When the Fire Ends: Straw Burning, Regulation, and Pollution Substitution

Hai Hong[1]; Kevin Chen[1,2*]
(1. China Academy for Rural Development, School of Public Affairs, Zhejiang University. 2. International Food Policy Research Institute)

Abstract
Environmental regulations can trigger unintended pollution externalities if they lack well-designed economic incentives or fail to account for the responses of polluters. This paper examines the effectiveness and unintended consequences of the Universal Prohibition on Straw Burning (UPSB) policy in China. By exploiting a generalized difference-in-differences design, we find that the UPSB policy significantly reduces agricultural fires and thereby air pollution through top-down campaign-style enforcement. However, as straw burning is commonly used to kill pests and fertilize the soil, the UPSB policy also increases the use of chemical fertilizers and pesticides, leading to magnified water pollution. Our findings highlight the importance of considering the potential responses of individuals subject to the regulation when conducting the policy evaluation.

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1. Introduction

Environmental regulations can trigger unintended pollution externalities if they lack well-designed economic incentives or fail to account for the responses of polluters. For instance, when the government controls air pollution with punitive measures, the regulated firms may dissolve harmful gases in liquids, causing regulation-induced water pollution (Greenstone 2003; Gibson 2019).[1] Yet, the extent to which such regulations can cause unanticipated negative externalities remains less understood. In this paper, we leverage China's Universal Prohibition on Straw Burning (UPSB) policy as a quasi-experiment, and provide the first evidence of the effectiveness and the unintended pollution externalities of environmental regulation in the agricultural sector.

China had a long tradition of burning straws since ancient times.[2] Farmers burn straws for several reasons. First, burning residue is conducive to new crops since it can eradicate potential invasive plant species, weeds, fungi, and bacteria (Levine 1991; Graff Zivin et al. 2020). Second, the ashes after burning can fertilize farmland (He, Liu, and Zhou 2020; Nian 2023). Lastly, it helps clear the field and save on labor input, preparing the land for the next round of cultivation (Guo 2021). However, such open-ground burning activities also heavily contribute to severe air pollution, with detrimental effects documented on health and economic outcomes (Rangel and Vogl 2019; Graff Zivin et al. 2020; He, Liu, and Zhou 2020; Guo 2021; Lai

* Corresponding author: Kevin Chen; E-mail: kzchen@zju.edu.cn.

[1] Another specific example is that firms may shift production and pollution activities from regulated to unregulated plants, leading to pollution substitution between plants (Chen et al. forthcoming).

[2] In China, straw burning activities usually involve the burning of the stalk of wheat, maize, and rice after harvesting. This is a common practice in many developing countries such as India, Thailand, and the Philippines (Gadde et al. 2009). Throughout this paper, we interchangeably use "agricultural fire", "crop fire" and "straw burning" to refer the same issue.

et al. 2022).[3]

In response to the deteriorating air quality caused by straw burning, the Chinese government has introduced the UPSB policy across provinces since 2013. In practice, to motivate local officials (mostly county and prefectural leaders), provincial governments adopt campaign-style enforcement that incorporates the performance in reducing agricultural fires into local officials' appraisal system.[4] Officials with the worst performance may receive serious punishment (Wang, Wang, and Yin 2022). Driven by strong mobilization of the UPSB policy, local officials impose significant monetary and administrative penalties on farmers who burn straws, and resort to costly measures (e.g., relocating government staffs in the field for on-site monitoring) to prevent straw burning activities.[5]

Despite its stringency, the UPSB policy offers limited economic incentives for farmers and may distort the agricultural production process. Since farmers are no longer allowed to burn the residues, they are forced to clear fields through either straw returning or recycling, both of which are time-consuming and labor-intensive. More importantly, the UPSB policy also increases the likelihood of pests and diseases, which can negatively impact agricultural output and productivity (see more discussion in the Background section). To combat these negative shocks, farmers may adjust their production behavior by using more fertilizers and pesticides. Such change in factor inputs may trigger environmental externalities in the form of water pollution (Lai 2017; Dias, Rocha, and Soares 2023), resulting in a potential pollution substitution effect (Greenstone 2003; Gibson 2019).

To identify the validity and pollution substitution effects of the UPSB policy, we compile a comprehensive dataset from multiple sources. We first create a grid-level dataset that covers the entire China's mainland at a 10km × 10km resolution (with almost a hundred thousand units). We then match it with several satellite-based observations that measure the number of agricultural fires and air pollution concentration. We also use the satellite-based cropland share to construct a treatment intensity measure of the UPSB policy (see below). Second, we exploit the rural household survey data to investigate how farmers respond to the UPSB regulation. The data is drawn from the National Fixed Point Survey (NFPS) dataset, which records detailed agricultural production (e.g., input and output) information. Third, we leverage readings from water monitoring stations to identify the potential effects of the UPSB policy on water pollution.[6]

Our estimation strategy relies on a generalized DiD framework, which exploits two sources of variations. The first is the temporal variation arising from the staggered implementation of the UPSB policy, and the second is cross-sectional variations stemming from differences in *ex-ante* cropland cultivating areas of each grid cell. Such design is akin to the general case that combines both continuous treatment with staggered adoption in recent DiD econometric literature (Callaway, Goodman-Bacon, and Sant'Anna 2024; de Chaisemartin and D'Haultfœuille 2024). Conditional on the UPSB policy, our identification assumption is that units with more *ex-ante* cropland should be more exposed to the policy, as burning activities are more

[3] The burning activities are concentrated in seasons after harvesting, such intensive burning of crop residues can lead to a substantial escalation in air pollution level within few weeks.

[4] For instance, the upper governments (e.g., central and provincial) require local authorities to specify the corresponding penalties on straw burning activities, and link straw burning prohibition efforts with project approval (essential for local economic growth), total air pollutant emission reduction assessments, so as to motivate the local officials to continuously improve the utilization of straw and most importantly, the prohibition of straw burning.

[5] Some anecdotal evidence reveals that the county expenses on local cadres' meal within a single month during the period of high incidence of straw burning (e.g., seasons after harvesting of before cultivating) can even amount 100,000 RMB (approximately 13,760 USD). See report from https://www.guancha.cn/politics/2024_03_29_730046.shtml. Accessed at 2024-07-11.

[6] We will introduce in more detail how we merge the household-level survey data and station-level data to our grid-level dataset in later sections.

prevalent in these areas (Garg, Jagnani, and Pullabhotla 2024). Our main specification compares the relative change in the number of agricultural fires in post-treatment periods relative to the pre-treatment periods, between grid cells with higher cropland shares *ex-ante* versus those with less.

We first estimate the UPSB policy's effect on straw burning activities and air pollution. Our main results show that grids with higher cropland shares in the pre-treatment periods experienced a significantly larger decrease in agricultural fires after the UPSB policy. Specifically, in our preferred specification that includes grid cell fixed effects, county-by-year fixed effects, and treatment-intensity-by-year fixed effects, we identify an approximately 14 percent decrease in agricultural fires after the policy implementation. This reduction corresponds with a decrease in particulate matter ($PM_{2.5}$), which is in line with findings from existing literature (He, Liu, and Zhou 2020; Guo 2021). We provide several pieces of evidence to show that political incentives and top-down accountability are the driving forces of the observed reduction in agricultural fires. Nevertheless, we also show that high enforcement costs could weaken the effectiveness of the policy.

We then examine how farmers respond to the UPSB policy by adjusting their factor inputs. Using data from multiple sources (e.g., satellite observation, household surveys, and official statistics), we find consistent evidence that farmers increased their fertilizer and pesticide usage after the implementation of the UPSB policy. This is in line with our hypothesis that the UPSB policy leads to negative shocks to agricultural production by decreasing soil fertility and increasing the incidence of pest disease.

Lastly, we investigate how the UPSB policy unintendedly leads to increased water pollution, as the consequence of increased fertilizer and pesticide usage. Using both station-level and grid-level data, we find that the UPSB policy leads to worsened water quality, and higher concentrations of chemical oxygen demand (COD) and ammonia nitrogen (NH_3-N), both of which are highly correlated with the intensive usage of chemical fertilizer and pesticide (Lai 2017). In accordance with the political incentive narratives, we show that the effect of the UPSB policy on water pollution is magnified when local officials have higher promotion incentives. Several heterogeneous exercises confirm that our results are indeed driven by the UPSB policy. Specifically, we show that the effects on water pollution are stronger when enforcement costs are lower, fertilizer usage is higher, or precipitation increases, causing surface runoff that carries fertilizers and pesticides into water bodies. In addition, we conduct a series of robustness checks to ensure that our results are not from spurious correlations. In particular, we show that our results are robust to (1) the exclusion of other confounding factors such as change in regulation intensity and industrial water pollution, (2) using an upstream-downstream specification, and (3) adopting alternative measures of water pollution, such as the occurrence of algal bloom.

While conducting a rigorous and comprehensive cost-benefit analysis of the UPSB policy is beyond the scope of our paper, we provide a rough estimate of the net benefits based on our empirical findings and several conservative assumptions. Specifically, we estimate that the benefit of the UPSB policy through improved air quality is 34.11 billion CNY or 5.25 billion USD, while the enforcement cost of the UPSB policy is estimated to be 10.26 billion CNY or 1.60 billion USD. A simple comparison of the benefits and costs leads to the conclusion that the UPSB policy is cost-effective. However, if we further consider the production cost (e.g., increased fertilizer and pesticide) and the related environmental consequences, the adjusted health benefit would be 20.02 billion CNY or 3.08 billion USD, and the adjusted policy cost would be 27.36 billion CNY or 4.21 billion USD. Adjusting for the policy benefits and costs leads to an overall negative gain of the UPSB policy, which amounts to a total cost of 7.34 billion CNY or 1.13 billion USD.

This paper makes three contributions to the literature. First, we speak to the burgeoning literature that discusses how to effectively reduce straw burning activities (He, Liu, and Zhou 2020; Jack et al. 2022; Cao and Ma 2023; Nian 2023; Dipoppa and Gulzar 2024). Specifically, this strand of literature discusses both the role of providing economic incentives, as well as leveraging direct regulations, in reducing agricultural fires. For instance, Cao and Ma (2023) and Nian (2023) find that the entry of biomass power plants can reduce straw burning activities in plant-nearby regions. They also discuss the role of command and control policies and find limited evidence that environmental regulations exert positive effects in curbing agricultural fires. Using exogenous change in wind direction, Dipoppa and Gulzar (2024) establish that leveraging bureaucrat incentives can effectively reduce agricultural fires in India. We contribute to this literature by providing comprehensive evidence on the effectiveness and unintended consequences of China's nationwide straw burning bans. Unlike Cao and Ma (2023), who focus on the same policy but on a limited geographic scale, we show that the policy's effectiveness increases at the national level when it is backed by strong political incentives for local officials. This insight aligns with findings from Dipoppa and Gulzar (2024) on the role of political motivation but provides new evidence for the role of centralized policies and cross-regional enforcement in China.

Second, we contribute to the studies investigating the pollution substitution effect in environmental regulations. The empirical evidence on policy-induced pollution substitution effects is relatively scarce, with most discussions focused on the industrial sector (Greenstone 2003; Gibson 2019). To the best of our knowledge, this is the first paper to study the regulation-induced pollution substitution effect in the agricultural sector. Our findings suggest that farmers' factor input adjustment is the main driving mechanism that causes the unintended pollution substitution. This differs from the finding in the industrial sector that polluting firms intentionally substitute regulated pollutants for unregulated pollutants.

Third, our work fits into the broader literature that evaluates the effects and consequences of environmental regulations in developing countries (Greenstone and Hanna 2014; Cai, Chen, and Gong 2016; He, Wang, and Zhang 2020; Xie and Yuan 2023). The effectiveness of environmental regulations does not only hinge on whether they are carefully designed to provide appropriate incentives and effective monitoring mechanisms to motivate the agent (Kahn, Li, and Zhao 2015; Cai, Chen, and Gong 2016; He, Wang, and Zhang 2020; Xie and Yuan 2023; Axbard and Deng 2024), but also depend on whether these policies consider the strategic behaviors of pollution emitters (Greenstone 2003; Gibson 2019; Zou 2021). By studying the regulation over farmers' straw burning behaviors, we find that although the banning policy is effective in curbing agricultural fires, mostly through top-down accountability, it fails to take farmers' responses into account, and eventually leads to the unforeseen pollution substitution effect. Our study thus underpins the importance of providing complementary policies to avoid such unintended consequences.

The rest of this paper proceeds as follows. Section 2 discusses the institutional background of straw burning and the related banning policy. Section 3 describes the data, while Section 4 presents our econometric specification. Section 5 examines the effects of the UPSB policy on agricultural fires. Section 6 extends our discussion to examine how the banning policy leads to pollution substitution effects. Section 7 concludes.

2. Background

2.1 Straw burning and disposing in China

China is the largest grain and straw producer globally, with wheat, maize, and rice as the primary sources of straw that contribute to more than 80% of the total amount of straw in China.[7] A significant portion of this straw, approximately 31%, is burnt in situ (Graff Zivin et al. 2020).

[7] According to the World Bank data, China's agricultural value added accounted for 31.1 percent of the world's total agricultural value added in 2021. See https://www.gov.cn/xinwen/2022-11/02/content_5723319.htm. Accessed at 2024-07-11.

Farmers burn the crop residue for several reasons. First, it is a traditional agricultural practice in China, and farmers believe that burning activity helps kill pests and fertilize the soil (He, Liu, and Zhou 2020; Nian 2023). Meanwhile, as grain production increases, the amount of crop residues requiring disposal also rises. To quickly clear the field for the next round of planting, farmers opt to burn crop residue in the open ground after harvesting, as it is the most economical disposal method.

Besides burning, there are alternative ways of straw disposal, but are often time-consuming, labor-intensive, or costly. Two primary alternatives are straw recycling and straw returning. To recycle the straws for other uses, such as industrial inputs for biomass power plants (Cao and Ma 2023; Nian 2023), farmers often need to pack up the scattered straws and transport them to the nearest power plant, which requires additional labor inputs. The economic incentives for recycling straws are thus low if no adjacent biomass power plants exist or if the farmland is small (He, Liu, and Zhou 2020; Cao and Ma 2023; Nian 2023). Straw returning, which involves crushing and burying straw, requires machinery and incurs additional labor and financial costs. Moreover, insufficiently crushed straw can adversely impact planting and harvesting by leaving residues that may not decompose fully or harbor pests. In comparison, burning left to be the prevalent practice of farmers for straw disposal.

2.2 Regulations on straw burning

Straw burning also causes severe air pollution (Guo 2021). During the burning seasons, typically from late May to late July and from late September to late November (He, Liu, and Zhou 2020), farmers frequently set fires over a few days to clear their fields. The intensive burning, however, contributes heavily to emissions of $PM_{2.5}$ and other toxic compounds, which are detrimental to human health and cognitive performance (Graff Zivin et al. 2020; He, Liu, and Zhou 2020; Lai et al. 2022). According to Zhang, Liu, and Hao (2016), annual $PM_{2.5}$ emissions from open crop burning in China amount to approximately 1.036 million tons, representing 7.8% of the total $PM_{2.5}$ emissions.

China first introduced regulations on straw burnings in the 1990s. In 1999, the Ministry of Environmental Protection (MEP) issued the first ban, known as the No Burning Zone (NBZ) policy, which prohibits burning within specific areas: (1) within 15km of airports, (2) within 2km of expressways and railways, and (3) within 1km of national roads and provincial roads. Local officials are required to patrol these zones regularly to discipline or penalize farmers who violate the ban. Despite its stringency, the NBZ policy was shown to be less effective (Nian 2023).

The ineffectiveness of the NBZ policy may be due to a lack of incentives for local officials to enforce it. Firstly, monitoring agricultural fires set by households is often costly for local officials (Cao and Ma 2023). Second, Local agents tasked with implementing the NBZ policy face neither reward with effective enforcement nor severe penalties for non-compliance. In the end, rural households continued to burn straw regardless of the NBZ policy, as well as other burning regulations.

In response to the failure of previous regulations against straw burning, the Chinese government initiated a new round of regulation in 2013, which is aimed at completely prohibiting open straw burning.[8] This regulation, known as the Universal Prohibition on Straw Burning (hereafter, UPSB for simplicity), features a "campaign-style enforcement" (Wang, Wang, and Yin 2022) with a strong administrative structure and associated incentives to ensure compliance. Specifically, the central government proposed for the first time that the enforcement of banning straw burnings is directly integrated into the assessment of environmental performance, which is critical for the promotion of local officials (Wu and Cao 2021).

[8] See document from https://www.gov.cn/zwgk/2013-05/27/content_2411933.htm. Accessed at 2024-12-11.

After the announcement of this document, provincial governments introduce their specific regulations and policies progressively. Appendix Table A3 outlines the specific provisions and details of the provincial policies. The timing in which the provincial government implements the UPSB policy may not be random, there are several factors that may explain why provinces introduce the UPSB policy at different times. For instance, the occurrence of agricultural fires. It is not difficult to imagine that provinces with more *ex-ante* agricultural fires may be more likely to implement the UPSB policy earlier. One particular example is that, in 2014, the central government criticized Henan Province for its inadequate enforcement of straw burning regulations.[9] The Henan provincial government soon implemented the UPSB policy in the following year. Other factors, such as the *ex-ante* pollution level, may likely drive the implementation of the UPSB policy as well. We will return to the issue of potential endogenous policy adoption when we formally present our research design.

Unlike previous practices that only relied on regular enforcement to curb agricultural fires, the UPSB policy explicitly mandates that no burning activities are allowed within the entire administrative territory. Specifically, provincial governments are responsible for campaign-style enforcement, where provincial leaders initiate enforcement campaigns and allocate resources (e.g., personnel, funding, etc.) to the county officials, who are fully mobilized to enforce the UPSB policy and are held accountable if they fail to fulfill the pre-specified mandated targets (Wang, Wang, and Yin 2022).

For instance, the Henan Province declares that each additional fire point detected by satellite results in a fine of 50,000 RMB (approximately 7,800 USD) for the county government. County officials face admonishment and censure from provincial leaders if more than five fire points are detected. For counties that fail to enforce the policy effectively, the provincial government will impose restrictions on the approval of construction projects, which are crucial for economic development.[10] In addition to the strict accountability of local officials, the Henan government has invested in resources and advanced technologies to ensure successful policy implementation. The province installed a total of 19,262 cameras for real-time monitoring and established 35,343 emergency response teams, to achieve full coverage of agricultural areas.[11] These practices are shown to be effective. During the burning season of 2017 (late September to late November), no fire points were detected by the satellite.

Shandong province is another agricultural province that adopts strict accountability mechanisms to regulate straw-burning activities. Local officials in agricultural counties are subject to suspension or censure for failing to prohibit open burning. For example, in the first half of 2020, only 14 agricultural fire points were detected in total, yet more than 50 local leaders were punished.[12] In China's political system, such accountability is typically enforced through intra-party supervision, where officials may face punishment such as warnings, removal from party positions, or other administrative penalties, which are detrimental to their future political careers. This incentivizes local officials to enforce the UPSB policy with full dedication, as minor oversight may result in severe consequences.

However, the effectiveness of campaign-style enforcement comes with high enforcement costs. Monitoring the numerous small-scale farmers who have the potential possibility to burn crop residues is costly (Cao and Ma 2023), requiring local officials to mobilize a mass of grassroots cadres, which creates additional fiscal pressure on local governments. Anecdotal evidence reveals that in some counties implementing the

[9] See document from https://www.mee.gov.cn/gkml/hbb/bgth/201409/t20140918_289253.htm. Accessed at 2024-12-11.

[10] See report from https://www.gov.cn/xinwen/2015-05/30/content_2870801.htm. Accessed at 2024-04-07.

[11] See report from https://www.gov.cn/xinwen/2017-11/22/content_5241523.htm. Accessed at 2024-04-07.

[12] See report from https://news.iqilu.com/shandong/yuanchuang/2020/0712/4588871.shtml. Accessed at 2024-04-09.

UPSB policy, monthly fiscal expenditures on cadres' catering alone exceed a hundred thousand RMB, and the effects of curbing burning activities are merely moderate.

After the rollout of the UPSB policy, the NBZ policy remains in effect. Although the central government banned the NBZ policy in 2015, some provinces still emphasize intensifying regulation efforts in these key areas, such as those surrounding airports, expressways, and railways. However, local officials may only be willing to resort to more efforts in areas that are more easily noticed by their superiors. In order to supervise local officials, provincial leaders (sometimes the prefectural leaders) often do random inspections to examine whether local agents are devoted to enforcing the given task. Expressways are the major transportation network that facilitates to the random spot, given their convenience and concealability, and lack of time constraints (relative to railway). As a result, local officials are more incentivized to enforce strict regulations in areas near expressways, while devoting less effort to other NBZs that may not be easily supervised.

2.3 Potential consequences of the UPSB policy

Despite its efficiency in curbing agricultural fires, the UPSB policy also imposes additional costs on farmers. As mentioned above, farmers need to devote additional resources to dispose of crop residues, with straw returning being the most prevalent way.[13] Nonetheless, straw returning has significant drawbacks.

First, it is susceptible to pests and diseases. In the returning process, germs and pests hidden in the straws are returned as well, affecting crop yields and quality. For example, the Department of Agriculture of Zhejiang Province states that although the province's UPSB policy has improved air quality, it has brought adverse effects such as exacerbating diseases like rice blast. In Changsha, Hunan Province, agricultural statistics show rice planthoppers (a typical rice pest) in 2022 were 14.8 times higher than those before the UPSB policy in 2017.

Moreover, it takes time for straws to be decomposed and absorbed by the soil. This matters especially in northern regions with lower temperatures, where the process of decomposition into fertilizer is slower. If straws are not fully decomposed, they can cause crop roots to rot. A critical example is Heilongjiang Province, the northernmost region of China. Even though the province has ramped up enforcement against straw burning, farmers still burn straws secretly before the sowing season, as the costs of straw returning are way larger than burning.[14] In addition, once the amount of straw returned to the field exceeds the soil's optimal capacity, decomposition time will be significantly prolonged, and the over-accumulation of straws can result in excessive soil erosion and land degradation.

