Two Birds, One Stone: Responses of Agriculture to Water Pollution Regulation

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Abstract:

In many developing nations, addressing non-point source water pollution often involves reducing agricultural fertilizer usage, potentially jeopardizing national food security. However, leveraging a Chinese environmental regulation as a natural experiment, this study illustrates that environmental protections can be implemented without compromising food security. Our analysis reveals that the increase in agricultural productivity following the policy intervention is the primary factor maintaining agricultural output despite reduced fertilizer usage. This productivity growth may be attributed to improvements in water quality and reallocating land to more productive users. Additionally, our findings suggest that local governments in China may still perceive environmental protection and food security as conflicting goals, highlighting the need to rectify this misconception to achieve greater environmental benefits.

Key words: Water Pollution Regulation; Fertilizer; Food Security

JEL Classifications: Q53, Q10, Q19

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1. Introduction

Over the past decades, industrial water pollution in major emerging economies has been steadily decreasing, primarily as a result of environmental regulations that specifically target this sector. In turn, agricultural pollution has become their leading source of water quality degradation (FAO, 2013; WWAP, 2015; EPA, 2016; FAO, 2017). The growing reliance on chemical fertilizers in intensified agricultural practices significantly contributes to the escalating problem of agricultural water pollution (Garnache et al., 2016; McArthur & McCord, 2017). Although fertilizer application intensity has declined in the developed world, most developing countries still rely heavily on fertilizer to sustain agricultural output. For Instance, China, the largest grain producer in the world, feeds 18% of the global population while utilizing only 8% of the world's cultivated land and 6% of its fresh water resource (Han & Chen, 2018),[1] with its crop yield being 20% above the global average. However, this significant achievement comes at the cost of consuming over one-third of the world's chemical fertilizers (Lin, 1992). As a result, agriculture, which accounts for only 7% of China's GDP, is responsible for around half of the nation's water pollution according to the first National Census of Pollution Sources in 2008.

Therefore, reducing the chemical fertilizer application in agricultural production appears to be crucial at the current stage to further improve the water environment. Restricting fertilizer use, however, may hurt food security and place significant economic burdens, particularly on developing countries given the importance of agriculture in these economies and their heavy reliance on fertilizers for food production. Surprisingly, with a detailed county-level agricultural production dataset, we document in this paper with a difference-in-differences (DID) strategy that a water quality control program implemented in major Chinese water basins starting from 2009 effectively reduced fertilizer application without sacrificing agricultural output. Reassuringly, this result is robust to a battery of model specification tests.

This finding is particularly inspiring for two reasons: (1) opportunity exists to achieve the environment-food security balance, an important consideration for most developing countries; (2) economically, regulating agricultural water pollutants is much less costly than regulating industrial pollutants, at least in China. The literature has documented high cost associated with abating industrial water pollutions. For example, He et al. (2020) calculates that reducing major industrial water pollution emissions by one ton costs almost 400 thousand Chinese Yuan (~55 thousand US dollar). In contrast, our study indicates that abating water pollution through reducing fertilizer application is almost costless. Shifting policy focus from mainly regulating point-source industrial pollution to incorporating non-point-source agricultural pollution into the regulation scheme may significantly reduce the cost burden of environmental regulations.

Motivated by this finding, we continue to study channels through which the policy might have affected agricultural production with a production function approach. It turns out that other agricultural inputs, including labor, machinery, and planted area, all

[1] See the report in English by the Ministry of Water Resources, People's Republic of China. http://www.mwr.gov.cn/english/mainsubjects/201604/P020160406508110938538.pdf

decreased following the policy implementation. The increases in TFP alone stabilized agricultural output under the policy pressure. Given the large productivity gap between the farming and industrial sectors in developing countries like China (Lagakos & Waugh, 2013; McCullough, 2017; Adamopoulos et al., 2022), the policy-induced increase in agricultural TFP might have created an economic developing dividend by reallocating more productive resources such as labor and capital from the farming sector to the industrial sector.

Unlike industrial firms that are mainly pollution sources, the agriculture sector is both water pollution emitters and clean water beneficiary. Using a supplementary water quality monitor reading dataset, we show that the policy significantly reduced the concentration of key agricultural water pollutants in the affected water basins. The improved water quality thus enhanced agricultural productivity. We also document evidence that treated counties which historically rely more heavily on irrigation enjoy higher post-policy increase in agricultural TFP. This is consistent with the water-quality improvement story since the impact of water quality should be more pronounced for counties that irrigate more.

Another possible reason for the improvement in agricultural productivity is that less productive farmers might have also responded to the pressure of fertilizer use limitation by renting out their land to more productive units or exiting farming. Consistent with this hypothesis, we show that there is a significant increase in the number of large efficient family farms in the affected counties. As is widely documented in the trade and environmental regulation literature, this positive reallocation effect effectively increases aggregate TFP (Melitz & Ottaviano, 2008; Eslava et al., 2013; Andersen, 2018; Impullitti & Licandro, 2018). Lastly, we also document weak evidence that government investment in agriculture infrastructure increased in affected counties following policy implementation. This increase in agriculture-related public expenditure, if deemed as a cost of stabilizing agricultural production under the policy, is at most moderate compared to the cost of regulating industrial pollutions.

Although the results above indicate that environmental preservation and the sustenance of food security are not inherently contradictory objectives, the tendency to perceive these dual aims as conflicting priorities may still persist within the existing political framework of China. Specifically, different counties are assigned different priorities by the upper-level government, and the promotion prospects of local officials are largely contingent upon their fulfillment of these prioritized objectives. We find that national major grain-producing counties (MGCs) that prioritize on food production did not reduce fertilizer application, even though it manifests that agricultural output remained largely unchanged in non-MGCs where fertilizer application was significantly reduced.

The finding above is consistent with a (likely wrong) belief that regulating fertilizer use may hurt agricultural production, making local officials in MGCs reluctant to take the risk to curb fertilizer use. Starting from 2014, the Chinese central government initiated a reform in the promotion criteria for local officials, with the objective of reallocating greater emphasis towards *environmental protection* or *agricultural production*. As of 2022, the reform has been implemented in approximately 25% of counties across the nation. However, only one-third of the reformed counties simultaneously emphasize these two goals. Our results above indicate that aligning these two goals for all reforming counties may help to attain greater environmental benefits without hampering food security.

Broadly speaking, our paper relates to three areas of literature. First, it complements a large literature that evaluates the impact of environmental regulation targeting industrial firms on firm/industry production (Berman & Bui, 2001; Greenstone, 2002; List et al., 2003; Ryan, 2012; Shapiro & Walker, 2018; Keiser & Shapiro, 2019; Najjar & Cherniwchan, 2021) and in particular the context of China (Chen et al., 2018; Wang et al., 2018; He et al., 2020; Cui et al., 2021). While the Porter Hypothesis states that polluting firms may benefit from environmental policies, most of the studies in the literature document a decline in firm- or industry-level output/productivity following policy implementation, with only a few exceptions (Mohr & Saha, 2008; Cohen & Tubb, 2018). This study, in contrast, estimates the impact of a policy that regulates the *agriculture sector* instead of the industrial sector, and we document robust findings that agriculture output is unaffected by the policy due to an increase in agriculture productivity.

In a recent study, Viard et al. (2022) shows that although air quality regulations reduced firm competitiveness, the policy-induced air quality improvement enhanced industrial firms' productivity. Our finding that the policy-induced water quality improvement may contribute to agricultural TFP increase echoes this finding in the context of water quality regulation.

