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When the fire ends: Straw burning, regulation, and pollution substitution

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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 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. Cost-benefit analysis suggests that much of the health benefit from improved air quality is offset by the health cost from degraded water quality. Our findings highlight the importance of considering the potential responses of individuals subject to the regulation when conducting policy evaluation.

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 (Gibson, 2019; Greenstone, 2003).[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 has had a long tradition of burning straw since ancient times.[2] Farmers burn straws for several reasons. First, burning is conducive to new crops since it can eradicate potential invasive plant species, weeds, fungi, and bacteria (Graff Zivin et al., 2020; Levine, 1991). Second, the ashes after burning can fertilize the soil (He et al., 2020a; 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 (Graff Zivin et al., 2020; Guo, 2021; He et al., 2020a; Lai et al., 2022; Rangel and Vogl, 2019).[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 the local officials' appraisal system.[4] Officials with the

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[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., 2025).

[2] In China, straw-burning activities usually involve the burning of the stalks 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 to the same issue.

[3] Burning activities are concentrated in seasons after harvesting. Such intensive burning of crop residues can lead to a substantial escalation in air pollution levels within a 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.

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worst performance may receive serious punishment (Wang et al., 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 staff 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 potentially distorts 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. To combat these negative shocks, farmers may adjust their production behavior by using more fertilizers and pesticides. Such changes in factor inputs may trigger environmental externalities in the form of water pollution (Dias et al., 2023; Lai, 2017), resulting in a potential pollution substitution effect (Gibson, 2019; Greenstone, 2003).

To identify the validity and pollution substitution effect of the UPSB policy, we compile a comprehensive dataset from multiple sources. First, we create a grid-level dataset that covers the entire Chinese mainland at a 10 km × 10 km resolution. We then match it with 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. Second, we exploit 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 variation. 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 acreage of each grid cell. Such a design is akin to the general case that combines both continuous treatment with staggered adoption in recent DiD econometric literature (Callaway et al., 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 prevalent in these areas (Garg et al., 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 (Guo, 2021; He et al., 2020a). 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 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 a 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 fertilizers and pesticides (Lai, 2017). In accordance with the political incentive narratives, we show that the effect of 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 this 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., input adjustment and potential output losses) 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 35.98 billion CNY or 5.54 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 15.96 billion CNY or 2.46 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 (Cao and Ma, 2023; Dipoppa and Gulzar, 2024; He et al., 2020a; Jack et al., 2025; Nian, 2023). 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 strand of literature by providing comprehensive evidence on the effectiveness and unintended consequences of China's nationwide straw burning bans. 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 studies that investigate the pollution substitution effect in environmental regulations. The empirical evidence on

[5] Some anecdotal evidence reveals that the county expenses on local cadres' meals within a single month during the period of high incidence of straw burning (e.g., seasons after harvesting or before cultivating) can even amount to 100,000 RMB (approximately 13,760 USD). See the report from https://www.guancha.cn/politics/2024_03_29_730046.shtml. Accessed at 2025-11-04.

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

policy-induced pollution substitution effects is relatively scarce, with most discussions focused on the industrial sector (Gibson, 2019; Greenstone, 2003). 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 force 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.

Lastly, our work fits into the broader literature that debates over and evaluates the effectiveness of environmental regulations in developing countries (Duflo et al., 2013, 2018; Greenstone and Hanna, 2014; He et al., 2020b). The effectiveness of environmental regulations does not only hinge on whether they are carefully designed to provide appropriate incentives and efficient monitoring technology to motivate the agent (Axbard and Deng, 2024; Cai et al., 2016; He et al., 2020b; Kahn et al., 2015; Xie and Yuan, 2023), but also depend on whether these policies consider the strategic behaviors of polluters (Gibson, 2019; Greenstone, 2003; Zou, 2021). By studying the regulation of agricultural fires and farmers' behavioral responses, our work addresses two key gaps in the literature: On the one hand, we shed new light on the specific circumstances under which command-and-control regulations can be effective. A similar work that studies the effectiveness of Indian straw burning regulation finds that the command-and-control policy is largely ineffective (Sekhri et al., 2023). In contrast, our evidence suggests that, through political incentives and top-down accountability, command-and-control regulations can effectively curb agricultural fires. On the other hand, we document the significant consequences (increased water pollution) that can arise precisely when such regulations succeed. In doing so, we provide crucial evidence that there is "no free lunch" in environmental regulation and underpin 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 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 disposal 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).

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 et al., 2020a; 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 (Cao and Ma, 2023; He et al., 2020a; 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 is 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 et al., 2020a), 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 et al., 2020a; Lai et al., 2022). According to Zhang et al. (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 burning 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 15 km of airports, (2) within 2 km of expressways and railways, and (3) within 1 km 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 for 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 regulations in 2013, which 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 et al., 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).

After the announcement of this document, provincial governments introduced their specific regulations and policies progressively. Appendix Table A3 outlines the specific provisions and details of the provincial policies. The timing of when 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

[7] According to the World Bank, 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 2025-11-07.

[8] See document from https://www.gov.cn/zwgk/2013-05/27/content_2411933.htm. Accessed at 2025-11-04.

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 et al., 2022).

For instance, the Henan Province declares that each additional fire point detected by satellite results in a fine of 50,000 RMB (approximately 7800 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 land.[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 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 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 access to random spots, given their convenience and concealability, and lack of time constraints (relative to railways). 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 manage 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 decompose and be absorbed by the soil. This matters especially in northern regions with lower temperatures, where the process of decomposing crop residues 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 straw 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 straw 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 change their production inputs 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 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

[9] See document from https://www.mee.gov.cn/gkml/hbb/bgth/201409/t20140918_289253.htm. Accessed at 2025-11-04.

[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 2025-11-04.

[13] According to the 2021 data, among crop residues that are not burned away, 62.5% are returned to the farmland, while the remaining 37.5% are recycled for other usage. See the report from https://m.thepaper.cn/baijiahao_20861205. Accessed at 2025-11-04.

[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 were held accountable. See more details from https://www.163.com/dy/article/HVBGFSSM0556165R.html. Accessed at 2025-11-04.

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

policy's intended benefits.