Given the potential negative shocks brought by the UPSB policy and the reluctant adoption of straw returning, farmers could adjust their production behavior to mitigate the losses in production. The most direct way is to adjust the farmland (i.e., the production scale). Faced with environmental regulations, farmers may reduce food production and seek urban employment. However, farmers who are less able to make such adjustments may adjust the production input to offset negative shocks.[15] Typically, to combat pests and diseases, farmers may use more fertilizers and pesticides. While the UPSB policy curbs air pollution from

[13] According to the 2021 data, among straws that are not burning away, 62.5% are returned to the farmland, while the rest 37.5% are recycled for other usage. See report from https://m.thepaper.cn/baijiahao_20861205. Accessed at 2024-04-09.

[14] In 2023, county governments were fined for 178 million RMB (approximately 28 million USD) due to ineffective enforcement in regulating straw burnings. Within the same year, 185 farmers were detained for engaging in open burning activity, and over 400 local officials are held accountable. See more details from https://www.163.com/dy/article/HVBGFSSM0556165R.html. Accessed at 2024-04-09.

[15] For instance, individuals who are more specialized in food production or unable to make occupation adjustments due to labor market friction, which are more prevalent in developing countries due to the incomplete labor market and dual economic structure. In China, the institutional barrier such as Hukou system also impede the process of rural-urban migration.

burning crop residues, the overuse of fertilizers and pesticides can lead to additional negative externalities, such as water pollution (Lai 2017). Eventually, this pollution substitution effect caused by farmers' adjustment behaviors may undermine the UPSB policy's intended benefits.

Despite the importance of the potential pollution substitution effect in the implementation of the UPSB policy, empirical investigation into these effects remains limited. We proceed to further investigate the effects and consequences of the UPSB policy and attempt to provide a comprehensive evaluation of its costs and benefits.

3. Data

3.1 Research sample

We assemble information on agricultural fires, air pollution, water pollution, and agricultural inputs from various sources and construct grid-level panel data with cells of 10km × 10km resolution covering all of China's mainland from 2001 to 2019.[16] The use of such disaggregated data possesses several merits. First, our primary measure of the treatment (i.e., adopting the UPSB policy) is at the provincial level, which may be confounded by unobserved time-varying factors. The grid-level data allows us to include grid fixed effects to control for unobserved heterogeneities. Second, by defining our treatment intensity (i.e., cropland shares) at the grid level, we can capture more variations in the data. This approach allows us to introduce cross-sectional variation and control for county-year fixed effects to address the selection bias of the implementation and enforcement stringency of the UPSB policy. This is particularly crucial, as county leaders serve as the local agents responsible for regulating straw burnings.

3.2 Data source

Agricultural fires data. The fire point data used in our paper is sourced from NASA's MODIS aboard the Terra and Aqua satellites, which has been frequently used in recent studies on agricultural fires (Cao and Ma 2023; Nian 2023). These satellites pass over China twice daily, typically occurring between 10 am and 3 pm, and between 9 pm and 2 am China Standard Time. MODIS sensors identify fires using a contextual algorithm that detects the strong emission of mid-infrared radiation from fires and reports their longitude and latitude. The satellites started to record fire points in November 2000, and we therefore use data from 2001 to 2019. We identify agricultural fire by leveraging land cover data from the China Land Cover Dataset (CLCD), a remotely sensed product providing nationwide land type classifications at 30-meter resolution from 1990 to 2020 (Yang and Huang 2021). We match the fire point data to the land cover raster and define fires as agricultural fires if they occur within cropland. Non-agricultural fires (i.e., fires that occur outside cropland) are also calculated, with both types aggregated at the grid-year level.

Cropland areas data. Our treatment intensity is defined as the total cropland share of major straw-producing crops within each grid cell. These crops, including wheat, maize, and rice, collectively contribute to over 80% of total straw output. We utilize data from Luo et al. (2020), accessible through the National Ecosystem Science Data Center (NESDC), to calculate cropland share.[17] The dataset covers the spatial distribution of maize, wheat, and rice cultivation in China from 2000 to 2019, with a resolution of 1km. To

[16] Since our data is derived from satellite observations with different resolutions. We choose the 10km × 10km resolution to ensure that all satellite data can be mapped to our grid cell coherently.

[17] See more details of the data from http://www.nesdc.org.cn/sdo/detail?id=627dfc4b7e28172589c2df9b. Accessed at 2024-04-12.

avoid reverse causality in our identification strategy, we only use data from 2001 to 2010, prior to the implementation of the UPSB policy.[18] We aggregate the cropland area dedicated to these three crops to establish the total cropland area, dividing it by 100 (the area of the 10km grid cell) to derive the cropland share. While most of the cropland shares range between zero and one, it may exceed one in some instances due to crop rotation and replanting.[19]

Satellite air pollution data. We obtain ground-level $PM_{2.5}$ data for each grid cell from the NASA Socioeconomic Data and Applications Center (SEDAC).[20] The dataset combines AOD retrievals from multiple satellite algorithms and exploits the GEOS-Chem chemical transport model to relate the total column measure of aerosol to near-surface PM2.5 concentration. Calibration is performed using Geographically Weighted Regression (GWR) to produce the final products. We aggregate the raw raster data of $PM_{2.5}$ concentrations, originally captured at a 1km resolution, to our 10km grid-level data and compute the annual average of $PM_{2.5}$ concentration for each grid.

Chemical fertilizer usage data. We employ annual grid-level nitrogen fertilizer use data from Yu et al. (2022).[21] Based on several official fertilizer data sources of China and FAO, and spatial information of cropland area, crop-specific planted area, and crop rotation, the dataset provides historical nitrogen fertilizer use at a 5 km × 5 km resolution, covering periods from 1952 to 2018. We then aggregate the fertilizer data into our grid level panel, ranging from 2001 to 2018. With the data in hand, we can evaluate how the UPSB policy leads to an unintended use of fertilizer use.

Water pollution data. We use two datasets to examine the UPSB policy effects on water pollution induced by higher fertilizer use. The first is automatic weekly surface water pollution data released by the Chinese National Environmental Monitor Center. The water pollution data spans from 2004 to 2018, and covers 148 water quality monitoring stations for major rivers, lakes, and reservoirs. Appendix Figure A1 shows the spatial distribution of water quality monitoring stations. We select water quality grade, ammonia nitrogen (NH_3-N), and chemical oxygen demand (COD) concentration as the main indicators for measuring water pollutants. Water quality grade, a categorical variable that ranges from 1 to 6, measures the overall water quality based on different water pollutant indicators including the pH scale, dissolved oxygen, COD, NH_3-N, and total phosphorus. The higher the water quality grade, the worse the water quality. NH_3-N is a measure of the total amount of ammonia (NH_3) and ammonium ions (NH_4+) present in the form of nitrogen in the water body. Chemical fertilizer application is one of the main sources of NH_3-N. The COD measures the amount of oxygen consumed to chemically oxidize organic water contaminants to inorganic end products in water. We first aggregate the weekly water pollution data into annual averages and then exploit two strategies to match station-level data to our grid-level data. The first strategy aggregates grid-level data to the station level, while the second strategy does the opposite. Both strategies have their pros and cons, which we will illustrate in further detail when investigating the policy effects on water pollution.

Fertilizer use is also associated with the occurrence of algal blooms due to excessive nutrient leaching (Taylor and Heal 2021). Our second dataset that measures water pollution uses algal bloom data of lakes from Wang et al. (2023)[22], which is generated using MODIS satellite observations. This dataset provides

[18] Our results are robust to alternative definition of the treatment intensity, as examined in the robustness checks.

[19] The results are not affected if we either discard observations with cropland shares greater than one or instead replace them with one.

[20] The data is from (Hammer et al. 2020; 2022). See more details from https://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod-v4-gl-03. Accessed at 2024-04-12.

[21] The data is from Yu et al. (2022). See more details from https://essd.copernicus.org/articles/14/5179/2022/. Accessed at 2022-11-23.

[22] The data is from Wang et al. (2023). See more details from https://doi.org/10.1029/2022WR033340. Accessed at

three key indicators in terms of bloom occurrence, potential occurrence period, and maximum bloom extent for 103 China freshwater lakes from 2003 to 2020. The bloom occurrence is defined as the ratio of the bloom pixels over the number of cloud-free MODIS pixels within a year, ranging from 0 to 100. The potential occurrence period represents the duration between the first and the last day of algal bloom each year, while the maximum bloom extent represents the maximum area covered by algal bloom within a year. The spatial distribution of lakes is depicted in Appendix Figure A2.

Household-level data. We use household-level fertilizer and pesticide use data to examine farmers' factor input adjustment. The data are drawn from the National Fixed-Point Survey, which is a rural household-level longitudinal survey collected by the Research Center for Rural Economy (RCRE) of the Chinese Ministry of Agriculture since 1986. We match the household-level data with grid-level data using the longitude and latitude of the village. Specifically, we use information on farmers' fertilizer and pesticide use, and their corresponding expenditure.

3.3 Supplementary data

Meteorological Data We obtain meteorological data from the fifth-generation European Center for Medium-Range Weather Forecasts reanalysis dataset (ECMWF ERA-5). The ERA-5 dataset provides hourly, daily, and monthly atmospheric conditions at a resolution of 0.1 degrees (which is approximately 11km). We download a sequence of monthly weather conditions, including temperature, precipitation, humidity, sea level pressure, and wind speed. We collapse the monthly data to the yearly average and assign weather conditions to the nearest grid based on the longitude and latitude of grid centroids. We also obtain hourly wind conditions for the year 2010[23], comprising east-west (u-component) and north-south (v-component) wind vectors, which are converted into wind angles using the vector decomposition method, and aggregated to the daily level by taking the mean. The wind direction data is originally on a 0.25-degree latitude-longitude grid, and we match it to the nearest grid based on longitude and latitude. The wind direction data serves two purposes. First, the daily wind direction is collapsed to the year level and interacted with linear year trends, serving as the control variable in our later specifications. Second, it allows us to determine whether a specific grid is located at the upwind region of the air pollution monitor (Xie and Yuan 2023; Axbard and Deng 2024), which gauges the extent of local enforcement stringency from the top-down accountability pressure (Xie and Yuan 2023). The definition of the upwind region is followed from the literature (Rangel and Vogl 2019; He, Liu, and Zhou 2020; Nian 2023; Xie and Yuan 2023; Axbard and Deng 2024) and illustrated in Appendix Figure C1. Geocoded data on air pollution monitoring stations is obtained from the China National Environmental Monitoring Center (CNEMC).

Geographical Data We draw on a high-resolution DEM raster file from NASA's Shuttle Radar Topography Mission (SRTM), to calculate elevation, slope, and terrain ruggedness for each grid. Specifically, the terrain ruggedness is calculated following Nunn and Puga (2012). To control for the potential effect of NBZ, we determine the distance of each grid cell to the nearest airports, expressways, railways, national roads, and provincial roads. The data is retrieved from the National Geomatics Center of China (NGCC) and is only available for the year 2010. We also control for the spherical distance of grid centroids to the county border, county center, and provincial center. Finally, we calculate the number of rivers within each grid cell and the

2023-10-16.

[23] We utilize one year of wind direction data primarily because of the computational intensity involved in processing the hourly ERA-5 satellite-derived raster. Nonetheless, following the suggestion of Xie and Yuan (2023), which indicates the stability of wind direction over time, we only use one year of data to serve as controls, and calculate the upwind grids relative to the air pollution monitoring stations described below.

distance from the grid centroid to the nearest rivers following Nian (2023). All time-invariant variables are interacted with flexible linear time trends.

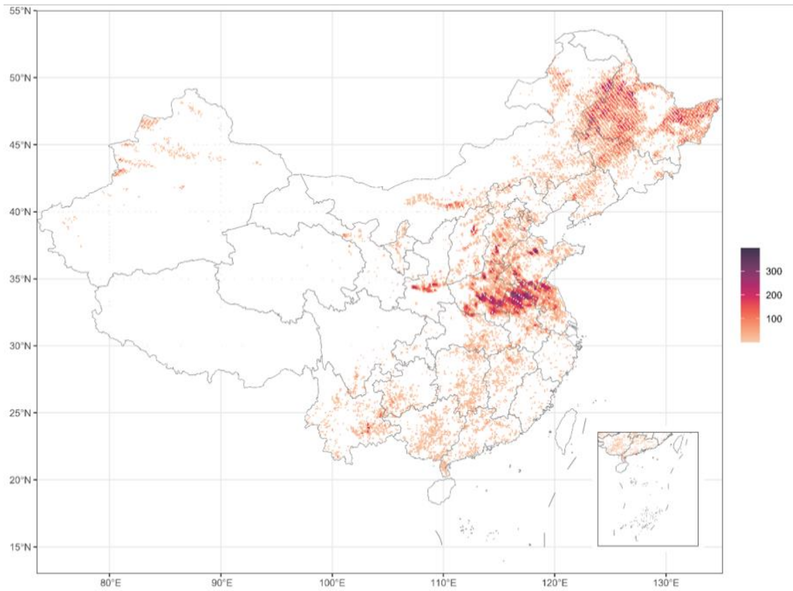

Figure 1. Satellite detected agricultural fires for each grid during 2001–2019

Notes: Colored red points represent the number of agricultural fires for each grid, with darker shades indicating higher levels of burning activity.

3.4 Descriptive statistics

Appendix Table A1 provides the summary statistics for all grid-level variables we described above, while Appendix Table A2 reports the summary statistics for the station-level variables as well as lake-level variables. Grid cells in our sample have on average 5.8 agricultural fire points, with significant variation between grids with high cropland versus those with low cropland. The average number of fires between treated and control provinces before the UPSB policy is 9.02 versus 4.64 (with a t-value of 48.99). After the implementation of the UPSB policy, the number of fires in treated provinces decreases to 6.18 (with a t-value of 16.96). The simple before-after comparison seems to imply that the UPSB policy may effectively curb open straw-burning activities.

Figure 1 plots the average agricultural fire points for each grid cell, while Figure 2 plots the average cropland area for the three major crops. These figures reveal a high spatial correlation between the number of fires and the cropland areas. Specifically, agricultural fires are concentrated in the central and northeastern regions, aligning with the pattern of other related papers (Graff Zivin et al. 2020; He, Liu, and Zhou 2020).[24]

[24] Graff Zivin et al. (2020) only plots the summer fires occurred in June, while burning activities is more prevalent in the northern region during the late November (He, Liu, and Zhou 2020).

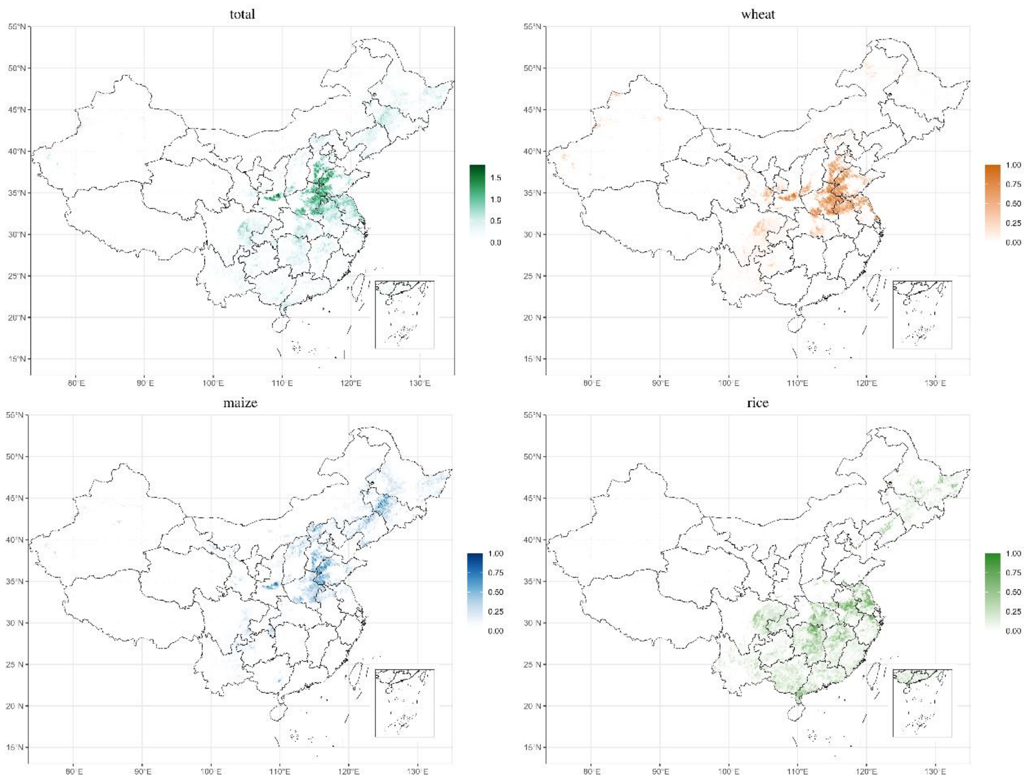

Figure 2. Average cropland shares for wheat, maize, and rice

Notes: This figure plots the average cropland share for each grid cell, from 2001 to 2010. The top left panel presents the sum of the three crops, while the rest three panels display the cropland share for each specific crop.

Figure 3 presents a binscatter plot of the number of agricultural fires against the cropland share. A clear linear relationship between the two variables is evident. Specifically, an increase in the cropland share from 0.25 to 0.75 could lead to an additional 31.4 agricultural fires on average, which is five times greater than the mean of the full sample. This provides an intuitive explanation for our research design introduced in the next section. Since the UPSB policy mobilizes local officials to fully reduce the occurrence of agricultural fires, local cadres would naturally allocate more resources to places where agricultural fires are most likely to occur or most frequent. The cropland share of each grid thus provides a good proxy to measure the policy intensity, as higher cropland shares are associated with higher occurrence of agricultural fires, local officials are likely to pay more attention to prevent fires in these places.

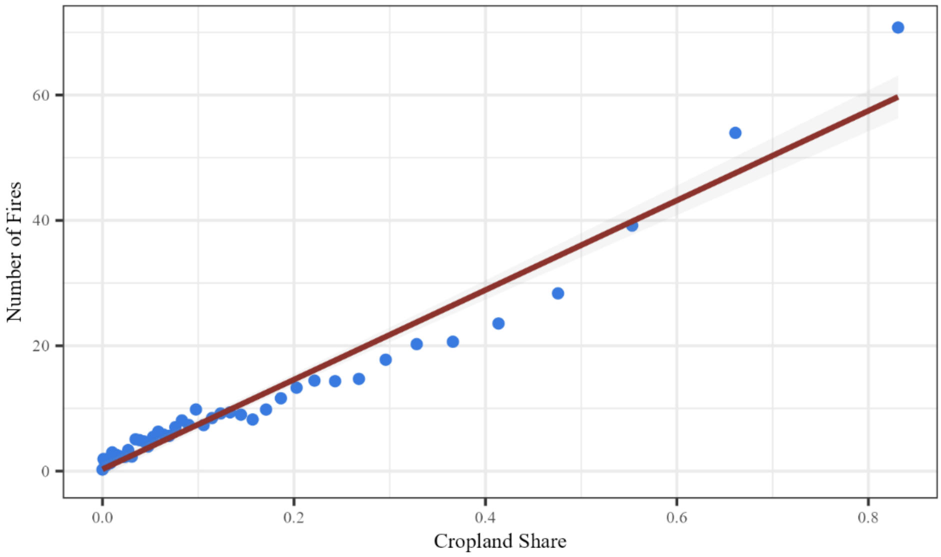

Figure 3. Binscatter plot on the relation between the number of fires and cropland share

Notes: This figure displays the binscatter plot between the number of agricultural fires and the cropland share. Additionally, it includes the fitted unconditional regression line and the corresponding 95% confidence intervals, shaded in grey.

Before introducing our empirical design, we conduct a preliminary test to examine the quasi-exogeneity of the UPSB policy. As discussed in the Background section, the timing of policy adoption may not be randomly assigned across different provinces, we therefore examine how observed characteristics may affect the timing of policy adoption. Specifically, we regress the UPSB policy dummy on a set of observable province characteristics, controlling for both province and year fixed effects. We focus on three sets of variables that could be correlated with the policy's implementation, (1) the level of agricultural development, (2) the level of economic development, and (3) the degree of pollution emissions.[25] Results are presented in Appendix Table A4. We find no suggestive evidence that these observed outcomes may affect the adoption of the UPSB policy. Although this exercise provides us with some confidence that the adoption of the UPSB policy are not affected by these factors, the insignificant results may as well be driven by the large standard errors due to the relatively small sample size. We control for additional grid-level characteristics in our subsequent robustness checks to ensure that our estimated effects are not driven by the potential endogenous adoption.

4. Empirical Design

We use the staggered Difference-in-Differences (DiD) strategy to identify the causal effects of the UPSB policy on straw burning activities. We start with a parsimonious specification to regress the number of agricultural fires on a dummy indicator denoting whether a province p has adopted the UPSB policy in year t, outlined in Equation (1):

$$y_{ipt} = \beta Post_{pt} + X_i \times T_t + Z_{it}\theta + \delta_i + \eta_t + \epsilon_{ipt} \qquad (1)$$

Where y_{ipt} represents the number of agricultural fires detected in grid i at year t of province p, or its inverse hyperbolic sine (IHS) transformation, capturing the level or the proportional change in the treatment effects.[26] The policy variable, $Post_{pt}$ is defined at the province-year level, which equals to 1 for

[25] Detailed variable descriptions can be found in the table notes of Table A4.

[26] Since the vast majority of grids has a zero agricultural fire, we use IHS to avoid missing these observations. We do

years after the implementation of UPSB policy and 0 otherwise. X_i and Z_{it} are two vectors denoting geographic controls and weather controls, respectively. The time-invariant geographic controls (e.g., slope, distance to the airport, etc.) are interacted with linear year trends to allow for their temporal effects. We also include grid fixed effects and year fixed effects to absorb grid-specific characteristics and time-varying common shocks. This setting compares the average changes in the number of agricultural fires in the treated provinces relative to the control provinces.

Since treatment status is only measured at the province-year level in Equation (1), this parsimonious specification cannot account for within-province variations that may confound our identification, potentially leading to omitted variable bias or simultaneity issues. For instance, the construction of rural roads could increase the likelihood of crop residue burning by inducing labor exits (Garg, Jagnani, and Pullabhotla 2024). Such omitted variable bias may lead to underestimation of the true policy effects. Simultaneity issues may arise from other concurrent policies that may affect the burning activities. One example is the land titling reform (Bu and Liao 2022; Liu et al. 2023), which has been widely proven to facilitate land consolidation by ensuring land property rights.[27] Land consolidation facilitates the use of machinery to recycle crop residues and therefore may reduce straw burning activity, potentially leading to overestimation.

