021)	
Property Rights Reform			-0.038	-0.050*	-0.026	-0.027	
			(0.024)	(0.026)	(0.026)	(0.026)	
Agricultural Tax Reform			-0.032	-0.032	-0.054	-0.051	
			(0.024)	(0.023)	(0.033)	(0.032)	
Temperature (Non-linear) and Other Climate Variables							
Average Temperature				0.040**	0.057***	0.057***	
				(0.015)	(0.021)	(0.020)	
(Average Temperature)^2				-0.0001**	-0.0001**	-0.0001**	
				0.000	0.000	0.000	
Humidity				0.002	0.002	0.002	
				(0.004)	(0.005)	(0.005)	
Atmospheric pressure				0.000	0.000	0.001***	
				0.000	0.000	0.000	

(to be continue)							
Household Labor and Education							
Number of Agricultural Labors					0.005	0.006	
					(0.009)	(0.010)	
Average Year of Education					0.000	0.000	
					(0.001)	(0.001)	
Additional Inputs							
Fertilizer					0.044***	0.042***	
					(0.008)	(0.009)	
Agricultural Chemicals					0.051***	0.050***	
					(0.014)	(0.015)	
Agricultural Films					-0.001	-0.001	
					(0.013)	(0.014)	
Restricted to Rice-Growing Households in 2002	No	No	No	No	No	Yes	Yes
Village Specific Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Villages	72	72	72	72	70	66	66
Number of Households	4803	4784	4784	4784	4708	3575	3588
Number of Obs.	55864	54315	54315	54315	43453	37368	47893
Within R-squared	0.008	0.08	0.081	0.087	0.116	0.12	0.009

Notes: This table shows the dam's effects on rice yields by adding additional control variables to check the robustness of the baseline models. Column (1) includes control variables for county and village GDP, as well as village-specific time trends. Column (2) adds labor and land inputs as additional controls. Column (3) additionally controls for three economic policies that may affect the main results: agricultural tax reform, and property rights reform (Chari et al., 2020), and the policy designed to return farmland to forest. In column (4), we control for average temperature, square of average temperature, and other climate variables such as humidity and atmospheric pressure. In column (5) we add controls for additional inputs, including fertilizer, pesticide, and agricultural films. We also add household-level control variables, including the average education level of household farm laborers and the ratio of household labor over the total household population. In columns (6) and (7), we estimate the baseline model using a subsample of households that cultivated rice in 2002. We used this sample to study farmers' adaptative behaviors. Column (6) adds all control variables. Column (7) uses the same control variables as column (1). Robust standard errors clustered at the village level are shown in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table A4. Effects of the TGD on Adaptation (Other Crops)

	Area of					
	Rice	Wheat	Corn	Soybean	Cotton	Vegetable
	(1)	(2)	(3)	(4)	(5)	(6)
0-200km*Post-2003	0.128**	-0.057	-0.055**	-0.004	0.018	0.013
	(0.057)	(0.043)	(0.026)	(0.023)	(0.047)	(0.045)
Number of Villages	66	66	66	66	66	66
Number of Households	3616	3616	3616	3616	3616	3376
Number of Obs.	45983	45983	45983	45983	45983	45983
Within R-squared	0.003	0.008	0.002	0.001	0.0001	0.0003
County and Village GDP	Yes	Yes	Yes	Yes	Yes	Yes
Village Specific Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Household and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the dam's effects on households' adaptation in cropping patterns. It shows the changes in the cropping area of all crops when households face a long-term negative precipitation shock. All models are estimated using the DID model specified in equation (3). The analytical sample only includes households that cultivated rice in 2002. For all specifications, we control for village and county GDP in addition to household and year fixed effects. Robust standard errors clustered at the village level are shown in parentheses. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table A5. Different Characteristics of Different Types of Households

	By Land Size			By Credit Access			By Market Experience		
	Low Mean/SE (1)	High Mean/SE (2)	Difference (1)-(2)	Low Mean/SE (1)	High Mean/SE (2)	Difference (1)-(2)	Low Mean/SE (1)	High Mean/SE (2)	Difference (1)-(2)
Yield of Rice	6.104	6.06	0.044	6.086	6.063	0.023	6.054	6.109	-0.055
	(0.027)	(0.042)		(0.031)	(0.031)		(0.028)	(0.039)	
Area of Rice	1.289	1.932	-0.642***	1.603	1.667	-0.063	1.363	1.868	-0.505***
	(0.048)	(0.090)		(0.074)	(0.094)		(0.062)	(0.093)	
Area of Other Crops	0.871	1.405	-0.534***	1.129	1.199	-0.07	0.971	1.314	-0.343***
	(0.068)	(0.103)		(0.078)	(0.102)		(0.090)	(0.093)	
Labor Input for Rice	3.565	3.187	0.378***	3.363	3.417	-0.054	3.577	3.171	0.406***
	(0.068)	(0.051)		(0.056)	(0.075)		(0.063)	(0.055)	
Non-agriculture (day)	1.983	1.908	0.075	1.918	2.065	-0.147	2.225	1.666	0.559**
	(0.209)	(0.228)		(0.182)	(0.205)		(0.201)	(0.222)	
Out-Migration (day)	1.408	1.54	-0.132	1.474	1.477	-0.003	1.504	1.445	0.058
	(0.147)	(0.098)		(0.113)	(0.102)		(0.131)	(0.121)	
Total Houshold Income	9.677	9.802	-0.125***	9.74	9.741	-0.001	9.714	9.767	-0.053
	(0.045)	(0.031)		(0.033)	(0.030)		(0.032)	(0.041)	
Land size				0.498	0.547	-0.049	0.299	0.716	-0.417***
(high v.s. low)				(0.047)	(0.050)		(0.043)	(0.040)	
Credit Access	0.173	0.203	-0.03				0.186	0.191	-0.005
(high v.s. low)	(0.022)	(0.022)					(0.025)	(0.022)	
Market Experience	0.289	0.705	-0.417***	0.499	0.507	-0.008			
(high v.s low)	(0.038)	(0.051)		(0.049)	(0.067)				

Notes: This table shows the differences in household characteristics between the "high" and "low" groups, which are used to differentiate the pattern of adaptation in this paper. *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.