Second, related to the first literature, several recent studies quantify the *indirect* impacts of environmental policy targeting industrial firms on agriculture. For example, Sanders and Barreca (2022) and Li et al. (2024) quantifies how environmental policies targeting industrial firms' SO_2 emissions affect agricultural yield and revenue in US and China. In contrast, our study shows that agricultural production would not be hurt by environmental policies that *directly* targeting agricultural pollution.

The remainder of the paper proceeds as follows. We briefly review the agriculture institution in China, the environmental consequences of agriculture production and the background of the water pollution control policy under investigation in Section 2. Section 3 presents the empirical strategy and the dataset we use to identify the policy effects. Section 4 discusses the main estimation results, Section 5 performs mechanism analyses and Section 6 performs heterogeneity analyses and discuss policy implications. Section 7 concludes the paper.

2. Background

2.1 The Water Quality Control Plan in Key Basins

Water quality degradation has long been a major environmental problem in China. The first law on water quality regulation, i.e., Law on Prevention and Control of Water Pollution, was enacted in 1984, requiring local and national governments to explicitly consider water environment protection in regional development planning. Supplementing the law, the administration of China's national environmental monitoring center established the national surface water quality monitoring network in 1988 to gather water quality information. Unfortunately, water quality degradation persists likely because the Ministry of Environmental Protection (MEP) did not impose explicit water quality targets for these stations, and local officials were not held accountable for the environmental quality within their jurisdiction (He et al., 2021; Chen et al., 2018).

Realizing these problems, enforcement efforts from the central government came into play since 2006, the first year of the eleventh five-year-plan (FYP), such that environmental performance became officially tied to local officials' promotion evaluation. In 2009, the MEP implemented the *Water Quality Control Plan in Key Basins* (hereafter, the plan), which assigned water quality reading targets for water monitoring stations in ten key basins and emphasized that achieving these targets are essential for local officials' promotions. To be concrete, the ten key water basins specified in the plan include the Songhua River basin, the Huai River basin, the Hai River basin, the Liao River basin, the middle and lower reaches of the Yangtze River basin, the upper and middle reaches basin of the Yellow River, the Taihu Lake basin, the Chaohu Lake basin and the Lake Dian basin. Starting from 2011, more stringent water quality reading targets were updated. Because of the strict policy enforcement, the fraction of water bodies in the key water basins with water quality reaching Grade III and above increased from 44% in 2010 to 63% in 2014.

Unlike previous water pollution regulations in the country, the plan also sets emission control targets for agricultural pollution in addition to those for industrial pollution. Compared to non-point source agricultural pollution, point-source industrial pollution is much easier to be monitored. Before 2009, there were no official statistics on the size of agricultural pollution emissions, neither at the national nor the regional levels. Therefore, environmental policies prior to 2009 mainly targeted industrial polluters.

The state council conducted the first national Census of Pollution Sources in 2008. In addition to industrial pollution, the census also tracked agricultural pollution emissions based on plot-level crop mixtures and land management practices such as agricultural chemical application and irrigation adoption. Census data collection was finished by the beginning of 2009, providing data support to agricultural pollution control under the 2009 water quality control plan. According to the statistics, around 44%, 57% and 67.4% of national emissions of three important water pollutants, i.e., chemical oxygen demand, nitrate and phosphorus, come from agriculture. The census, therefore, substantially heightened the imperative of agricultural pollution control during the plan. In the census data release, officials of the Chinese Ministry of Environmental Protection stated that "to fundamentally address the water pollution issue in China, it is imperative to integrate agricultural pollution control into the core agenda of environmental protection." [2] We therefore expect an adjustment in agriculture production following the 2009 water pollution control program.

2.2 Identify Treated Counties under the Plan

A basin is a water catchment area that can be divided into a set of inter-connected sub-basins such that each sub-basin can be the upstream or downstream area of one or more other sub-basins. Given this upstream-downstream linkage, a water monitoring station is only able to capture water pollution emissions from the sub-basin where it is located

[2] Source: the Chinanews, https://www.chinanews.com.cn/cj/cj-hbht/news/2010/02-09/2116321.shtml.

or that sub-basin's upstream areas; therefore, it is reasonable to expect that only counties located in these areas are affected by the 2009 plan.

To identify the affected counties, we overlay the county map of China with two other geo-coded map layers, namely, the locations of water quality monitoring stations and the basin division map.[3] In the latter dataset, each sub-basin in the ten key river basins are marked as being the downstream or upstream of other sub-basins according to hydrological conditions, such as river flow direction, drainage density and basin altitude.[4] To proceed, we first draw a 50KM-radius circle around each water quality monitoring stations located within the ten key water basins mentioned in the plan.[5] We then find counties with centroid falling inside the circle. Among these counties, those that falling inside the same sub-basin with the station or inside the upstream sub-basin of the station are identified as counties treated by the 2009 water quality control plan.

We illustrate the procedures described above in Figure 1. The triangle represents a water quality monitoring station and the circles represents the centroids of ten counties that fall within the circle. Areas delineated by the solid frames are different sub-basins, two of which, marked by B and C, are the upstream sub-basins of sub-basin A where the monitoring station locates. Seven out of the ten counties above, numbered from 1 to 7, also falls in sub-basin A, B, and C and therefore are categorized as treated counties.

[Figure 1]

Figure 2 shows the differences in two average variables between the treated counties and the control counties: fertilizer application and agricultural output. Shown by the figure, average fertilizer use across the treated counties declined dramatically after 2009 compared to counties in the control group, while the difference in average output level remains largely unchanged.

[Figure 2]

3. Empirical Strategy and Data

3.1 Empirical Strategy

We employ the following Difference-in-Differences (DID) regression to identify the impact of the water quality program on agricultural outcomes:

$$y_{ct} = \beta_0 + \beta_1 WP_c \times Post_t + \gamma \boldsymbol{X_{ct}} + \lambda_c + \theta_t + \varepsilon_{ct}, \quad (1)$$

where the dependent variable y_{ct} is the (logged) agriculture output, TFP and

[3] The basin division map is provided by HydroBasins. For more information on the dataset, please refer to https://www.hydrosheds.org/products/hydrobasins.

[4] There are seven levels of sub-basins in the dataset. Level-one basin is the largest sub-basin, which is divided into a set of level-two sub-basins, and then level-three sub-basins, etc. We choose to overlay the county map with level-six sub-basins when identifying treated counties since the average area of level-six sub-basins is similar to the area of an average county in China.

[5] The average radius of a county in eastern China is around 20KM. Water quality monitoring stations are typically located 100KM from each other; therefore, we set the radius of the circle drawn around each monitoring stations to 50KM to reduce circle overlap. Later we will perform a robustness check that increase the circle radius to 100KM. All empirical results are robust to the selected circle radius.

agriculture inputs of county *c* in year *t*. WP_c is a dummy variable that equals to 1 if county c is affected by the *water quality control program* and 0 for counties in the control group. Procedures we follow to identify treated counties are described in detail in Section 3.2. $Post_t$ is a dummy indicator that equals to 1 after 2009 and 0 otherwise. λ_c and θ_t are county- and year-fixed effects, respectively, and ε_{ct} is an *iid* error term. Additionally, $\boldsymbol{X_{ct}}$ is a vector of county-level time-varying control variables that includes total population, total agricultural areas affected by natural disasters, and annual averages of weather variables, i.e., precipitation, temperature and sunshine. Again, all variables are measured in log-scale. Standard errors are clustered at county level since this is the level at which policy takes effect (Abadie et al., 2023).

Lastly, one may worry that the locations of monitoring stations might be endogenously chosen, i.e., that monitoring stations are purposely placed in areas with high/low agriculture productivity. However, according to the Ministry of Environmental Protection (MEP), the locations of the monitoring stations were chosen based mainly on hydrological rather than economic considerations (He et al., 2020).