To address the above concerns, we refine our model by incorporating grid-level variations in the cropland share. Specifically, we augment the parsimonious specification in Equation (1) by interacting the policy variable $Post_{pt}$ with the grid-specific cropland share, specified as follows:

$$y_{icgpt} = \beta Post_{pt} \times Cropland_i + X_i \times T_t + Z_{it}\theta + \delta_i + \eta_{ct} + \zeta_{gt} + \epsilon_{icgpt} \quad (2)$$

Where $Cropland_i$ denotes the average cropland share of wheat, maize, and rice in grid i. This interaction allows us to exploit within-province variations and use more granular fixed effects to account for unobserved confounders. In particular, we additionally control for the county-year fixed effects η_{ct} to absorb county-specific time-varying heterogeneities. Since the enforcement of UPSB policy is largely relegated to the county officials, we control for the county-year fixed effects to restrict the comparison within the same county in the same year.[28] Standard errors are two-way clustered at the grid level and the county-year level to account for correlations across years within the same grid and correlations across all grids in the same county and same year, following Cameron, Gelbach, and Miller (2011).

We adopt such continuous measures for treatment intensity for two reasons. First, the original measure of treatment is defined at the provincial level, which may be rather coarse and underpowered. The continuous measure allows us to capture more variation in the data and thus lead to more precise estimates. Second, the provincial level measurement may be confounded by other unobserved heterogeneity, potentially biasing our estimates. By exploiting the grid-specific variation in cropland areas, we are able to partial out a wide range of within-province confounders with the inclusion of more granular fixed effects, leading to more credible inference.

The above generalized specification in Equation (2) can be interpreted as a variant of the canonical DiD design, with both treatment timing and treatment intensity varying across groups (Callaway, Goodman-Bacon, and Sant'Anna 2024; de Chaisemartin and D'Haultfœuille 2024). Typically, the decomposition in Callaway, Goodman-Bacon, and Sant'Anna (2024) indicates that the TWFE estimator is in essence using the

not use more conventional approach like log+1 transformation as it may be problematic to interpret the estimated coefficients as percentage changes and there could be potential bias in such transformation (Chen and Roth 2023). However, as pointed out by Chen and Roth (2023), using IHS transformation may not necessarily alleviate the concerns, and we address such issue in our robustness checks by using the Poisson pseudolikelihood regression as alternative specification.

[27] The timing of land titling reform is decided by the provincial governments, but county governments hold discretionary power to decide precisely to carry out the reform (Bu and Liao 2022).

[28] The policy variable itself is absorbed by the county-year fixed effects and is thus not included in the regression.

above-average treatment intensity units as the effective treatment group and below-average treatment intensity units as the effective control group.[29] This raises concerns that the TWFE estimator may be biased if the effective treatment groups and control groups have divergent trends even in the absence of the UPSB policy. This is plausible as the economic activities could vary in grids with different cropland shares.

To alleviate such concerns, we further include the (effective) group by year fixed effects ζ_{gt}. Specifically, we classify grids into high versus low treatment intensity groups based on their predetermined cropland share, and then interact the group variable with a full set of time dummies to control for potential diverging trends between the effective treatment and control groups. Conditioning on these fixed effects, we can leverage the narrowed within county-year and group-year variations for identification, leading to more credible and robust results. The coefficient β measures the relative change in the number of agricultural fires in post-treatment periods relative to the pre-treatment periods, between grid cells with higher cropland shares *ex-ante* versus those with less. We adopt equation (2) as our workhorse model and use equation (1) for additional support and comparisons.

Additionally, we also explore whether our estimates are sensitive to the potential negative weighting issues highlighted in recent econometric literature (Goodman-Bacon 2021; de Chaisemartin and D'Haultfœuille 2020; Callaway and Sant'Anna 2021; Sun and Abraham 2021; Callaway, Goodman-Bacon, and Sant'Anna 2024; de Chaisemartin and D'Haultfœuille 2024). Negative weighting issue arises in staggered adoption designs with heterogeneous treatment effects (Goodman-Bacon 2021; de Chaisemartin and D'Haultfœuille 2020), and recent work extends this issue to continuous treatment designs (Callaway, Goodman-Bacon, and Sant'Anna 2024; de Chaisemartin and D'Haultfœuille 2024).[30] Given our model's incorporation of staggered adoption and continuous treatment, the presence of the negative weighting problem could substantially bias our estimates. To examine whether the presence of negative weights significantly biased our results, we adopt the estimator proposed by de Chaisemartin and D'Haultfœuille (2024) that is robust to both continuous and staggered treatment (de Chaisemartin and D'Haultfœuille 2023).[31,32]

Finally, to provide visual support for our identification assumption (i.e., parallel trends), we use the following event study specification to scrutinize the presence of pre-trends:

$$y_{icgpt} = \sum_{k=-6,k\neq-1}^{4} \beta_k \, Post_{pt}^{k} \times Cropland_i + X_i \times T_t + Z_{it}\theta + \delta_i + \eta_{ct} + \zeta_{gt} + \epsilon_{icgpt} \tag{3}$$

Here, we replace the policy shock indicator $Post_{pt}$ with a set of time dummies indicating the periods relative to the UPSB policy implementation. The year prior to the policy enforcement (i.e., $k = -1$) is

[29] The comparison between the two groups (i.e., grids with above-average cropland share and below-average cropland share), across pre- and post-treatment periods yields the estimated results in our generalized DiD design. However, this approach requires additional identification assumptions for clear causal interpretation.

[30] Specifically, in our context, the negative weighting issues stemming from the staggered adoption should be of less concerns as we only have only a fairly small groups with different treatment timings and there is a vast majority of never treated group. And the inclusion of county by year fixed effects further alleviates concerns of "forbidden comparison" that compare the outcome between early treated groups with later treated groups.

[31] Although Callaway, Goodman-Bacon, and Sant'Anna (2024) provides nice and insightful decomposition of the TWFE estimates when treatment is continuous, their recommendation on fixing the potential negative weighting issue is hard to implement. We thus rely on the method developed by de Chaisemartin and D'Haultfœuille (2024) which is more intuitive and easy to implement.

[32] It worth noting that, although our fixed effects model may be troubled by the potential weighting issues, we prefer it as our workhorse model due to its flexibility that allows us to examine the heterogeneous effects of the UPSB policy, which could provide further insights from a policy relevant perspective. Reassuringly, our empirical results established below suggest that the negative weight does not lead to substantial bias to our findings.

omitted as the reference year. The parameters β_ks thus measure changes in agricultural fires in high versus low treatment intensity groups, between the kth period relative to the UPSB policy implementation, and the period prior to its implementation.

5. Impacts on Agricultural Fires

5.1 Main results

Baseline estimates. Table 1 presents our baseline results using the generalized DiD estimation specified in equation (2). Columns (1) to (3) examine the effects of UPSB policy on the number of fires, while columns (4) to (6) examine the effects on the IHS transformation of fires. Columns (1) and (4) include grid cell fixed effects, county-by-year fixed effects, and the (effective) group-by-year fixed effects. In columns (2) to (3) and (5) to (6), we sequentially add geographic and weather controls to examine the stability of our coefficients to observed grid characteristics. The results show minimal changes, with all estimated coefficients significant at the five percent level.[33]

Table 1 The effects of UPSB policy on agricultural fires

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Number of Fires			IHS (# of Fire)		
$Post \times Cropland$	-10.328**	-10.343**	-10.359**	-0.155**	-0.158**	-0.158**
	(4.160)	(4.162)	(4.165)	(0.069)	(0.069)	(0.069)
Observations	1,717,358	1,717,358	1,716,717	1,717,358	1,717,358	1,716,717
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	Yes	No	Yes	Yes
Weather Controls	No	No	Yes	No	No	Yes
Dep. Var. Mean	5.805	5.805	5.805	0.125	0.125	0.125
Adjusted R-squared	0.539	0.539	0.540	0.546	0.546	0.546

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows that the universal prohibition on straw burning (UPSB) policy can reduce agricultural fires in areas with high cropland share, using a generalized difference-in-differences strategy. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

In our preferred specifications, which include the full set of fixed effects and control variables (columns (3) and (6)), we find that the UPSB policy can effectively curb agricultural fires in areas with high cropland shares. Specifically, given that the average grid in our sample has an 8 percent cropland share prior to the UPSB policy, the estimate in column (3) suggests that the introduction of the UPSB policy is associated with a decrease in the number of agricultural fires of about 0.83 (= -10.359×0.08), which is approximately 14.4% drop relative to the sample mean (5.805). Alternatively, moving across the interquartile range of the cropland share (a change of about 0.07) implies a decrease of 0.77 in the number of agricultural fires after the implementation of the UPSB policy. The results remain robust when using the IHS transformation of agricultural fires as the dependent variable. Specifically, a one percentage increase in the cropland share would lead to a

[33] We also estimate the policy effect using the parsimonious specification outlined in equation (1), as reported in Appendix Table A5. We find similar results that the UPSB policy can effectively reduce agricultural fires. However, the estimated results should be interpreted with caution due to potential within-province confounding factors.

14.6% (=exp(-0.158)-1) decrease in the agricultural fire.[34] Our estimated effects are comparable to Cao and Ma (2023), who documented that the entry of biomass power plants (BPP) can decrease the number of agricultural fires by 14%. However, since their estimates are more localized (only within a certain radius surrounding the plant), the overall estimated magnitude of the UPSB policy should be larger than that obtained by Cao and Ma (2023).[35]

Another concern to our baseline empirical design is that we are comparing the relative change in straw burning activities between grids with higher cropland share and grids with lower cropland share. Though less plausible, the negative coefficients may reflect a relative increase in crop fires in grids with lower cropland share. To ensure that this is not the case, in Appendix Table A6, we run equation (1) separately for grids with high cropland share (above mean) and low cropland share (below mean) to pin down the absolute effects of the UPSB policy. As expected, we find that the decrease in crop fires is concentrated in grids with higher cropland share, and we do not find any significant policy effect on crop fires in grids with lower cropland share. This confirms our interpretation that the UPSB policy mainly exerts its effects by reducing crop fires in grids with higher cropland share (and thus more incidences of burning activities).

Although we've controlled for the initial cropland share in each grid, our specification does not allow us to identify whether the decrease is driven by extensive margin (i.e., decrease in cropland share) or intensive margin (i.e., decrease in burning intensity). If the decrease in crop fires is completely driven by the extensive margin, then conditional on the *ex-post* cropland share should fully absorb our estimated coefficients. If the decrease is driven by intensive margin, then conditional on the *ex-post* cropland share should have no effect on our estimates. We perform this test in Appendix Table A7, where we find that the estimated coefficients are not affected by the inclusion of the *ex-post* cropland share, suggesting that the decrease in crop fires is mainly driven by the intensive margin.

A direct effect of the reduction in agricultural fires is improved air quality. We thus explore how the UPSB policy contributes to decreased air pollution. The results are reported in Appendix Table A8, where we estimate both the parsimonious specification and the baseline specification. The parsimonious specification suggests that the UPSB policy is associated with a significant reduction in $PM_{2.5}$ by over 20%. However, this should be interpreted with caution, as other environmental policies aiming to reduce ambient air pollution, such as the Action on Pollution Prevention and Control Policy, and the gradual rollout of air pollution monitoring stations across cities, were also in effect at the time. Our baseline specification offers a more credible interpretation, suggesting that the UPSB policy leads to an approximately 0.1 percent reduction in $PM_{2.5}$ for a grid with an average cropland share.[36]

Event study. The identification of our generalized DiD design hinges on the parallel trends assumption, which requires that, in the absence of the UPSB policy intervention, there should be no differential trends between the high- and low-treatment intensity groups. It is important to note the parallel trends assumption does not necessitate that the treatment intensity (i.e., cropland share of each grid cell) be exogenous. Instead, it only requires that trends across groups with different treatment intensities evolve similarly. To provide support for the assumption, we exploit the event study approach specified in equation (3) and visualize the

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[34] Rigorously, the elasticity calculated should be $\beta \times \frac{\sqrt{y^2+1}}{y}$ when the dependent variable is IHS-transformed. In this case, our estimates imply a reduction of fires by a 14.8% (Bellemare and Wichman 2019).

[35] We also empirically examine the role of the BPP entry and compare its effects with our baseline findings in in Appendix Table B7. See Appendix B for further discussion.

[36] This estimate, however, should be interpreted with caution as it does consider the strategic behavior of local officials. For instance, by regulating straw burning activities, local officials may benefit from relaxing the regulation over pollution firms, which is more essential for the local economic growth, compared with the agricultural production.

estimated coefficients with corresponding 95% confidence intervals in Figure 4. The left panel plots the dynamic effects on the number of fires, while the right panel plots the effects on the IHS-transformed number of fires. Both panels exhibit similar patterns. In the pre-treatment periods, there are some upward trends; however, the estimated coefficients are jointly insignificant and fluctuate around zero. After the implementation of the UPSB policy, the number of agricultural fires decreases with one year lag. This is plausible as the burning of crop residues is often a seasonal activity. Within the same year, the burning could occur before the policy documents are released, and thus the policy can only reduce crop fires in the following years. Indeed, in the first year after thereafter of policy implementation, we estimate persistent and significant negative effects, suggesting that the UPSB policy is effective in curbing agricultural fires in both the short terms and long terms. We also present the event study estimates for the parsimonious specification in Appendix Figure A3. Consistent with our main findings, there is no evidence of pre-trends.

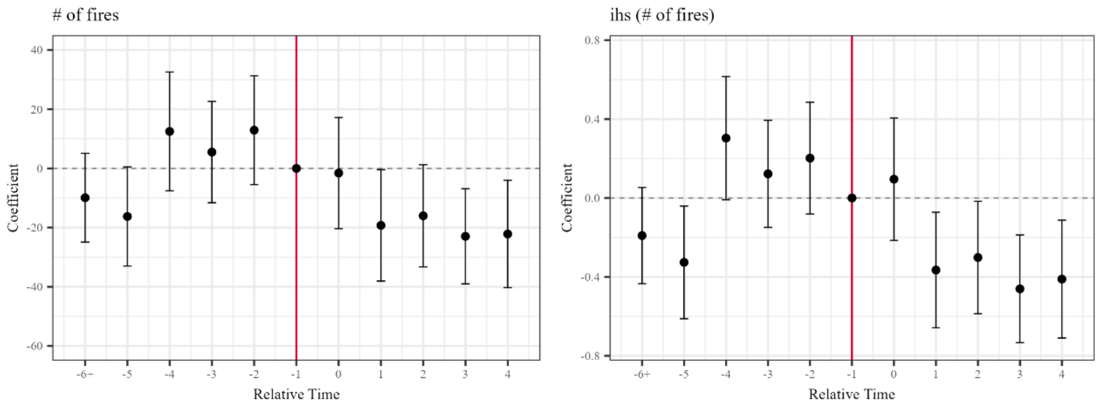

Figure 4. Event study estimates of the UPSB policy on agricultural fires

Notes: This figure plots the estimated event-study coefficients of the impact of the UPSB policy on agricultural fires. The left panel plots the effects on absolute number while the right panel plots the effects on the IHS-transformed number of fires. The unit of observation is 10 km × 10 km grid cells. Regression specification is presented in Equation (3). Coefficient estimates are plotted with the 95% confidence interval. All regressions include geographic and weather controls. Standard errors are two-way clustered at the grid level and the county-year level.

We further address the negative weighting issues in our generalized setting, where treatment effects may be heterogeneous in different units (Callaway, Goodman-Bacon, and Sant'Anna 2024). We adopt the DiD_l estimator proposed by de Chaisemartin and D'Haultfœuille (2024) which is robust to both staggered adoption and continuous treatment. Specifically, the DID_l estimator is a weighted average, across different time periods and possible values of treatment intensity, of 2 × 2 DiD building blocks that compare the outcome evolutions in grids with the same treatment intensity, between treatment and control groups (either pure control or not-yet treated groups), before and after the treatment. By carefully selecting the comparison groups, the DiD_l estimator avoids the pitfalls of negative weighting issues in conventional designs. Figure 5 presents the corresponding results. Reassuringly, our event study estimates remain robust after accounting for treatment effects heterogeneity. We do not detect any significant pre-trends that may violate the parallel trends assumption, and the dynamic policy effects remain negatively significant.

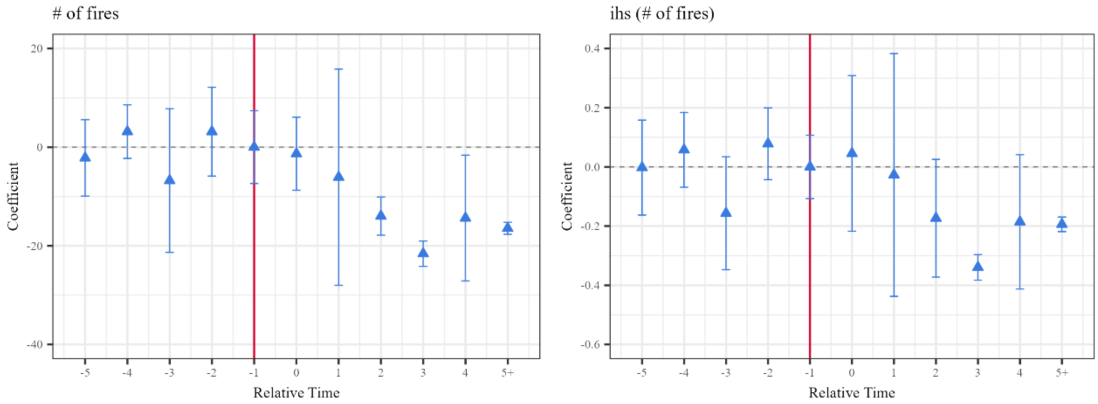

Figure 5. DiD_l estimates of the UPSB policy on agricultural fires

Notes: This figure plots the coefficients from the DiD_l estimator. The left panel plots the UPSB policy effects on the absolute number while the right panel plots the effects on the IHS-transformed number of fires. The unit of observation is 10 km × 10 km grid cells. The estimation exploits the did_multiplegt command in Stata. Coefficient estimates are plotted with the 95% confidence interval. All regressions include geographic and weather controls. Standard errors are two-way clustered at the grid level and the county-year level. Bootstrap standard errors are clustered at the group (here, the group is defined at the province) by year level.

Although the DiD_l estimator does not allow for an aggregation of treatment effects across different treatment periods as in Callaway and Sant'Anna (2021), we perform a simple aggregation to inform the implied estimated effects after correcting the negative weighting problem. Specifically, we calculate the weighted average of the post-treatment coefficients in Figure 5, with the weights being the number of observations used in the estimation of each treatment effect. This yields an estimated treatment effect of -12.815 (left panel) and -0.1489 (right panel), which is similar to our fixed effects estimates in Table 1.[37] This alleviates concerns that negative weights may substantially bias our results and presents supportive evidence that our fixed-effects estimator, at least to some extent, is valid in recovering the true policy effects.

To streamline our empirics, we refer interested readers to Appendix B for additional evidence that supports the validity and robustness of our baseline findings. Specifically, Appendix B scrutinizes the sensitivity of our baseline results to different specifications and discusses several potential confounding factors that may affect the estimated effects (e.g., straw recycling as in He, Liu, and Zhou (2020) and the entry of biomass power plant as in Cao and Ma (2023) and Nian (2023)). We also try out some alternative identification strategy, e.g., Difference-in-Discontinuities (DiDisc) that evaluates the UPSB policy at the provincial border. Results remain robust.

Before proceeding to investigate how farmers may respond to the policy shock and the corresponding consequences, we briefly discuss the heterogeneous effects of the UPSB policy on agricultural fires to shed some light on the potential mechanisms through which the UPSB policy comes into effect.

5.2 Heterogeneity

Having established a robust causal relationship between the UPSB policy and the reduction in agricultural fires, this section explores the potential mechanisms driving our results. Combined with the campaign-style nature of the UPSB policy that mobilizes local officials to enforce regulations, we hypothesize that political incentives and top-down accountability are the main driving forces behind the observed reduction effect. Additionally, enforcement costs and local officials' strategic responses associated with implementing

[37] Results are quantitatively the same if we instead use the unweighted average or use alternative weights, e.g., the number of first-time switchers that used in the estimation.

the UPSB policy may mediate our baseline estimates. We explore the role of these factors further below.

Table 2 The effects of political incentives

	(1)	(2)	(3)	(4)
Dep. Var.	Number of Fires		IHS (# of Fires)	
$Post \times Cropland \times High\ \ Incentive\ \ (PS)$	-13.156**		-0.308***	
	(5.620)		(0.082)	
$Post \times Cropland \times High\ \ Incentive\ \ (Mayor)$		-11.898**		-0.167*
		(5.592)		(0.087)
$Post \times Cropland$	-4.085	-6.406	0.012	-0.080
	(5.253)	(4.797)	(0.075)	(0.068)
Observations	1,716,717	1,716,717	1,716,717	1,716,717
Grid FE	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.805	5.805	0.125	0.125
Adjusted R-squared	0.540	0.540	0.549	0.549

Notes: The unit of observation is 10 km × 10 km grid cells. This table tests for the political incentive mechanism. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. High Incentive is a dummy indicator that equals one for city leaders (i.e., party secretaries (PS) and mayors) age below 57. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid and county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Political incentives. To effectively implement the UPSB policy, the provincial governments fully mobilize the local officials (i.e., county and prefecture leaders). As documented in the Background section, local leaders face penalties and accountability if they fail to achieve the policy targets. These penalties can significantly impact the careers of local leaders, especially those with strong incentives for promotion. We, therefore, hypothesize that local officials with higher political incentives are more likely to faithfully enforce the UPSB policy. We test this hypothesis using the information of prefecture leaders, obtained by surveying the local government websites and through Baidu Baike (Chinese version of Wikipedia). Higher promotion incentives are defined as the age of prefecture leaders (both party secretary (PS) and mayor) is below 57 (He, Wang, and Zhang 2020; Nian 2023; Axbard and Deng 2024), since the chance of promotion decreases significantly after this age. Table 2 shows that the policy effects are largely driven by local officials (both the party secretary and mayor) with higher promotion incentives, supporting our hypothesis that political incentives play a key role in this campaign-style environmental regulation.

