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Abstract

Land use policy is crucial for food security and ecological protection. This study explores the impact of the world's largest Grain for Green Program, which subsidizes more than 100 million farmers to convert sloped cropland to forests and grasslands, on crop productivity in China. By combining detailed county-level crop production data with remote sensing data, our difference-in-differences estimates suggest that while the program significantly reduced total cropland area, it led to an increase in total crop yield. The unexpected yield impact can be explained by the fact that the program significantly increased labor input and multiple cropping in the remaining cropland. More importantly, we find that the program substantially reduced the damage of drought and extreme heat on crop yield. Our findings suggest the possibility of adopting land use policy to protect the ecology without compromising food security in a developing country.

Keywords: land use, food security, ecological protection, climate shocks, Grain for Green
JEL: J43, Q15, Q18, Q54

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1 Introduction

Retiring of fragile cultivated farmland into resource-conserving covers offers a range of ecological benefits, including increasing forest afforestation, preventing soil erosion, and reducing the loss of wildlife habitat (Sims and Alix-Garcia, 2017; Fu et al., 2019; Howlader, 2024). However, in developing countries where food shortage is prevalent, the implementation of such programs may raise concerns regarding food security. It's widely believed that there is a competition for land between ecological conservation and crop planting, creating a trade-off between ecological protection goals and food security objectives. While a large amount of research has analyzed the ecological benefits and economic impacts of conservation set-aside programs (e.g., Wu, 2000; Uchida et al., 2009; Yan, 2019; Howlader, 2024; Wing et al., 2024), little is known about the causal effects of such programs on food security in developing countries.

We develop a simple conceptual model to illustrate that the impact of a land conservation set-aside program on crop yield is uncertain. While land retirement directly reduces crop yield by decreasing the area of land cultivated, it could also lead to more intensive use of the remaining cropland, thereby offsetting the yield loss. Specifically, the released labor from the retired land could be used to increase the labor input per sown area and increase the sown area (through multiple cropping) in the remaining cropland. More importantly, an improved ecosystem could increase the resilience of the remaining cropland to natural disasters, thus increasing crop yield. Therefore, the impact of the land conservation set-aside program on crop yield is an empirical question.

This paper uses data from China's Grain for Green Program to assess the impact of a land conservation set-aside program on food security in a developing country. Initiated in response to the devastating floods that affected several major river basins in 1998, the program was designed to increase forest cover and prevent soil erosion by converting cropland with slopes of 25 degrees or more into forested or grassland areas. Launched in 1999, the Grain for Green Program quickly became the world's largest ecological conservation initiative at the time. Our empirical study focuses on the first round of the program, which was implemented from 1999 to 2014, with a government investment of 405.7 billion yuan, involved 124 million farmers, and resulted in the conversion of 9.3 million hectares of cropland.

We estimate the impact of the Grain for Green Program by comparing counties with different shares of the targeted cropland (i.e., with slopes of 25 degrees or more). By combining detailed county-level crop production data with fine-scare remote sensing data, we confirm that the program significantly reduced cropland areas. Specifically, we estimate that for counties with a 1 percentage point more sloped cropland, the program reduced the farmland area by 0.414 percent. For an average county with a share of sloped cropland of 0.035, the program reduced its cropland area by 1.45 percent. In contrast, we find that the program significantly increased total crop yields. Specifically, for counties with a 1 percentage point more sloped cropland, the program increased the total crop yield by 0.573 percent. Event studies suggest that these findings are not driven by preexisting different trends across counties. We also show that these findings are robust to focusing on subsample, using different control groups, and adopting different estimation methods.

We reconcile the seemingly contradictory estimates of reduced cropland and increased total crop yield by two findings. First, we find that the program substantially increased the crop sown area in the remaining flat cropland. Specifically, we estimate that the program has no significant negative effect on the county-level crop sown area, implying a substantial increase in the sown area of the remaining cropland. When examining the cropping intensity (defined as the ratio of crop sown area to cropland area), we find that for counties with a 1 percentage point more sloped cropland, the program increased the cropping intensity by 0.340 percent. The effect on cropping intensity is much larger in counties with climatic conditions more suitable for double and triple cropping within a year.

Second, we find that the program significantly increased crop yield per sown area. For counties with a 1 percentage point more sloped cropland, the program increased the yield per sown area by 0.574 percent. The increased yield per sown area can be explained by the fact that the labor released from the retired cropland increased the labor input in the remaining flat cropland. More importantly, we find that the program substantially reduced the damage from drought and extreme heat on crop yield. With a 1 percentage point increase in sloped cropland, total crop yield would decrease by 0.165 percent and 0.207 percent due to high temperature and low precipitation shocks, respectively. However, the program could offset these negative impacts, increasing crop yield by 0.316

percent and 0.388 percent under high temperature and low precipitation shocks, respectively, with the same 1 percentage point increase in sloped cropland.

This paper contributes to evaluating the impact of the Grain for Green Program in China. Existing studies on this program have examined the cost-effectiveness and sustainability of the program (Xu et al., 2004; Uchida et al., 2005), the effects of the program on forest cover (Fu et al., 2019) and farmers' income (Uchida et al., 2009), and leakage of the program's implementation (i.e., precision of the targeting) (Yan, 2019). Based on national county-level data and a standard causal effect identification strategy, our paper complements these studies by estimating the effect of the program on cropland area, crop sown area, crop yield, production inputs, and the damage of climatic shocks.

This paper is also closely linked to the global literature on the consequence of conservation set-aside programs. A large number of studies based on data from different countries have examined the effect of conservation set-aside programs on the environment (Sims and Alix-Garcia, 2017; Howlader, 2024), farmers' livelihoods (Sullivan et al., 2004; Xu et al., 2023), land use (Rosenberg and Pratt, 2024), and transition to organic production (Wing et al., 2024). Existing studies most relevant to our paper are those evaluating the interaction effect between ecological protection and agricultural production. For example, Koch et al. (2019) finds that Brazil's flagship anti-deforestation strategies were paired with increases in cattle production and productivity, because capital intensification replaced agriculture expansion. Garibaldi et al. (2016) finds that ecological intensification through enhancing ecosystem services maybe a sustainable pathway toward greater food supplies. Consistent with these studies, our findings suggest that it is possible to protect the ecosystem without compromising food security in a developing country.

This paper proposes ecological protection as a possible way to reduce the damage of climate change on agricultural. Climate change represents a major challenge to global agricultural production (Mendelsohn et al., 1994; Schlenker and Roberts, 2009; Burke and Emerick, 2016). Existing studies have examined the possibility of offsetting the damage of climate change on agriculture through various adaptation methods, such as crop-switching (Kurukulasuriya and Mendelsohn, 2008), improving soil quality (Qiao et al., 2022), labor reallocation (Huang et al., 2020), improving agricultural infrastructure (Huang et al., 2024b), and reducing the irrational response of farmers (Huang et al., 2024a).

Our study finds that the Grain for Green Program in China substantially reduced the damage of climatic shocks on crop yield, suggesting that ecological protection is another critical way for agriculture to adapt to climate change.

Finally, we emphasize that the main finding of this study is more applicable to countries and regions with relatively low levels of economic development. Our study focuses on the first round of the Grain for Green Program and uses data from 1994 to 2007. During this sample period, per capita GDP in China was very low (about 1/30 the United States during the same period) and off-farm working opportunities were not abundant. As suggested by our conceptual framework and empirical findings, labor reallocation from the retired cropland to the remaining cropland to increase multiple cropping is a key mechanism of the positive effect of the program on crop yield. In developed economies with sufficient off-farm working opportunities, the labor released from the retired cropland may not be reallocated to increase crop intensity. Nevertheless, we still expect that improved ecosystem could offset the damage of climatic shocks even in a developed economy.

The remainder of this paper is organized as follows: Section 2 introduces the Grain for Green Program in China. Section 3 presents a conceptual framework to guide our empirical analysis. Section 4 discusses the data source and empirical strategy. Section 5 presents the empirical findings. Section 6 provides concluding remarks.

2 Background

2.1 An overview of the Grain for Green Program in China

China's Grain for Green Program is the largest ecological conservation initiative in the world. The program has been carried out in two major rounds. The first round began in 1999 and lasted for 15 years, until 2014. During this period, 9.3 million hectares of farmland were retired and converted into forests and grasslands, 17.5 million hectares of barren mountains and lands were afforested, and 3.1 million hectares of hillsides were closed for afforestation. By 2014, the central government had invested 405.7 billion yuan in the first round of the program, involving 124 million farmers. In 2015, China launched a new round of the program with the aim of returning approximately 2.8 million hectares of sloped cropland and severely desertified cropland to forests and grasslands by 2020.[1]

Given the more complex policy environment in the second round of the program and the lack of data, our empirical study focuses on the first round. The first round of the Grain for Green Program was initiated in response to the severe flooding during the 1998 rainy season in the Yangtze, Pearl, and Songhua River basins, with the aim of curbing soil erosion. Due to long-term deforestation and land reclamation, over 2 billion tons of sediment flowed annually from steep-sloped cropland into the Yangtze and Yellow Rivers, with approximately two-thirds of this coming from sloped cropland.[2] This led to severe siltation of rivers, lakes, and reservoirs, raising riverbeds and severely affecting the national economy and people's livelihoods.

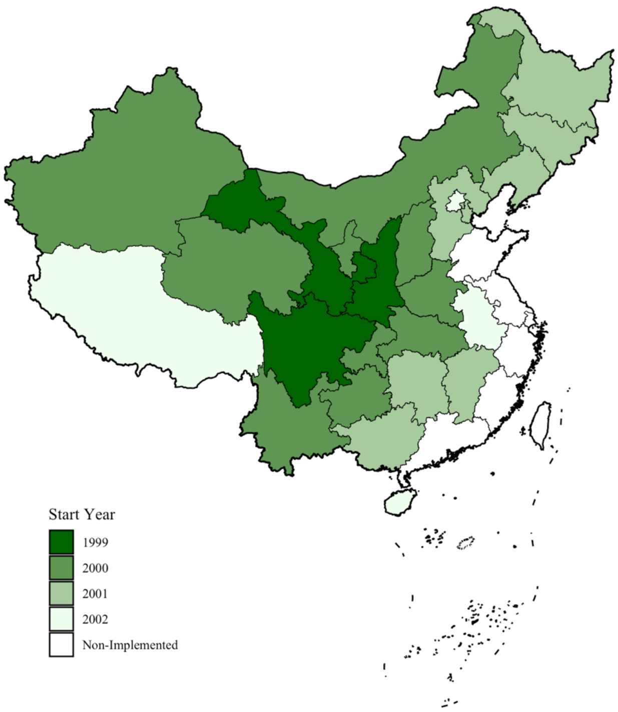


FIGURE 1 Rollout of the Grain for Green Program across provinces

Notes: This figure illustrates the four phases of the first round of the program. Provinces shaded in white are those that have not implemented the program, including Shandong, Shanghai, Zhejiang, Jiangsu, Fujian, and Guangdong provinces.