Despite the importance of the potential pollution substitution effect in the implementation of UPSB policy, empirical investigation into these effects remains limited. We proceed to further examine 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 10 km × 10 km 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 have 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 a.m. and 3 p.m., and between 9 p.m. and 2 a.m. 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-m 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 acreage 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 1 km. To 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 acreage dedicated to these three crops to establish the total cropland acreage, dividing it by 100 (the area of the 10 km grid cell) to derive the cropland share. While most of the cropland shares range between zero and one, they 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 $PM_{2.5}$ 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 1 km resolution, to our 10 km 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 acreage, crop-specific planted acreage, 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 unintended use of fertilizer.

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 Monitoring 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 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

[16] Since our data is derived from satellite observations with different resolutions. We choose the 10 km × 10 km 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.

[18] Our results are robust to an 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

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

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

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° (which is approximately 11 km). 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 year2010,[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 in the upwind region of the air pollution monitor (Axbard and Deng, 2024; Xie and Yuan, 2023), 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 (Axbard and Deng, 2024; He et al., 2020a; Nian, 2023; Rangel and Vogl, 2019; Xie and Yuan, 2023) 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 distance from the grid centroid to the nearest rivers following Nian (2023). All time-invariant variables are interacted with flexible linear time trends.

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 decreased to 6.18 (with a t-value of 16.96). The simple before-and-after comparison seems to imply that the UPSB policy may effectively curb open straw-burning activities.

Fig. 1 plots the average agricultural fire points for each grid cell, while Fig. 2 plots the average cropland acreage for the three major crops. These figures reveal a high spatial correlation between the number of fires and the cropland acreage. 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 et al., 2020a).[24]

Fig. 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 preventing fires in these places.

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 is 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

[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.

[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 et al., 2020a).

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

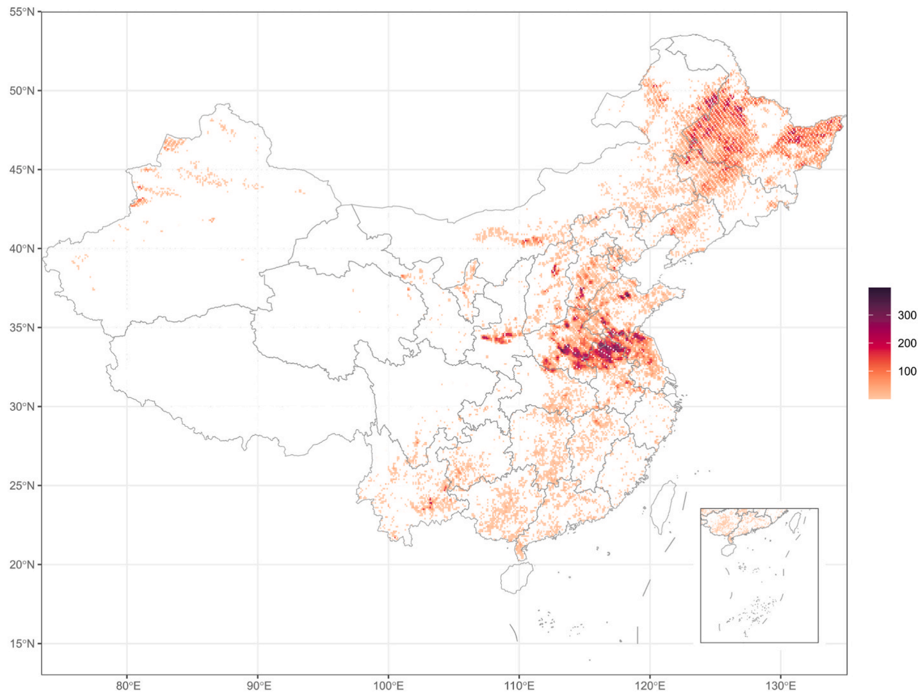

Fig. 1. Satellite-detected agricultural fires for each grid during 2001–2019
Notes: Colored red points represent the number of agricultural fires for each grid, with darker shades indicating higher levels of burning activity. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

has adopted the UPSB policy in year t, outlined in Equation (1):

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

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 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 et al., 2024). Such omitted variable bias may lead to an 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 et al. (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 leads 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

[26] Since the vast majority of grids has a zero agricultural fire, we use IHS to avoid missing these observations. We do 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, 2024). However, as pointed out by Chen and Roth (2024), 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.