Top-down accountability. The success of the UPSB policy also depends on how effectively upper-level governments monitor the performance of their subordinates (Axbard and Deng 2024). We then investigate this by leveraging two sources of variation. First, we analyze whether the grid cells located upwind from their nearest air pollution monitoring station within the same prefecture face more stringent regulations.[38] The large-scale automated air pollution monitoring program has been staggered rollout since 2013, aiming to improve urban air quality (Greenstone et al. 2022; Xie and Yuan 2023; Axbard and Deng 2024). According to Xie and Yuan (2023), firms located upwind from monitoring stations face stricter regulations. In practice, however, the monitoring stations can also detect air pollution originating from the straw burning

[38] Appendix Figure C1 gives an illustration of how we determine the upwind region, following the common practice in the literature (Rangel and Vogl 2019; He, Liu, and Zhou 2020; Xie and Yuan 2023; Axbard and Deng 2024).

activities in rural areas (He, Liu, and Zhou 2020; Guo 2021).[39] We therefore hypothesize that grids located upwind of monitoring stations experience more stringent top-down accountability. Results in Table 3, columns (1) and (3) confirm that these girds face more stringent regulations, implying that enhanced monitoring technology facilitates more effective environmental regulations.

Table 3 The effects of top-down accountability

	(1)	(2)	(3)	(4)
Dep. Var.	Number of Fires		IHS (# of Fires)	
$Post \times Cropland \times Upwind$	-6.931*		-0.117**	
	(3.557)		(0.052)	
$Post \times Cropland \times Dist.Expressway$		16.285***		0.270***
		(4.304)		(0.072)
$Post \times Cropland$	-7.645*	-11.078***	-0.089	-0.147**
	(4.386)	(4.262)	(0.065)	(0.063)
Observations	1,716,717	1,716,717	1,716,717	1,716,717
Grid FE	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.805	5.805	0.125	0.125
Adjusted R-squared	0.540	0.540	0.549	0.549

Notes: The unit of observation is 10 km × 10 km grid cells. This table tests for the top-down accountability mechanism. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. Upwind is a dummy indicating whether the grid is located in the upwind direction relative to its closest air pollution monitoring station. Dist. Expressway measures the distance of the grids to the nearest expressway (unit: 10 km). Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid and county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Second, we consider the role of enhanced on-site supervision from upper-level government. To discipline the performance of local agents, the superiors often adopt measures like random on-site inspections. Anecdotal evidence from Zhou (2022) suggests that expressways can promote impromptu inspections by enabling upper-level government officials to conduct inspections more flexibly and promptly. Results in columns (2) and (4) of Table 3 imply that our treatment effects are largely driven by grid cells that are closer to the expressway, aligning with our narratives.

We also rule out some competing mechanisms. For instance, if the UPSB policy intensified enforcement in no-burning zones (NBZs), this might explain the larger treatment effects observed near expressways, as fires that occur within the NBZs can result in severe accidents. To test this, in Appendix Table C1, we examine how the treatment effect varies across the distance to other NBZs (e.g., airports, railways, national and provincial roads). Contrary to the above hypothesis, we do not find any significant evidence suggesting that the stringency of the UPSB policy is stronger near these NBZs. Another related issue is the bottom-up mechanism in the top-down enforcement. This may arise if local officials themselves have the incentive to control the agricultural fires, even if it is costly. As documented by Dipoppa and Gulzar (2024), local officials may be more motivated to regulate agricultural fires if fires affect most of the home district. Similarly, local officials would be more motivated to regulate crop burnings near the government headquarters as the burning may bear health costs to the officials. In Appendix Table C2, we examine whether the UPSB policy effects

[39] Some provinces also strength the enforcement of the UPSB policy in the dominant upwind region, see for example http://sthjt.gxzf.gov.cn/gxhd/myzz/W020200327288457747562.pdf. Accessed at 2024-04-29.

differ in locations that are (i) closer to county centers, where the government headquarters are located; and (ii) closer to county administrative border, where pollution externalities may motivate local officials to enforce more lenient regulations. We find no evidence that the policy effect varies with the distance of the grid from either the county center or county border, ruling out a bottom-up mechanism.

Enforcement Cost. A major reason that farmers burn crop residues is that it facilitates next year's cultivation by fertilizing the soil with ashes. Alternative approaches, such as straw returning, may bear the risk of increased pests and plant diseases. Moreover, the decomposition of straws into fertilizer often takes time, particularly in northeastern regions where low temperature impedes microbiological degradation activities. Consequently, farmers may be reluctant to adopt straw returning as an alternative to dispose of straws, which may greatly distort the agricultural production process (e.g., delaying the optimal planting time). Therefore, the enforcement costs may be larger in places with lower temperatures as farmers may insist on burning crop residues. Columns (1) and (3) of Table 4 explore such heterogeneity in enforcement costs, revealing that the treatment effects increase with the grid's annual temperature, indicating weaker policy effects in colder places. This piece of evidence is in line with news reports and governments notice that straw burning activities are harder to regulate in northeastern region.[40]

Table 4 The heterogeneous effects of enforcement costs

	(1)	(2)	(3)	(4)
Dep. Var.	Number of Fires		IHS (# of Fires)	
$Post \times Cropland \times Temperature$	-30.340***		-0.547***	
	(11.223)		(0.158)	
$Post \times Cropland \times Ruggedness$		4.551***		0.047**
		(1.255)		(0.019)
$Post \times Cropland$	16.220	-11.890***	0.342**	-0.152**
	(11.122)	(4.438)	(0.156)	(0.065)
Observations	1,716,717	1,714,202	1,716,717	1,714,202
Grid FE	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.805	5.805	0.125	0.125
Adjusted R-squared	0.540	0.540	0.549	0.549

Notes: The unit of observation is 10 km × 10 km grid cells. This table presents the heterogeneous analysis regarding the enforcement costs. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. All pairwise interactions are included in the model but not reported. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid and county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Enforcement costs may also rise in places with more fragmented and rugged land, as monitoring and regulating the burning activities of small-scale farmers is more challenging.[41] We therefore hypothesize that enforcement costs are higher in places with more fragmented lands, as measured by terrain ruggedness. Results in columns (2) and (4) of Table 4 support this hypothesis, showing that the policy effects diminish with the terrain's ruggedness, suggesting higher enforcement costs in more rugged grids.

[40] See, for example, https://www.guancha.cn/politics/2024_03_29_730046.shtml. Accessed at 2024-12-16.

[41] To regulate crop fires and penalize farmers, local cadres needs to catch the burning behavior on the spot. Fires on small-scale farmland may be relatively small and therefore more difficult to regulate.

Overall, the heterogeneous analyses in this subsection indicate that, while political incentives and top-down accountability are the primary forces driving the effectiveness of the UPSB policy, the high enforcement costs could also undermine its impact.

6. Farmers' Responses and Consequences of the UPSB Policy

This section delves into how farmers, as rational agents, would respond to the negative shocks induced by the UPSB policy. We document that farmers increased their fertilizer (both intensively and extensively) and pesticide usage, as the response to increased weed and pest. We then proceed to investigate the potential environmental consequences of farmers' responses and find consistent evidence that the increased fertilizer and pesticide usage leads to the deterioration in water quality.

6.1 Farmers' responses

As discussed in the Background section, an important factor that farmers burn crop residue is that it fertilizes the soil and kills pests. Consequently, a direct effect of the UPSB policy is an increased risk of pests and diseases. Anecdotal evidence suggests that after the implementation of the UPSB policy, grain production in some provinces has suffered from severe pests and diseases. Such negative shocks may incentivize farmers to increase their fertilizer and pesticide usage to mitigate the impact on grain output.

We first verify such responses in fertilizer input using grid-level data. Table 5 shows that the UPSB policy has resulted in a significant increase in nitrogen fertilizer usage. Specifically, our estimates suggest an increase in fertilizer intensity by 0.03 SD, roughly a 6 percent change relative to the mean. Due to data limitations, we lack a direct measure of pesticide usage at the grid cell level. Instead, we resort to a coarser measure at the provincial level, which provides annual total pesticide usage as well as total fertilizer usage (by different categories) to complement our analyses.[42] However, using more aggregated data has limitations, as it prevents us from capturing granular variations and the results may be confounded by other unobserved heterogeneity. Thus, the results should be interpreted with caution.

With this caveat in mind, we report our estimated coefficients in Appendix Table D1 and Table D2. In Appendix Table D1, columns (1) and (4), we regress the total fertilizer and pesticide usage on the treatment dummy, conditional on the province and year fixed effects, and treatment-specific linear trends to absorb potential differential trends between treatment and control provinces. In columns (2) and (5), we include a set of controls that may be correlated with agricultural production as well as fertilizer and pesticide usage. In columns (3) and (6), we weight our regressions by rural population a la Fletcher and Noghanibehambari (2024). Across different specifications, we find consistent and significant evidence that the UPSB policy unintentionally increases in total fertilizer and pesticide usage.

In Appendix Table D2, we further examine fertilizer usage by different categories (i.e., nitrogen (N), phosphorus (P), and potassium (K)). One potential is that although nitrogen is essential for crop growth, the ash from straw burning contains mainly potassium. Thus, the increase in nitrogen fertilizer could be due to other unobserved negative shocks (although the increase in the pests and disease risk may also incentivize higher nitrogen fertilizer use). But if we do not find any increase in potassium fertilizer, the concern would be exacerbated since potassium is a direct substitute for ash. Reassuringly, in Appendix Table D2, we find that both nitrogen and potassium fertilizer usage have increased after the UPSB policy, which lends further credence to our hypothesis that farmers indeed increased fertilizer usage in response to the policy.

Similar results are observed using household-level data, as reported in Appendix Table D3. We find

[42] The data are drawn from the Provincial Statistical Yearbook.

strong evidence that household increased their fertilizer and pesticide usage per plot of land, and correspondingly, the expenditure spent on these factor inputs has significantly increased.

Table 5 Farmers' responses to the UPSB policy

	(1)	(2)
Dep. Var.	Fertilizer Usage (Standardized)	
$Post \times Cropland$	0.033**	0.030**
	(0.014)	(0.014)
Observations	1,650,006	1,649,574
Grid FE	Yes	Yes
County by Year FE	Yes	Yes
Group by Year FE	Yes	Yes
Geo Controls	No	Yes
Weather Controls	No	Yes
Dep. Var. Mean	2.923	2.923
Dep. Var. Standard Deviation	5.738	5.738
Adjusted R-squared	0.991	0.991

Notes: The unit of observation is 10 km × 10 km grid cells. This table investigates how fertilizer usage responds to the UPSB policy. The dependent variables are standardized Nitrogen fertilizer usage intensity (Yu, Liu, and Kattel 2022). Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid and county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

We provide further validation to the above results by examining whether the UPSB policy leads to increased weeds and pests. To perform the test, we exploit data on the occurrence of major crop field diseases in China, which is conducted in the years 2013, 2017, and 2018 (covering the pre-policy and post-policy periods).[43] The dataset was collected through field surveys on crops across several provinces, mainly investigating the occurrence of weeds for maize and wheat. It includes detailed survey locations, which allows us to geocode the data and merge it with our grid level dataset. The dataset also includes information on the occurrence density and coverage intensity of weeds, which we exploit to measure the intensity of crop diseases. We present the results in Appendix Table D4, where we find that the UPSB policy significantly increases the occurrence density and coverage intensity of weeds on wheat, while the magnitude for maize is small and not significant at conventional level. This lends additional credits to our exclamation that the UPSB policy indeed increases the occurrence of weeds and pests, which leads farmers to use more fertilizers and pesticides as input adjustment. In what follows, we examine the environmental consequences of this unintended factor adjustment.

6.2 Consequences on water pollution

In this subsection, we investigate how the unintended increase in fertilizer and pesticide usage due to the implementation of the UPSB policy can deteriorate the water quality. As there is no grid-level water pollution measure, we resort to data from water quality monitoring station, which are widely used to examine the causes and consequences of water pollution (He, Wang, and Zhang 2020; Fan and He 2023). A key challenge in exploiting monitoring station level data is how to integrate it with our grid level data. Theoretically, one could either aggregate grid level data to the station level or disaggregate station level data to the

[43] The data is derived from National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn). See detailed description at https://www.geodata.cn/data/data-details.html?dataguid=188509254879198&docId=10613. Accessed at 2024-09-02.

grid level. On the one hand, aggregate the grid level data to the station level avoids the manipulation of the outcome variable (e.g., water quality), but requires additional assumption on defining the treatment intensity for each station. Moreover, the relatively small sample size at the station level may invalid the statistical inference, leading to insignificant results. And since we need to abstract the grid level information when doing the aggregation, we must rely on fewer information at the aggregate level to conduct further analyses (e.g., exploring the heterogeneity). On the other hand, however, disaggregate station level data to the grid level involves the manipulation of the outcome variable, which also requires strong assumption and the outcomes are likely to be measured with error. Nevertheless, the abundance of grid level information allows us to explore potential mechanism and provides more detailed analyses. As both approaches have their own pros and cons, we adopt both methods to ensure that our results are robust.

Aggregate grid level data to the station level. First, we aggregate our grid-level data to the station level by mapping the two datasets and assign each grid to its nearest monitoring station. We filter grids within a 100km radius to its nearest station, as fertilizer increase in more remote grids should have less impact on water pollution detected by the monitoring station. We then calculate the weighted average of cropland shares for each station (as the measure of treatment intensity), with the distance to the station serving the weight. Controls are collapsed to the station level in a similar fashion. We then run the following regression to examine the effects of the UPSB policy on water pollution.

$$y_{sgpt} = \beta Post_{pt} \times Cropland_s + X_s \times T_t + Z_{st}\theta + \delta_s + \eta_{pt} + \zeta_{gt} + \epsilon_{icgpt} \quad (4)$$

Where y_{sgpt} represents the station-year level outcome. We use water quality grades (a categorical variable ranging from 1-6, with the higher the value, the worse the quality), COD, and NH_3-N to measure the degree of water pollution. We standardize the water quality grades to a mean of 0 and standard deviation of 1, following Perez-Truglia (2020) by using the Probit-OLS method to assign values. $Cropland_s$ measure treatment intensity for station s, aggregated from the grid level. Geographic controls and weather controls are similarly defined at the station level. We also include station-level fixed effects δ_s, province-year fixed effects η_{pt} and treatment group by year fixed effects ζ_{gt} with identical definitions to the previous specifications. Standard errors in parentheses are two-way clustered at the station level and the province-year level.

Table 6 Effects of the UPSB policy on water pollution (station level)

	(1)	(2)	(3)	(4)	(5)	(6)
	100 KM	50 KM	100 KM	50 KM	100 KM	50 KM
Dep. Var.	Water Quality Grade (Standardize)		COD		NH3-N	
$Post \times Cropland$	0.673***	0.562***	0.400**	0.462**	0.208**	0.209***
	(0.184)	(0.141)	(0.188)	(0.175)	(0.077)	(0.067)
Observations	1,386	1,386	1,511	1,511	1,513	1,513
Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Province by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0	0	4.272	4.272	0.547	0.547
Adjusted R-squared	0.794	0.793	0.852	0.852	0.790	0.790

Notes: The unit of observation is at the station-year level. This table presents the results of the UPSB policy on water pollution. The dependent variables are Water Quality Grade (standardized a la Perez-Truglia (2020)), chemical oxygen demand (COD), and ammonia nitrogen (NH3-N). Post is an indicator for years after the policy implementation. Cropland is the cropland share for each station, aggregated from the grid level. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the station level and the province-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table 6 reports the results based on equation (4). In columns (1), (3), and (5), we find strong evidence that the UPSB policy resulted in worsened water quality grades, and increased COD and NH3-N pollution. With an average cropland share of about 0.25 surrounding the station, our estimates suggest that the UPSB policy generally leads to a deterioration in water quality grades by 0.168 SD, and increases in COD and NH_3-N by 0.1 and 0.05 units (which translate into an increase of 2.3% and 9.1% relative to the mean), respectively. In columns (2), (4), and (6), we test the robustness of using alternative bandwidth for calculating the treatment intensity within a 50 km radius of each station. The results remain unaffected. This is in line with our interpretation that the water pollution detected by the monitoring stations is largely caused by grids near the station.

We examine the identifying assumption underlying the above specification using an event study estimation. The results are reported in Appendix Figure 6. We find no significant pre-trends for all three outcome variables, suggesting that the parallel trends assumption holds plausibly. After the implementation of the UPSB policy, we find that water pollution significantly increases, with stronger effects in subsequent years. This alleviates concerns of omitted variable bias and reverse causality, as we only detected significant effects in periods after policy implementation, and in stations with higher treatment intensity. Any other confounding factors must simultaneously mimic the temporary variation in treatment timing and cross-sectional variation in treatment intensity, which, we believe is less plausible. In addition, the results are also robust if we alternatively use the DiD_l estimator proposed by de Chaisemartin and D'Haultfœuille (2024), which helps to aid the potential negative weighting issues (shown in Appendix Figure D1).

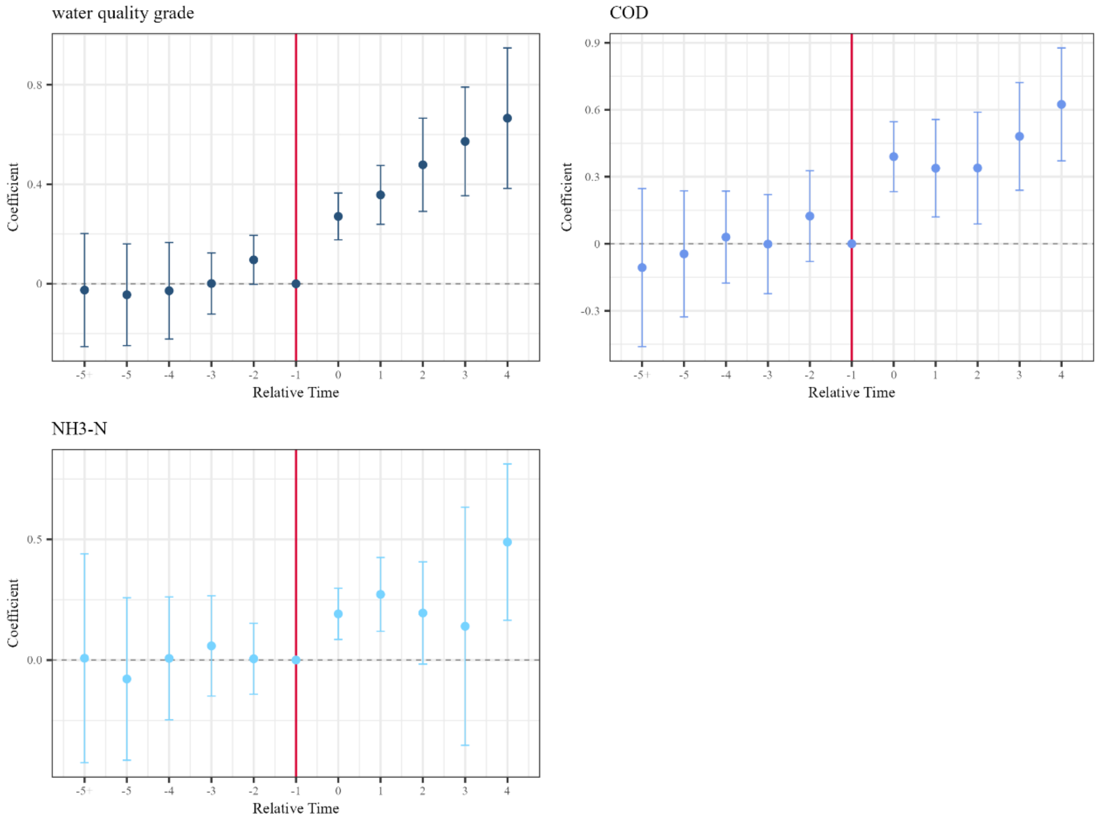

Figure 6. Event study estimates of the UPSB policy on water pollution

Notes: This figure plots the estimated event-study coefficients of the impact of the UPSB policy on water pollution. The upper left panel plots the effects on standardized water quality grade, the upper right panel plots the effects on COD, and the lower left panel plots the effects on NH3-N. The unit of observation is at the station-year level. Regression specification is presented in Equation (4). Coefficient estimates are plotted with the 95% confidence interval. All regressions include geographic and weather controls. Standard errors are clustered at the province level.

We conduct several robustness checks to ensure that our results are not driven by other confounding factors. First, we run a falsification test that randomly assigns a cropland share to each station, and interacts the placebo shares with the UPSB policy dummy. If the increased water pollution is driven by reduced agricultural fires (i.e., the pollution substitution effects), we should find no effects in these placebo specifications. We conduct the falsification test for 500 times and plot the kernel density of estimated coefficients in Appendix Figure D2, where we find that the placebo coefficients are all centered at zero, and the magnitudes from true specification are way larger than these placebo estimates.

Second, we control for other possible factors that may affect water pollution. A leading confounder is the selective water pollution regulations. As documented in the literature (Cai, Chen, and Gong 2016; Lipscomb and Mobarak 2017), water pollution is significantly rampant at administrative boundaries due to its negative externality, which leads to a "polluting the neighbor" effect where local officials may strategically reduce regulation efforts at these boundaries. Another potential confounder is emissions from water-polluting firms. As the reading from monitoring stations cannot distinguish whether the pollution is from industrial pollution or agricultural pollution, deteriorating water quality can also be attributed to increased firm emissions. To ensure that our estimated effects are not driven by the selective regulation, we generate a dummy variable indicating whether a monitoring station is located at the provincial border and interact it with a full set of year fixed effects to control for the effects of potential selective regulation. Similarly, to ensure that the effects are not confounded by firm emissions, we calculate the number of water-polluting firms within a 100km radius of each station and interact with a full set of year fixed effects.[44] Reassuringly, our estimated effects on water pollution remain significant and quantitatively unchanged (Appendix Table D5).

Table 7 The effects of political incentives on water pollution

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Water Quality Grade (Standardize)		COD		NH3-N	
$Post \times Cropland \times High\ \ Incentive\ \ (PS)$	-0.039		0.403**		0.025	
	(0.067)		(0.156)		(0.061)	
$Post \times Cropland \times High\ \ Incentive\ \ (Mayor)$		0.406**		0.792***		0.581***
		(0.168)		(0.208)		(0.065)
$Post \times Cropland$	0.681***	0.278	0.313	-0.374	0.203**	-0.359***
	(0.186)	(0.180)	(0.208)	(0.277)	(0.077)	(0.082)
Observations	1,386	1,386	1,511	1,511	1,513	1,513
Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Province by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0	0	4.272	4.272	0.547	0.547
Adjusted R-squared	0.794	0.793	0.852	0.852	0.790	0.790

Notes: The unit of observation is at the station-year level. This table tests for the political incentive mechanism. The dependent variables are Water Quality Grade (standardized a la Perez-Truglia (2020)), chemical oxygen demand (COD), and ammonia nitrogen (NH3-N). Post is an indicator for years after the policy implementation. Cropland is the cropland share for each station, aggregated from the grid level. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the station level and the province-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

[44] The data on polluting firms are drawn from the Environmental Survey and Reporting Database (ESRD), which is compiled by the Ministry of Ecology and Environment (MEP) that record all heavy polluters that collectively contribute to 85% of total emissions (He, Wang, and Zhang 2020). We follow the guideline of MEP to select water polluting firms.