Figure 1 illustrates the four phases of the first round of the program. The pilot program launched in 1999 initially targeted the three western provinces of Sichuan, Gansu, and Guizhou. In that year, the program achieved the conversion

1. Data are derived from *China's Grain for Green Program: Twenty Years (1999-2019).*
2. https://www.gov.cn/gzdt/2009-07/02/content_1355261.htm

of 0.4 million hectares of farmland to forests and grasslands. In 2000, the scope of the pilot program was expanded to include 13 provinces along the upper Yangtze and middle reaches of the Yellow River, as well as 174 counties in Xinjiang province. In 2002, the program was expanded to 25 provinces, with 2.6 million hectares of farmland converted to forests. However, due to concerns about food security, the program's progress was significantly scaled back after 2004. New tasks for converting farmland to forests and grasslands were largely suspended, although efforts to reforest barren mountains and implement hillside afforestation continued. Appendix Figure A.1 presents the area of cropland converted in each year.

2.2 Participation criterion and subsidy of the program

The primary criterion for participation in the program is the steepness of the cropland, specifically targeting cropland with a slope of 25 degrees or more. In the program, farmers reallocate all or part of their sloped land to plant grass or trees, while retaining ownership of the converted cropland. The Ministry of Forestry, Agriculture, and the Ministry of Land and Resources have jointly formulated monitoring and evaluation methods to assess the qualification rate and retention rate of the Grain for Green Program in each province, and to monitor whether the program has been implemented on the designated land for conversion.[3]

The government compensates participants through in-kind grain allocations, cash payments, and free seedlings. The subsidy standard is 2250 kilograms of grain per hectare annually for regions in the Yangtze River Basin and southern areas, and 1500 kilograms of grain per hectare annually for regions in the Yellow River Basin and northern areas.[4] In addition, a one-time subsidy of 750 yuan per hectare is provided. Farmers are incentivized to participate due to the substantial compensation, which exceeds the opportunity cost of retiring the land. Compared to the United States' Conservation Reserve Program, the subsidy levels in the Yellow River and Yangtze River basins are significantly higher—2.5

3. https://www.ndrc.gov.cn/hdjl/yjzq/201604/W020210709577443067272.pdf.

4. The duration of subsidies varies: grassland restoration subsidies are for 2 years, economic forest subsidies are for 5 years, and ecological forest subsidies are for 8 years. Before 2000, subsidies were provided to farmers in the form of grain, but since 2004, the subsidized grain has been converted into cash or vouchers. The corresponding price of subsidized grain is set at 1.4 yuan per kilogram.

times and 3.6 times, respectively (Xu et al., 2004; Uchida et al., 2005).

3 Conceptual framework

This section develops a simple model to illustrate the potential effects of the Green for Grain Program on crop production. The model highlights that the program reduces crop yield by retiring the sloped land and increases crop yield by shifting labor to the remaining flat land to increase the cropping intensity. In addition, the model also characterizes how the program could increase crop yield by increasing the resilience of crop production to climate shocks.

3.1 Model setup

A representative household is endowed with one unit of flat cropland, one unit of sloped cropland, and L units of labor. Agricultural productivity of flat cropland is higher than that of sloped cropland, i.e., $A_f > A_s$. The labor can be allocated to farm work on the flat cropland (L_f), farm work on the sloped cropland (L_s) and off-farm work (L_o). For farm works, labor can be allocated to increase the yield of the existing sown area of the flat and sloped cropland (denoted as L_{f1} and L_{s1}, respectively) or to increase the cropping intensity through multiple cropping (L_{f2} and L_{s2}). We denote the cropping intensity on flat cropland as $I_f = \beta L_{f2}$ and cropping intensity on sloped cropland as $I_s = \beta L_{s2}$, where the coefficient $0 < \beta < 1$. Agricultural production follows a Cobb-Douglas function:

$$Y = A_f L_{f1}^{\alpha} I_f^{1-\alpha} + A_s L_{s1}^{\alpha} I_s^{1-\alpha}, \tag{1}$$

where the coefficient $0 < \alpha < 1$. We use the cropping intensities I_f and I_s to measure the sown areas per unit of flat cropland and per unit of sloped cropland, respectively. For simplicity, we assume that off-farm wages and food prices are exogenously given; relaxing these assumptions will not affect the qualitative prediction of the model.[5]

5. In reality, the program tends to reduce off-farm wage by increasing off-farm labor supply and to increase the price of crops by reducing yield. These changes could strengthen the predicted positive effect of the program on crop yield.

3.2 Equilibrium without the Grain for Green Program

The household maximizes total income from the agricultural and off-farm works:

$$
\begin{aligned}
\max_{L_{f1},L_{f2},L_{s1},L_{s2},L_o} \quad & A_f L_{f1}^{\alpha}(\beta L_{f2})^{1-\alpha} + A_s L_{s1}^{\alpha}(\beta L_{s2})^{1-\alpha} + W L^o \\
\text{s.t.} \quad & L_{f1} + L_{f2} + L_{s1} + L_{s2} + L_o = L \\
& 1 \leq \beta L_{f2} \leq \bar{I}_f \\
& 1 \leq \beta L_{s2} \leq \bar{I}_s
\end{aligned}
\tag{2}
$$

where W is the exogenous off-farm wage and $\bar{I}_f$ and $\bar{I}_s$ are the upper limits of cropping intensity. The marginal returns to labor allocated to different uses are:

$$
\begin{aligned}
& MR_{flat,1} = \alpha\beta^{1-\alpha} A_f L_{f1}^{\alpha-1} L_{f2}^{1-\alpha}, \\
& MR_{flat,2} = (1-\alpha)\beta^{1-\alpha} A_f L_{f1}^{\alpha} L_{f2}^{-\alpha}, \\
& MR_{sloped,1} = \alpha\beta^{1-\alpha} A_s L_{s1}^{\alpha-1} L_{s2}^{1-\alpha}, \\
& MR_{sloped,2} = (1-\alpha)\beta^{1-\alpha} A_f L_{s1}^{\alpha} L_{s2}^{-\alpha}, \\
& MR_{offfarm} = W.
\end{aligned}
\tag{3}
$$

Let the equilibrium allocations of labor be denoted as $L_{f1}^*, L_{f2}^*, L_{s1}^*, L_{s2}^*, L_o^*$. When $MR_{flat,1} = MR_{flat,2}$ and $MR_{sloped,1} = MR_{sloped,2}$, we have the equilibrium condition $\frac{L_{f1}^*}{L_{f2}^*} = \frac{L_{s1}^*}{L_{s2}^*} = \frac{\alpha}{1-\alpha}$. In the current model setting, the inequalities $MR_{flat,1} > MR_{sloped,1}$ and $MR_{flat,2} > MR_{sloped,2}$ always hold. The underlying assumption is that farmers allocate labor to the sloped cropland even though the marginal return to labor is lower than that from other labor uses. This assumption is valid in China as contingent use of the land is necessary to secure land property rights.

3.3 Equilibrium with the Grain for Green Program

Under the Grain for Green Program, the household retires the sloped cropland and receives a subsidy of S. The optimization problem is:

$$\begin{aligned} \max_{L_{f1},L_{f2},L_{i,o}} \quad & A_f L_{f1}^{\alpha}(\beta L_{f2})^{1-\alpha} + WL^o + S \\ \text{s.t.} \quad & L_{f1} + L_{f2} + L_o = L \\ & 1 \leq \beta L_{f2} \leq \bar{I}_f \end{aligned} \tag{4}$$

The marginal returns to labor allocations are:

$$\begin{aligned} & MR_{flat,1} = \alpha\beta^{1-\alpha} A_f L_{f1}^{\alpha-1} L_{f2}^{1-\alpha} \ , \\ & MR_{flat,2} = (1-\alpha)\beta^{1-\alpha} A_f L_{f1}^{\alpha} L_{f2}^{-\alpha} \ , \\ & MR_{offfarm} = W \ . \end{aligned} \tag{5}$$

Equilibrium occurs when $MR_{flat,1} = MR_{flat,2} = W$ and markets clear. Let the equilibrium allocation of labor be denoted as $L_{f1}^{**}, L_{f2}^{**}, L_o^{**}$ with $\frac{L_{f1}^{**}}{L_{f2}^{**}} = \frac{\alpha}{1-\alpha}$ holding.

3.4 The impact of the Grain for Green Program

The Grain for Green Program leads to labor reallocation from the retired sloped cropland to the flat cropland and off-farm work. Although the quantity of labor allocated to the flat cropland and off-farm work is an empirical issue, we always have $L_{f1}^{**} + L_{f2}^{**} > L_{f1}^{*} + L_{f2}^{*}$ and $\frac{L_{f1}}{L_{f2}} = \frac{\alpha}{1-\alpha}$.

Proposition 1 *The Grain for Green Program leads farmers to increase labor input per sown area and cropping intensity of the flat cropland.*

Yield per sown area after the program is

$$\frac{Y^{**}}{\beta L_{f2}^{**}} = A_f \left(\frac{L_{f1}^{**}}{\beta L_{f2}^{**}}\right)^{\alpha} = A_f \left[\frac{\alpha}{\beta(1-\alpha)}\right]^{\alpha} \ . \tag{6}$$

Yield per sown area before the program is

$$\begin{aligned}
&\frac{Y^*}{\beta L_{f2}^* + \beta L_{s2}^*} \\
&= \frac{1}{\beta L_{f2}^* + \beta L_{s2}^*}[A_f \beta L_{f2}^* (\frac{L_{f1}^*}{\beta L_{f2}^*})^\alpha + A_s \beta L_{s2}^* (\frac{L_{s1}^*}{\beta L_{s2}^*})^\alpha] \\
&= \frac{1}{\beta L_{f2}^* + \beta L_{s2}^*}(A_f \beta L_{f2}^* + A_s \beta L_{s2}^*)[\frac{\alpha}{\beta(1-\alpha)}]^\alpha \\
&< A_f[\frac{\alpha}{\beta(1-\alpha)}]^\alpha \ .
\end{aligned} \tag{7}$$

Proposition 2 *The Grain for Green Program increases yield per sown area.*

Total crop yield after the program is

$$Y^{**} = A_f \beta L_{f2}^{**} (\frac{\alpha}{1-\alpha})^\alpha \ . \tag{8}$$

Total crop yield before the program is

$$Y^* = [A_f \beta L_{f2}^* + A_s \beta L_{s2}^*](\frac{\alpha}{1-\alpha})^\alpha \ . \tag{9}$$

As such, the effect of the program on total crop yield is:

$$\Delta Y = \underbrace{A_f \beta (L_{f2}^{**} - L_{f2}^*)}_{>0} - \underbrace{A_s \beta L_{s2}^*}_{>0} \tag{10}$$

As the labor reallocation increases cropping intensity, the net impact of the program on total crop yield is uncertain.