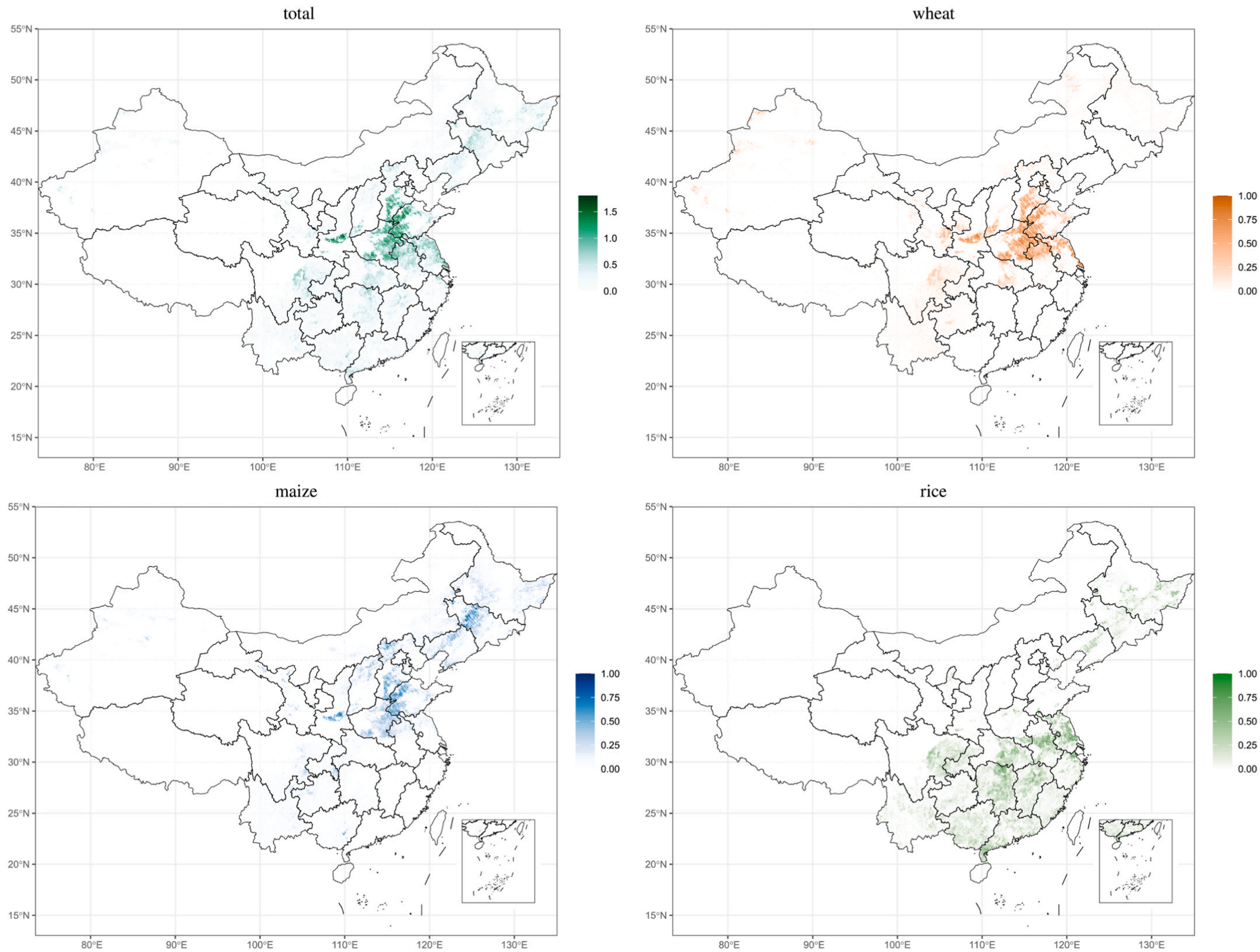

Fig. 2. Average cropland shares for wheat, maize, and rice

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.

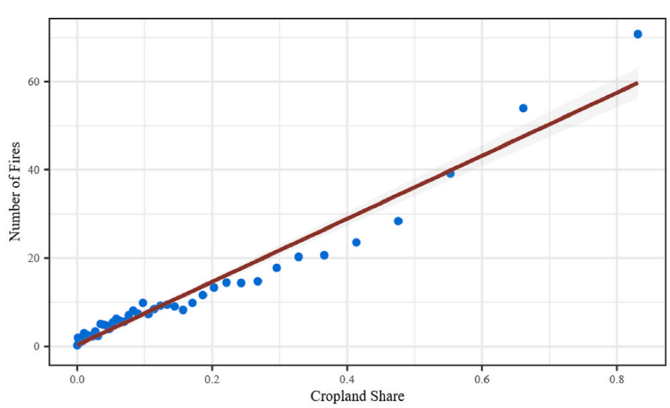

Fig. 3. Binscatter plot on the relation between the number of fires and cropland share

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.

variation in cropland acreage, 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 et al., 2024; de Chaisemartin and D'Haultfœuille, 2024). Typically, the decomposition in Callaway et al. (2024) indicates that the TWFE estimator is, in essence, using the 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, which 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

[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.

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 (Callaway et al., 2024; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2024; 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021). Negative weighting issue arises in staggered adoption designs with heterogeneous treatment effects (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021), and recent work extends this issue to continuous treatment designs (Callaway et al., 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]

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:

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

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

5. Impacts on agricultural fires and air pollution

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.[32]

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 ($=-10.359 \times 0.08$), 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 14.6% (=exp(-0.158)-1) decrease in the agricultural fire.[33] 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).[34]

Another concern with our baseline empirical design is that we are comparing the relative change in straw-burning activities between grids with a higher cropland share and grids with a lower cropland share. Though less plausible, the negative coefficients may reflect a relative increase in crop fires in grids with a 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 a higher cropland share, and we do not find any significant policy effect on crop fires in grids with a lower cropland share. This confirms our interpretation that the UPSB policy mainly exerts its effects by reducing crop fires in grids with a 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 the extensive margin (i.e., decrease in cropland share) or the 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 the 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 Table 2, where we estimate

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

[31] It is 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 in our findings.

[32] 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.

[33] 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).

[34] We also empirically examine the role of the BPP entry and compare its effects with our baseline findings in Appendix Table B8. See Appendix B for further discussion.

Table 1
The effects of UPSB policy on agricultural fires.

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
	Number of Fires			IHS (# of Fire)		
Post × *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 a 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.

Table 2
The effects of UPSB policy on $PM_{2.5}$.

Dep. Var.	(1)	(2)	(3)	(4)
	log($PM_{2.5}$)			
Post	−0.221***	−0.214***		
	(0.080)	(0.055)		
Post × *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 specifications. The dependent variable is 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.

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.[35]

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 that 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 estimated coefficients with corresponding 95% confidence intervals in Fig. 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 decreased with a 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 term and long term. 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.

We further address the negative weighting issues in our generalized setting, where treatment effects may be heterogeneous in different units (Callaway et al., 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

[35] 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 agricultural production.