Although aggregating the grid-level data to the station level results in the loss of sample information, the station-level data allows us to test an important mechanism, that is, the political incentives of local officials. Interestingly, as we show in the previous section, higher promotion incentives lead to more faithful implementation of the UPSB policy (which leads to better air quality), it may also result in worse water quality. Therefore, we hypothesize that increased water pollution induced by the UPSB policy is more pronounced when local officials are more politically incentivized. In Table 7, we examine this mechanism by interacting our treatment variable with city leaders' political incentives. We find consistent evidence that water pollution effects are more significant when local leaders face higher promotion incentives, which aligns with our hypothesis.

Disaggregate station-level variables to the grid level. To cross-validate our findings, and to provide more evidence on how the UPSB policy leads to unintended water pollution, we adopt an alternative strategy by disaggregating station-level variables into the grid level. To do so, we need to assign station-level water pollution readings to grid observations. Since water pollution is measured at specific monitoring stations, only grids that are closer to monitoring stations can exert effects on observed water pollution. We thus restrict our grid-level sample to grids within a 100km radius of the nearest monitoring station. To avoid any manipulation of the raw water pollution data, we assign the exact monitoring readings to those grids as the outcome variable at the grid level.

Table 8 The effects of the UPSB policy on water pollution (grid level)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Water Quality Grade (Standardize)		COD		NH3-N	
$Post \times Cropland$	0.671**	0.660**	0.521**	0.495**	0.143*	0.132*
	(0.285)	(0.288)	(0.213)	(0.203)	(0.075)	(0.074)
Observations	244,273	244,114	266,536	266,365	266,447	266,276
Station FE	Yes	Yes	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes
Dep. Var. Mean	0	0	4.288	4.288	0.767	0.767
Adjusted R-squared	0.984	0.984	0.982	0.982	0.971	0.971

Notes: The unit of observation is the 10 km × 10 km grid cells. This table presents the results of the UPSB policy on water pollution, using the grid level sample. The dependent variables are Water Quality Grade (standardized a la Perez-Truglia (2020)), chemical oxygen demand (COD), and ammonia nitrogen (NH3-N). Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid. All regressions are weighted by the inverse of the distance to the nearest monitoring station. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are clustered at the station level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

We rerun our baseline regression using the inverse of the distance to the nearest station as weights, since fertilizer usage in grids closer to the monitoring station may contribute more significantly to water pollution. As outcomes are the same across grids that belong to the same station, we therefore control for the station fixed effects and cluster the standard errors at the station level. Reassuringly, the results reported in Table 8 again confirm that all three water pollution measures increased after the implementation of the UPSB policy. Moreover, the estimated coefficients from Table 8 is similar from those obtained in Table 6, which lends additional credence to the validity of our estimates. Specifically, our estimation from Table 8 suggests that, when evaluate at the mean cropland share (0.192), the implementation of the UPSB policy leads to a degradation of water quality by 0.129 SD, and increases COD and NH_3-N by 0.095 and 0.025 unit (which translate into an increase of 2.2% and 3.3% relative to the mean), respectively.

We also examine the identification assumption for the grid-level sample. In Appendix Figure D3 and Figure D4, we report the event study estimates using both the fixed effects estimator and the DiD_l estimator. Both estimators show no significant pre-trends, which again provides valid support for the parallel trend assumption and ensures that our results are not driven by the potential negative weighting issues.

Additionally, the grid level specification allows us to conduct several heterogeneous exercises and robustness checks to verify that we are accurately estimating the effects of the UPSB policy on water pollution. First, same as our previous finding that water pollution increases more if local officials have higher promotion incentives, the effects of the UPSB policy on water pollution should be weaker if the enforcement cost is relatively higher. We examine this heterogenous effect by replicating the results from Table 4, with the dependent variable replaced with corresponding water pollution measures. Table 9 reports the results, using temperature and terrain ruggedness as measures of enforcement cost. Symmetrically, we find the effects on water pollution are lower if the temperature is lower and the terrain is more rugged. This aligns with the results from Table 4, which state that the enforcement cost is higher if the temperature is lower or the terrain is more rugged.

Table 9 Heterogeneous effects on water pollution: Enforcement cost

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Water Quality Grade (Standardize)		COD		NH3-N	
$Post \times Cropland \times Temperature$	0.128*		0.857***		0.638**	
	(0.071)		(0.307)		(0.264)	
$Post \times Cropland \times Ruggedness$		-0.010		-0.547**		-0.277***
		(0.016)		(0.248)		(0.099)
$Post \times Cropland$	-0.037	0.070**	-0.255	0.583***	-0.446*	0.186**
	(0.062)	(0.030)	(0.281)	(0.214)	(0.243)	(0.078)
Observations	244,114	243,663	266,365	265,868	266,276	265,782
Station FE	Yes	Yes	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0	0	4.288	4.288	0.767	0.767
Adjusted R-squared	0.984	0.984	0.982	0.982	0.971	0.971

Notes: The unit of observation is the 10 km × 10 km grid cells. This table presents the heterogenous results of the UPSB policy on water pollution, regarding the enforcement cost. The dependent variables are Water Quality Grade (standardized a la Perez-Truglia (2020)), chemical oxygen demand (COD), and ammonia nitrogen (NH3-N). Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid. All regressions are weighted by the inverse of the distance to the nearest monitoring station. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are clustered at the station level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Second, since worsened water pollution is primarily driven by the overuse of fertilizers and pesticides in our setting, stronger effects should be observed in grids with higher fertilizer usage. To examine the mediating effects of fertilizer usage, we analogously estimate an augmented model by interacting the fertilizer variable with our key independent variable. The results in Appendix Table D6 show that the estimated effects on water pollution are stronger in grids with more intensive fertilizer usage.

Third, as another indirect validation, we expect stronger effects on water pollution in grids with higher precipitation. Increased precipitation leads to more surface runoff, which dissolves the fertilizers and pesticides applied on the cropland and carries them to nearby water bodies, thus exacerbating the negative externalities of fertilizer and pesticide usage. if increased water pollution is not driven by fertilizers and pesticide overuse (e.g., stemming from industrial pollution), we should observe no heterogeneous effects as the industrial activities should be less relevant to these conditions. Appendix Table D7 confirms this argument, where we find larger and more salient effects on water pollution in grids with higher precipitation, reinforcing the causal link between capturing the effects of the UPSB policy on water pollution.

Fourth, in our baseline specification, we use cropland shares of grids within a 100km radius of their closest monitoring station to construct the treatment intensity. Since only upstream fertilization activities can be detected by the monitoring station, we should observe effects solely from grids that are located upstream of the monitoring station. We use DEM raster to predict river flow direction and determine upstream grid direction. Appendix Table D8 reports the results from separate regressions for upstream and downstream subsamples. Reassuringly, we find consistent evidence that the effects on water pollution are entirely driven by upstream subsample, providing further support to our findings.

Finally, using the same specification, we provide additional evidence showing that the UPSB policy has led to intensified occurrence of algal blooms, a common eutrophication pollution in water bodies. The results are reported in Appendix Table D9. For the ease of interpretation, we standardize all variables to a mean of 0 and a standard deviation of 1. We find significant increases in the Bloom Occurrence (columns (1) and (2)) and the Maximum Bloom Extent (columns (5) and (6)), though effects on the Potential Occurrence Period are not significant (columns (3) and (4)). Our estimates suggest that the Bloom Occurrence increased by 0.27 SD, which is roughly equivalent to a 40% increase relative to the mean. Similar magnitudes are found for the effects on Maximum Bloom Extent, which suggests a 37.6% increase relative to the mean. We also verify our results by using PCA to extract the first component of the three variables.

Overall, the above results lend strong support to our hypothesis that the implementation of the UPSB policy has unintendedly caused severe water pollution, due to farmers' increasing fertilizer use in response to the negative shocks induced by the policy.

7. Welfare Discussion

Through our previous investigation, we have shown that, although the UPSB policy decreases air pollution through direct regulation over straw burning activities, it also unintendedly leads to increased water pollution. However, several questions remain. First, to what extent does the increased water pollution undermine the policy's effects on air pollution? What is the net environmental benefit of the UPSB policy? Second, given the high enforcement cost associated with regulating straw burning activities (as documented in the Background section), what are the economic costs of policy implementation? Does these costs outweigh the environmental benefit? In this section, we combine our empirical estimates with relevant statistics to address these questions.

7.1 Net health benefit

Since our main identification strategy compares grids with high treatment intensity to grids with low treatment intensity, before and after the UPSB policy, we first consider a simple hypothetical case where we increase the treatment intensity from 0 to 1, and compare the gains from reduced air pollution with the losses from increased water pollution. Specifically, looking at the policy effects on air pollution, our estimates from Table 1 show that the implementation of the UPSB policy would lead to a decrease of 10.4 agricultural fires (column (3)). Combined with the estimates from He, Liu, and Zhou (2020), which suggest that 10 additional crop fires lead to a 4.79 μg/m^3 increase in $PM_{2.5}$ (see column (3) of Table 2 in their paper). This implies that the UPSB policy would decrease $PM_{2.5}$ by 4.98 μg/m^3.[45] We then relate the estimated effects on air pollution with studies that investigate the mortality effects of pollution to back out the health benefit of the UPSB policy. In particular, estimates from Fan, He, and Zhou (2020) suggest that a 10 point increase in $PM_{2.5}$ would increase mortality rate by 2.5%.[46] Given that the mortality rate documented by the Chinese Center for Disease Control and Prevention's (CCDC) Disease Surveillance Points (DSP) system is 131.76 per 100,000 people (Fan, He, and Zhou 2020),[47] this imply that the UPSB policy could save 1.64 life per 100,000 population through improved air quality.

On the other hand, consider the policy effects on water pollution. Our estimates from Table 6 reveal that the implementation of the UPSB policy would leads to an increase in water quality grade by 0.56 standard deviation (column (2)), which approximately translates into 0.46 unit deterioration of water quality. Combined with the estimates from Ebenstein (2012), which finds that an escalation of water quality by a single grade increases the digestive cancer death rate by 9.7%. Given the average mortality rate of digestive cancer death is 26 per 100,000 people (Ebenstein 2012), these figures imply that the UPSB policy could lead to 1.16 additional death per 100,000 population through degraded water quality. Altogether, the above statistics suggest that the UPSB policy, when evaluated as relative change in treatment intensities, could only decrease 0.48 additional death per 100,000 population.[48] Through comparison, we find that much of the health benefit from improved air quality is offset by the health cost from degraded water quality.

The above estimates only reveal the relative change in health benefit due to changes in treatment intensity. To evaluate the overall policy impacts, we now rely on our estimates from equation (1), which directly compares pollution outcomes between treated and control provinces, before and after the policy implementation. The estimated results on agricultural fires are reported in Appendix Table A5. We additionally report the effects on water pollution estimated from equation (1) in Appendix Table D10. Following the same procedure as above, we find that the implementation of the UPSB policy decreases 5.83 number of agricultural fires, which turns into a reduction in $PM_{2.5}$ by 2.79 μg/m^3 and approximately saves 0.92 life per 100,000 population. Turning to the estimates of water pollution, our results imply that the implementation of the UPSB policy increases water quality grade by 0.12 SD, which translates into 0.15 unit degradation in water quality grade, and results in 0.38 additional death per 100,000 population. Overall, the UPSB policy saves 0.54 additional death per 100,000 population, which is similar to our previous calculation, that the unintended increase in water pollution offset a substantial amount of health benefit due to improved air quality. Given the total population in all treated provinces is approximately 0.71 billion, the UPSB policy could save 3,834 lives in net.

[45] We do not use our estimated coefficients on air pollution as it may be biased due to the strategic behavior of local officials. As the gain from reduced air pollution in regulating straw burnings may incentivize local officials to relax the regulation on other air pollution related manufacturing firms, which would lead to an underestimate of the policy effects on air pollution.

[46] We do not use estimate from He, Liu, and Zhou (2020) since they do not provide the average mortality rate, but their estimates on the effects of air pollution on mortality is similar to the ones obtained by Fan, He, and Zhou (2020).

[47] The measure of mortality rate in Fan, He, and Zhou (2020) is at the monthly level, we multiply it by 12 to roughly approximate the annual mortality rate. This number aligns with estimates from other reports, see, for example, https://rs.yiigle.com/CN112338202201/1349882.htm. Accessed at 2024-12-19.

[48] We note, however, that these results should be interpreted with great caution as the estimated net health benefit crucially hinges on the mortality rate, which may change over time. Although both Ebenstein (2012) and Fan, He, and Zhou (2020) use data from DSP, their research periods differ: Ebenstein (2012) studies mortality rate during 1991 to 2000 while Fan, He, and Zhou (2020) conduct their analysis during 2014 and 2015.

Using the value of statistical life (VSL), we can further monetize the heath benefit of the UPSB policy. Specifically, Fan, He, and Zhou (2020) adjust the VSL from Qin, Li, and Liu (2013) and estimate that the VSL is around 7.46 million CNY or 1.15 million USD in 2015. We adopt their calculation and similarly discount it by 30% due to the fact that the elderly is more suspicious to pollution exposure (Fan, He, and Zhou 2020). This yields a net benefit of 20.02 billion CNY or 3.08 billion USD. Decomposing the net health benefit into gain in air quality and loss in water pollution, we find that the gain from improved air quality is 34.11 billion CNY or 5.25 billion USD, while the loss from degraded water pollution is 14.09 billion CNY or 2.17 billion USD.

7.2 Policy costs and net gains

After establishing the health benefit, we now turn to estimate the net gain of the UPSB policy. To do this, we need an estimate for the policy cost, which include both enforcement costs and costs on agricultural production. However, since both cost are hard to obtain, we can only make indirect inference on these costs. Again, these results should be interpreted with particular caution as they require strong and sometimes ad hoc assumptions. To keep our estimates conservative, we restrict our calculation within the so-called Major Grain Production (MGP) Provinces. These provinces produce over 78% of overall grain and cereals in China and contribute heavily to straw burning activities. In total, there are 13 MGP provinces,[49] among which 7 provinces have implemented the UPSB policy. We focus on these provinces mainly because that they produce much of the straws and are the main targets of the UPSB policy.

We first estimate the enforcement costs of the UPSB policy. To regulate and prevent straw burning activities, the local officials, especially grassroot officials (township or village cadres) need to allocate a substantial amount of manpower to the fields. From official statistics, we can gauge the amount spent by local government on straw burning regulations. For example, Huoqiu County, spend about 500 thousand CNY (or 76.92 thousand USD) on regulating straw burning activities in 2022.[50] Suixi County, spend about 600 thousand CNY (or 92.31 thousand USD) on regulating straw burning activities in 2022.[51] Lianyungang City, spend about 2 million CNY (or 0.31 million USD) in 2014 to regulate straw burning.[52] If we use the spending of Lianyungang City as our estimates for the enforcement cost (which is likely to be a lower bound estimate as a typically city comprises a dozen or so of counties), we can simply calculate the annual enforcement costs for all treated MGP provinces (equals to 2 million times 90, the total number of cities in all treated MGP provinces), which gives an annual spending of 1.8 billion CNY or 0.28 billion USD. Given that on average the treated MGP provinces have implemented the UPSB policy for 5.7 years in our sample period, we estimate a total enforcement cost of 10.26 billion CNY or 1.60 billion USD.

We then consider the production cost of the UPSB policy. To be conservative, we only consider the policy effects on fertilizer and pesticide expenses. We should note that could be other input adjustment (e.g., increased machinery costs to return to straw), we abstract these additional adjustment cost and focus on the most relevant ones.[53] From our estimates in Table D3, we find that household increase their fertilizer and pesticide expenses by 47.49 CNY or 7.31 USD after the implementation of the UPSB policy. Given that in

[49] These provinces are Heilongjiang, Henan, Shandong, Sichuan, Jiangsu, Hebei, Jilin, Anhui, Hunan, Hubei, Inner Mongolia, Jiangxi, and Liaoning.

[50] https://www.huoqiu.gov.cn/public/6600621/36722059.html. Accessed at 2024-12-19.

[51] https://www.sxx.gov.cn/group1/M00/09/C3/CqET9GZqtV-AVGVYAAbIlvfd_Tk531.pdf. Accessed at 2024-12-19.

[52] https://www.lyg.gov.cn/zglygzfmhwz/sjxx/content/shibmzdly_46506_1.html. Accessed at 2024-12-19.

[53] The increased production cost could also force out some farmers or change their production structure (e.g., from planting maize or wheat to other crops). Our focus on the MGP provinces alleviates this concerns to some extent as these provinces are required by the central government to cultivate grain crop.

our sample, an average household owns 9.6 mu cropland, this implies an increase in input expenses by 4.85 CNY (or 0.75 USD) per mu.[54] Since there is a total of 0.60 billion mu cropland in all treated MGP provinces, and an average 5.7 year of policy implementation, we can calculate that the increase in input expenses is approximately 17.10 billion CNY or 2.63 billion USD.

After laying out these figures, we can now make a rough evaluation of the policy gain. To start, we first consider an ideal case where there is no input adjustment (and hence no production cost and negative effect on water pollution). Under this scenario, the only cost of the UPSB policy is the enforcement cost and the policy gain is the health benefit through improved air quality. In this case, we find that the UPSB policy is cost-effective, leading to a total net gain of 23.85 billion CNY or 3.67 billion USD. However, this ideal case ignores the policy burden imposed implicitly on farmers and their endogenous responses, let alone potential consequences. If we further consider the production cost of the UPSB policy and the negative benefit stemming from increased water pollution, we find that the UPSB policy is no longer cost-effective. It leads to a total cost of 7.34 billion CNY or 1.13 billion USD. This again underscore the importance of considering the responses of individuals subject to the regulation. The ignorance of such responses may result in misleading policy implications.

8. Conclusion

This paper investigates the effectiveness and pollution substitution effects of a command-and-control policy in China. We use the case of a recent straw-burning ban, which aims to regulate air pollution. We find that the straw burning ban significantly decreases agricultural fires and related air pollution. The political incentives, along with the top-down accountability associated with implementing straw-burning bans, are the driving forces. Heterogenous analysis shows that the reduction of agricultural fires is weaker in grids with lower temperatures, and in rugged terrain areas, where enforcement cost and monitoring costs are higher. We also find the reduction effects are less significant in grids with high wind speeds. The interpretation is quite intuitive here. High wind speed can help to disperse the smoke from burning activities, reducing the incentives for local officials to enforce the regulation.

However, we find that the top-down straw burning ban also leads to unintended consequences of increased water pollution. This result is driven by farmers' input adjustment in their use of chemical fertilizers and pesticides. Prior to the ban, straw burning would naturally fertilize the soil and help control pests. With the ban in place, farmers have compensated by increasing their application of chemical inputs, which has in turn contributed to water pollution. This finding highlights that overlooking how farmers might strategically respond to the regulation can result in an unintended pollution substitution effect.

[54] In China, 1 mu equals to one fifteenth of a hectare.

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Appendix A: Additional figures and tables

Additional Tables

Table A1 Summary statistics for grid-level data

Variable	Obs	Mean	SD	Min	Max
Number of agricultural fires	1,719,529	5.805	48.49	0	492
log (Number of agricultural fire+1)	1,719,529	0.125	0.778	0	6.201
Average cropland share	1,719,529	0.0810	0.180	0	1.752
Distance to level 1-3 rivers (in km)	1,719,529	75.99	78.07	0	450.3
Distance to level 4 rivers (in km)	1,719,529	76.79	81.95	0	515.4
Distance to level 5 rivers (in km)	1,719,529	31.34	49.98	0	391.7
Number of level 1-3 rivers	1,719,529	0.0920	0.566	0	22
Number of level 4 rivers	1,719,529	0.0610	0.318	0	9
Number of level 5 rivers	1,719,529	0.183	0.561	0	38
Slope	1,719,529	3.680	3.794	0.0220	29.83
Ruggedness	1,719,529	1.006	0.0100	1	1.160
Elevation	1,719,529	188.6	193.8	0	1594
Distance to railway (in km)	1,719,529	130.7	181.2	0	1008
Distance to expressway (in km)	1,719,529	242.8	335.4	0	1430
Distance to airport (in km)	1,719,529	132.9	103.1	0	609.2
Distance to national road (in km)	1,719,529	57.66	74.45	0	471.8
Distance to provincial road (in km)	1,719,529	29.97	42.93	0	294.5
Temperature (℃)	1,719,529	7.710	8.028	-11.81	25.91
Wind speed (10m/s)	1,719,529	2.596	0.911	0.576	5.675
Humidity (RH)	1,719,529	0.00600	0.00300	0.00200	0.0180
Rainfall (mm)	1,719,529	18.61	16.67	0	92.36
Air pressure (pa)	1,719,529	82961	15750	50916	101800

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows the summary statistics for the main grid-level variables that are used for the baseline analyses.

Table A2 Summary statistics for station (lake)-level data

Variable	Obs	Mean	SD	Min	Max
Panel A: Station level					
Water quality (categorical)	1604	3.031	1.225	1	6
Water quality (normalized)	1604	0	1	-2.227	2.043
COD reading	1753	4.272	2.726	1.233	13.15
NH3-N reading	1756	0.547	0.646	0.0100	2.616
Panel B: Lake level					
Bloom occurrence (BO, in %)	247928	0.923	1.362	0.00100	11.84
Potential occurrence period (POP, in days)	247928	143.2	66.34	0	350
Maximum bloom extent (MBE, in km2)	247928	50.30	187.7	0.534	1692
Distance to the nearest lake	247928	55.30	26.81	0	100.00

Notes: The unit of observation in Panel A is at the station level, while the unit of observation in Panel B is 10 km × 10 km grid cells, where we restrict the sample that are within a radius of 100km to its nearest lake. This table shows the summary statistics for the main outcome variables that are used for the further analyses that investigate the potential effects of the UPSB policy on water pollution.