Nonetheless, to further alleviate this selection concern, we follow the literature and include in $\boldsymbol{X_{ct}}$ the interactions between time dummies and $\boldsymbol{Z_c}$, a series of pre-regulation socio-economic variables that may affect the location choices of monitoring stations (Chen et al., 2018; Gollin et al., 2021). In particular, $\boldsymbol{Z_c}$ include two broad categories of variables. First, geographical and general economic conditions, including dummy variables indicating whether the county has experienced financial stress by 2004, has been designated as a national poor county in 2004, is located at province boarder, is a city-level county, and is passed by a large river; Second, agriculture production conditions, including pre-policy agricultural GDP (measured in 2005) and a dummy variable indicating whether the county is a major food-producing county.

3.2 Data Description

Our study employs two major datasets, namely, the county-level agriculture input-output dataset and the locations of water monitoring stations. The county-level agriculture unbalanced panel data covering a majority of Chinese counties from 2006 to 2015 is maintained by the Ministry of Agriculture and Rural Affairs of China, which contains county-level fertilizer use and agricultural output on a yearly basis. Other agricultural inputs such as labor, machinery, and land are also reported in the dataset. The full input-output information additionally allows us to estimate county-level annual agriculture TFP following Chen and Gong (2021), and the Detailed estimation procedures and discussions are relegated to Appendix A.

We choose this 2006-2015 as the study period for two reasons. First, Chinese national and local policies are often updated in governments' five-year plans. The water quality regulation under investigation started at 2009 during the 11^{th} Five-year Plan and ended at 2015, the last year of the 12^{th} Five-year Plan. To make things other than water quality regulation stringency comparable as much as possible during the sampling period, we restrain the data to cover only these two consecutive five-year plans, i.e., from 2006 to 2015. Second, agricultural tax was abolished nationally in China at 2006. Focusing on the post-2006 period thus further ensures a stable agricultural production environment during the study period.

To determine the set of counties affected by the water quality control program, conduct mechanism and heterogeneity analyses, we complement the two major datasets by several other datasets, namely, the water basin connection dataset and the China Agri-research Database. Detailed summary statistics can be found in Table 1

[Table 1]

4. Main Results

4.1 Declining Fertilizer Application but Unaffected Agricultural Output

We first assess whether the pollution control program achieved agriculture-related pollution reduction. Due to the non-point source nature of agricultural water pollution, it is impossible to track the exact contribution of each farm household or each county to the pollution reading of monitoring stations. Instead, we use fertilizer application to approximate agricultural pollution since, as discussed in section 2, fertilizer is an important production faction in Chinese agriculture and contributes significantly to rural water pollution. Although local officials are unable to directly control the non-point source water pollution emissions from individual farmers, they can, however, control the supply of fertilizers through changing fertilizer subsidy rate.

The first three columns of Table 2 report the estimated effects of the pollution control program on fertilizer application. The specifications alternate based on the control variables that we include. No control variables are reported in the first column. In the second column, we include in the regression interactions between year dummies and county-level pre-policy characteristics to control for the possible selection problem where these characteristics may affect the location choices of monitoring stations.[6] Finally, in the last column, we additionally include other control variables that may also affect the outcome variables. The detailed list of the pre-policy and control variables can be found in Section 3.1.

[Table 2]

The estimated coefficients are significantly negative in all three columns. Overall, the water pollution control program reduced the fertilizer applications for counties in the upstream of water monitoring stations by roughly 6%. This size of reduction in fertilizer, one of the most important agricultural production factors, is already meaningful to affect agricultural output.

However, as shown by the last three columns of Table 2, agricultural output of the treated counties remains largely unchanged. The estimated effect is both small and statistically insignificant. The finding that the regulation reduced agricultural pollution while maintaining the ability of agriculture to feed the country is encouraging given the

[6] An alternative to this specification is to use a matched sample for the estimation. Specifically, for each treated county, we identify five counties in the control group based on the estimated propensity score of being treated. The unmatched sample are not used in the estimation. The pre-regulation variables used to estimate the propensity score are the same as those in $\boldsymbol{Z_c}$. As Appendix Figure A1shows, counties in the treated group and the control group share much more similar characteristics after the match, making the matched control group a more nature counterfactual than the unmatched control group. It turns out that the estimation results in Appendix Table A2 are similar to the results presented in Table 2.

well-documented negative effects of environmental regulations on the economic output of, in particular, industrial firms. We next conduct a battery of robustness checks before proceeding to the mechanism analysis in subsection 4.3.

4.2 Robustness Checks

There are several potential threats to the identification of the water quality control program's treatment effects. First, a necessary condition for the validity of the DID strategy is that the pre-regulation time trends of the outcome variables are the same for the treated and control counties. To make sure that there are no pre-trends that might drive our results, we conduct an event study and examine how the policy's impact evolved over time by including a series of interactions between the WP dummy and year dummies. Specifically, we estimate the following equation:

$$log(y_{ct}) = \alpha + \sum_{\tau \geq 2006, \tau \neq 2008}^{2015} \rho_\tau \, WP_c \times Year_t^\tau + \gamma \boldsymbol{X_{ct}} + \lambda_c + \theta_t + \varepsilon_{ct}, \qquad (2)$$

where $Year_t^\tau = 1$ if $t = \tau$. We choose $\tau = 2008$, one year before the policy took effect, as the base year for the event study, so that the post-treatment effects are relative to the period immediately prior to the start of the water quality control program.

The parallel trend analysis results for fertilizer application and agricultural output are plotted in the top panel of Figure 4. Reassuringly, the estimated ρ_τs for $\tau \leq 2007$ are close to zero and are all statistically insignificant; therefore, there is no difference in the pre-regulation trends of the two outcome variables between the treated and control groups, further indicating that water quality monitoring stations are not strategically sited, especially after conditioning on the pre-policy county characteristics.

[Figure 3]

Second, as discussed in Section 2, the radius of the circle we draw to assign treatment status to counties around the water quality monitoring stations is 50KM. To test whether our results are sensitive to the radius of the circle, we make the radius 100KM and re-estimate model (1) and the results are reported in the first two columns of Table 3. Our results are robust to this change.

Third, as prefectures are responsible for agricultural production in China, the reduction in fertilizer or agricultural output of the treated counties may be partially offset by the increase in these variables in the control counties located in the same prefectures of the treated counties. If such spillover effects exist, the standard errors should cluster at the prefecture level since this is the level at which the policy takes effect, and the treatment effects would be also be overestimated by the DID strategy. To address this concern, we first change the level of clustering to prefecture level in the previous regression, and the standard errors reported in the last two columns of Table 3 remain largely unchanged compared to the third and sixth columns of Table 2. We then drop control counties that are the in the same prefecture with treated counties from the sample, expecting that cross-prefecture spillover effects are expected to be much weaker than that within prefectures. Reassuringly, the estimation results reported in the first two columns of Table 4 are similar to the main estimation results reported in Table 2.

[Table 3]

Following similar spirits, the right panel of Table 4 presents the results of a direct spillover effect test. Specifically, we examine whether the outcome variables changed after the policy implementation for counties in the same prefecture with treated counties, compared to counties outside prefectures with at least one treated county. Again, we do not document statistically meaningful changes. Therefore, there is little evidence on policy spillovers in this application.

[Table 4]

4.3 Decomposing Agricultural Output

The finding that the policy reduced fertilizer application while maintaining agricultural output indicates that there must be an increase in agricultural productivity or other farming inputs. Therefore, we re-estimate model (1) by replacing the dependent variable by the log of labor, machinery, land and TFP. All these variables pass the parallel-trend analysis, as indicated by the middle and bottom panels of Figure 2. The estimation results are presented in Table 5.