Proposition 3 *The net impact of the Grain for Green Program on total crop yield is uncertain.*

Finally, the program could have a positive effect on the ecological environment. A better ecological environment may increase agricultural productivity ($A_f^{**} > A_f^*$) by increasing the resilience of agriculture to natural disasters, such as climatic shocks.

Proposition 4 *The Grain for Green Program could increase crop yield by mitigating the damage of natural disasters.*

4 Data and method

4.1 Data

Agricultural production data. Our main analysis depends on county-level agricultural production data for 1,620 counties from 1994 to 2007, derived from the database maintained by the Ministry of Agriculture and Rural Affairs of China. China has approximately 1,860 counties with significant agricultural production. The agricultural counties missing from our dataset are mainly due to the changes in administrative divisions (merger and division of counties). We exclude data after 2007 to avoid the confounding effect of later programs. The dataset contains information on county-level annual production input and output of the three major crops (i.e., rice, wheat, and corn), which account for about 90% of China's total crop production.

Geographic data. We calculate the county-level intensity of the program based on gridded data on land slope and land use. The land slope data are derived from the Digital Elevation Model Dataset, and the land use type data are derived from the China Land Cover Dataset. Both datasets are in 30-meter resolution and developed by the Chinese Academy of Sciences. The China Land Cover Dataset contains gridded data on nine major types of land use (i.e., Cropland, Forest, Shrub, Grassland, Water, Snow and Ice, Barren, Impervious, and Wetland) for each decade (Jie and Xin, 2021).[6] Based on these two datasets, we utilize ArcGIS to calculate the share of cropland in each county with a slope equal or higher than 25 degrees in 1990.

Climate data. To evaluate the offsetting effect of the program on climatic shocks, we construct climatic shock measures based on daily precipitation and temperature data derived from the latest state-of-the-art global reanalysis dataset, the Enhanced Global Dataset for the Land Component of the Fifth Generation of European ReAnalysis (ERA5-Land). The dataset provides long-term climate data with a resolution of 9 km $\times$ 9 km. More details of ERA5-Land can be found in Muñoz-Sabater et al. (2021). The calculation of the climatic shock measures will be introduced in the analysis.

6. As the land use type data is only available for sparse years, it is not suitable for identifying the changes in land types caused by the program.

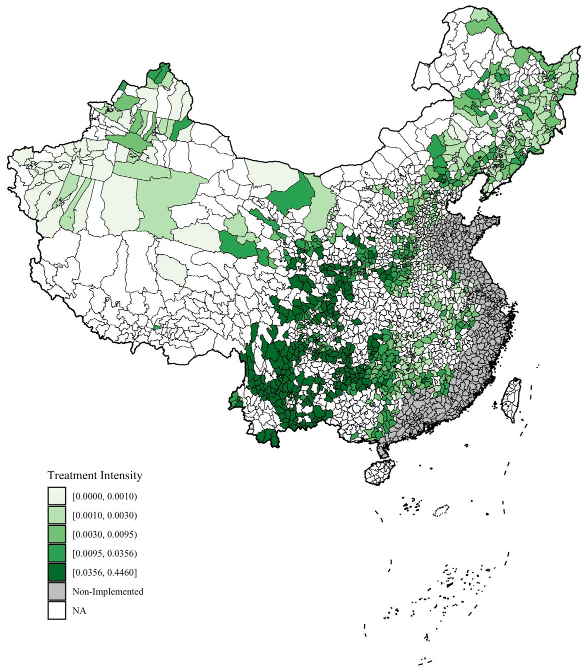


FIGURE 2 Share of cropland with a slope greater than or equal to 25 degrees

Notes: The color gradient, ranging from light green to dark green, represents the county share of cropland with a slope greater than or equal to 25 degrees, from low to high. Counties shaded in gray are those that have not implemented the Grain for Green Program, while counties marked as NA are those without agricultural data.

Figure 2 presents the county-level intensity measure of the Grain for Green Program: the share of cropland with a slope greater than or equal to 25 degrees in 1990. We find a large variation in the program intensity across counties. Although the mean intensity is only 3.5% (with a standard deviation of 6.8%), the intensity could be as high as 45% in some counties. Appendix Figure A.2 presents changes in the distribution of key outcome variables before and after the program (in 1994 and 2007, respectively). We find a substantially rightward shift in the distribution of total crop yield and crop yield per sown area, suggesting a positive effect of the program on crop output. Appendix Table A.1 presents the summary statistics of key variables.

4.2 Method

4.2.1 The baseline model

We estimate the impact of the Grain for Green Program based on a generalized difference-in-differences (DID) model that compares counties with different shares of sloped cropland before and after the program:

$$Y_{it} = \beta Post_{it} * Rate_i + X_{it}\gamma + \theta_i + \theta_{pt} + \epsilon_{it} \tag{11}$$

where Y_{it} is one of the outcomes of interest in county i and year t, the dummy variable $Post_{it}$ equals one if county i has participated in the program in year t, and zero otherwise, and the continuous variable $Rate_i$ is the share of cropland in county i with a slope greater than or equal to 25 degrees in 1990. X_{it} is a vector of control variables that will be detailed later. The model also controls for the county-fixed effects (θ_i) and province-by-year fixed effects (θ_{pt}). Finally, ϵ_{it} is the error term. Standard errors are clustered at the county level.

The key outcome variables of interest are log cropland area, log total crop yield, log crop yield per sown area, and log crop sown area. As detailed in subsection 4.1, our analysis focuses on the three major crops accounting for about 90% of China's total crop production (i.e., rice, wheat, and corn). All of the variables are calculated for these three crops together. We do not provide crop-specific estimation because in a significant number of counties, multiple crops are cultivated in different seasons of a year.

4.2.2 Addressing endogeneity concerns

The coefficient of interest β would capture the causal effect of the program based on the assumption that counties with different shares of sloped croplands follow the same trends without the program. However, this assumption is not necessarily valid given that counties with different share of sloped farmland may differ in various aspects. We adopt the following four approaches to address the endogeneity concerns.

First, we include fixed effects to account for potential confounding factors. Specifically, we include county-fixed effects to account for all county-specific time-invariant confounding factors and include the province-by-year fixed effects to account for province-specific annual shocks. These fixed effects substantially reduce the concern about the endogeneity bias caused by preexisting time-invariant differences across counties and annual shocks.

Second, we include a rich set of control variables to account for the potential time-varying confounding factors. Specifically, we include the county-specific time trends to account for the effects of different trends caused by preexisting factors. We control for the interactions between a full set of year dummies and an array of pre-treatment (1990) county characteristics, including elevation, the share of crop areas damaged by natural disasters, per capita agricultural output, rural income, and proportion of minority population. We control for the county-level annual flooding intensity, calculated following the method of He and Liu (2024).[7] This control variable is important because the severe flooding in 1998 in China directly led to the initiation of the Grain for Green Program. All of these control variables are included in the vector of X_{it} of the model.

Third, we control for the potential confounding effects of the three most important contemporary events. First, we control for the State-Owned Enterprise Reform in 1998, which resulted in the layoff of a large number of workers. We control for this event by the share of state-owned enterprise output at the city level in 1998 (multiplied by year dummies).[8] Second, we control for the Higher Education Expansion in 1999, which could have substantially affected human capital and accelerated rural-urban migration. We control for this policy by the share of students in the population in each county in 2000 (multiplied by year dummies), calculated based on data from the sixth National Population Census. Third, we control for the effect of China's joining the WTO in 2001. We follow Topalova (2010) to construct a measure of county-level intensity for this event.[9]

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

$$Y_{it} = \sum_{k=-5,k\neq-1}^{5} \beta_k D_{it}^k \times Rate_i + X_{it}\gamma + \theta_t + \theta_{pt} + \epsilon_{it} \tag{12}$$

where D_{it}^k is an indicator variable for the k^{th} year relative to the event time (the program start year). The base year omitted from the model is $k = -1$. All other variables are the same as that in model (11). As presented in Figure 3, we find that the estimates of β_k are all close to zero and statistically insignificant when $k < 0$ for key outcome variables. This finding supports the parallel-trends

7. We calculate the county-level flooding intensity as the deviation of the annual total precipitation from the mean annual total precipitation from 1950 to 1997 in each county.

8. The data are derived from the *China Regional Statistical Yearbook*. This control variable is at the city level because the corresponding county-level data is not available.

9. The measure is calculated as $Tariff_{i,1999} = \frac{\sum_j \text{Worker}_{i,j,1999} Tariff_{j,1999}}{\text{Totalworker}_{i,1999}}$, where $\text{Worker}_{i,j,1999}$ is the number of workers in industry j and county i, $\text{Totalworker}_{i,1999}$ is the total number of workers in the county, and $Tariff_{j,1999}$ is the industry specific tariff before joined the WTO. The county-level industry-specific employment data is sourced from the sixth National Population Census.

assumption that counties with high and low share of sloped cropland have no different trends before the implementation of the program. Comparable results are found when replacing the continuous measure of the treatment intensity by a dummy variable (Figure 4).

5 Results

We first present the baseline results in subsection 5.1, followed by robustness checks in subsection 5.2. Next, we show heterogeneous effects in subsection 5.3. Then, we explore the underlying mechanisms in subsection 5.4.

5.1 Baseline results

The baseline results are presented in Table 1. All estimations are based on Equation (11), which includes controls for the county-fixed effects, province-year fixed effects, treatment-year trends, pre-treatment county characteristics (interacted with year dummies), and other contemporaneous policies. The dependent variables analyzed include cropland area, crop yield, crop yield per sown area, and crop sown area. Definitions of these variables are provided in subsection 4.1.