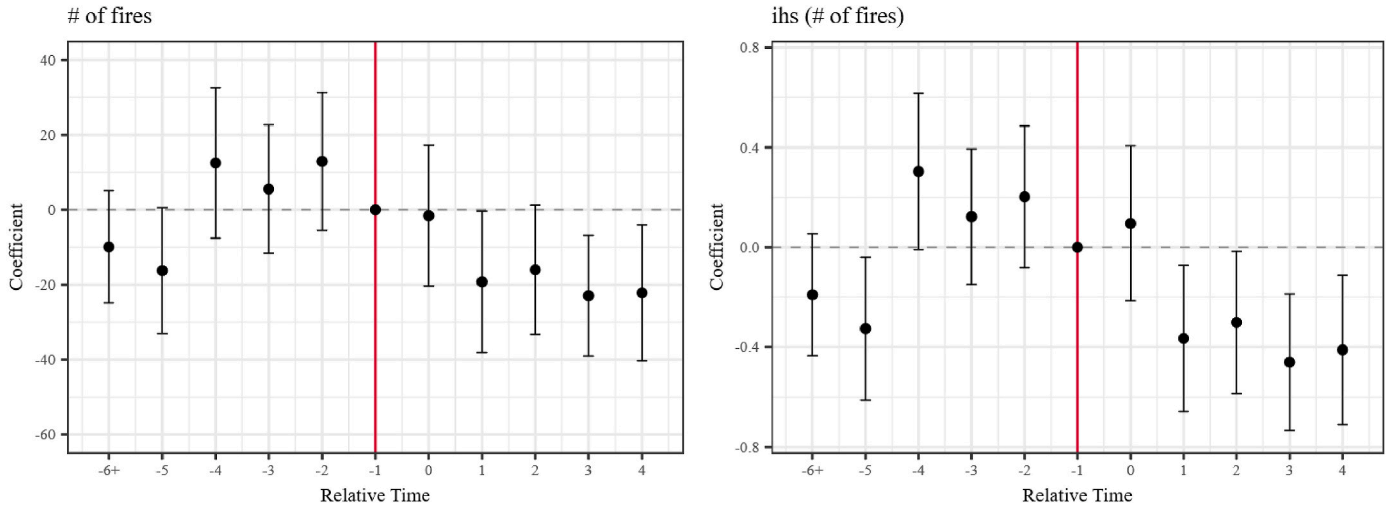

Fig. 4. Event study estimates of the UPSB policy on agricultural fires

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 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. 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.

the comparison groups, the DiD_l estimator avoids the pitfalls of negative weighting issues in conventional designs. Fig. 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.

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 Fig. 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.[36] 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.

In Appendix Figure A4, we also present the corresponding event study estimates for $PM_{2.5}$. Consistent with results from Figs. 4 and 5, we find no evidence of significant pre-trends while identifying a persistent decline in air pollution, suggesting that the regulation against straw burning is effective in reducing air pollution.

Robustness. 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 et al. (2020a), the entry of biomass power plant as in Cao and Ma (2023) and Nian (2023), and other concurrent environmental policies). We also try out some alternative identification strategy, e.g., Difference-in-Discontinuities (DiDisc) that evaluates the UPSB policy at the provincial border. The 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 the UPSB policy may mediate our baseline estimates. We explore the role of these factors further below.

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 (Axbard and Deng, 2024; He et al., 2020b; Nian, 2023), since the chance of promotion decreases significantly after this age. Table 3 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

[36] 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.

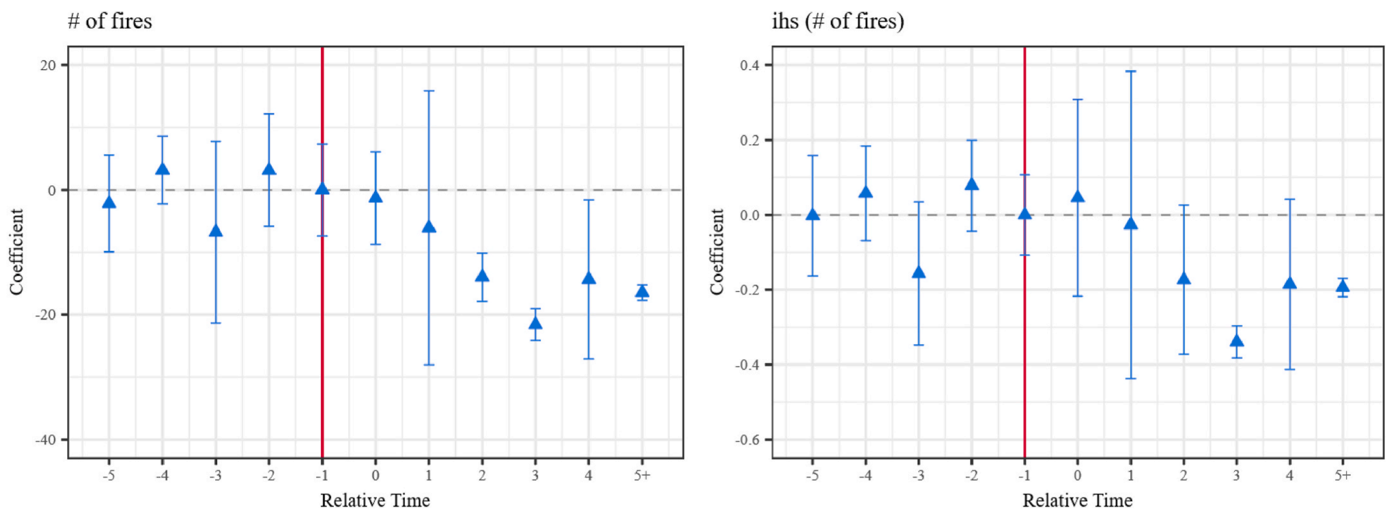

Fig. 5. DiD$_l$ estimates of the UPSB policy on agricultural fires
Notes: This figure plots the coefficients from the DiD$_l$ estimator. The left panel plots the UPSB policy effects on the absolute number while the right panel plots the effects on the IHS-transformed number of fires. The unit of observation 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. Bootstrap standard errors are clustered at the group (here, the group is defined at the province) by year level.

Table 3
The effects of political incentives.

Dep. Var.	(1)	(2)	(3)	(4)
	Number of Fires		IHS (# of Fires)	
Post × *Cropland* × *High Incentive* (*PS*)	−13.156**		−0.308***	
	(5.620)		(0.082)	
Post × *Cropland* × *High Incentive* (*Mayor*)		−11.898**		−0.167*
		(5.592)		(0.087)
Post × *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) aged 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.

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.[37] The large-scale automated air pollution monitoring program has been staggered rollout since 2013, aiming to improve urban air quality (Axbard and Deng, 2024; Greenstone et al., 2022; Xie and Yuan, 2023). 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 activities in rural areas (Guo, 2021; He et al., 2020a).[38] We therefore hypothesize that grids located upwind of monitoring stations experience more stringent top-down accountability. Results in Table 4, columns (1) and (3), confirm that these grids face more stringent regulations, implying that enhanced monitoring technology facilitates more effective environmental regulations.