[Table 5]

It turns out that, following the policy implementation, all three major agricultural inputs mentioned above declined, possibly due to the complementarity of these inputs to fertilizer in agricultural production. In contrast, the policy significantly pushed up agricultural TFP in affected counties, shielding agricultural output from being negatively affected by the water quality control program. It is, therefore, interesting to delve into the reasons behind the increase in TFP.

5. Mechanisms

A natural explanation of the increase in agricultural productivity is that the regulation increases the quality of irrigation water. We test this hypothesis with a DID strategy similar to that specified in equation (1). Specifically, we estimate the following equation with monitoring station-level datasets.

$$R_{it} = \beta_0 + \beta_1 Key_i \times Post_t + \gamma \boldsymbol{X_{it}} + \rho_i + \tau_t + \varepsilon_{it}, \quad (2)$$

where R_{it} is the concentration reading of relevant water pollutants recorded by station i in year t, and Key_i is a dummy variable indicating whether station locates in one of the key basins. ρ_i and τ_t are station- and year- fixed effects, respectively. The estimation results are reported in Table 6.

[Table 6]

As expected, the regulation significantly reduced the concentrations of Permanganate Value (PV), Biochemical Oxygen Demand (BOD), Ammonia Nitrogen (NH3-N) and Petroleum Pollutants (PP). The Dissolved Oxygen (DO) also increased. All of these changes indicate an increase in water quality. As a placebo test, we also show in the bottom panel of Table 6 that the policy has little impact on the concentration of mercury and lead, two non-agricultural water pollutants that are mainly emitted by industrial sources. Reassuring, we show that the increase in TFP is more pronounced for counties that rely more heavily on irrigation.

Besides the change in water quality, actions taken by both farmers and the local governments may also affect the county-level TFP. The policy may push farmers to engage in modern agricultural management. For example, the decline in agricultural outputs of small farmers may drive them out from farming, triggering land transfer and thus fostering larger farms or agricultural enterprises. Local governments may also encourage the development of large family farms and/or local agricultural enterprises by providing more subsidies to these entities in the affected counties. This will also increase TFP at aggregate levels and stabilizing aggregate agricultural outputs. In addition, local officials, facing the dual responsibility of environmental protection and maintaining food security, may provide more financial support to agriculture. We test these hypotheses in columns (1) - (4) of Table 8. Although the water quality control program has no statistically significant effect on agriculture-related enterprises, the number of large family farmers in the treated counties increased significantly, which might have contributed to the increase in county-level TFP following the policy implementation. We also document weak evidence on the financial support channel.

[Table 7]

6. Heterogeneous Response to the Policy by Local Officials' Differentiated Priority

Although the results above indicate that environmental preservation and the sustenance of food security are not inherently contradictory objectives, the tendency to perceive these dual aims as conflicting priorities may still persist within the existing political framework of China. Specifically, different counties are assigned different priorities by the upper-level government, and the promotion prospects of local officials are largely contingent upon their fulfillment of these prioritized objectives. We find that national major grain-producing counties (MGCs) that prioritize on food production did not reduce fertilizer application, even though it manifests that agricultural output remained largely unchanged in non-MGCs where fertilizer application was significantly reduced.

[Table 8]

The finding above is consistent with a (likely wrong) belief that regulating fertilizer use may hurt agricultural production, making local officials in MGCs reluctant to take the risk to curb fertilizer use. Starting from 2014, the Chinese central government initiated a reform in the promotion criteria for local officials, with the objective of reallocating greater emphasis towards *environmental protection* or *agricultural production*. As of 2022, the reform has been implemented in approximately 25% of counties across the nation. However, only one-third of the reformed counties simultaneously emphasize these two goals. Our results above indicate that aligning these two goals for all reforming counties may help to attain greater environmental benefits without hampering food security

7. Short Conclusions (Tentative)

In this paper, we present a surprising result that an environmental regulation in China significantly reduced agricultural fertilizer application without hampering food production. This result is policy-relevant in that it shows that environmental protection can be compatible with maintaining food security, and that regulating non-point source water pollution in this stage might be far less costly than regulating point-source industrial water pollutions. Despite these positive findings, it seems that local government in China still perceive the two goals as conflicting objectives, which limits the potential of environmental benefits materialization, highlighting the need to rectify this misconception to achieve greater environmental benefits.

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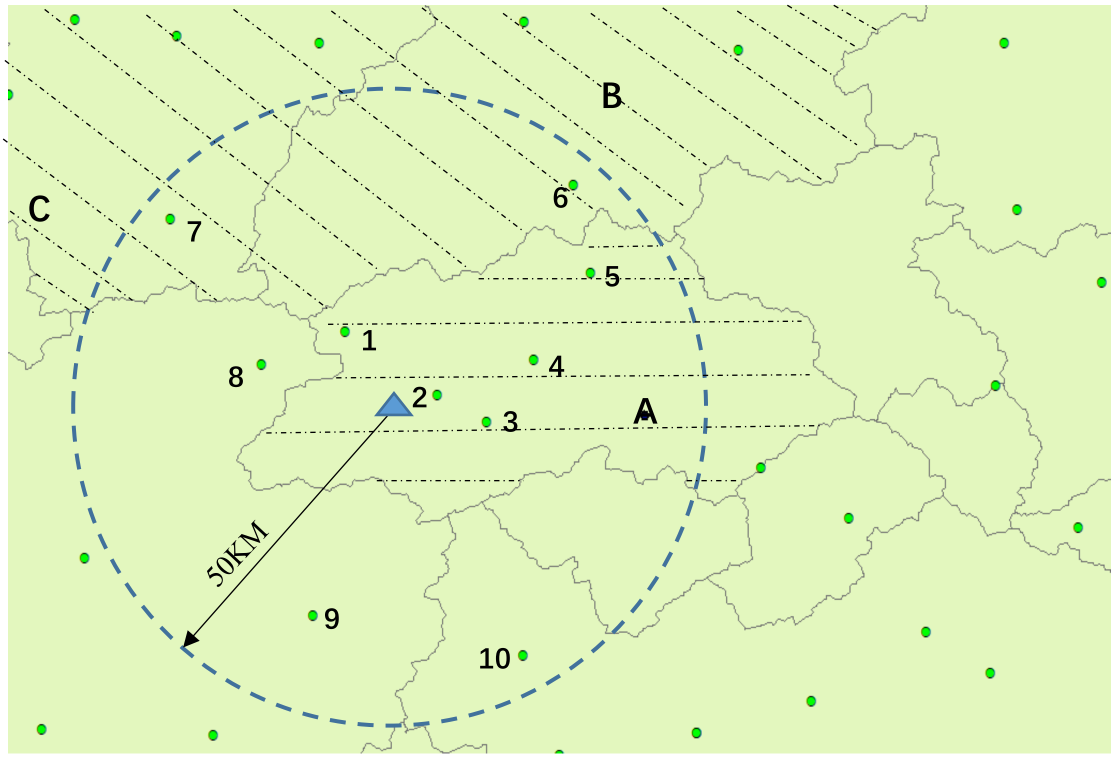

Figure 1. Treatment County Assignment Illustration

Notes: In this figure, the delineated regions enclosed by solid outlines represent basins; the triangular marker pins down the location of a monitoring station; the dots represent county centroids. The monitoring station is within basin A. Basins B and C are the upstream basins of basin A. The radius of the circle drawn around the monitor is 50KM; therefore, those in the shaded basins and within the 50KM circle, i.e., those indexed by 1-7.