Column (1) shows that the Grain for Green Program significantly reduced cropland area. Specifically, the estimate indicates that a 1 percentage point increase in sloped cropland (with a gradient exceeding 25 degrees) led to a 0.414 percent reduction in farmland area. Given that the county-average share of sloped cropland is 0.035 (with a standard deviation of 0.068), the program reduced the cropland area of an average county by 1.5 percent (with a standard deviation of 2.8 percent). In sharp contrast, column (2) suggests that the program significantly increased total crop yield. Specifically, a 1 percentage point increase in sloped cropland resulted in a 0.573 percent increase in total crop yield. This finding is unexpected, as a reduction in cropland area would typically be associated with a decrease in total crop yield, assuming constant yield per unit of cropland.

TABLE 1 Effect of the Grain for Green Program on agricultural outcomes

	(1)	(2)	(3)	(4)
	Cropland area	Total crop yield	Yield per sown area	Crop sown area
$Post_{it} \times Rate_i$	-0.414***	0.573***	0.574***	-0.001
	(0.121)	(0.155)	(0.101)	(0.140)
County FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	19,833	19,833	19,833	19,833
R-squared	0.959	0.953	0.821	0.957

Notes: This table reports the DID estimates of the baseline model (11). The dependent variables are cropland area, crop yield, crop yield per sown area, and crop sown area in column (1)–(4), respectively. The control variables included are detailed in section 4.2. Clustered standard errors are reported in parentheses. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Estimates in columns (3) and (4) help reconcile these contrasting findings. Column (4) shows that the crop sown area is virtually unaffected by the program, implying that a substantial increase in multiple cropping on the remaining cropland offsets the negative impact of the program on cropland areas. We present direct evidence on the increase of multiple cropping in section 5.4. Column (3) finds a marginal positive effect of 0.574 percent on crop yield per sown area due to the program. We will investigate the reasons behind this increase in yield per sown area later. Combining estimates from columns (3) and (4), we are able to explain how the program led to an increase in total crop yield while simultaneously reducing cropland area: the increase in multiple cropping offset the negative impact on the cropland area, and the increase in yield per sown area led to the increase in total crop yield.

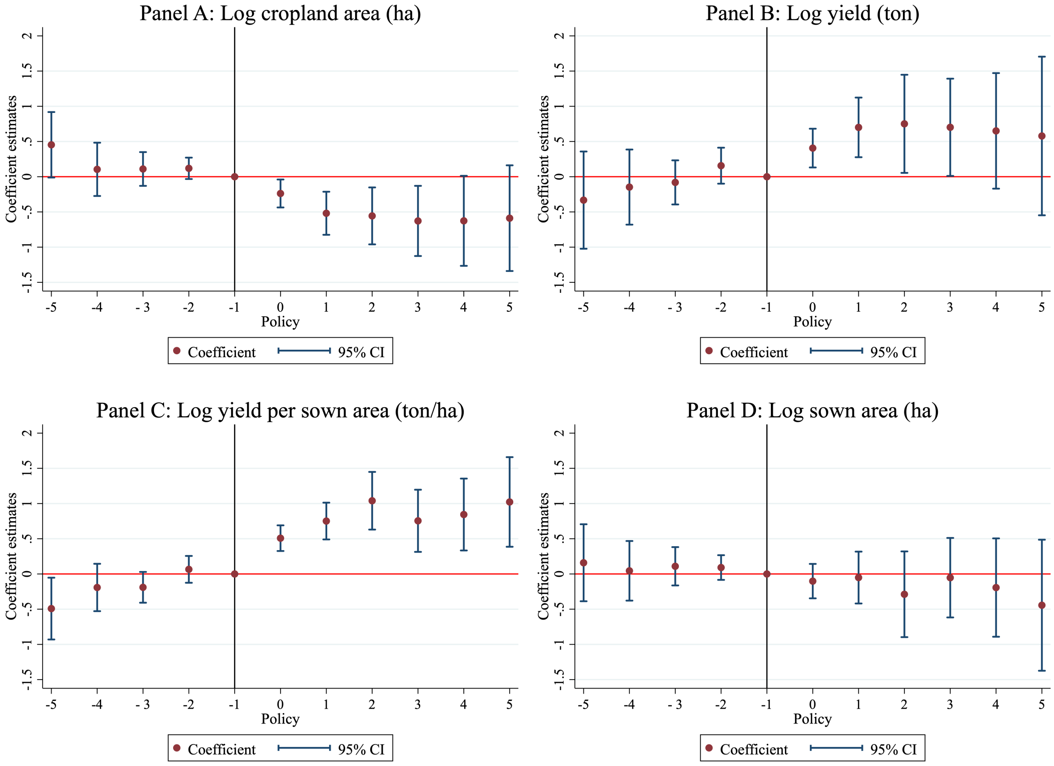


FIGURE 3 Dynamic effects of the program on agricultural outcomes

Notes: This figure presents the event-study estimates based on model (11). The dependent variables are the log cropland area, total crop yield, crop yield per sown area, and crop sown area in Panels A, B, C, and D, respectively. The vertical capped lines denote the 95% confidence intervals.

Figure 3 presents the dynamic effects of the program, estimated based on the event-study model (12). The estimates of β_k are statistically insignificant and close to zero for $k < 0$, supporting the identification assumption that there were no different pre-existing trends before the program between counties with high and low shares of sloped cropland. Panel A shows significantly negative effects of the program on cropland area, Panel B shows significantly positive effects on total crop yield, Panel C shows significantly positive effects on yield per sown area, and Panel D shows insignificant effects on crop sown area. These dynamic effects are consistent with the DID estimates presented in Table 1. The dynamic effects in Panels A, B, and C diminish after about three periods, at least in terms of wider confidence intervals. This finding is consistent with the fact that the program's progress was significantly scaled back after 2004 (see section 2 for details) .

5.2 Robustness

In this subsection, we conduct a series of robustness checks to verify the baseline results. All robustness checks use the same model specification as in the baseline analysis, except for the one specified in each check. To save space, all robustness checks focus on the program's effects on the two most important outcome variables: cropland area and total crop yield.

Including only the western regions. Western China has agro-climatic and socioeconomic characteristics that differ substantially from those of other regions in China. As a robustness check, we restrict the sample to the western China and re-estimated model (11). As presented in columns (1)–(2) of Table 2, we still find that the program significantly reduces cropland area and increase total crop yield, although the estimated marginal effect on cropland area is smaller than that from the baseline estimation.

Excluding city districts. In China, five levels of local administrative units exist (from the highest to the lowest level): province, prefecture, county/district, town/jiedao, and village/community. Our analysis is based on the administrative unit of the county/district. However, most districts have only a small share of agricultural labor and thus may not be comparable to agricultural production in counties. However, as presented in columns (3) and (4) of Table 2, excluding districts from our sample does not significantly affect the estimated effects on cropland area and crop yield.

Excluding pure control provinces. Our baseline estimation includes sample counties from provinces that were not subject to the program during our sample period (i.e., Shandong, Shanghai, Zhejiang, Jiangsu, Fujian, and Guangdong provinces). Including a pure control group is important to avoid the bias of the staggered DID estimation (Borusyak et al., 2021). However, one may concern that these pure control provinces are not comparable to other provinces. To address this concern, columns (5) and (6) of Table 2 exclude the sample from the pure control provinces. The estimated results are very close to the baseline estimates.

Clustering at the city level. Our baseline analysis clusters the standard error at the county level to address the potential bias from autocorrelation, which is a major concern in this study as agricultural production presents strong trends. As a robustness check, we cluster the standard error at the prefectural-city level to address the potential spatial correlation across counties within a prefectural city. As presented in the last two columns of Table 2, doing so does not affect the significance level of the estimated effects.

TABLE 2 Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Only include the western regions		Exclude city districts		Exclude pure control provinces		Cluster at the city level	
	Cropland area	Yield	Cropland area	Yield	Cropland area	Yield	Cropland area	Yield
$Post_{it} \times Rate_i$	-0.288*	0.466**	-0.395***	0.695***	-0.440***	0.542***	-0.414***	0.573***
	(0.153)	(0.168)	(0.123)	(0.156)	(0.120)	(0.156)	(0.124)	(0.204)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,951	7,951	17,561	17,561	16,501	16,501	19,833	19,833
R-squared	0.963	0.959	0.966	0.959	0.964	0.956	0.959	0.953

Notes: This table presents robustness checks for the baseline estimates presented in columns (1) and (2) of Table 1. The only difference of each check from the baseline estimation is indicated in the column header and detailed in the main text. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Heterogeneous treatment effects. In a staggered DID design, estimation bias may occur in the presence of heterogeneous treatment effects across different treatment groups and time points. We employ three frequently used heterogeneous-robust estimators to exam the robustness of our findings: calculating cohort-specific average treatment effects on the treated, using an imputation estimator to construct counterfactual results for estimation, and constructing the stacked regression estimator (Borusyak et al., 2021; Sun and Abraham, 2021; Cengiz et al., 2019). Since the baseline model setting with a continuous treatment variable is not suitable for conducting heterogeneous-robust estimation, these robustness checks measure the treatment by a treatment-control dummy variable constructed based on the median of the share of sloped cropland. As presented in Figure 4, the estimated dynamic effects are comparable to the baseline estimates.

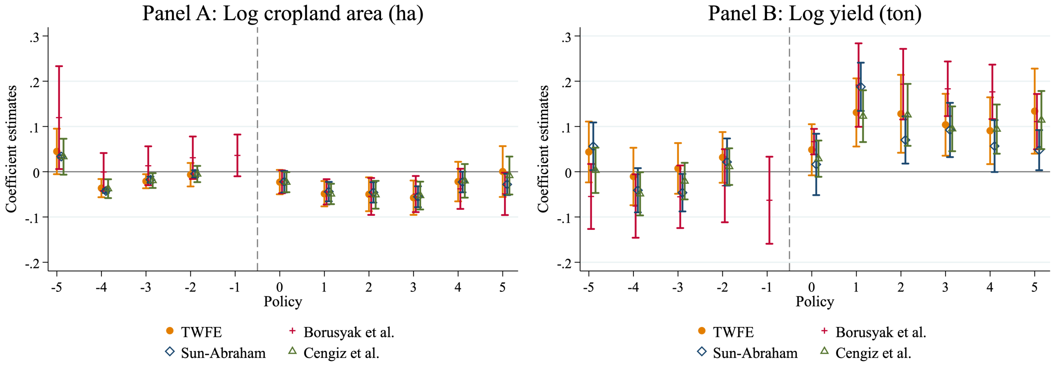


FIGURE 4 Heterogeneous-robust estimation

Notes: This figure examines the robustness of the event-study estimates to heterogeneous treatment effects by adopting the methods of Borusyak et al. (2021), Sun and Abraham (2021), and Cengiz et al. (2019), respectively. Since the baseline model setting with a continuous treatment variable is not suitable for conducting heterogeneous-robust estimation, these robustness checks measure the treatment by a treatment-control dummy variable constructed based on the median of the share of sloped cropland. The vertical capped lines denote the 95% confidence intervals.