Table A3 Provinces with straw burning bans and the specific policy provisions

Province/province level city	Release year	Specific provisions
Beijing	2014	Open burning of straw, leaves, dead grass, rubbish, electronic waste, linoleum, rubber, plastic, leather and other pollutants emitted into the atmosphere shall not be carried out by any unit or individual.
Tianjin	2013	Comprehensively prohibit straw burning, promote comprehensive utilization of straws.
Hebei	2015	Comprehensively prohibit the open burning of straw, leaves and grasses within the administrative area of the province, and gradually establish a system for the collection, storage, transport and utilization of straw.
Shanxi	2013	Comprehensive ban on straw burning
Jilin	2013	A total ban on the open burning of crop residues across the province.
Shanghai	2013	The City prohibits the open burning of straw, withered branches and leaves and other substances that produce smoke and dust, as well as asphalt, linoleum, rubber, plastics, rubbish, leather and other substances that produce poisonous, harmful, malodorous or strongly odorous gases.
Jiangsu	2013	By the end of 2012, the basic establishment of the straw collection system, the basic formation of a reasonable layout, multi-purpose use of straw comprehensive utilization of industrial patterns, a comprehensive ban on open burning of straw.
Zhejiang	2016	Open burning of asphalt, linoleum, rubber, plastics, leather, rubbish and other substances that produce toxic and harmful soot and foul-smelling gases is prohibited in the administrative areas of the province, as is the open burning of straw, fallen leaves and other substances that produce soot pollution.
Fujian	2014	Comprehensively prohibit straw burning and promote straw comprehensive utilization demonstration projects.
Shandong	2016	By the end of 2017, open burning of straw will be completely banned in Shandong Province.
Henan	2015	By comprehensively carrying out the work of straw burning ban and comprehensive utilization across the province, the comprehensive utilization of straw at multiple levels, in multiple ways and from multiple angles has been promoted in depth, and the phenomenon of straw burning has been completely eliminated.
Hubei	2015	Since 1 May 2015, open burning of straw has been prohibited in the administrative areas of the province.
Hunan	2013	Accelerating the development of clean energy in rural areas, encouraging the comprehensive utilization of crop straw, promoting biomass-forming fuel technology, vigorously developing rural biogas, and comprehensively banning the open burning of straw and other agricultural and forestry waste.

Notes: This table summarizes the release time of the UPSB policy of each province and the specific policy provisions. We define a province is treated by the UPSB policy only when the government documents have explicitly mentioned the comprehensive and universal banning on open burnings of crop residues.

Table A4 Testing the quasi-exogeneity of the UPSB policy

	(1)	(2)	(3)
Agricultural GDP	0.008	0.007	0.009
	(0.011)	(0.011)	(0.011)
Agricultural employment	0.027	0.038	0.058
	(0.023)	(0.031)	(0.035)
Cultivated area in grain crops	-0.004	-0.003	0.002
	(0.016)	(0.014)	(0.012)
Grain production	0.010	0.011	0.005
	(0.021)	(0.020)	(0.015)
GDP		0.001	0.001
		(0.001)	(0.001)
Fiscal revenue		-0.009	-0.001
		(0.013)	(0.011)
Fiscal expenditure		-0.000	-0.002
		(0.010)	(0.009)
Resident income		0.002	0.002
		(0.003)	(0.003)
Urban area		-0.001	-0.002
		(0.004)	(0.004)
# industrial firms		-0.000	-0.000
		(0.000)	(0.000)
Waste water emissions			-0.000
			(0.000)
SO2 emissions			0.063
			(0.254)
NOx emissions			-0.276
			(0.187)
Dust emissions			0.154
			(0.471)
PM emissions			-0.022
			(0.018)
Thermal power generation			0.008
			(0.017)
Coal consumption			-0.002
			(0.002)
Observations	476	476	476
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R-squared	0.533	0.545	0.582

Notes: The unit of observation is at the province-year level. This table examine the quasi-exogeneity of the UPSB policy. The dependent variable is a dummy indicating the timing of the UPSB policy (i.e., equals to 1 in years after the policy implementation). We use three sets of variables to predict the implementation timing of the UPSB policy. The first set of variables are related to agricultural development, which includes agricultural GDP (10 billion RMB), agricultural employment (million), cultivated area in grain crops (100 thousand hectares), and grain production (million tons). The second set of variables are related to general economic development, which includes the provincial GDP (10 billion RMB), fiscal revenue and expenditure (10 billion RMB), residential income (100 RMB), urban area (100 square kilometers) and number of industrial firms (100 units). The third set of variables are related to pollution emissions, which includes waste water emissions (million tons), sulfur dioxide (SO_2) emissions (million tons), nitrogen oxide (NO_x) emissions (million tons), dust emissions (million tons), particulate matter (PM) emissions (million tons), thermal power generation (10 billion kilowatt hours), and coal consumption (million tons). All regressions include province and year fixed effects. Standard errors in parentheses are clustered at the province level.

Table A5 Parsimonious results

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Number of Fires			IHS (# of Fires)		
$Post$	-5.937**	-5.713**	-5.832**	-0.079**	-0.073*	-0.074*
	(2.332)	(2.483)	(2.542)	(0.036)	(0.039)	(0.040)
Observations	1,719,529	1,719,529	1,718,888	1,719,529	1,719,529	1,718,888
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	Yes	No	Yes	Yes
Weather Controls	No	No	Yes	No	No	Yes
Dep. Var. Mean	5.805	5.805	5.805	0.125	0.125	0.125
Adjusted R-squared	0.259	0.259	0.260	0.313	0.313	0.314

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows that the universal prohibition on straw burning (UPSB) policy can reduce agricultural fires in the treated provinces, using a staggered difference-in-differences strategy. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the province-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table A6 Parsimonious results for high-versus-low cropland subsample

	(1)	(2)	(3)	(4)
Dep. Var.	Number of Fires	IHS (# of Fires)	Number of Fires	IHS (# of Fires)
	High Cropland Share		Low Cropland Share	
$Post$	-18.623***	-0.251**	-0.565	-0.005
	(6.978)	(0.105)	(0.522)	(0.009)
Observations	408,805	408,805	1,310,083	1,310,083
Grid FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	20.45	0.418	1.234	0.0341
Adjusted R-squared	0.257	0.295	0.208	0.290

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows that the universal prohibition on straw burning (UPSB) policy can reduce agricultural fires in grids with higher cropland share, while having no effects on agricultural fires in grids with lower cropland share, using a staggered difference-in-differences strategy. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the province-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table A7 Extensive margin versus intensive margin

	(1)	(2)	(3)	(4)
Dep. Var.	Number of Fires		IHS (# of Fires)	
$Post \times Cropland$	-10.318**	-10.360**	-0.135**	-0.138**
	(4.173)	(4.176)	(0.061)	(0.061)
Observations	1,717,358	1,716,717	1,717,358	1,716,717
Grid FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Ex-post Cropland Share	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes
Dep. Var. Mean	5.805	5.805	0.125	0.125
Adjusted R-squared	0.539	0.540	0.549	0.550

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows that the universal prohibition on straw burning (UPSB) policy reduces agricultural fires mainly through intensive margin, by controlling for the *ex-post* cropland share. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the province-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table A8 Effects of the UPSB policy on PM2.5

	(1)	(2)	(3)	(4)
Dep. Var.	log(PM2.5)			
$Post$	-0.221***	-0.214***		
	(0.080)	(0.055)		
$Post \times Cropland$			-0.012**	-0.012**
			(0.006)	(0.006)
Observations	1,755,780	1,755,200	1,753,682	1,753,102
Grid FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	-	-
County by Year FE	-	-	Yes	Yes
Group by Year FE	-	-	Yes	Yes
Geo Controls	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes
Dep. Var. Mean	3.045	3.045	3.045	3.045
Adjusted R-squared	0.892	0.914	0.989	0.989

Notes: The unit of observation is 10 km × 10 km grid cells. This table reports the effects of the IPSB policy on air pollution, using both parsimonious and baseline specification. The dependent variables are the log transformation of $PM_{2.5}$. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the province-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Additional Figures

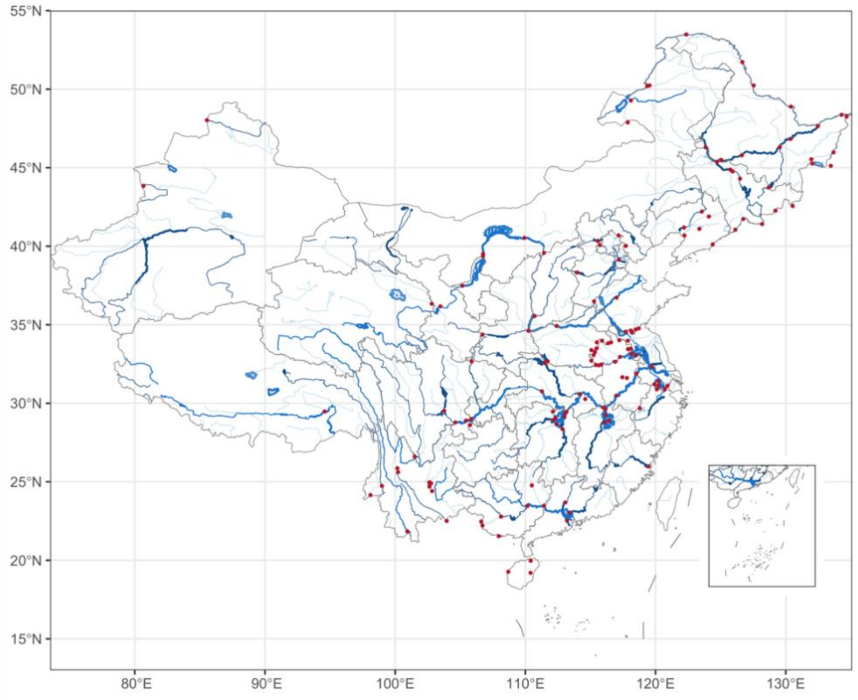

Figure A1. Spatial distribution of water monitoring stations

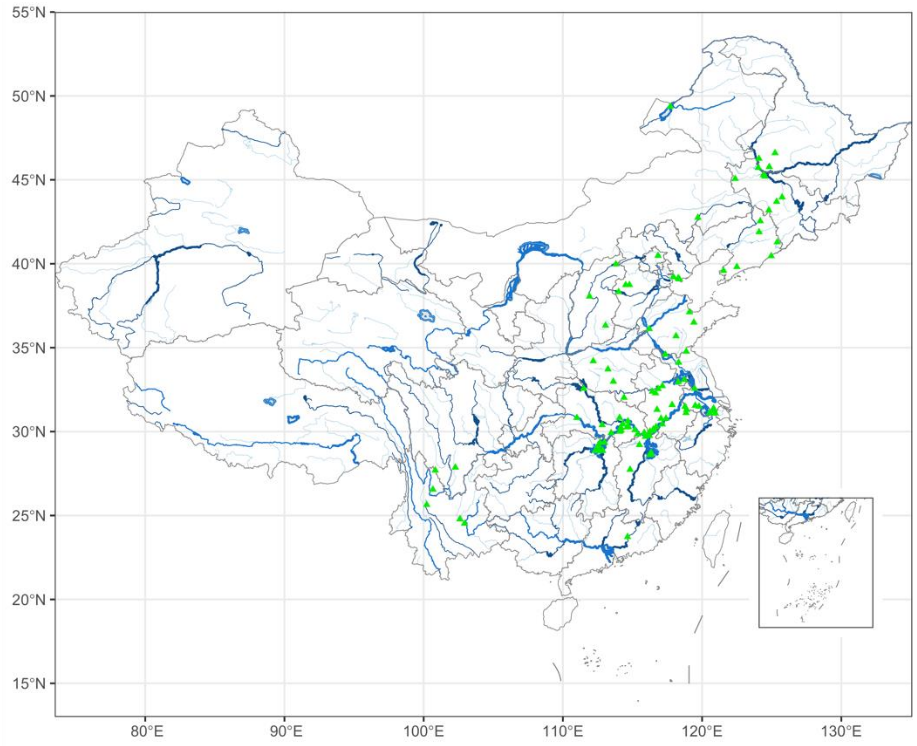

Figure A2. Spatial distribution of lake samples

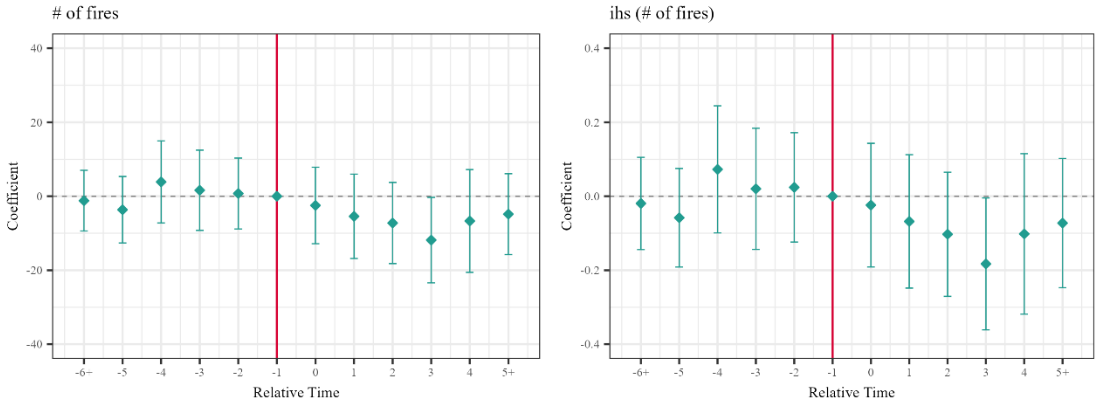

Figure A3. Event study estimates for the parsimonious specification

Notes: This figure plots the estimated event-study coefficients of the impact of the UPSB policy on the agricultural fires based on the parsimonious specification. The left panel plots the effects on absolute number while the right panel plots the effects on the IHS-transformed number of fires. The unit of observation is 10 km × 10 km grid cells. Coefficient estimates are plotted with the 95% confidence interval. All regressions include geographic and weather controls. Standard errors are two-way clustered at the grid level and the province-year level.

Appendix B: Robustness checks

Sensitivity to sample selection. First, we exclude grids with no ex-ante cropland cultivated (i.e., cropland share equals zero). Intuitively, these observations have no variations in both treatment timing and treatment intensity, and thus enter the regression only through fixed effects. Therefore, excluding these samples should have no substantial impact on our estimated results if our identification strategy accurately captures the causal effect of the UPSB policy. Column (1) of Table B1 reports the corresponding results with the number of agricultural fires being the dependent variable in Panel A and the IHS-transformed number of fires in Panel B. Despite excluding over half of the sample, the estimated coefficients closely match those in Table 1.

Second, we restrict our sample periods after 2008, when overall regulations on air pollution activities, including straw burning, were strengthened and unified coinciding with the opening of the 2008 Beijing Olympic Games (He, Fan, and Zhou 2016). By exploiting only post-2008 observations, we can better balance the regulation stringency across treatment and control groups. The results from column (2) of Table B1 confirm the robustness of our results. Third, to improve the comparability between high- and low-treatment intensity groups, we restrict our analysis to data from treated provinces. As shown in column (3) of Table B1, results remain robust. In Table B2, we exclude grids with cropland shares greater than one to avoid the contamination of extreme values. We also restrict our sample to grid cells with cropland shares greater than zero and smaller than one. The estimated results remain significant and are slightly larger than our baseline estimates.

Alternative definition of treatment intensity. In our baseline specification, the treatment intensity is defined as the average cropland share of each grid cell from 2001 to 2010. This measure aims to smooth the potential temporary shocks that may affect our identification. However, averaging over a long period may raise concerns that our treatment intensity measure could capture other unobserved factors, such as structural transformation. To address such concerns, we use the 2001 or the 2009 cropland share as alternative measures of treatment intensity. The estimated coefficients in columns (4) and (5) of Table B1 are similar despite differences in these measures.

Another related issue concerns the aggregation process used to construct our treatment intensity measure, where we opt for a simple approach by summing the cropland share of the three major crops. This method reduces data manipulation, which may involve arbitrary weighting. Nonetheless, simple summation also abstracts out the cropping structure underlying the cropland share, which may fail to fully characterize treatment intensity. To accommodate such potential pitfalls, we employ the Principal Component Analysis (PCA) to maximize the information in cropland shares across different crops, offering a more representative depiction of treatment intensity. The estimated results, using the first principal component interacted with the $Post$ dummy, are shown in column (6) of Table B1. After normalization, the principal component variable is centered at zero with an SD of 1. The estimated coefficients thus suggest that a one standard deviation increase in treatment intensity is associated with an average decrease of 2.5 agricultural fire points, accounting for over a 43% reduction relative to the sample mean.

We also discretize the continuous treatment intensity measure to allow for a clearer causal interpretation. In the spirit of Callaway, Goodman-Bacon, and Sant'Anna (2024), we classify grids with above-mean cropland share as the treatment group and girds with below-mean as the control group. The classification is denoted by the variable $High\ Cropland$. Column (7) of Table B1 displays the corresponding estimated results, with the coefficients remaining significant at the 1% level.

Cluster level adjustment. In our baseline specification, we adopt the two-way clustering strategy to account for both serial correlations within each grid as well as the cross-sectional correlations within each county. However, since the UPSB policy is implemented at the provincial level, there could be concerns that our inference may fail to account for within-province correlations. Adjusting the clustering level to the provincial level may lead to invalid inference as the number of clusters is too small (29 provinces in our sample). We therefore exploit the wild bootstrap clustering to infer the significance of our estimated coefficients. The results are reported in column (8) of Table B1, with the corresponding t-values shown the brackets. Reassuringly, our estimates remain significant at the conventional significance level.

Control for lagged fires. We also account for the persistence of fires following Nian (2023) by controlling for the lagged dependent variable, as the burning activity may be correlated with cropping decisions made in previous years. More importantly, the lagged occurrence of fires may be correlated with the adoption of the UPSB policy. By controlling for the lagged fires, it may help to alleviate concerns about the endogenous policy adoption. Although the results may be biased when considering the dynamic effects using a fixed effects model (Nickell 1981), our results remain largely unchanged when the lagged outcome variable is included, as shown in column (9) of Table B1.

Control for *ex-ante* pollution level. Another concern related to the endogenous policy adoption is that the timing of treatment may be related to the pollution level. Since straw burning can cause significant deterioration in air quality, provinces may implement the UPSB policy due to heightened air pollution. We address this concern by including the air pollution of each grid in 2013, interacted with full set of year dummies to flexibly control for the effects of *ex-ante* pollution levels. The results are reported in Table B3. We find only marginally change in the estimated coefficients.

Using seasonal fires. As previously mentioned, burning activity is highly seasonal, occurring shortly after harvesting. Consequently, there may be concerns that our measurement of annual agricultural fires, which aggregates fire occurrences in cropland across all months, might inadvertently capture other activities, such as the burning of organic waste in rural villages. We therefore only exploit the fire points in high fire seasons following Cao and Ma (2023). We then rerun our baseline specification and report the estimated results in Table B4. We find consistent evidence that the treatment effects we estimate are indeed driven by the reduction in crop fires.

Using non-agricultural fires. As the UPSB policy is primarily aimed at regulating agricultural fires, it should have no effect on the occurrence of non-agricultural fires if our identification strategy is valid. We therefore use non-agricultural fires as a placebo test. The estimates in Table B5 are close to zero and have opposite signs, with none of them being statistically significant at the conventional level. We also report the event study estimates in Figure B1, which show no significant effect of the UPSB policy on non-agricultural fires in both pre- and post-treatment periods. This is not surprising as the occurrence of non-agricultural fires should be largely orthogonal to cropland share, which is then differenced out by our DiD specification.

Placebo test. We also conduct an additional placebo test by randomly assigning a value between zero and one as the placebo treatment intensity to each grid, and then rerun our baseline regression with the true treatment intensity replaced by the placebo intensity. We repeat the random assignment exercise for 500 times and plot the distribution of the estimated coefficients in Figure B2. We find that the distribution of the placebo estimates is closely centered around zero and is far less comparable in magnitude to the true coefficients.

Control for confounding policies. Another related concern is the confound of other concurrent policies that may bias the identification of the true causal parameters. One example is the implementation of the straw recycling subsidy policy in several provinces since 2016, which has been found to have positive effects on curbing crop fires (He, Liu, and Zhou 2020). There is some overlap between provinces that implement straw recycling subsidy policy and those that enforce UPSB policy. To account for the potential confounding effect of straw subsidy, we include an interaction term of the policy dummy of straw subsidy $Post_{pt}^{subsidy}$ and the treatment intensity in our baseline regression.[55] The results in Table B6 show that, after accounting for the potential effect of straw subsidy policies, the coefficient of our main regressor is still significant at the 5% level and the estimated magnitude remains largely unchanged, suggesting that we're indeed capturing the effect of the UPSB policy. Meanwhile, the estimates for the effect of the subsidy policy are overall insignificant and the magnitude of the coefficients is relatively small. This is plausible as the subsidy effects may be constant within the same county, which is then absorbed by the county-year fixed effects.

Control for the effects of biomass power plants. One may also worry that the entry of biomass power plants (BPPs) may potentially bias our estimates (Cao and Ma 2023; Nian 2023), potentially overstating the true policy effect. We adopt two strategies to alleviate concerns. First, we control for the distance of each grid to its nearest BPP, with the time-invariant distance variable interacted with time trends to allow for time-varying effects. Information on the entry of BPPs is obtained from Cao and Ma (2023). Second, we assign the timing of exposure to BPP entry to each grid based on the operational timing of the nearest BPP, and interact with the entry dummy variable with distance to account for spatial variations in the effects of BPPs. (Cao and Ma 2023; Nian 2023). We then run a horserace regression by controlling for the BPP entry effects. Table B7 reports the corresponding results, with odd columns controlling for the distance to the nearest BPP, and even columns presenting the horserace results. Our estimates for the UPSB policy effect remain robust in both exercises. We find some suggestive evidence showing that the entry of BPP can also reduce crop fires, but the estimated coefficients are volatile and sensitive to the inclusion of control variables. This might be attributed to the fact that the effect of BPP is limited to a relatively narrow region (e.g., within a 100 km radius of the power plant, as documented by Cao and Ma (2023)). As the distance to the BPP increases, transportation costs rise, leading to decreased willingness among farmers to recycle crop residue for use in BPPs.