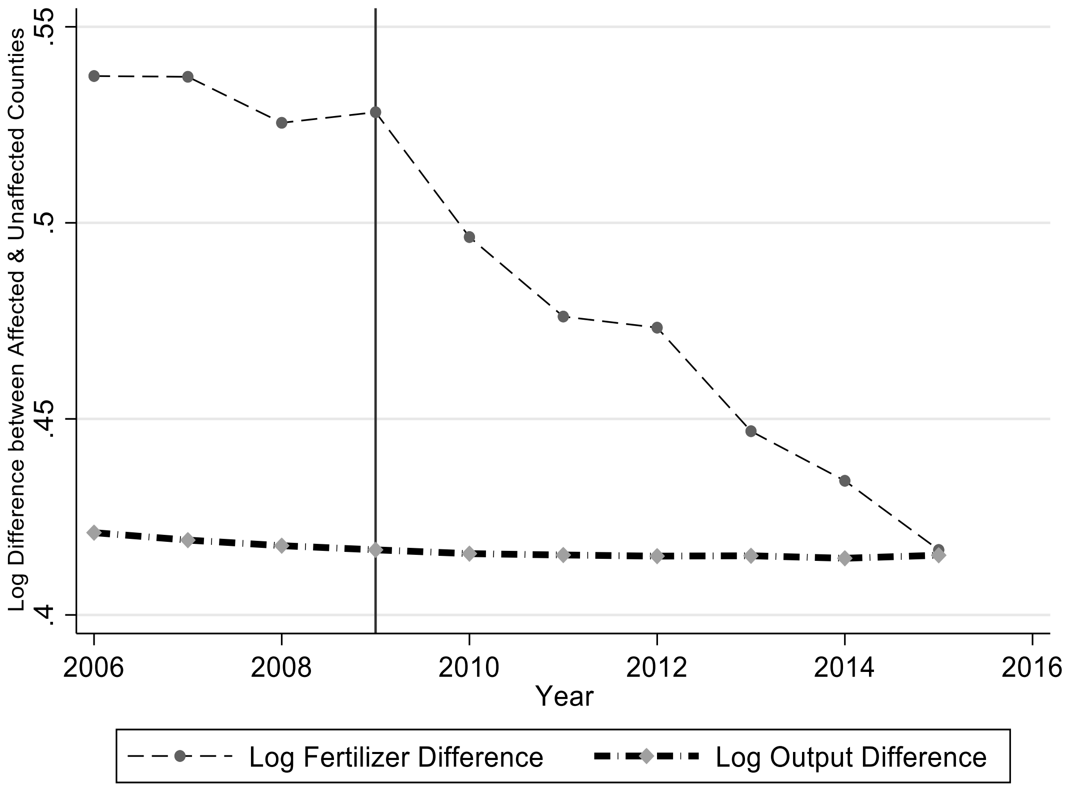

Figure 2. Differences in Average Fertilizer Application (in log) and Agricultural Output (in log) Between Counties Affected and Unaffected by the 2009 Plan

Notes: In this figure, we plot the differences in county-level average fertilizer application and agricultural output between counties in the treatment and control groups under the 2009 Plan. As will be discussed in more detail in Section 2.2, treated counties satisfy two conditions: (i) they are within 50KM from a monitoring station located inside the ten key water basins, and (ii) they are in the same water sub-basin with the station or in the upstream sub-basin of the station. The solid vertical line is draw at year = 2009.

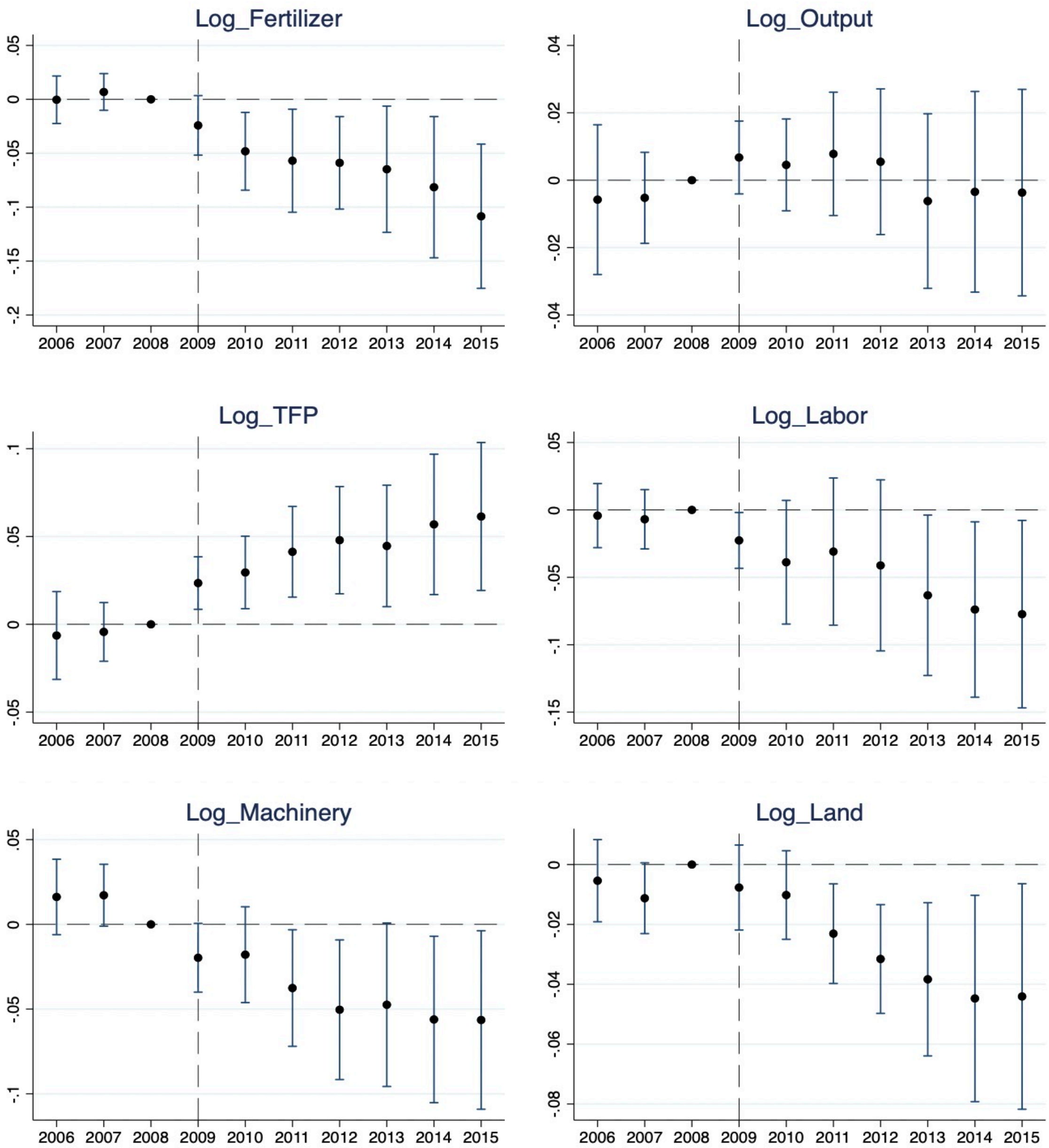

Figure 3. Parallel Trend Test Results

Notes: This figure plots the results of the event-study regressions for the six dependent variables in Table 2 and Table 3. Markers in the figure represent point estimates of β_τ, and the vertical solid lines represent the corresponding 95% confidence intervals. Standard errors used to calculate the confidence intervals are multiple clustered at the province-by-year and county levels. We choose $\tau = -1$, one year before the law reform implementation, as the base year in the event studies.