Second, we consider the role of enhanced on-site supervision from the 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 4 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 differ in locations

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

[38] Some provinces also strengthen 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.

Table 4
The effects of top-down accountability.

Dep. Var.	(1)	(2)	(3)	(4)
	Number of Fires		IHS (# of Fires)	
Post × *Cropland* × *Upwind*	−6.931*		−0.117**	
	(3.557)		(0.052)	
Post × *Cropland* × *Dist. Expressway*		16.285***		0.270***
		(4.304)		(0.072)
Post × *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.

that are (i) closer to county centers, where the government headquarters are located; and (ii) closer to county administrative borders, 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 5 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' notices that straw-burning activities are harder to regulate in the northeastern region.[39]

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.[40] We therefore hypothesize that enforcement costs are higher in places with more fragmented lands, as

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

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

Table 5
The heterogeneous effects of enforcement costs.

Dep. Var.	(1)	(2)	(3)	(4)
	Number of Fires		IHS (# of Fires)	
Post × *Cropland* × *Temperature*	−30.340***		−0.547***	
	(11.223)		(0.158)	
Post × *Cropland* × *Ruggedness*		4.551***		0.047**
		(1.255)		(0.019)
Post × *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.

measured by terrain ruggedness. Results in columns (2) and (4) of Table 5 support this hypothesis, showing that the policy effects diminish with the terrain's ruggedness, suggesting higher enforcement costs in more rugged grids.

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 water pollution consequences

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 in response to increased weeds and pests. 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 deterioration in water quality.

6.1. Farmers' responses

Main results. 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 6 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

Table 6
Farmers' responses to the UPSB policy.

Dep. Var.	(1)	(2)
	Fertilizer Usage (Standardized)	
Post × *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 variable is standardized Nitrogen fertilizer usage intensity (Yu et al., 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.

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.[41] 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 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 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 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.

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 was conducted in the years 2013, 2017, and 2018 (covering the pre-policy and post-policy periods).[42] 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 the conventional level. This lends additional credence to our assertion that the UPSB policy indeed increases the occurrence of weeds and pests, which leads farmers to use more fertilizers and pesticides as input adjustment.

Discussion. While the above findings provide strong evidence that banning straw burning and implementing straw returning increases fertilizer and pesticide use, there is contradictory evidence in the existing agronomic and crop science literature. For example, several studies suggest that returning crop residues to the soil (instead of burning) is associated with improvements in soil health that can aid crop growth and productivity (e.g., Fu et al., 2021), and burning itself is linked to long-term detrimental effects on soil quality (Amorim et al., 2021; Dutta et al., 2022). To reconcile our evidence with the existing literature, we provide two pieces of arguments.

First, we note that the relation between straw burning/returning and soil quality depends crucially on the local environment. Temperature, precipitation, and cropping traditions (e.g., double cropping, rotation cropping, and intercropping), among others, can have a significant impact on whether it is suitable for straw returning. In China, due to the prevalence of double cropping and crop rotations, the period available for straw decomposition and fermentation during crop intervals is extremely limited. Several studies also find consistent evidence that straw returning could increase the risk of root rot, pest infection, and other diseases (Zhu et al., 2014; Wang et al., 2020; Zhang et al., 2022). This also aligns with our evidence that weed increases following the implementation of the UPSB policy.

Second, even if straw returning is beneficial to soil quality, farmers' priori belief may also drive up fertilizer and pesticide application. If farmers believe that straw burning is conducive to soil quality, then banning straw burning can increase fertilizer use even if there is no actual decline in soil quality. This is exactly the dilemma proposed by (Oraby et al., 2025), which suggests that burning is a culturally embedded practice and is *believed* to enhance soil fertility.[43] Therefore, how farmers perceive the practice of burning is also an important driver of their behavior in responding to government regulation.

On the empirical front, we provide three pieces of evidence to complement the above arguments. First, we present the event study estimates of grid-level fertilizer application in Appendix Figure D1, which is informative about the dynamic responses of fertilizer usage. If, in the long run, straw returning is conducive to soil quality, then the observed increase in fertilizer usage only represents a short-term adjustment. Our evidence from Figure D1 suggests that the response is less likely to be a short-term adjustment, as we observe a significant and

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

[42] The data is derived from the 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/datadetails.html?dataguid=188509254879198&docId=10613. Accessed at 2024-09-02.

[43] Whether straw burning is conducive to soil quality remains a debate in the agronomic literature (Roper et al., 2021). Based on our interview with local cadres, the effect of straw burning on soil fertility also depends on the soil characteristics (e.g., soil moisture and soil type).

persistent increase throughout post-treatment periods.

Second, we conduct two heterogeneity exercises to help better understand how the local environment affects farmers' fertilizer application decisions. As suggested by the meta-analysis of Zhang et al. (2022), temperature and precipitation act as important catalysts in the process of straw decomposition, and they show that the effect of straw returning on pest disease is more significant in regions with lower temperature and lower precipitation. Therefore, we should find a stronger effect of fertilizer responses to UPSB policy in these regions. We provide consistent evidence in Appendix Table D5, where, using a similar triple-difference specification as in Table 5, we show that the policy effect on chemical fertilizer is more pronounced in grids with lower temperature (column (1)) and lower precipitation (column (2)). Finally, we investigate the effect of UPSB policy on soil quality, which is measured by soil organic carbon content.[44] While being an imperfect proxy, this measure allows us to empirically investigate whether straw returning in China is conducive to soil quality. We provide the corresponding results in Appendix Table D6, where we find significant evidence that UPSB policy leads to substantial decreases in soil quality. Specifically, our estimates suggest a 0.055 SD decrease in soil quality, roughly a 9.6 percent change relative to the sample mean.[45]

6.2. The effect 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 stations, which are widely used to examine the causes and consequences of water pollution (Fan and He, 2023; He et al., 2020b). 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 grid level. On the one hand, aggregating the grid-level data to the station level avoids the manipulation of the outcome variable (e.g., water quality) but requires additional assumptions on defining the treatment intensity for each station. Moreover, the relatively small sample size at the station level may invalidate 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 less information at the aggregate level to conduct further analyses (e.g., exploring the heterogeneity). On the other hand, however, disaggregating station-level data to the grid level involves the manipulation of the outcome variable, which also requires strong assumptions, and the outcomes are likely to be measured with error. Nevertheless, the abundance of grid-level information allows us to explore potential mechanisms 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.