Poisson regression. We consider potential problems associated with the log-like transformation for the number of agricultural fires (Chen and Roth 2023). We follow the recommendation of Chen and Roth (2023) and rerun our baseline regressions using the Poisson pseudo maximum likelihood (PPML) estimator. The results in Table B8 indicate that our baseline estimates remain robust across alternative model specifications and adjustments for potential biases in identifying the treatment effect, particularly when the outcome variable is count data and may include potential zero values.

Alternative identification strategy. Our baseline specification exploits variation that stemming from the different treatment timing across provinces and different treatment intensity across grids. Although the granular fixed effects and control variables included in the model alleviate concerns about endogeneity and the comparability between treatment and control groups, there might still be other unobserved concurrent factors that may pose challenges on the causal interpretation of our results. To address this issue, we exploit the sharp policy change at the provincial border and estimate the Difference-in-Discontinuity specification as an alternative empirical strategy. Specifically, we re-estimate our baseline model while restricting our sample to those close to the provincial border. In addition, we control for up to third-order polynomial of distance to the provincial border, and interact them with full set of year dummies. The corresponding results are reported in Table B9. Across different bandwidth, we find little change in the magnitude of estimated coefficients. The significance level drops in some specifications as the standard error increases due to sample

[55] Control solely for the straw recycling subsidy policy is infeasible as the policy effects are fully absorbed by the county-year fixed effects.

size shrinkage. Yet, this alternative specification lends additional support to the validity of our baseline empirical design.

Table B1 Summary of robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sample with cropland > 0	Sample after 2008	Keep treated provinces	Alternative cropland measures		Principal component	Dummy treatment intensity	Wild bootstrap cluster	Control for lagged fires
Panel A: Number of Fires									
$Post \times Cropland$	-10.081**	-21.207***	-9.692**	-9.376***	-11.450***			-10.359*	-11.123***
	(4.209)	(5.119)	(4.216)	(3.371)	(3.598)			(5.848)	(4.183)
$Post \times Cropland\ \ (PCA)$						-2.498***			
						(0.747)			
$Post \times High\ \ Cropland$							-5.665***		
							(1.051)		
Observations	820,098	997,373	564,980	1,716,717	1,716,717	1,716,717	1,716,736	1,716,717	1,593,396
Dep. Var. Mean	11.86	6.794	8.157	5.805	5.805	5.805	5.805	5.805	6.794
Adjusted R-squared	0.537	0.566	0.594	0.540	0.540	0.540	0.539	0.540	0.553
Panel B: IHS (# of Fires)									
$post \times Cropland$	-0.153**	-0.374***	-0.146**	-0.160***	-0.164***			-0.155*	-0.177**
	(0.070)	(0.083)	(0.070)	(0.055)	(0.058)			(0.093)	(0.069)
$post \times Cropland\ \ (PCA)$						-0.036***			
						(0.012)			
$post \times High\ \ Cropland$							-0.097***		
							(0.018)		
Observations	820,098	997,373	564,980	1,716,717	1,716,717	1,716,717	1,716,736	1,716,717	1,593,396
Dep. Var. Mean	0.254	0.146	0.164	0.125	0.125	0.125	0.125	0.125	0.125
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Adjusted R-squared	0.537	0.566	0.594	0.540	0.540	0.540	0.539	0.540	0.553

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows the robustness of the baseline results. The dependent variable in Panel A is the number of fires and the IHS transformation of agricultural fires in Panel B. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Columns (1)–(3) show the robustness to different sample selections. Columns (4)–(7) show the robustness to alternative definitions of the treatment intensity measure. Column (8) reports the results from wild cluster bootstrap. Column (9) controls for the lagged dependent variable. Standard errors in parentheses are two-way clustered at the grid and county-year level, except for column (8). * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B2 Robustness: sample restriction on cropland share

	(1)	(2)	(3)	(4)
Dep. Var.	Number of Fires		IHS (# of Fires)	
$Post \times Cropland$	-15.041***	-15.127***	-0.191***	-0.192***
	(4.408)	(4.434)	(0.064)	(0.065)
Observations	1,701,857	805,255	1,701,857	805,255
Grid FE	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.368	11.05	0.118	0.240
Adjusted R-squared	0.539	0.537	0.549	0.543

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows that the baseline results are robust to alternative restricted samples with cropland share either restricted to smaller than one or between zero and one. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B3 Robustness: control for ex-ante pollution levels

	(1)	(2)
Dep. Var.	Number of Fires	IHS (# of Fires)
$Post \times Cropland$	-10.946***	-0.168**
	(4.187)	(0.069)
Observations	1,711,441	1,711,441
Grid FE	Yes	Yes
Geo Controls	Yes	Yes
Weather Controls	Yes	Yes
Dep. Var. Mean	5.805	0.144
County by Year FE	Yes	Yes
Group by Year FE	Yes	Yes
Adjusted R-squared	0.540	0.547

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows the robustness of our baseline results to the inclusion of *ex-ante* air pollution. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the UPSB policy implementation. Cropland is the cropland share for each grid cell. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B4 Robustness: using fire points in high fire season

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Number of Fires			IHS (# of Fires)		
$Post \times Cropland$	-9.000***	-9.065***	-9.075***	-0.117**	-0.120**	-0.121**
	(2.142)	(2.144)	(2.145)	(0.050)	(0.050)	(0.050)
Observations	1,717,358	1,717,358	1,716,717	1,717,358	1,717,358	1,716,717
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	Yes	No	Yes	Yes
Weather Controls	No	No	Yes	No	No	Yes
Dep. Var. Mean	3.361	3.361	3.361	0.165	0.165	0.165
Adjusted R-squared	0.313	0.313	0.314	0.435	0.435	0.435

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows the robustness of our baseline results using fire points in high fire seasons, where the high fire season is defined a la Cao and Ma (2023). The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B5 Robustness: using non-agricultural fires as the dependent variable

	(1)	(3)	(4)	(6)
Dep. Var.	Number of Fires		IHS (# of Fires)	
$Post \times Cropland$	1.162	1.083	0.011	0.009
	(0.840)	(0.841)	(0.016)	(0.016)
Observations	1,717,358	1,716,717	1,717,358	1,716,717
Grid FE	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes
Dep. Var. Mean	2.202	2.202	0.0751	0.0751
Adjusted R-squared	0.252	0.252	0.322	0.322

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows the robustness of our baseline results using non-agricultural fires as a placebo test. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B6 Robustness: controlling for the effect of straw recycling subsidy

	(1)	(3)	(4)	(6)
Dep. Var.	Number of Fires		IHS (# of Fires)	
$Post \times Cropland$	-9.056**	-9.268***	-0.113**	-0.117**
	(3.578)	(3.581)	(0.053)	(0.053)
$Post^{subsidy} \times Cropland$	-2.279	-1.954	-0.037	-0.034
	(3.705)	(3.697)	(0.055)	(0.055)
Observations	1,717,358	1,716,717	1,717,358	1,716,717
Grid FE	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes
Dep. Var. Mean	5.805	5.805	0.125	0.125
Adjusted R-squared	0.539	0.540	0.549	0.549

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows the robustness of our baseline results after accounting for the effect of the straw recycling subsidy policy. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the UPSB policy implementation. $\text{Post}^{\text{subsidy}}$ is a dummy indicator for years after the implementation of the subsidy policy. Cropland is the cropland share for each grid cell. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B7 Robustness: controlling for the effect of BPP entry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Number of Fires				IHS (# of Fires)			
$Post \times Cropland$	-10.368**	-10.356**	-10.731**	-10.540**	-0.136**	-0.136**	-0.146**	-0.142**
	(4.165)	(4.165)	(4.320)	(4.321)	(0.061)	(0.061)	(0.064)	(0.064)
$Entry \times Dist.BPP$		0.436*		16.450		0.003		-0.001
		(0.249)		(13.899)		(0.004)		(0.208)
Observations	1,716,717	1,716,717	613,992	613,992	1,716,717	1,716,717	613,992	613,992
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dist. BPP × Year Trends	Yes	No	Yes	No	Yes	No	Yes	No
Dep. Var. Mean	5.805	5.805	5.805	5.805	0.125	0.125	0.125	0.125
Adjusted R-squared	0.540	0.540	0.536	0.536	0.549	0.549	0.546	0.546

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows the robustness of our baseline results after accounting for the effect of the straw recycling subsidy policy. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the UPSB policy implementation. Entry is a dummy indicator for years after the BPP entry. Cropland is the cropland share for each grid cell. Dis. BPP represents the distance of each grid to the nearest BPP. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B8 Robustness: estimation using PPML estimator

	(1)	(2)
Dep. Var.	Number of Fires	
$Post \times Cropland$	-0.275**	-0.288**
	(0.120)	(0.122)
Observations	161,914	161,914
Grid FE	Yes	Yes
Geo Controls	No	Yes
Weather Controls	No	Yes
Dep. Var. Mean	5.805	5.805
County by Year FE	Yes	Yes
Group by Year FE	Yes	Yes
Pseudo R-squared	0.707	0.708

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows the robustness of our baseline results to alternative model specification (i.e., using the PPML estimator to account for potential bias in estimating the treatment effects). The dependent variable is the number of fires. Post is an indicator for years after the UPSB policy implementation. Cropland is the cropland share for each grid cell. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table B9 Robustness: Difference-in-Discontinuity

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Number of Fires			IHS (# of Fires)		
	100KM	70KM	50KM	100KM	70KM	50KM
$Post \times Cropland$	-10.167**	-10.581**	-10.435**	-0.149**	-0.167**	-0.124
	(4.341)	(4.710)	(5.306)	(0.072)	(0.077)	(0.087)
Observations	1,202,436	995,430	817,389	1,202,436	995,430	817,389
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
$f(DistBorder) \times Year$	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	7.155	7.293	7.251	0.175	0.179	0.178
Adjusted R-squared	0.545	0.544	0.549	0.547	0.545	0.546

Notes: The unit of observation is 10 km × 10 km grid cells. This table shows the robustness of our baseline results using alternative identification strategy, the Difference-in-Discontinuity. The specification is similar to our baseline DiD model, but we restrict our analysis to grids that near provincial borders. In addition, we also control for the third-order polynomial of the distance to the provincial border, interacted with full set of year dummies. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. DistBorder is the distance of each grid to the provincial border, which takes positive values for treatment groups and negative values for control groups. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level and the county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

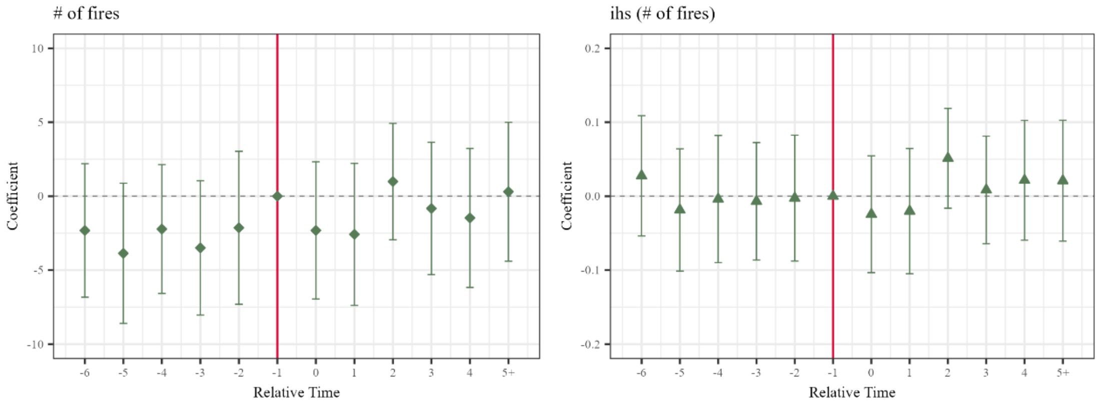

Figure B1. Event study estimates for non-agricultural fires

Notes: This figure plots the estimated event-study coefficients of the impact of the UPSB policy on non-agricultural fires based on the generalized DiD specification outlined in equation (3). The left panel plots the effects on absolute number while the right panel plots the effects on the IHS-transformed number of fires. The unit of observation is 10 km × 10 km grid cells. Coefficient estimates are plotted with the 95% confidence interval. All regressions include geographic and weather controls. Standard errors are two-way clustered at the grid level and the county-year level.

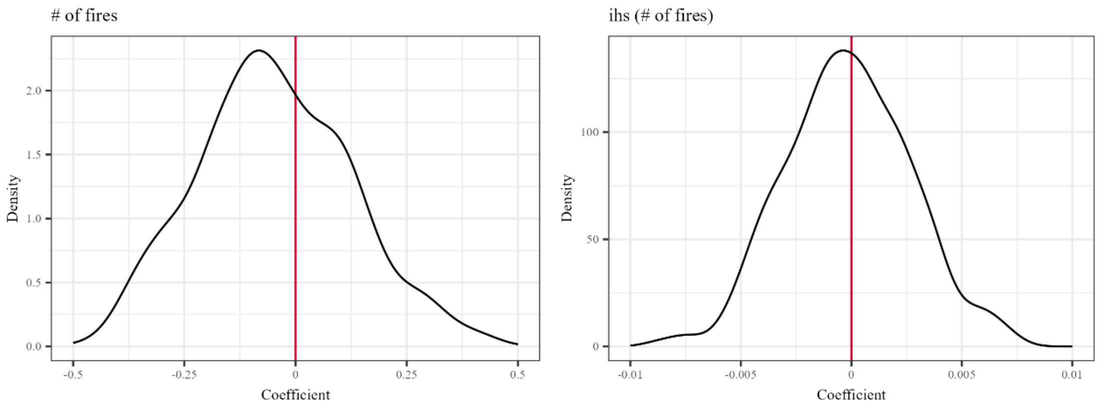

Figure B2. Placebo test by randomly assigning treatment intensity

Notes: This figure illustrates the distribution of the placebo coefficients estimated through random assignment of treatment intensity. The left panel plots the distribution on absolute number while the right panel plots the distribution on the IHS-transformed number of fires. The unit of observation is 10 km × 10 km grid cells. All placebo regressions include geographic and weather controls.

Appendix C: Additional results for the mechanism

Table C1 The effects of the No Burning Zones (NBZ)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.	Number of Fires				IHS (# of Fires)			
$Post \times Cropland \times Dist.Airport$	-33.704				-0.483			
	(61.286)				(0.905)			
$Post \times Cropland \times Dist.National\ \ Road$		0.182				0.003*		
		(0.137)				(0.002)		
$Post \times Cropland \times Dist.Provincial\ \ Road$			0.138				0.003	
			(0.194)				(0.003)	
$Post \times Cropland \times Dist.Railway$				0.012*				0.000
				(0.006)				(0.000)
$Post \times Cropland$	-7.943	-12.804***	-11.228**	-10.723**	-0.101	-0.182***	-0.155**	-0.142**
	(6.283)	(4.541)	(4.465)	(4.275)	(0.093)	(0.068)	(0.066)	(0.063)
$Post \times Dist.Airport$	2.257				0.022			
	(3.852)				(0.057)			
$Post \times Dist.National\ \ Road$		0.015***				0.000***		
		(0.003)				(0.000)		
$Post \times Dist.Provincial\ \ Road$			0.006**				0.000	
			(0.003)				(0.000)	
$Post \times Dist.National\ \ Road$				0.001				0.000
				(0.003)				(0.000)
Observations	1,716,717	1,716,717	1,716,717	1,716,717	1,716,717	1,716,717	1,716,717	1,716,717
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.805	5.805	5.805	5.805	0.125	0.125	0.125	0.125
Adjusted R-squared	0.540	0.540	0.540	0.540	0.549	0.549	0.549	0.549

Notes: The unit of observation is 10 km × 10 km grid cells. This table tests for the competing mechanism on the strengthened effects in NBZs. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. The distance variables measure the distance of the grids to the nearest transportation (e.g., airports, national and provincial roads, and railway). The unit for the distance measures is 10 km. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid and county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table C2 Test for the bottom-up mechanism

	(1)	(2)	(3)	(4)
Dep. Var.	Number of Fires		IHS (# of Fires)	
$Post \times Cropland \times Dist.County\ \ Border$	1.784		0.041	
	(2.561)		(0.036)	
$Post \times Cropland \times Dist.County\ \ Government$		-0.001		-0.000
		(0.014)		(0.000)
$Post \times Cropland$	-10.790**	-10.354**	-0.146**	-0.136**
	(4.273)	(4.172)	(0.063)	(0.062)
$Post \times Dist.County\ \ Border$	-0.017		-0.000	
	(0.043)		(0.001)	
$Post \times Dist.County\ \ Government$		0.000		-0.000
		(0.002)		(0.000)
Observations	1,716,717	1,716,717	1,716,717	1,716,717
Grid FE	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.805	5.805	0.125	0.125
Adjusted R-squared	0.540	0.540	0.549	0.549

Notes: The unit of observation is 10 km × 10 km grid cells. This table tests for the bottom-up mechanism. The dependent variables are the number of fires and the IHS transformation of agricultural fires. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. The distance variables measure the distance of the grids to either the county center or the county border. The unit for the distance measures is 10 km. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid and county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

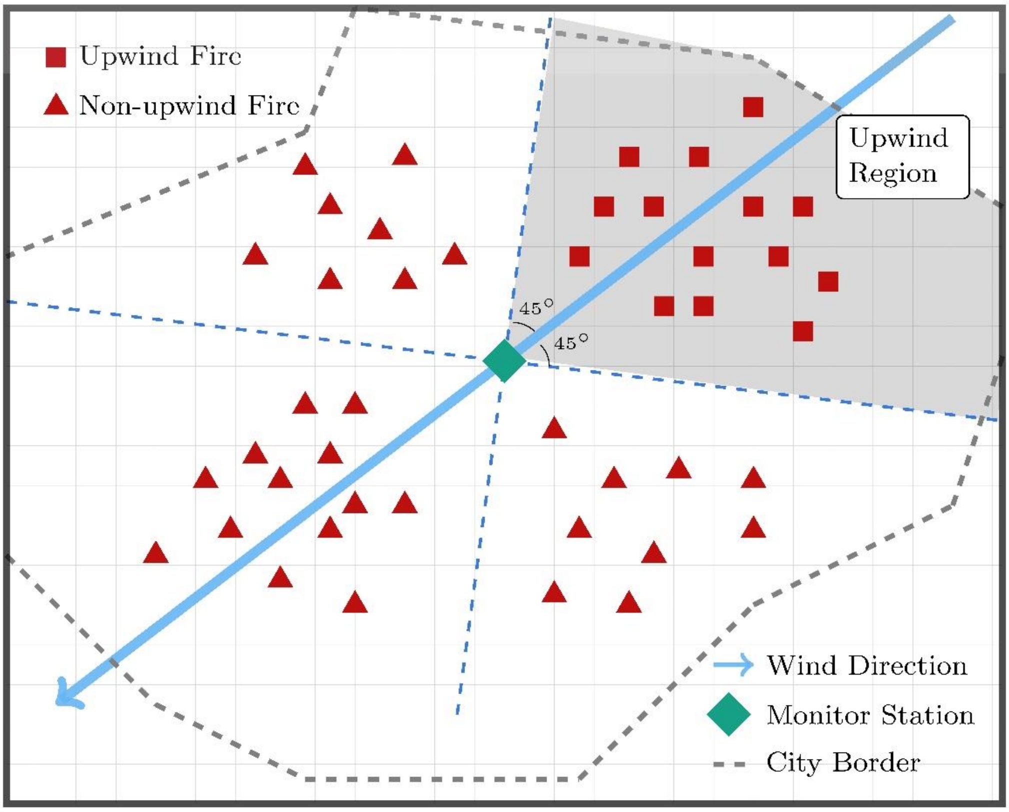

Figure C1. Illustration for the upwind regions relative to the monitoring station

Appendix D: Additional results for farmers' responses and the effects on water pollution

Table D1 Provincial fertilizer & pesticide usage

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	log (fertilizer)			log (pesticide)		
$Post$	0.086**	0.146**	0.138**	0.054	0.077*	0.058*
	(0.040)	(0.064)	(0.055)	(0.033)	(0.039)	(0.030)
Observations	476	476	476	476	476	476
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Treatment-Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Weight by Population	No	No	Yes	No	No	Yes
Dep. Var. Mean	7.493	7.493	7.493	1.271	1.271	1.271
Adjusted R-squared	0.960	0.961	0.934	0.989	0.990	0.983

Notes: The unit of observation is at the province-year level. This table examines the effects of the UPSB policy on total fertilizer usage and total pesticide usage. The dependent variables are the logged value of fertilizer and pesticide, respectively. Post is an indicator for years after the policy implementation. Controls include rural population, share of agricultural output in GDP, the amount of financial support on agricultural, and the level of agricultural mechanization. Standard errors in parentheses are clustered at the provincial level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table D2 provincial fertilizer usage (by categories)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var.	log (Nitrogen fertilizer)			log (Phosphate fertilizer)			log (Potash fertilizer)		
$Post$	0.034	0.061*	0.045*	-0.000	0.039	0.050	0.068**	0.086***	0.070**
	(0.021)	(0.032)	(0.026)	(0.026)	(0.044)	(0.039)	(0.027)	(0.030)	(0.027)
Observations	476	476	476	476	476	476	476	476	476
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Treatment-Year Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Weight by Population	No	No	Yes	No	No	Yes	No	No	Yes
Dep. Var. Mean	3.997	3.997	3.997	2.870	2.870	2.870	2.530	2.530	2.530
Adjusted R-squared	0.993	0.994	0.988	0.987	0.988	0.984	0.984	0.986	0.983

Notes: The unit of observation is at the province-year level. This table examines the effects of the UPSB policy on total fertilizer usage by different categories. The dependent variables are the logged value of nitrogen, phosphate, and potash fertilizer, respectively. Post is an indicator for years after the policy implementation. Controls include rural population, share of agricultural output in GDP, the amount of financial support on agricultural, and the level of agricultural mechanization. Standard errors in parentheses are clustered at the provincial level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table D3 Fertilizer & pesticide usage and expense (household level)

	(1)	(2)	(3)	(4)
Dep. Var.	Fertilizer	Fertilizer Expenses	Pesticide	Pesticide Expenses
$Post \times Cropland$	26.418***	32.152***	0.643***	15.333***
	(3.411)	(4.298)	(0.244)	(5.826)
Observations	74,939	74,761	81,681	81,681
Household FE	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes
Household Controls	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	20.63	37.05	1.426	28.47
Adjusted R-squared	0.365	0.350	0.455	0.455