Table 1 Summary Statistics

Variables	N	Mean	St.D	P10	P90
Log-scaled Variables					
Log (Fertilizer)	13,096	9.721	1.039	8.378	11.018
Log (Output)	13,096	9.721	1.039	8.378	11.018
Log (TFP)	13,096	-0.998	0.534	-1.620	-0.320
Log (Labor)	13,096	11.507	0.818	10.451	12.478
Log (Machinery)	13,096	12.507	0.960	11.295	13.762
Log (Land)	13,096	10.984	0.775	10.018	11.959
Log (Soil Mulch)	11,451	-5.343	1.122	-6.796	-3.939
Log (Ag Infrastructure)	4,822	-5.289	1.569	-7.300	-3.322
Log (Ag Support Fund)	8,731	-4.269	1.610	-6.406	-2.280
Log (Precipitation)	13,096	6.718	0.510	6.149	7.316
Log (Temperature)	13,096	2.549	0.480	1.900	2.958
Log (Sunshine)	13,096	7.552	0.283	7.140	7.898
Log (Population)	13,096	12.900	0.730	11.977	13.829
Log (Disaster)	13,096	5.981	4.766	0.000	11.136
Dummy Variables					
Impoverished	12,020	0.314	0.464		
Major Food-producing	12,020	0.389	0.487		
Boundary	13,096	0.397	0.489		

Table 2. Effects of the Water Quality Plan on Fertilizer Use and Agriculture Outcome

Dependent Variables	Log (Fertilizer)			Log(Output)		
	(1)	(2)	(3)	(4)	(5)	(6)
WP×Post2008	-0.058***	-0.060***	-0.062***	0.007	0.007	0.006
	(0.018)	(0.018)	(0.019)	(0.012)	(0.012)	(0.013)
County FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
$\boldsymbol{Z_i}$ ×Year FE	No	Yes	Yes	No	Yes	Yes
Other Controls	No	No	Yes	No	No	Yes
# Observations	15,360	15,243	13,096	15,360	15,243	13,096
Adjusted R^2	0.940	0.940	0.938	0.982	0.982	0.982

Notes: The dependent variables in this table are county-level logged total fertilizer use and logged real total agricultural output. The vector of county-level time-invariant and pre-determined variables $\boldsymbol{Z_i}$ can be divided into the following three groups. First, geographical and general economic conditions, including dummy variables indicating whether the county has experienced financial stress by 2004, has been designated as a national poor county in 2004, is located at province boarder, is a city-level county, and is passed by a large river; Second, agriculture production conditions, including pre-policy agricultural GDP (measured in 2005) and a dummy variable indicating whether the county is a major food-producing county. It is possible that there are systematical differences between counties in the treated and control group in these aspects, which may also be correlated simultaneously with agricultural production and the selection of assessed water cross sections. Interacting these time-invariant and pre-determined variables with year dummies helps to tease out the possible post-treatment variations in the outcome variables created by these confounding variables. Other control variables include county-level population, total agricultural areas affected by natural disasters, and annual averages of weather variables, i.e., precipitation, temperature and sunshine. Standard errors clustered at county level are reported in the parentheses. *, **, and *** denote significant at 10%, 5%, and 1% levels, respectively.

Table 3. Robustness Checks: Model Specification

	Treatment Assignment Radius = 100KM		Cluster Standard Errors at Prefectures	
Dependent Variables	Log (Fertilizer)	Log (Output)	Log (Fertilizer)	Log (Output)
	(1)	(2)	(3)	(4)
WP×Post2008	-0.057***	0.003	-0.062***	0.006
	(0.019)	(0.012)	(0.024)	(0.017)
County FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
$\boldsymbol{Z_i}$ ×Year FE	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
# Observations	13,096	13,096	13,096	13,096
Adjusted R^2	0.938	0.982	0.938	0.982

Notes: The dependent variables in this table are county-level logged total fertilizer use and logged real total agricultural output. The vector of county-level time-invariant and pre-determined variables $\boldsymbol{Z_i}$ can be divided into the following three groups. First, geographical and economic conditions, including dummy variables indicating whether the county has experienced financial stress by 2004, has been designated as a national poor county in 2004, is located at province boarder, is a city-level county, and is passed by a large river; Second, agriculture production conditions, including pre-policy agricultural GDP (measured in 2005) and a dummy variable indicating whether the county is a major food-producing county. It is possible that there are systematical differences between counties in the treated and control group in these aspects, which may also be correlated simultaneously with agricultural production and the selection of assessed water cross sections. Interacting these time-invariant and pre-determined variables with year dummies helps to tease out the possible post-treatment variations in the outcome variables created by these confounding variables. Other control variables include county-level population, total agricultural areas affected by natural disasters, and annual averages of weather variables, i.e., precipitation, temperature and sunshine. Standard errors, clustered at county level for the first two columns and at prefecture level for the last two columns, are reported in the parentheses. *, **, and *** denote significant at 10%, 5%, and 1% levels, respectively.

Table 4. Robustness Checks: Spillover Effects

Dependent Variables	Exclude Counties in the "Treated Prefectures"		Placebo Tests	
	Log (Fertilizer)	Log (Output)	Log (Fertilizer)	Log (Output)
	(1)	(2)	(3)	(4)
WP×Post2008	-0.053**	0.005	0.033	-0.000
	(0.021)	(0.014)	(0.026)	(0.014)
County FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
$\boldsymbol{Z_i}$ ×Year FE	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
# Observations	10,345	10,345	9,204	9,204
Adjusted R^2	0.940	0.982	0.935	0.982

Notes: "Treated Prefectures" means prefectures that have at least one treated (monitored) county; therefore, the control counties in the first set of regressions are those that located outside the treated prefectures, while the treated counties are the same as treated counties in the main regression. In the second set of regressions, we set treated counties as those that are not monitored but located at prefectures with at least one monitored county. In contrast, the control counties are those that located outside the treated prefectures. The dependent variables in this table are county-level logged total fertilizer use and logged real total agricultural output. The vector of county-level time-invariant and pre-determined variables $\boldsymbol{Z_i}$ can be divided into the following three groups. First, geographical and economic conditions, including dummy variables indicating whether the county has experienced financial stress by 2004, has been designated as a national poor county in 2004, is located at province boarder, is a city-level county, and is passed by a large river; Second, agriculture production conditions, including pre-policy agricultural GDP (measured in 2005) and a dummy variable indicating whether the county is a major food-producing county. It is possible that there are systematical differences between counties in the treated and control group in these aspects, which may also be correlated simultaneously with agricultural production and the selection of assessed water cross sections. Interacting these time-invariant and pre-determined variables with year dummies helps to tease out the possible post-treatment variations in the outcome variables created by these confounding variables. Other control variables include county-level population, total agricultural areas affected by natural disasters, and annual averages of weather variables, i.e., precipitation, temperature and sunshine. Standard errors clustered at county level are reported in the parentheses. *, **, and *** denote significant at 10%, 5%, and 1% levels, respectively.

Table 5. Decomposing the Effects on Agriculture Outcome

Dependent Variables	Log (Labor)	Log (Machinery)	Log (Land)	Log (TFP)
	(1)	(2)	(3)	(4)
WP×Post2008	-0.043**	-0.050***	-0.021**	0.045***
	(0.020)	(0.018)	(0.009)	(0.015)
County FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Time-varying Control	Yes	Yes	Yes	Yes
$\boldsymbol{Z_i}$ ×Year FE	Yes	Yes	Yes	Yes
# Observations	13,096	13,096	13,096	13,096
Adjusted R^2	0.907	0.947	0.974	0.913

Notes: The vector of county-level time-invariant and pre-determined variables $\boldsymbol{Z_i}$ can be divided into the following three groups. First, geographical and economic conditions, including pre-policy industrial GDP in 2005 and dummy variables indicating whether the county has experienced financial stress by 2004, has been designated as a national poor county in 2004, is located at province boarder, is a city-level county, and is passed by a large river; Second, agriculture production conditions, including pre-policy agricultural GDP (measured in 2005) and a dummy variable indicating whether the county is a major food-producing county. Other control variables include county-level population, total agricultural areas affected by natural disasters, and annual averages of weather variables, i.e., precipitation, temperature and sunshine. Standard errors clustered at county level are reported in the parentheses. *, **, and *** denote significant at 10%, 5%, and 1% levels, respectively.