6.2.1. Aggregate grid-level data to the station level

Baseline estimates. First, we aggregate our grid-level data to the station level by mapping the two datasets and assigning each grid to its nearest monitoring station. We filter grids within a 100 km radius of their nearest station, as fertilizer increases 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 as the weight. Controls are collapsed to the station level in a similar fashion. We then run the following regression to examine the effects of UPSB policy on water pollution.

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

Where y_{sgpt} represents the station-year level outcome. We use water quality grades (a categorical variable ranging from 1 to 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 a 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 7 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 NH_3-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 an 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 Fig. 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 D2).

Robustness. 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 D3, where we find that the placebo coefficients are all centered at zero, and the magnitudes from the 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 et al., 2016; Lipscomb and Mobarak, 2017), water pollution is significantly rampant at administrative boundaries due to its negative externality, which leads to a

[44] The data is provided by the National Tibetan Plateau Data Center (TPDC). TPDC offers the 1 km grid-level soil information from 2010 to 2018, which was created by Liu and Zhang (2021). We follow the same procedure described in the Data section to process the data and aggregate them to our 10 km grid level. See more detailed descriptions of the dataset at https://www.tpdc.ac.cn/zh-hans/data/e1ccd22c-348f-41a2-ab46-dd1a8ac0c955/.

[45] One potential concern with our soil quality results is that the increase in fertilizer and pesticide application may also contribute to the decline in soil quality. To ensure this is not the case, we control for fertilizer usage in columns (3) and (4) of Table D6; the results remain robust.

Table 7
The effects of UPSB policy on water pollution (station level).

Dep. Var.	(1) 100 KM	(2) 50 KM	(3) 100 KM	(4) 50 KM	(5) 100 KM	(6) 50 KM
	Water Quality Grade (Standardized)		COD		NH3-N	
Post × *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	1386	1386	1511	1511	1513	1513
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 (NH_3-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.

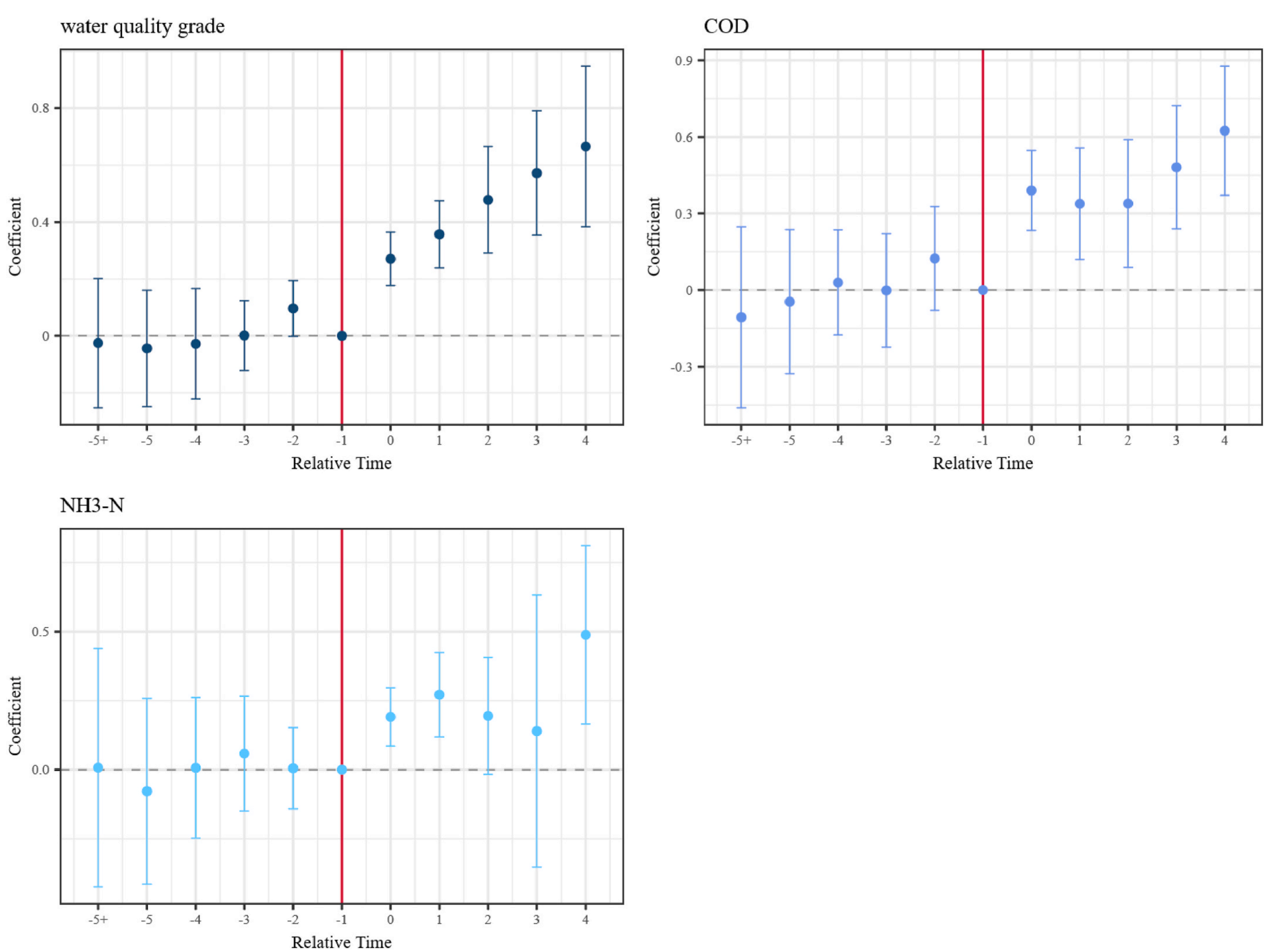

Fig. 6. Event study estimates of the UPSB policy on water pollution
Notes: This figure plots the estimated event-study coefficients of the impact of the UPSB policy on water pollution. The upper left panel plots the effects on standardized water quality grade, the upper right panel plots the effects on COD, and the lower left panel plots the effects on NH_3-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 in parentheses are two-way clustered at the station level and the province-year level.