5.3 Heterogeneity and non-linear effects

The results presented so far focus on the average treatment effects of the program. We expect these effects may vary across counties with different economic development levels and agro-climatic conditions. Figure 5 presents the heterogeneity of the effect with respect to different county features. We estimate the heterogeneity effects by extending the baseline DID model (11) to additionally include the interaction between a dummy variable of the feature and the DID variable ($Post_{it} \times Rate_i$). The dummy variable of the feature is constructed based on the median value of each feature. All other model settings are the same as the baseline model. We focus on the heterogeneity of the effect on crop yield. Similar results are obtained when examining the heterogeneity of the effect on yield per sown area (Appendix Figure A.3). It is trivial to examine the heterogeneity effect on cropland area, which is determined by the program design and the geographic conditions of the counties.

First, we find that the positive impact of the program on crop yield applies mainly to counties with low economic development levels, as measured by GDP per capita and share of non-agricultural employment. The estimates indicate that while the program had a significantly positive effect on the crop yield in counties with the GDP per capita and share of non-agricultural employment below the median, the effects are statistically insignificant for counties with these measures above the median. A potential explanation is that farmers in counties with better non-agricultural working opportunities may reallocate labor to off-farm work after the program reduces their cropland. However, in counties with limited non-agricultural working opportunities, the program may lead farmers to reallocate labor and other production inputs to the remaining cropland. This finding is consistent with what will be presented in section 5.4 that the reallocation of production factor is an important mechanism for the program to increase crop yield.

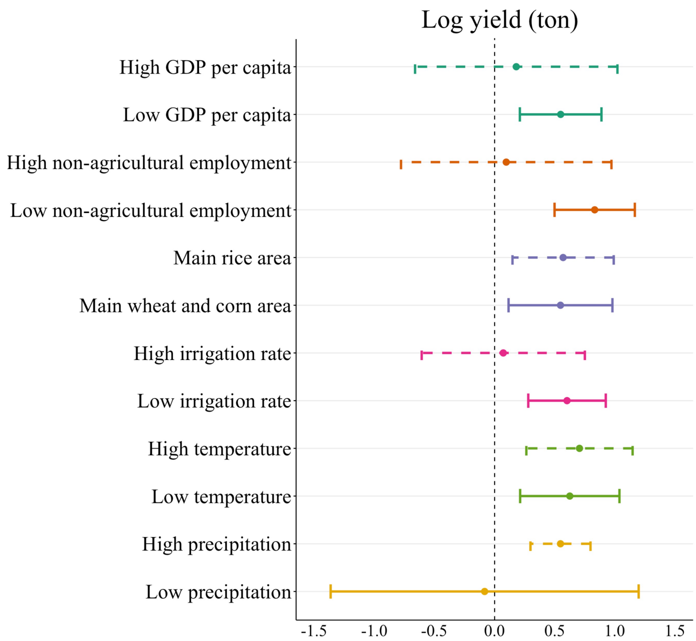


FIGURE 5 Heterogeneity of the effect on crop yield

Notes: This figure estimates the heterogeneity of the effect of the program on crop yield with respect to different county features. The corresponding point estimates are presented in Appendix Table A.2. The capped lines denote the 95% confidence intervals.

Second, we find no significant heterogeneity of the effect with respect to crop types, but significant heterogeneity with respect to the irrigation condition. Specifically, similar significant and positive effects are found for counties cultivating rice and counties cultivating wheat and corn.[10] However, the significantly

10. In China, rice is generally cultivated in counties different from those cultivating wheat and corn, while wheat and corn are usually cultivated in the same counties in the pattern of winter wheat and summer corn.

positive effect is found in counties with a low irrigation rate but not in counties with a high irrigation rate. A potential explanation is that multiple cropping has been widely adopted in counties with good irrigation conditions before the program but not in counties lacking irrigation conditions. As such, counties with a low irrigation rate are more likely to increase the rate of multiple cropping after the program. We will show in section 5.4 that increases in multiple cropping significantly contribute to the increase in crop yield.

Third, we find no difference in the effect across counties with different annual mean temperatures, but we find substantially different effects for counties with high and low annual total precipitation. Specifically, the positive effect on crop yield applies mainly to counties with high annual total precipitation. Given other factors, such as the irrigation condition, precipitation determines the possibility of multiple cropping. Regions with low precipitation that occurs only during the rainy season are less suitable for multiple cropping than counties with high precipitation throughout the year.

Finally, as presented in Figure 6, we examine the potential non-linear effect of the share of sloped cropland on crop yield. Specifically, we estimate the second-order and third-order effects based on modified versions of model (11) that additionally include the interactions between $Post_{it}$ and the square and cubic of $Rate_i$. We then plot the estimated marginal effects across counties with the share of sloped cropland ranging from zero to two standard deviations above the mean (0.036+0.068*2). The estimates suggest there is no significant non-linearity of the effect across counties with different share of sloped cropland.

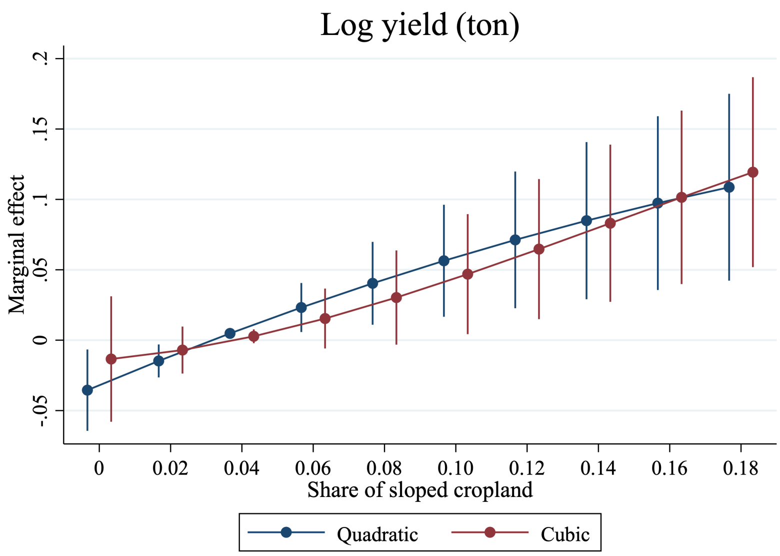


FIGURE 6 Non-linear impacts across counties with different shares of sloped cropland

Notes: This figure examines the potential non-linear effect of the share of sloped cropland on crop yield, estimated based on modified versions of model (11) that additionally include the interactions between $Post_{it}$ and the square and cubic of $Rate_i$. The corresponding point estimates are presented in Appendix Table A.4. The capped lines denote the 95% confidence intervals.

5.4 Mechanism

This section explains why a program that reduces cropland area could increase total crop yield. We find that increases in multiple cropping, labor reallocation, and offsetting the damage of climatic shocks could explain the impact of the program on crop yield.

5.4.1 Increases in multiple cropping

Table 3 presents strong evidence that the program increased multiple cropping. We measure the cropping intensity as the ratio of crop sown area to cropland area. We estimate the effect of the program on the cropping intensity based on a modified version of model (11) that uses the cropping intensity as the dependent variable. As presented in column (1), the estimates suggest that with a 1 percentage point increase in sloped cropland, the program will increase the cropping intensity by 0.340 percent.

To further verify this finding, we examine the effects in regions suitable for single cropping, double cropping, and triple cropping, respectively. The county-level cropping zones data is derived from the National Meteorological Information Center of China, constructed based on data from 778 agro-climatic monitoring sites.[11] We find a marginal effect of 0.334 percent in the double-cropping regions and a marginal effect of 1.374 percent in the triple-cropping regions. In other words, we find strong evidence that the program substantially increased the cropping intensity in regions with multiple cropping.

TABLE 3 Effect of the Grain for Green Program on cropping intensity

	(1)	(2)	(3)	(4)
	Cropping intensity (crop sown area/cropland area)			
	Total	Single cropping region	Double cropping region	Triple cropping region
$Post_{it} \times Rate_i$	0.340***	-0.069	0.334***	1.374***
	(0.082)	(0.215)	(0.100)	(0.397)
County FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Observations	19,833	3,361	9,528	6,923
R-squared	0.889	0.838	0.836	0.867

Notes: This table estimates the effect of the program on the cropping intensity based on a modified version of model (11) that uses the cropping intensity as the dependent variable. Clustered standard errors are reported in parentheses. Column (1) estimates the effect for the whole sample, while columns (2)–(3) focus on subsample of regions suitable for single cropping, double cropping, and triple cropping, respectively. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.4.2 Input adjustment

Land retirement would reduce agricultural labor input if farmers reallocate labor from the retired farmland to non-agricultural work. However, as presented in column (1) of Table 4, we find that the Grain for Green Program had no significant effect on total agricultural labor input. This finding suggests that the program does not lead farmers to significantly reallocate labor out of agri-

11. http://data.cma.cn/site.

culture. Column (2) shows that the program significantly increased labor input per cropland area, indicating a reallocation of labor from the retired cropland to the remaining cropland. As per unit area crop yield generally increases with per area labor input (Ball et al., 1997), the labor reallocation also contributes to the increased crop yield. We also examined the effect of the program on machinery input, and found no significant effect for both total input and per area input (columns 3 and 4). We do not examine the effect on the input of fertilizers and pesticides due to lack of data.