Notes: The unit of observation is at the household-year level. This table examines the effects of the UPSB policy on rural household fertilizer and pesticide usage, as well as expenses. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. Household controls include the number of family members, whether the household head is village cadre, household total income and total expenditure. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid and county-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table D4 Effects of the UPSB policy on weed occurrence

	(1)	(2)	(3)	(4)
Dep. Var.	Occurrence Density		Coverage Intensity	
$Post \times Cropland$	34.905***	3.099	15.211**	2.732
	(13.251)	(10.347)	(6.207)	(5.528)
Observations	1,115	1,459	1,115	1,459
County by Year FE	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes
Crop Type	Wheat	Maize	Wheat	Maize
Geo Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
Dep. Var. Mean	9.590	9.590	2.822	2.822
Adjusted R-squared	0.0387	0.0366	0.0115	-0.0216

Notes: The unit of observation is at the 10 km × 10 km grid cells. This table examines the effects of the UPSB policy on weed occurrence, focusing on wheat and maize. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid cell. Due to sparse sample, we do not include grid fixed effects as they would fully absorb the coefficients. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the grid level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table D5 Robustness on the effects of the UPSB policy on water pollution

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	Water Quality Grade (Standardize)		COD		NH3-N	
$Post \times Cropland$	0.601***	0.614***	0.517**	0.479*	0.212***	0.225***
	(0.175)	(0.178)	(0.259)	(0.272)	(0.072)	(0.075)
Observations	1,386	1,386	1,511	1,511	1,513	1,513
Station FE	Yes	Yes	Yes	Yes	Yes	Yes
Province by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Selective Regulation	Yes	Yes	Yes	Yes	Yes	Yes
Water Polluting Firms	No	Yes	No	Yes	No	Yes
Dep. Var. Mean	0	0	4.272	4.272	0.547	0.547
Adjusted R-squared	0.792	0.790	0.852	0.850	0.790	0.788

Notes: The unit of observation is at the station-year level. This table presents the robustness check results of the UPSB policy on water pollution, by considering the effects on selective regulation and water polluting firms. The dependent variables are Water Quality Grade (standardized a la Perez-Truglia (2020)), chemical oxygen demand (COD) and ammonia nitrogen (NH3-N). Post is an indicator for years after the policy implementation. Cropland is the cropland share for each station, aggregated from the grid level. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the station level and the province-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table D6 Heterogeneous effects on water pollution: Fertilizer Usage

Dep. Var.	(1) Water Quality Grade (Standardize)	(2) COD	(3) NH3-N
$Post \times Cropland \times Fertilizer$	0.006*	0.021*	0.016**
	(0.003)	(0.012)	(0.007)
$Post \times Cropland$	0.025	0.359	-0.082
	(0.046)	(0.339)	(0.114)
Observations	241,115	263,053	262,972
Station FE	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes
Geo Controls	No	No	No
Weather Controls	No	No	No
Dep. Var. Mean	0	4.288	0.767
Adjusted R-squared	0.984	0.983	0.971

Notes: The unit of observation is the 10 km × 10 km grid cells. This table presents the heterogeneous of the UPSB policy on water pollution using the grid level sample, by exploiting the role of fertilizer usage. The dependent variables are Water Quality Grade (standardized a la Perez-Truglia (2020)), chemical oxygen demand (COD) and ammonia nitrogen (NH3-N). Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid. All regressions are weighted by the inverse of the distance to the nearest monitoring station. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are clustered at the station level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table D7 Heterogeneous effects on water pollution: Precipitation

	(1)	(2)	(3)
Dep. Var.	Water Quality Grade (Standardize)	COD	NH3-N
$Post \times Cropland \times Precipitation$	0.004**	0.020*	0.012**
	(0.002)	(0.011)	(0.006)
$Post \times Cropland$	-0.034	-0.068	-0.220
	(0.053)	(0.388)	(0.196)
Observations	244,114	266,365	266,276
Station FE	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes
Geo Controls	No	No	No
Weather Controls	No	No	No
Dep. Var. Mean	0	4.288	0.767
Adjusted R-squared	0.984	0.982	0.971

Notes: The unit of observation is the 10 km × 10 km grid cells. This table presents the heterogeneous of the UPSB policy on water pollution using the grid level sample, by exploiting the role of precipitation. The dependent variables are Water Quality Grade (standardized a la Perez-Truglia (2020)), chemical oxygen demand (COD) and ammonia nitrogen (NH3-N). Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid. All regressions are weighted by the inverse of the distance to the nearest monitoring station. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are clustered at the station level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table D8 Upstream-downstream comparison

	(1)	(2)	(3)	(4)	(5)	(6)
	Upstream	Downstream	Upstream	Downstream	Upstream	Downstream
Dep. Var.	Water Quality Grade (Standardize)		COD		NH3-N	
$Post \times Cropland$	0.127*	-0.004	0.913***	-0.013	0.128*	0.047
	(0.072)	(0.034)	(0.313)	(0.189)	(0.073)	(0.102)
Observations	107,798	134,994	117,575	147,358	117,564	147,280
Station FE	Yes	Yes	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0	0	4.288	4.288	0.767	0.767
Adjusted R-squared	0.991	0.984	0.992	0.982	0.984	0.973

Notes: The unit of observation is the 10 km × 10 km grid cells. This table presents the upstream-downstream comparison of the UPSB policy on water pollution, using the grid level sample. The dependent variables are Water Quality Grade (standardized a la Perez-Truglia (2020)), chemical oxygen demand (COD) and ammonia nitrogen (NH3-N). Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid. All regressions are weighted by the inverse of the distance to the nearest monitoring station. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are clustered at the station level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table D9 The effects of the UPSB policy on algal bloom

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var. (Standardized)	Bloom Occurrence		Potential Occurrence Period		Maximum Bloom Extent		First Component from PCA	
$Post \times Cropland$	0.270*	0.274*	0.006	0.008	0.098***	0.100***	0.189**	0.192**
	(0.139)	(0.139)	(0.030)	(0.029)	(0.031)	(0.031)	(0.090)	(0.089)
Observations	244,800	244,460	244,800	244,460	244,800	244,460	244,800	244,460
Lake FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo Controls	No	Yes	No	Yes	No	Yes	No	Yes
Weather Controls	No	Yes	No	Yes	No	Yes	No	Yes
Dep. Var. Mean	0.923	0.923	143.2	143.2	50.30	50.30	0	0
Dep. Var. Standard Deviation	1.362	1.362	66.34	66.34	187.7	187.7	1	1
Adjusted R-squared	0.974	0.974	0.973	0.973	0.998	0.998	0.980	0.980

Notes: The unit of observation is the 10 km × 10 km grid cells. This table presents the results of the UPSB policy on algal bloom, using the grid level sample. The dependent variables are Bloom Occurrence, Potential Occurrence Period, Maximum Bloom Extent, and the first component of these three variables obtained using PCA. Post is an indicator for years after the policy implementation. Cropland is the cropland share for each grid. All regressions are weighted by the inverse of the distance to the nearest monitoring station. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and number of rivers; distance to airports, distance to expressways, distance to railways, distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are clustered at the lake level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

Table D10 Parsimonious results for water pollution (station level)

	(1)	(2)	(3)
Dep. Var.	Water Quality Grade (Standardize)	COD	NH3-N
$Post$	0.124**	0.373**	0.004
	(0.058)	(0.162)	(0.035)
Observations	1,472	1,604	1,606
Station FE	Yes	Yes	Yes
Province by Year FE	Yes	Yes	Yes
Group by Year FE	Yes	Yes	Yes
Geo Controls	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Dep. Var. Mean	0	4.272	0.547
Adjusted R-squared	0.782	0.827	0.788

Notes: The unit of observation is at the station-year level. This table presents the parsimonious results of the UPSB policy on water pollution. The dependent variables are Water Quality Grade (standardized a la Perez-Truglia (2020)), chemical oxygen demand (COD), and ammonia nitrogen (NH3-N). Post is an indicator for years after the policy implementation. Geographic controls include slope, ruggedness, elevation; distance to the county border, county center, and provincial center; distance to rivers, and the number of rivers; distance to airports, distance to expressways, distance to railways, and distance to national roads and provincial roads. Weather controls include temperature, precipitation, humidity, sea level pressure, wind speed, and wind direction. Standard errors in parentheses are two-way clustered at the station level and the province-year level. * denotes significance at the 10% level. ** denotes significance at the 5% level. *** denotes significance at the 1% level.

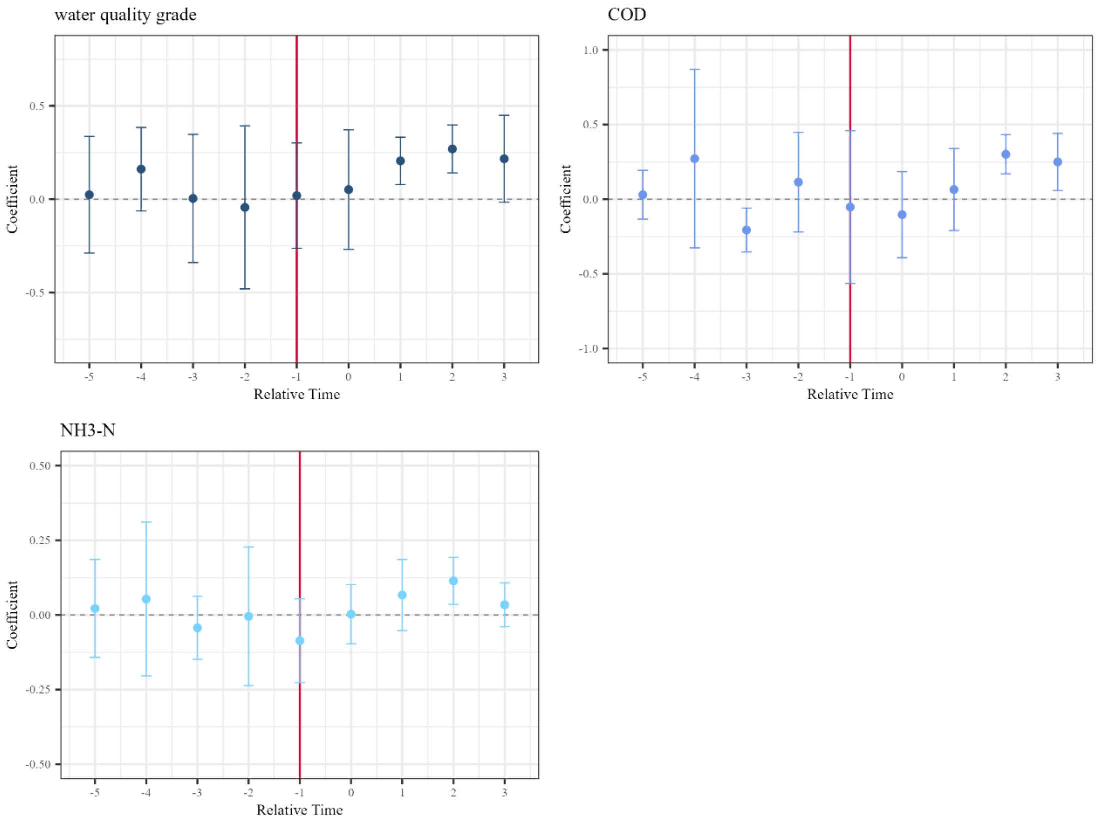

Figure D1. DiD$_l$ estimates of the UPSB policy on water pollution

Notes: This figure plots the coefficients from the DiD$_l$ estimator. The upper left panel plots the effects on standardized water quality grade, the upper right panel plots the effects on COD, and the lower left panel plots the effects on NH3-N. The unit of observation is at the station-year level. The estimation exploits the did_multiplegt command in Stata. Coefficient estimates are plotted with the 95% confidence interval. All regressions include geographic and weather controls. Bootstrap standard errors are clustered at the group (here, the group is defined at the province) by year level.

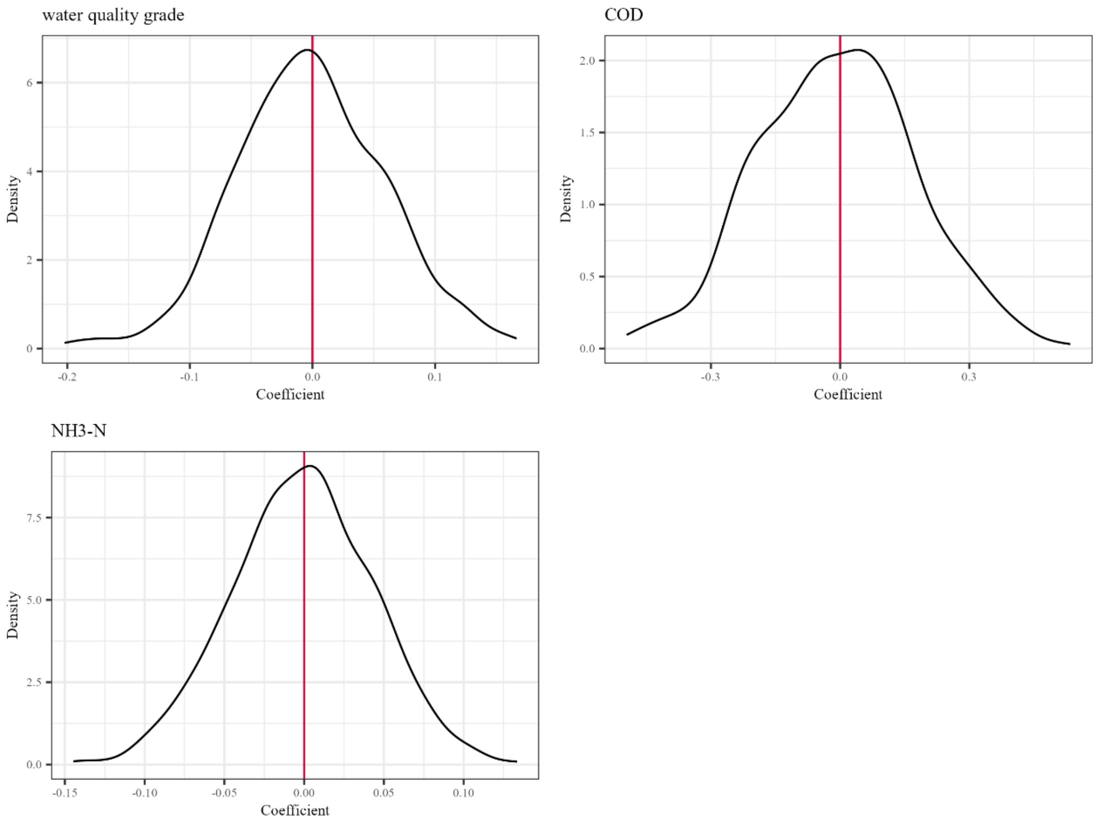

Figure D2. Placebo test by randomly assigning treatment intensity for station

Notes: This figure illustrates the distribution of the placebo coefficients estimated through random assignment of treatment intensity, using the station-level specification to identify the UPSB policy effects on water pollution. The left upper panel plots the distribution on water quality grade, the right upper panel plots the distribution on COD, and the left bottom panel plots the distribution on Nh3-N. The unit of observation is at the station-year level. All placebo regressions include geographic and weather controls.

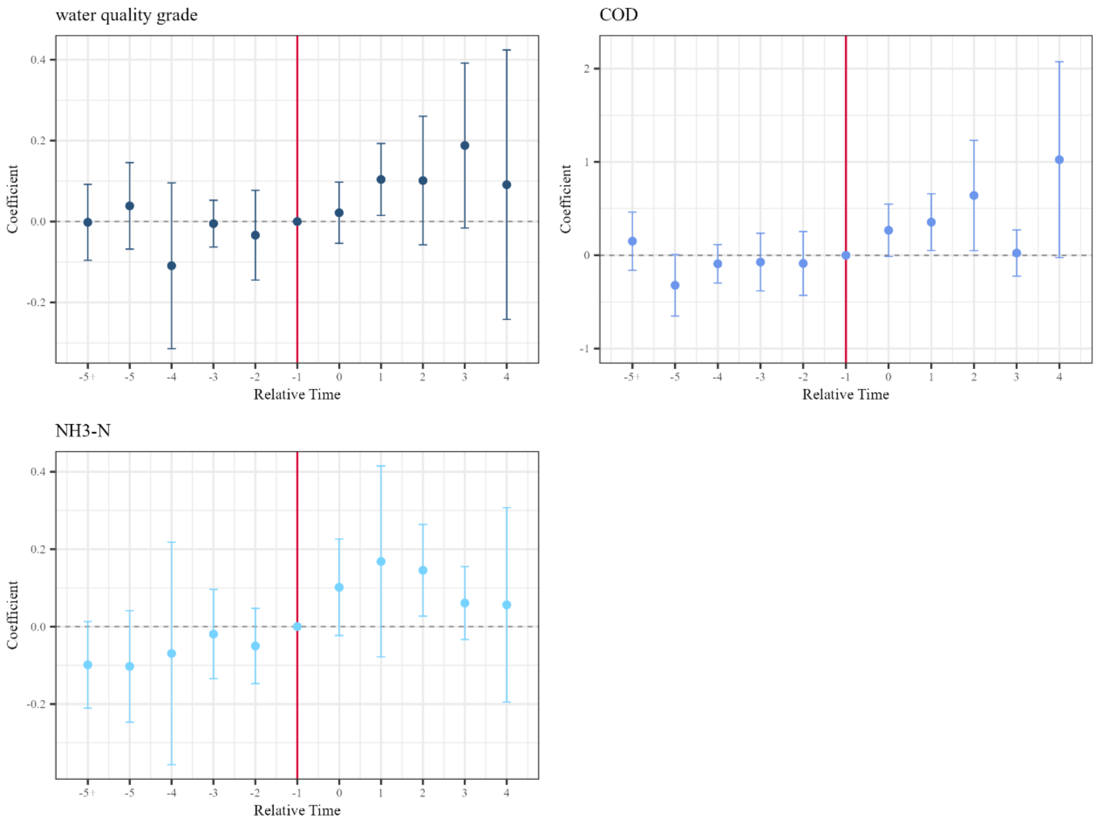

Figure D3. Event study estimates of the UPSB policy on water pollution (grid level)

This figure plots the estimated event-study coefficients of the impact of the UPSB policy on water pollution. The upper left panel plots the effects on standardized water quality grade, the upper right panel plots the effects on COD, and the lower left panel plots the effects on NH3-N. The unit of observation is at 10 km × 10 km grid level. Regression specification is presented in Equation (1), and is weighted by the inverse of the distance to the nearest monitoring station. Coefficient estimates are plotted with the 95% confidence interval. All regressions include geographic and weather controls. Standard errors are clustered at the station level.

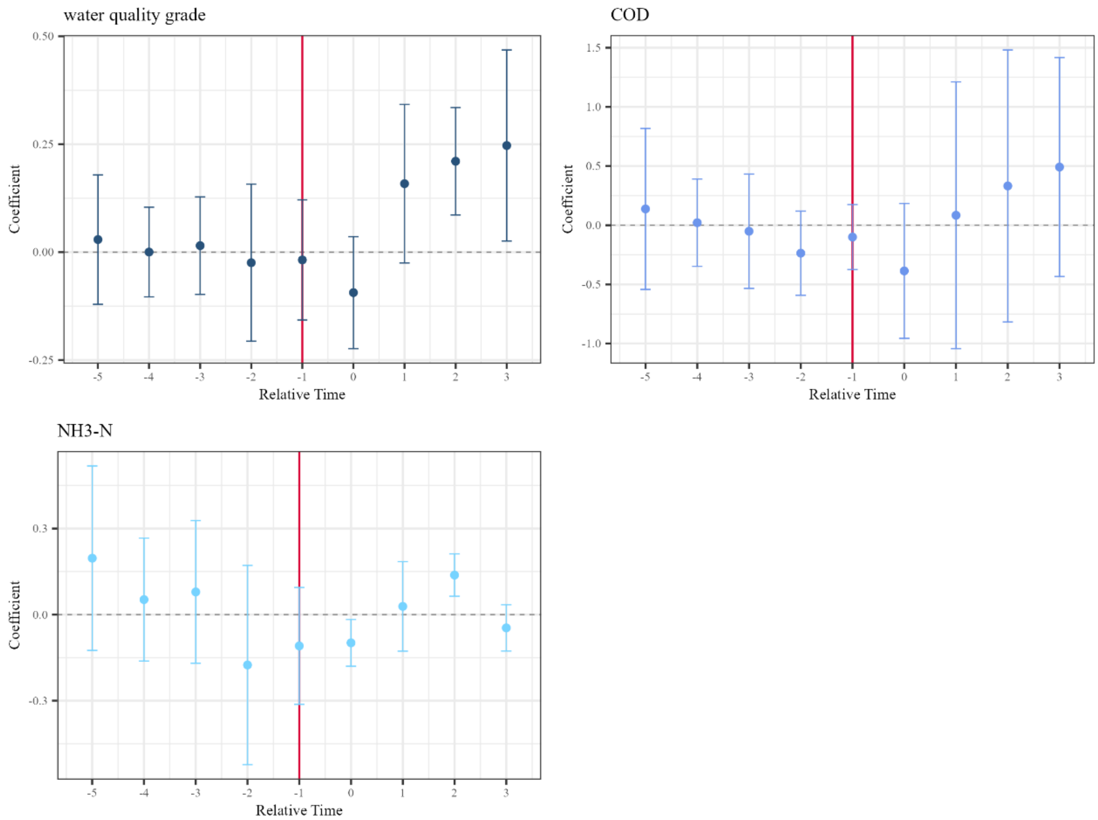

Figure D4. DiD$_l$ estimates of the UPSB policy on water pollution (grid level)

Notes: This figure plots the coefficients from the DiD$_l$ estimator. The upper left panel plots the effects on standardized water quality grade, the upper right panel plots the effects on COD, and the lower left panel plots the effects on NH3-N. The unit of observation is at 10 km × 10 km grid level. The estimation exploits the did_multiplegt command in Stata. All specifications are weighted by the inverse of the distance to the nearest monitoring station. Coefficient estimates are plotted with the 95% confidence interval. All regressions include geographic and weather controls. Bootstrap standard errors are clustered at the group (here, the group is defined at the province) by year level.