Table 6. Behind the Increase in TFP: Changes in Water Quality

Panel A: Agricultural Pollutants	Log (PV)	Log (BOD)	Log (NH3-N)	Log (PP)	Log (DO)
	(1)	(2)	(3)	(4)	(5)
WP×Post2008	-0.108**	-0.208***	-0.212**	-0.143*	0.106***
	(0.045)	(0.068)	(0.085)	(0.082)	(0.026)
Station FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
# Observations	2,386	2,383	2,389	2,324	2,386
Adjusted R^2	0.922	0.895	0.917	0.825	0.775

Panel B, Placebo: Non-Agricultural Pollutants	Log (Mercury)	Log (Lead)
	(1)	(2)
WP×Post2008	-0.037	0.052
	(0.078)	(0.141)
Station FEs	Yes	Yes
Year FEs	Yes	Yes
# Observations	2,276	2,302
Adjusted R^2	0.580	0.704

Panel C: Treated County	Log(TFP) Irrigation-Heavy Counties	Log(TFP) Irrigation-Light Counties
	(1)	(2)
WP×Post2008	0.098***	0.036**
	(0.030)	(0.016)
County FEs	Yes	Yes
Year FEs	Yes	Yes
Controls	Yes	Yes
$\boldsymbol{Z_i}$ ×Year FE	Yes	Yes
# Observations	9,748	12,552
Adjusted R^2	0.906	0.903

Notes: The (log) depend agricultural pollutants in the five columns of Panel A are Permanganate Value (PV), Biochemical Oxygen Demand (BOD), Ammonia Nitrogen (NH3-N), Petroleum Pollutants (PP), and Dissolved Oxygen (DO), respectively. Greater values of the first four indices signify diminished water quality, whereas the opposite holds for the last index. The results of the analyses presented in Panel B act as placebo tests since the emissions of both Mercury and Lead from agricultural sources are minimal. The sample covers annual station-level readings of the five indices from 2006 to 2010. Post-2010 readings are not publicly available. Panel C separately reports the treatment effects for counties that rely more heavily and less heavily on irrigation. Standard errors clustered at sub-river level are reported in the parentheses. *, **, and *** denote significant at 10%, 5%, and 1% levels, respectively.

Table 7. Behind the Increase in TFP: Responses from Farmers and Local Governments

Dependent Variables	Log (Large Family Farms)	Log (Agriculture-related Enterprises)	Log (Agriculture Infrastructure Investment)	Log (Agriculture Support Funds)
	(1)	(2)	(3)	(4)
WP×Post2008	0.124***	-0.011	0.059*	0.040
	(0.034)	(0.019)	(0.034)	(0.030)
County FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Time-varying Controls	Yes	Yes	Yes	Yes
$\boldsymbol{Z_i}$ ×Year FE	Yes	Yes	Yes	Yes
# Observations	13,096	13,096	4,817	8,725
Adjusted R^2	0.627	0.954	0.976	0.969

Notes: The (log) depend variables in the five columns are: (1) number of large family farms, (2) number of agriculture-related enterprises, (3) agriculture infrastructure investment per agriculture labor, and (4) agriculture support funds per agriculture labor. All variables are measured at the county level. The vector of county-level time-invariant and pre-determined variables $\boldsymbol{Z_i}$ can be divided into the following three groups. First, geographical and economic conditions, including pre-policy industrial GDP in 2005 and dummy variables indicating whether the county has experienced financial stress by 2004, has been designated as a national poor county in 2004, is located at province boarder, is a city-level county, and is passed by a large river; Second, agriculture production conditions, including pre-policy agricultural GDP (measured in 2005) and a dummy variable indicating whether the county is a major food-producing county. Other control variables include county-level population, total agricultural areas affected by natural disasters, and annual averages of weather variables, i.e., precipitation, temperature and sunshine. Standard errors clustered at county level are reported in the parentheses. *, **, and *** denote significant at 10%, 5%, and 1% levels, respectively.

Table 8. Heterogeneity Analysis Results by County's Assigned Priority

Panel B	**Non-Major Grain-Producing County**			**Major Grain-Producing County**		
Dependent Variables	Log (Fertilizer)	Log (Output)	Log (TFP)	Log (Fertilizer)	Log (Output)	Log (TFP)
	(1)	(2)	(3)	(5)	(6)	(7)
WP×Post2008	-0.097***	0.002	0.058**	-0.011	0.016	0.035*
	(0.026)	(0.019)	(0.023)	(0.027)	(0.016)	(0.019)
# Observations	8,015	8,015	8,015	4,671	4,671	4,671
Adjusted R^2	0.915	0.975	0.905	0.889	0.965	0.896
County FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
$\boldsymbol{Z_i}$ ×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the heterogeneous treatment effects by whether a county is a major grain-producing county (MGC). Non-major grain-producing counties and counties with young city secretaries are expected to face tighter environmental regulation. The vector of county-level time-invariant and pre-determined variables $\boldsymbol{Z_i}$ can be divided into the following three groups. First, geographical and economic conditions, including pre-policy industrial GDP in 2004 and dummy variables indicating whether the county has experienced financial stress by 2004, has been designated as a national poor county in 2004, is located at province boarder, is a city-level county, and is passed by a large river; Second, agriculture production conditions, including pre-policy agricultural GDP (measured in 2005) and a dummy variable indicating whether the county is a major food-producing county. Other control variables include county-level population, total agricultural areas affected by natural disasters, and annual averages of weather variables, i.e., precipitation, temperature and sunshine. For brevity, the estimated coefficients on the other interaction terms in equations (3) and (4) are not reported in this table. Standard errors clustered at county level are reported in the parentheses. *, **, and *** denote significant at 10%, 5%, and 1% levels, respectively.