TABLE 4 Effect of the Grain for Green Program on agricultural inputs

	(1)	(2)	(3)	(4)
	Agriculture labor	Agriculture labor/ Cropland area	Machinery power	Machinery power/ Cropland area
$Post_{it} \times Rate_i$	0.152	0.551***	-0.392	0.005
	(0.139)	(0.144)	(0.397)	(0.396)
County FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	17,619	17,619	17,567	17,567
R-squared	0.938	0.904	0.770	0.665

Notes: This table estimates the effect of the program on agricultural labor (column 1), agricultural labor per cropland area (column 2), agricultural machinery power (column 3), and agricultural machinery power per cropland area (column 4), based on the DID regression model (11) . Clustered standard errors are reported in parentheses. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

5.4.3 Mitigating the damage of climatic shocks

Mitigating the impact of climatic shocks is another potential channel through which the Grain for Green Program may enhance crop yield. The primary goal of the program was to reduce soil erosion by returning sloped cropland to forests and grasslands. Existing studies suggest that a more resilient ecological system can help agriculture withstand natural disasters, thus increasing grain yields (Liang et al., 2016; Yamamoto et al., 2019; Huang et al., 2024b). Given that the program increases the share of forests and grasslands, it may increase the resilience of the local ecosystem.

We verify this effect channel by examining whether the damage of climatic shocks could be mitigated by the program. Specifically, we extend the baseline DID model (11) to include the interaction between climatic shock measures and the DID term:

$$\begin{aligned} Y_{i,t} = &\beta_1 Post_{it} \times Rate_i + \beta_2 shock_{it} + \beta_3 Rate_i \times shock_{it} \\ &+ \beta_4 Post_{it} \times shock_{it} + \beta_5 Post_{it} \times Rate_i \times shock_{it} \\ &+ \lambda treatment_i \times t + \theta selection_i \times \gamma_t + \alpha_i + \gamma_t + w_{pt} + \epsilon_{i,t} \end{aligned} \tag{13}$$

where $shock_{it}$ is a climatic shock measure in county i and year t and all other model settings are the same as those the baseline model.

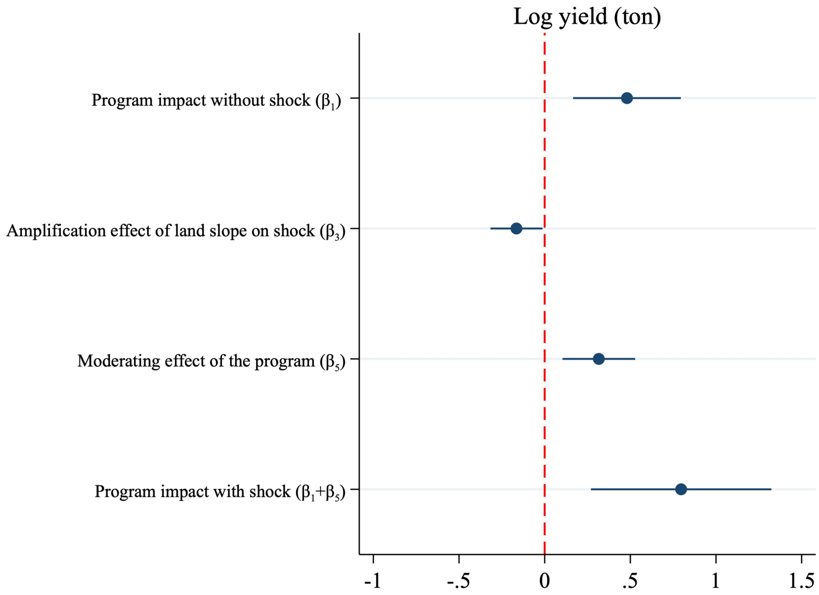
We follow the literature (e.g., Kaur, 2019; Huang et al., 2024a) to construct four climatic shock measures: high temperature shock, low temperature shock, high precipitation shock, and low precipitation shock. A county is defined as having experienced a high (low) temperature shock in a given year if its annual mean temperature exceeds (falls below) the 85th (15th) percentile of the county's long-term distribution over the past 30 years. Similarly, a county is considered to have experienced a high (low) precipitation shock in a given year if its total annual precipitation is above (below) the 85th (15th) percentile of the county's long-term distribution over the past 30 years. We adopt the annual measures of temperature and precipitation rather than growth season measures, because the multiple cropping of different crops within a year makes it difficult to identify a clear growing season. The daily temperature and precipitation data used to calculate these climatic shock measures are derived from ERA5-Land (see subsection 4.1).

In model (13), the coefficient β_1 represents the impact of the program in the absence of the climate shock. The coefficient β_2 is the impact of the climate shock on flat cropland. The coefficient β_3 reflects the amplifying effect of land slope on the impact of the climate shock in the absence of the program. The coefficient β_4 captures the additional effect of the climate shock on flat cropland after the program. The coefficient β_5 indicates the moderating effect of the program on the impact of the climate shock. The total effect of the climatic shock under the program is $\beta_1 + \beta_5$.

Figure 7 presents the estimated effects on total crop yield under high temperature shock and low precipitation shock, which are widely recognized as harmful to agricultural production (Mendelsohn et al., 1994; Deschênes and Greenstone, 2007; Huang and Sim, 2021; Huang et al., 2024b). We find that sloped cropland has a significantly negative amplification effect (β_3) on the damage of high temperature shock and low precipitation shock on crop yield and that the Grain for Green Program could offset these negative effects (β_5). Specifically, with a 1 percentage point increase in sloped cropland, the damage of high temperature shock and low precipitation shock will increase by 0.165 percent and 0.207 percent, respectively. However, with a 1 percentage point increase in sloped cropland, the program could additionally increase crop yield by 0.316 percent and 0.388 percent under high temperature shock and low precipitation shock, respectively.

Appendix Figure A.4 presents the effect of low temperature shock and high precipitation shock (i.e., the favorable shocks) and shows the opposite effect of the program. In our model setting, the negative interaction effect of the program under a favorable climatic shock could be interpreted as that the effect of the program being low when there is a favorable climatic shock. Appendix Figure A.5 presents similar results by using crop yield per sown area instead of total crop yield as the dependent variable. All corresponding point estimates are reported in Appendix Tables A.5. Appendix Figure A.6 adopts extreme heat (measured by harmful degree-days) to measure the positive temperature shock and finds comparable results.

Panel A: High temperature shock



Panel B: Low precipitation shock

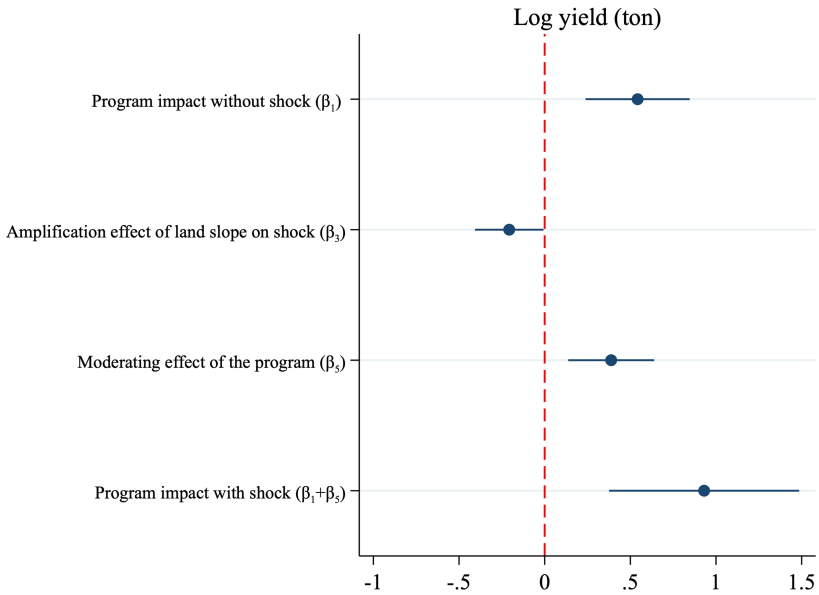


FIGURE 7 Mechanism: Response to climate change shock

Notes: The policy impact without shock is the coefficient of β_1. The amplification effect of land slope on shock is the coefficient of β_3. The moderating effect of the program is β_5. The policy impact with shock is the coefficient of $\beta_1 + \beta_5$. The corresponding point estimates are presented in Appendix Tables A.5. The horizontal lines denote the 95% confidence intervals.

6 Conclusion

The impact of conservation set-aside programs on economic and ecological outcomes has long been a subject of study. While many ecological conservation programs have been adopted and evaluated in developed countries, little is known about the effects of land conservation on food security, particularly in developing countries. This paper examines the effects of China's Grain for Green Program on crop yield. Exploiting the differences in the share of cropland targeted by the program across counties, we find that the program significantly increased crop yield. Mechanism analyses reveal that farmers' response by increasing cropping intensity in the remaining cropland is the main reason of the observed positive impact on crop yield. In addition, in line with the program's objectives, we find that the program substantially mitigated the damage from climatic shocks on crop yield. Our findings suggest the possibility of adopting land use policy to protect the ecosystem without compromising food security in a developing country.

Several limitations in our study warrant future considerations. First, the unavailability of data on other production inputs such as fertilizers and pesticides prevents us from examining whether adjustments of these inputs also contribute to explain the effect of the program on crop yield. Second, the absence of detailed subsidy information of the program limits further investigation into the role of economic incentives in managing the agricultural-ecological trade-offs. Finally, considering that our study focuses on a period in China when the economic development level was relatively low, the main finding of this study may apply only to developing countries.

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A Appendix for online publication

A.1 Data appendix

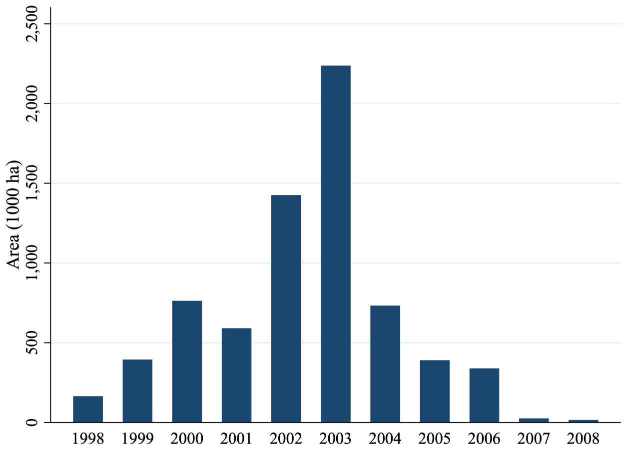

FIGURE A.1 Land converted from cropland to forests and grasslands in each year

Notes: The data are derived from the *China Land and Resources Bulletin*. Comparable data are not available after 2009.