"polluting thy neighbor" effect where local officials may strategically reduce regulation efforts at the boundaries. Another potential confounder is emissions from water-polluting firms. As the readings 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 100 km radius of each station and interact with a full set of year fixed effects.[46] Reassuringly, our estimated effects on water pollution remain significant and quantitatively unchanged (Appendix Table D7).

Third, to ensure that our results are not driven by other local contemporaneous programs, we additionally examine the robustness of our results to the inclusion of watershed-by-year trends or watershed-by-year fixed effects, which allows us to control for local environmental regulations specific to certain watersheds.[47] The corresponding results are reported in Appendix Table D8, where we do not find large changes in our estimated coefficients. Lastly, to ensure that our results are not contaminated by upstream water station readings, we exclude immediately adjacent and upstream monitoring stations that are located in the same watershed. The results from Appendix Table D9 suggest that our estimated effects are less subject to the intercorrelation between upstream-downstream water stations.

Heterogeneity. Similar to the heterogeneity discussion in Section 5.2, we can explore how political incentives and enforcement costs (discussed next) affect the magnitude of water pollution. Intuitively, as we've shown that the effect of UPSB policy on reducing agricultural fires is more significant when local officials have higher promotion incentives, then we should expect a symmetric effect on water pollution, i. e., strong political incentives lead to more significant increases in water pollution. In Table 8, we replicate the specification from Table 3 and examine whether the increase in water pollution following the UPSB policy is largely driven by promotion incentives of local officials. The corresponding results confirm our argument, where we do find that the effect of UPSB policy on water pollution is more significant if local officials, especially the mayor, have higher incentives. Such a symmetric structure between the reduction in agricultural fire/air pollution and the increase in water pollution lends further confidence to our identification of the pollution substitution effect.

6.2.2. Disaggregate station-level variables to the grid level

Baseline estimates. 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 100 km 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.

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 9 again confirm that all three water pollution measures increased after the implementation of the UPSB policy. Moreover, the estimated coefficients from Table 9 are similar to those obtained in Table 7, which lends additional credence to the validity of our estimates. Specifically, our estimation from Table 9 suggests that, when evaluated 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 units (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 D4 and Figure D5, 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.

Robustness and heterogeneity. The grid level specification allows us to conduct several heterogeneous exercises and robustness checks to verify that we are accurately estimating the effects of UPSB policy on water pollution. First, similar to our previous finding that water pollution increases more if local officials have higher promotion incentives, the effects of UPSB policy on water pollution should be weaker if the enforcement cost is relatively higher. We examine this heterogeneous effect by replicating the results from Table 5, with the dependent variable replaced with corresponding water pollution measures. Table 10 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 5, which state that the enforcement cost is higher if the temperature is lower or the terrain is more rugged.

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 D10 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 D11 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 UPSB policy on water pollution.

Fourth, in our baseline specification, we use cropland shares of grids within a 100 km 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 a DEM raster to predict river flow direction and determine upstream grid direction. Appendix Table D12 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 the upstream subsample, providing further support to our findings.

[46] 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 records all heavy polluters that collectively contribute to 85% of total emissions (He et al., 2020b). We follow the guidelines of MEP to select water-polluting firms.

[47] Examples include the recent transboundary ecological compensation programs launched in several Chinses provinces (Wang et al., 2025).

Table 8
The effects of political incentives on water pollution.

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
	Water Quality Grade (Standardized)		COD		NH3-N	
Post × Cropland × High Incentive (PS)	−0.039		0.403**		0.025	
	(0.067)		(0.156)		(0.061)	
Post × Cropland × High Incentive (Mayor)		0.406**		0.792***		0.581***
		(0.168)		(0.208)		(0.065)
Post × 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	1386	1386	1511	1511	1513	1513
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 (NH_3-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 9
The effects of UPSB policy on water pollution (grid level).

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
	Water Quality Grade (Standardized)		COD		NH3-N	
Post × 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 (NH_3-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.

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 D13. 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 (columns (7) and (8)), and find significant and consistent evidence.

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, while 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, what's the policy's effect on agricultural production? Second, 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? Third, given the high enforcement cost associated with regulating straw-burning activities, what are the economic costs of policy implementation? Finally, do these costs outweigh the environmental benefits? In this section, we explore the potential production costs of UPSB policy and combine our empirical estimates with relevant statistics to provide a rough estimate of the policy's net benefit.

7.1. The effect on agricultural production

We first estimate the effect of UPSB policy on agricultural productivity, measured by the commonly used Normalized Difference

Table 10
Heterogeneous effects on water pollution: Enforcement cost.

Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
	Water Quality Grade (Standardized)		COD		NH3-N	
Post × *Cropland* × *Temperature*	0.128*		0.857***		0.638**	
	(0.071)		(0.307)		(0.264)	
Post × *Cropland* × *Ruggedness*		−0.010		−0.547**		−0.277***
		(0.016)		(0.248)		(0.099)
Post × *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 heterogeneous 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 (NH_3-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.

Vegetation Index (NDVI).[48] We then estimate our baseline specification with the dependent variable replaced by the standardized NDVI. Columns (1) and (2) of Table D15 report the corresponding results, where we find a significant decrease in NDVI by 0.05 SD, suggesting an overall reduction in agricultural productivity following the implementation of the UPSB policy. We note that, since farmers respond by increasing fertilizer and pesticide use, as shown in the previous section, the estimated effect should be interpreted as the total effect after accounting for adaptation behavior. To estimate the direct effect, we further control for the fertilizer usage in columns (3) and (4). We find a larger estimated coefficient, aligning with our expectation that farmers increase fertilizer application to alleviate the negative shock induced by the UPSB policy. A rough calculation suggests that farmers' adaptation behavior can mitigate the negative impact by around 13.7%.