Appendices

Appendix B. Miscellaneous Empirical Results

1) Matched DID Estimation

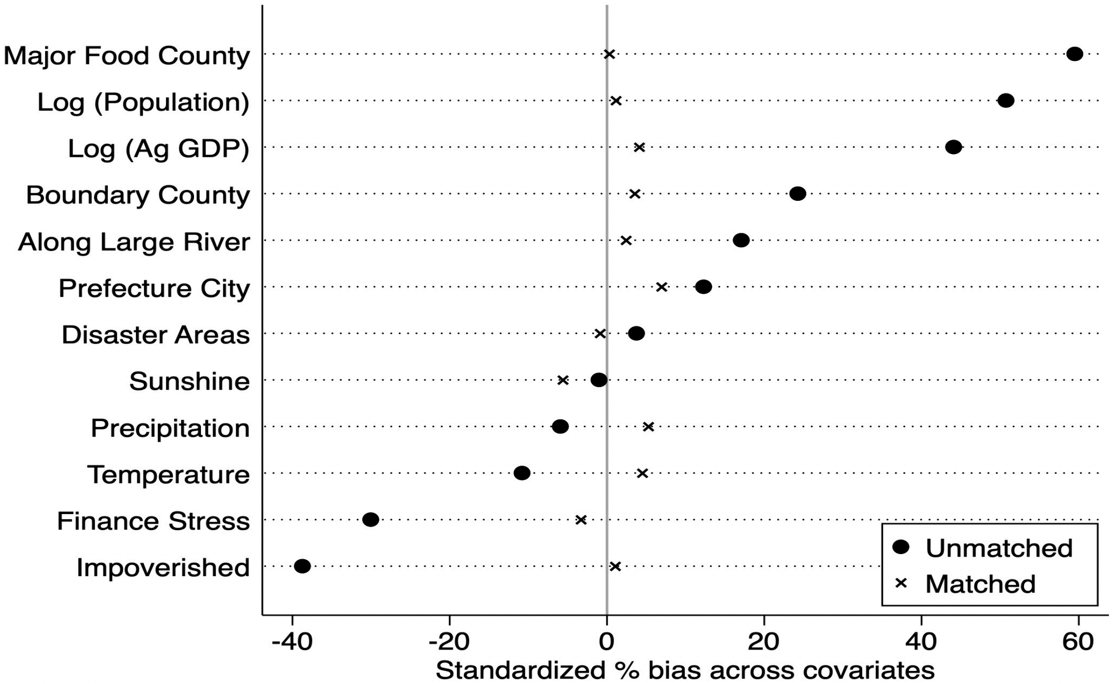

Figure B1. Standardized Percent Bias (Balance Tests) Across Covariates for the Unmatched and Matched Sample

Notes: This figure illustrates the balance tests for the covariates of counties in the treated and control group in the unmatched and matched sample. The horizontal axis represents standardized percentage bias across covariates, and the vertical axis denotes covariates used for the matching, which include county-level log population, agriculture GDP, sunshine, precipitation, temperature, dummy variables indicating whether a county is a major food-producing county, is located on province boundaries, is along a large river, is located in a prefecture-level city, is a national impoverished county and experienced financial stress in the past. All matching covariates listed above are pre-policy measures.

Table B2. Results of the PSM-DID Estimation

	PSM-DID	
Dependent Variables	Log (Fertilizer)	Log (Output)
	(1)	(2)
WP×Post2008	-0.063***	0.007
	(0.020)	(0.013)
County FEs	Yes	Yes
Year FEs	Yes	Yes
$\boldsymbol{Z_i}$ ×Year FE	Yes	Yes
Other Controls	Yes	Yes
# Observations	10,132	10,132
Adjusted R^2	0.933	0.981

2) Falsified Treatment Group Test

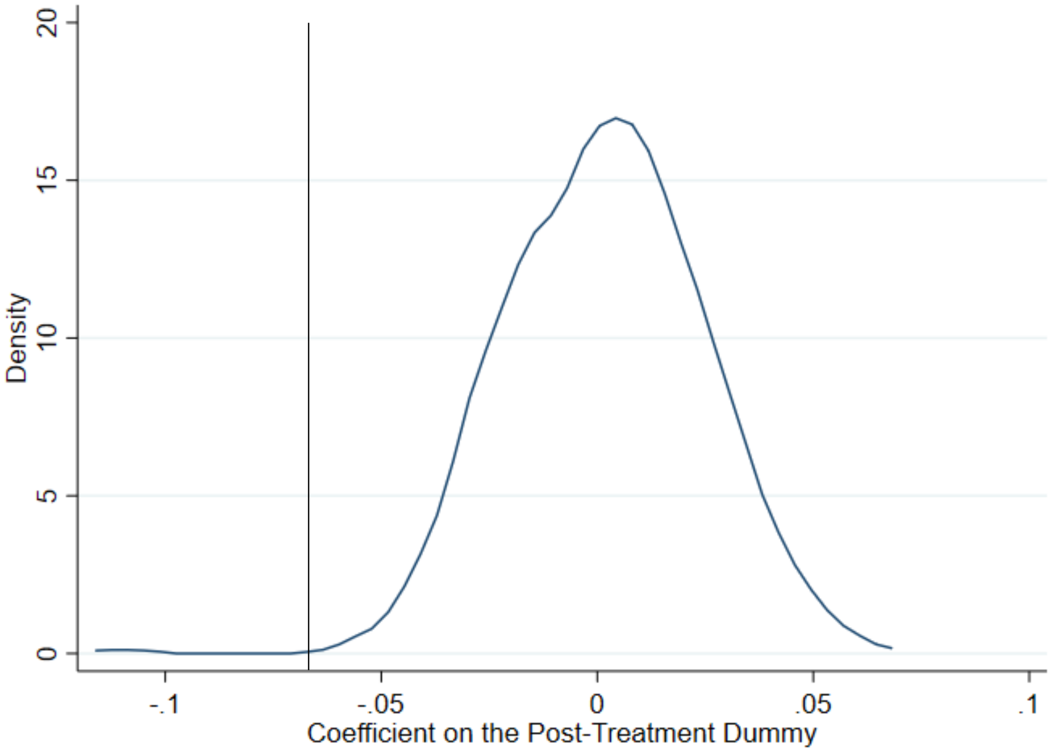

Figure B2. The Kernal Density Function of the Falsified Treatment Effects Estimated with 500 Placebo Samples

Notes: In each placebo sample, we randomly select 466 counties as falsified "treatment counties" to the 1,770 counties in our sample. The number of falsified treatment counties is consistent with the number of true treatment counties in our dataset. The mean of the estimated falsified treatment effect is 0.0015, which is very close to 0, and the standard deviation is 0.022. The vertical line is drawn at x=-0.062, the treatment effect reported in Column (3) of Table 2 estimated with the true treatment group, which is 2.83 standard deviations from the mean of the falsified treatment effects.

3) Robustness to Sample Selection

Table B3. Robustness Checks: Model Specification

	Dropping Counties in Provinces with Special Agriculture Conditions		Estimation with Balanced Panel	
Dependent Variables	Log (Fertilizer)	Log (Output)	Log (Fertilizer)	Log (Output)
	(1)	(2)	(3)	(4)
WP×Post2008	-0.052***	0.003	-0.057***	0.003
	(0.019)	(0.012)	(0.022)	(0.013)
County FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
$\boldsymbol{Z_i}$ ×Year FE	Yes	Yes	Yes	Yes
Other Controls	Yes	Yes	Yes	Yes
# Observations	12,437	12,437	10,356	10,356
Adjusted R^2	0.938	0.982	0.942	0.985

Notes: In the left panel, we drop counties from five province-level administration from the sample, namely, Xinjiang, Xizang, Shanghai, Beijing, and Tianjin. They are dropped because either their agriculture conditions are fairly different from other provinces in the sample, or because they have minimal agriculture. In the right panel, we estimate equation (1) with a balanced panel dataset. The dependent variables in this table are county-level logged total fertilizer use and logged real total agricultural output. The vector of county-level time-invariant and pre-determined variables $\boldsymbol{Z_i}$ can be divided into the following three groups. First, geographical and economic conditions, including dummy variables indicating whether the county has experienced financial stress by 2004, has been designated as a national poor county in 2004, is located at province boarder, is a city-level county, and is passed by a large river; Second, agriculture production conditions, including pre-policy agricultural GDP (measured in 2005) and a dummy variable indicating whether the county is a major food-producing county. It is possible that there are systematical differences between counties in the treated and control group in these aspects, which may also be correlated simultaneously with agricultural production and the selection of assessed water cross sections. Interacting these time-invariant and pre-determined variables with year dummies helps to tease out the possible post-treatment variations in the outcome variables created by these confounding variables. Other control variables include county-level population, total agricultural areas affected by natural disasters, and annual averages of weather variables, i.e., precipitation, temperature and sunshine. Standard errors, clustered at county level for the first two columns and at prefecture level for the last two columns, are reported in the parentheses. *, **, and *** denote significant at 10%, 5%, and 1% levels, respectively.