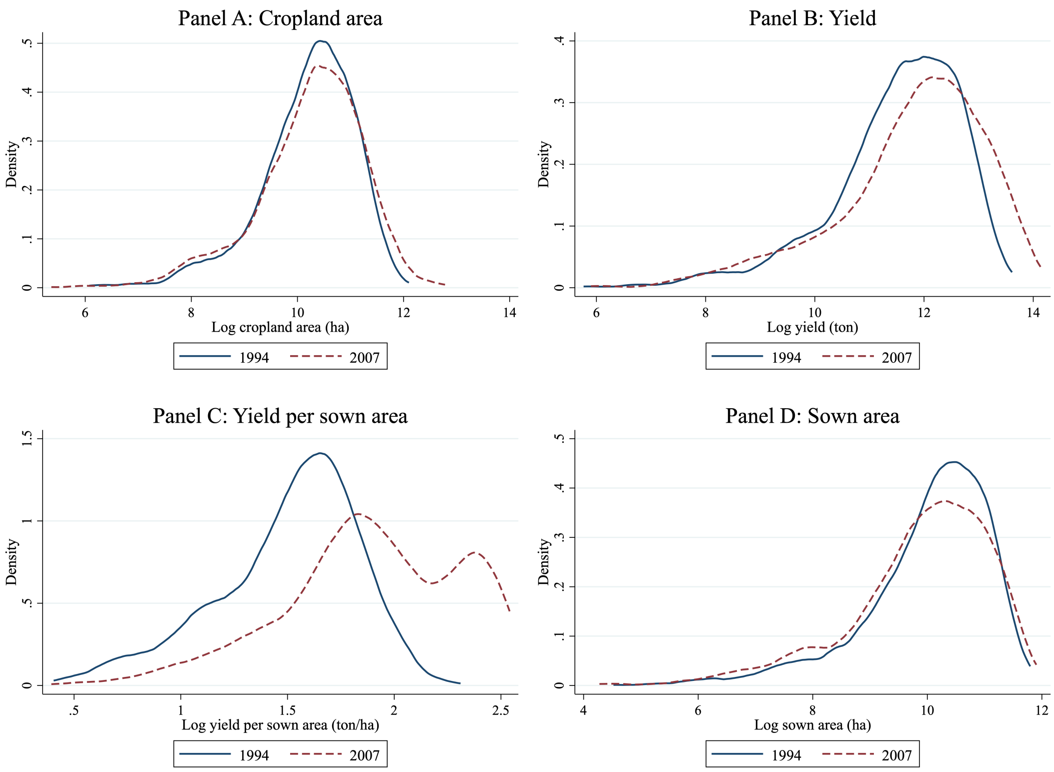

FIGURE A.2 Change in the distribution of cropland area and agricultural output before and after the program

Notes: This figure displays the distribution of the four key outcome variables in 1994 and 2007, respectively.

TABLE A.1 Summary statistics of key variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Cropland area (ha)	19833	39200	34360	161	674753
Total crop yield (ton)	19833	182436	167861	251	1429176
Crop sown area (ha)	19833	32673	26181	69	147729
Yield per sown area (ton/ha)	19833	5.38	1.684	1.467	12.689
Share of sloped cropland	19833	0.035	0.068	0	0.446
Cropping intensity	19833	0.89	0.385	0.029	1.838

Notes: All variables are calculated at the county level for the three major crops (i.e., rice, wheat, and corn). The share of sloped cropland refers to the share of cropland in each county with a slope greater than or equal to 25 degrees in 1990. The cropping intensity is calculated as the ratio between the total sown area and the total cropland area.

A.2 Result appendix

TABLE A.2 Heterogeneity of the effect on yield

	Total crop yield					
	(1)	(2)	(3)	(4)	(5)	(6)
	High GDP per capita	Low GDP per capita	High non-agricultural employment	Low non-agricultural employment	Main rice area	Main wheat and corn area
$Post_{it} \times Rate_i$	0.180	0.549***	0.097	0.832***	0.569***	0.548***
	(0.429)	(0.139)	(0.446)	(0.170)	(0.214)	(0.127)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10481	9528	10409	9419	8723	9637
R-squared	0.951	0.957	0.935	0.953	0.946	0.962
	(7)	(8)	(9)	(10)	(11)	(12)
	High irrigation rate	Low irrigation rate	High temperature	Low temperature	High precipitation	Low precipitation
$Post_{it} \times Rate_i$	0.072	0.602***	0.706***	0.625***	0.548***	-0.083
	(0.346)	(0.164)	(0.225)	(0.210)	(0.127)	(0.652)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11495	8307	9867	9924	9637	10196
R-squared	0.958	0.951	0.949	0.953	0.962	0.951

Notes: This table reports the heterogeneous effect on yield per sown area. Samples were divided by the median values of baseline GDP per capita,non-agricultural employment, main producing area, irrigation rate, temperature, and precipitation. Clustered standard errors are reported in parentheses. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

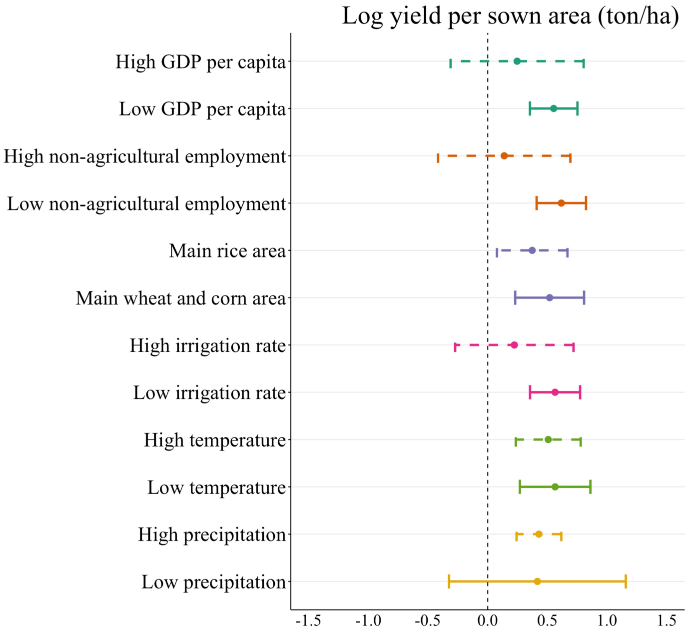

FIGURE A.3 Heterogeneity of the effect on yield per sown area

Notes: This figure estimates the heterogeneity of the effect of the program on crop yield per sown area with respect to different county features. The corresponding point estimates are presented in Appendix Table A.3. The capped lines denote the 95% confidence intervals.

TABLE A.3 Heterogeneity of effect on yield per sown area

	Yield per sown area					
	(1)	(2)	(3)	(4)	(5)	(6)
	High GDP per capita	Low GDP per capita	High non-agriculture employment	Low non-agriculture employment	Main rice area	Main wheat and corn area
$Post_{it} \times Rate_i$	0.246	0.552***	0.138	0.616***	0.372**	0.518***
	(0.284)	(0.101)	(0.282)	(0.105)	(0.150)	(0.147)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10481	9303	10409	9419	8723	11045
R-squared	0.781	0.848	0.814	0.830	0.845	0.812
	(7)	(8)	(9)	(10)	(11)	(12)
	High irrigation rate	Low irrigation rate	High temperature	Low temperature	High precipitation	Low precipitation
$Post_{it} \times Rate_i$	0.223	0.564***	0.507***	0.564***	0.429***	0.416
	(0.253)	(0.107)	(0.138)	(0.151)	(0.096)	(0.377)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11495	8307	9867	9924	9637	10196
R-squared	0.790	0.845	0.867	0.800	0.890	0.792

Notes: This table reports the heterogeneous effect on crop yield per sown area. Samples were divided by the median values of baseline GDP per capita,non-agriculture employment, main producing area, irrigation rate, temperature, and precipitation. Clustered standard errors are reported in parentheses. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

TABLE A.4 Non-linear impacts across counties with different shares of sloped cropland

	(1)	(2)
	Total crop yield	
	Quadratic	Cubic
$Post_{it} \times Rate_i$	1.481***	1.318***
	(0.345)	(0.441)
$Post_{it} \times Rate_i^2$	-2.860**	-0.856
	(1.190)	(4.036)
$Post_{it} \times Rate_i^3$		-4.552
		(9.111)
County FE	Yes	Yes
Province-Year FE	Yes	Yes
Control variables	Yes	Yes
Observations	19,833	19,833
R-squared	0.951	0.951

Notes: This table presents the point estimations of non-linear model, estimated based on modified versions of model (11), that additionally include the interactions between $Post_{it}$ and the square and cubic of $Rate_i$. Clustered standard errors are reported in parentheses. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

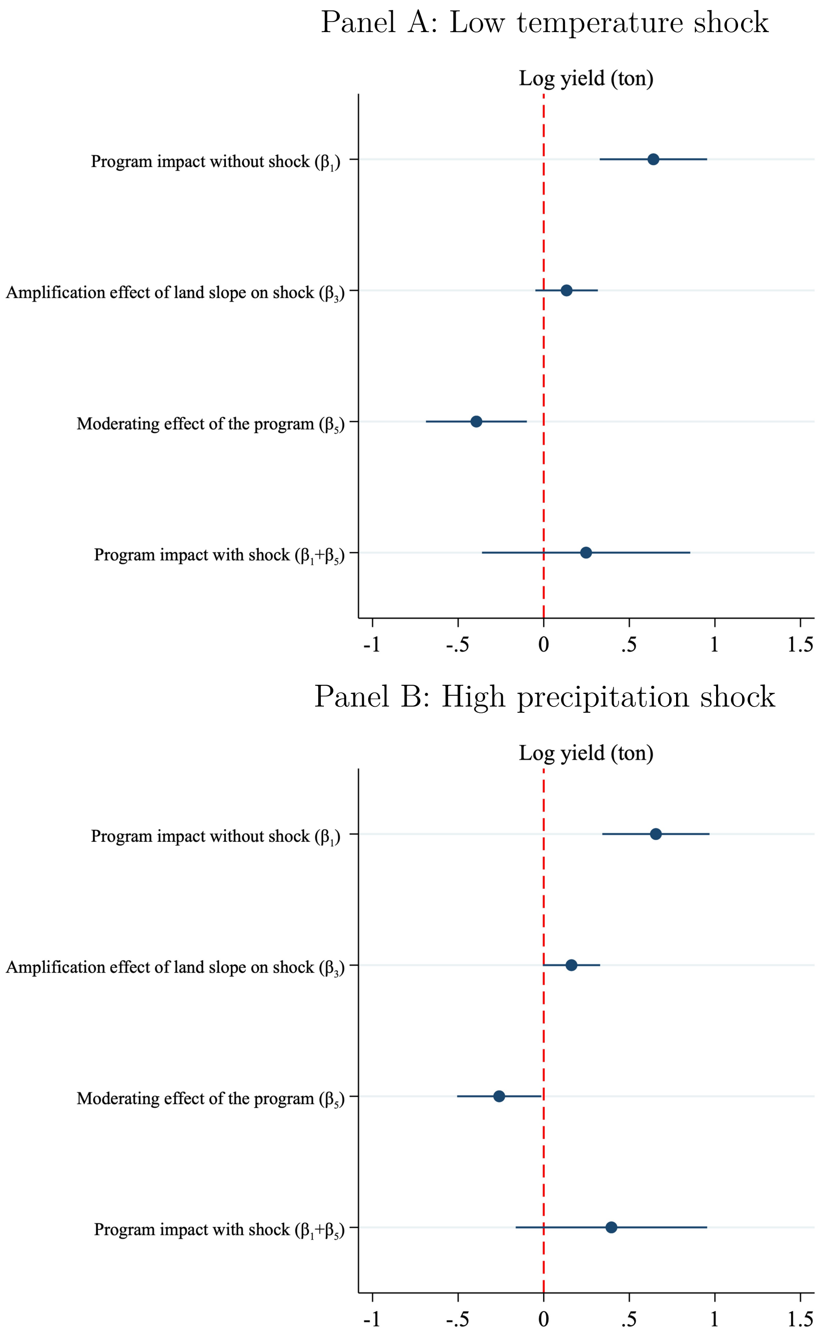

FIGURE A.4 Mechanism: Response to climate change shock

Notes: The policy impact without shock is the coefficient of β_1. The amplification effect of land slope on shock is the coefficient of β_3. The moderating effect of the program is β_5. The policy impact with shock is the coefficient of $\beta_1+\beta_5$. Other specifications are consistent with Equation (11). Here, we show the most interesting coefficients. The corresponding point estimates are presented in Appendix Tables A.5. The horizontal lines denote the 95% confidence intervals.

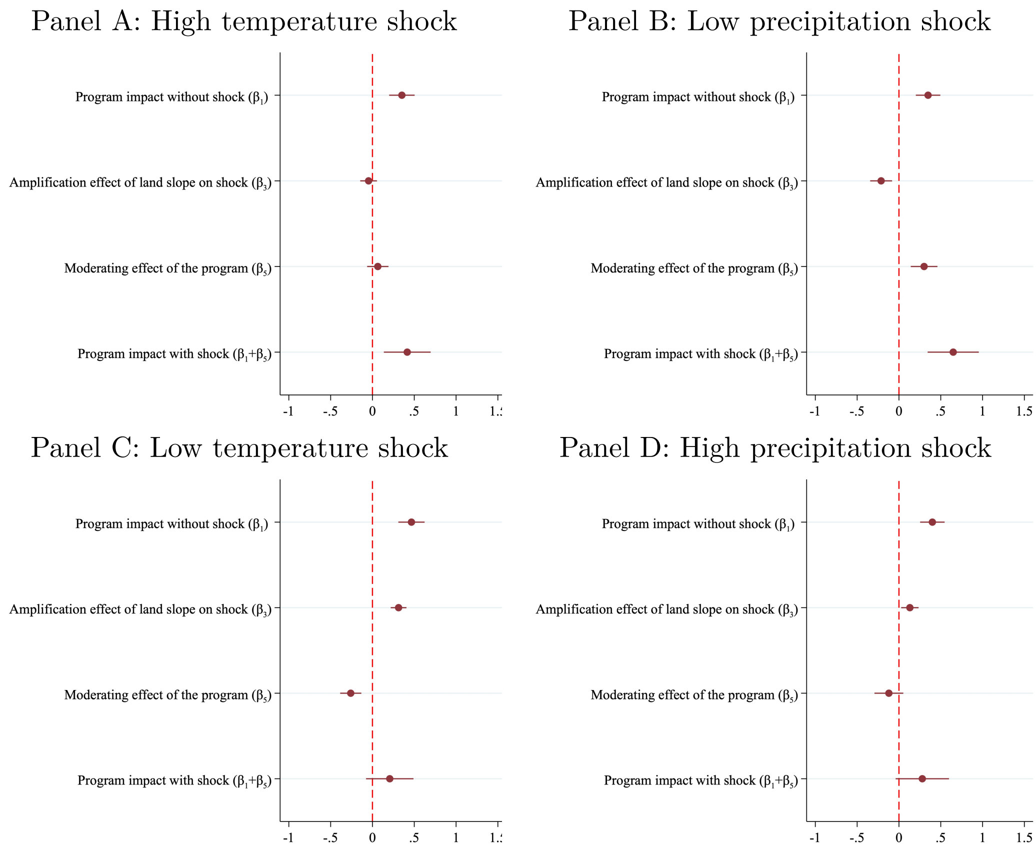

FIGURE A.5 Mechanism: Response of yield per sown area to climate change shock

Notes: The policy impact without shock is the coefficient of β_1. The amplification effect of land slope on shock is the coefficient of β_3. The moderating effect of the program is β_5. The policy impact with shock is the coefficient of $\beta_1+\beta_5$. Other specifications are consistent with Equation (11). Here, we show the most interesting coefficients. The corresponding point estimates are presented in Appendix Tables A.5. The horizontal lines denote the 95% confidence intervals.

HDD shock Past literature uses harmful degree days (HDD) to quantify the time exposed to detrimental temperatures that negatively affect yields. Following Chen and Gong (2021), we classify the temperatures of 33°C and above as harmful. We sinusoidally interpolate between daily maximum and minimum temperatures to reflect the within-day distribution. A county is defined as having experienced a high HDD shock in a given year if the annual HDD in that year is above the 85th percentile of the county's long-term distribution (over the past 30 years). Figure A.6 presents the estimated effects.

Panel A: Total crop yield

Panel B: Yield per sown area

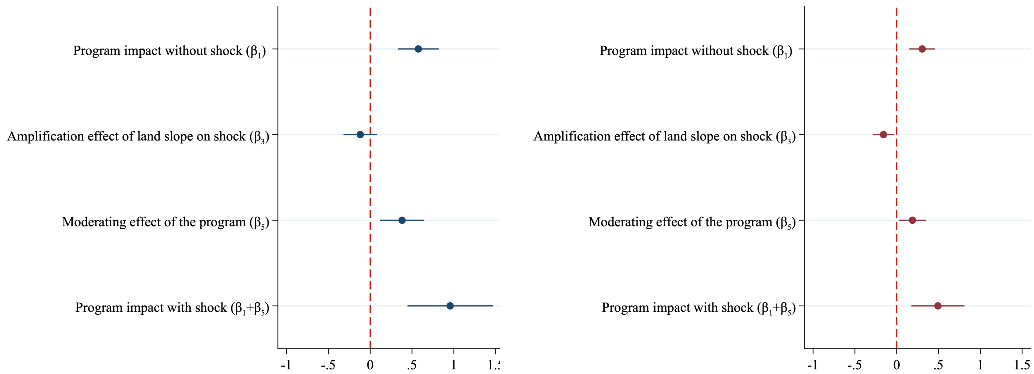

FIGURE A.6 Mechanism: Response to extreme heat shock

Notes: The policy impact without shock is the coefficient of β_1. The amplification effect of land slope on shock is the coefficient of β_3. The moderating effect of the program is β_5. The policy impact with shock is the coefficient of $\beta_1+\beta_5$. Other specifications are consistent with Equation (11). Here, we show the most interesting coefficients. The corresponding point estimates are presented in Appendix Tables A.5. The horizontal lines denote the 95% confidence intervals.

TABLE A.5 Agriculture response to climate change shock

	(1)	(2)	(3)	(4)	(5)
	Total crop yield				
	Higher temperature shock	Lower temperature shock	Higher Precipitation shock	Lower Precipitation shock	Higher HDD shock
$Rate_i \times shock_{it}$	0.481***	0.641***	0.655***	0.543***	0.407**
	(0.160)	(0.160)	(0.160)	(0.155)	(0.165)
$shock_{it}$	-0.005	-0.074***	-0.019**	-0.021**	-0.031***
	(0.011)	(0.027)	(0.009)	(0.010)	(0.011)
$Rate_i \times shock_{it}$	-0.165**	-0.002	0.162*	-0.207**	-0.126
	(0.078)	(0.011)	(0.085)	(0.102)	(0.099)
$Post_{it} \times shock_{it}$	0.000	0.134	0.023*	-0.000	0.004
	(0.015)	(0.093)	(0.014)	(0.013)	(0.016)
$Post_{it} \times Rate_i \times shock_{it}$	0.316***	0.032	-0.260**	0.388***	0.371***
	(0.108)	(0.024)	(0.125)	(0.128)	(0.134)
County FE	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	19,833	19,833	19,833	19,833	19,833
R-squared	0.953	0.953	0.953	0.953	0.953
	(6)	(7)	(8)	(9)	(10)
	Yield per sown area				
	Higher temperature shock	Lower temperature shock	Higher Precipitation shock	Lower Precipitation shock	Higher HDD shock
$Rate_i \times shock_{it}$	0.523***	0.614***	0.629***	0.556***	0.514***
	(0.102)	(0.103)	(0.104)	(0.100)	(0.103)
$shock_{it}$	-0.006	-0.015**	-0.010**	-0.010*	-0.017***
	(0.005)	(0.007)	(0.004)	(0.006)	(0.005)
$Rate_i \times shock_{it}$	-0.096*	0.176***	0.230***	-0.205***	-0.114*
	(0.055)	(0.058)	(0.049)	(0.069)	(0.063)
$Post_{it} \times shock_{it}$	0.002	0.001	0.003	-0.009	-0.005
	(0.008)	(0.015)	(0.007)	(0.008)	(0.008)
$Post_{it} \times Rate_i \times shock_{it}$	0.157**	-0.214**	-0.150**	0.275***	0.152*
	(0.070)	(0.088)	(0.065)	(0.083)	(0.080)
County FE	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	19,833	19,833	19,833	19,833	19,833
R-squared	0.821	0.821	0.821	0.821	0.821

Notes: This table presents the point estimations of how agriculture outcomes response to climate change shock, based on the equation (13). The dependent variables area yield and yield per sown area. Clustered standard errors are reported in parentheses. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.