Next, we examine how UPSB policy affects the agricultural production decisions of rural households. In Appendix Table D16, we report the estimates for three key variables: agricultural income, cultivated acreage, and crop yield, using the NFPS dataset.[49] We find consistent evidence that the UPSB policy decreases household agricultural income, acreage, and crop yield. Specifically, when evaluated at the average treatment intensity, our estimates suggest that the UPSB policy reduces agricultural income, acreage, and crop yield by 3.9%, 3.1%, and 7.3%, respectively. Given that the average agricultural income is 6317 CNY, the estimated monetary costs to agricultural production amount to 246.4 CNY.

[48] The data is derived from the National Earth System Science Data Center (http://www.geodata.cn). See detailed description at https://www.geodata.cn/data/datadetails.html?dataguid=197351408897313&docid=0. Accessed at 2025-10-16. This dataset provides monthly NDVI values from 2001 to 2024 at a spatial resolution of 1km. To measure the agricultural counterpart of NDVI, we selected only data samples located within farmland (determined by land use raster) during the crop growing season. We then aggregate these pixel readings to out 10km grid level.

[49] The NFPS provides detailed documentation on crop-specific cultivated acreage and yield. When aggregating these two variables at the household level, we only include crops that are affected by the UPSB policy (namely wheat, maize, and rice).

7.2. Cost-benefit analysis

To credibly calculate the net health benefit that takes both the reduction in air pollution and increase in water pollution into account, we rely on our reduced-form estimates and adopt two alternative methods that calculate the net health benefit using either the relative change in treatment intensity or the overall change in policy enforcement. Below, we introduce the two methods in turn. Fig. 7 summarizes our main calculated results.

Relative change. Since our main identification strategy compares grids with high treatment intensity to grids with low treatment intensity, before and after the UPSB policy, our first strategy considers 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. This gives us the upper-bound estimates of both the benefit of decreased air pollution and the cost of increased water pollution. Specifically, looking at the policy effects on air pollution, our estimates from Table 1 show that the implementation of the

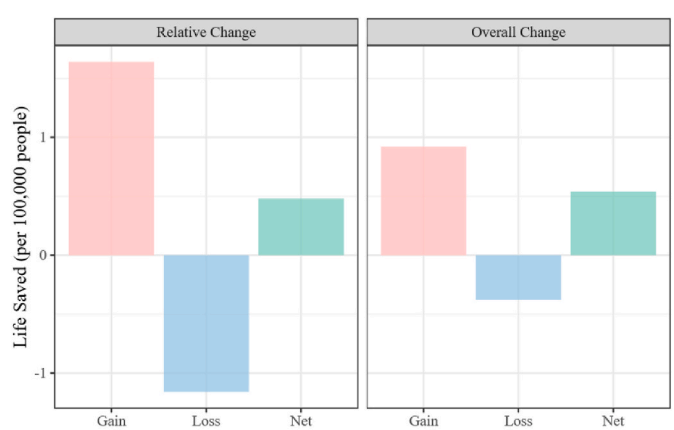

Fig. 7. Health benefit components
Notes: This figure plots the health benefit components (gain from improved air quality, loss from increased water pollution, and net health benefit), using two alternative calculating methods (relative change or overall change). The calculation is based on estimates from Ebenstein (2012), Fan et al. (2020), and He et al. (2020a).

UPSB policy would lead to a decrease of 10.4 agricultural fires (column (3)). Combined with the estimates from He et al. (2020a), which suggest that 10 additional crop fires lead to a 4.79 μg/m^3 increase in $PM_{2.5}$.[50] This implies that the UPSB policy would decrease $PM_{2.5}$ by 4.98 μg/m^3.[51] 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 et al. (2020) suggest that a 10-point increase in $PM_{2.5}$ would increase the mortality rate by 2.5%.[52] 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 et al., 2020),[53] this implies that the UPSB policy could save 1.64 lives per 100,000 population through improved air quality.

On the other hand, consider the policy effects on water pollution. Our estimates from Table 7 reveal that the implementation of the UPSB policy would lead 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 find 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 deaths per 100,000 population through degraded water quality. Altogether, the above statistics suggest that the UPSB policy, when evaluated as a relative change in treatment intensities, could only decrease 0.48 additional deaths per 100,000 population.[54] Through comparison, we find that much of the health benefit (approximately 70%) from improved air quality is offset by the health cost from degraded water quality.

Overall change. 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 D14. 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 lives 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 deaths per 100,000 population. Overall, the UPSB policy saves 0.54 additional deaths 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 (approximately 41.3%). Given the total population in all treated provinces is approximately 0.71 billion, the UPSB policy could save 3834 lives in net.

Using the value of statistical life (VSL), we can further monetize the health benefit of the UPSB policy. Specifically, Fan et al. (2020) adjust the VSL from Qin et al. (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% since the elderly are more susceptible to pollution exposure (Fan et al., 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. In comparison, the loss from degraded water pollution is 14.09 billion CNY or 2.17 billion USD.

If we are willing to impose several strong assumptions, we can take one step further to consider the enforcement cost of the UPSB policy (including the administration costs of regulating straw burning and the private agricultural production costs, e.g., input adjustments and yield losses). This allows us to compare the policy cost with its net health benefit, and to determine whether the UPSB policy is cost-effective. However, due to space limitations and to avoid potential distraction of our empirical findings, we regretfully relegate this part of the discussion to Appendix E for interested readers. In that Appendix, we discuss in further detail how to estimate the enforcement cost, especially the administration cost, of the UPSB policy, and how we can combine our causal estimates with the Marginal Value Public Funds (MVPF) approach and other estimates of willingness to pay (WTP) parameters to infer the welfare impact of the UPSB policy (Finkelstein and Hendren, 2020).

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. Heterogeneous analysis shows that the reduction of agricultural fires is weaker in grids with lower temperatures and in rugged terrain areas, where enforcement costs and monitoring costs are higher. We also find that the reduction effects are less significant in grids with high wind speeds.

However, we find that the top-down straw-burning regulation 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. Before the regulation, 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.

CRediT authorship contribution statement

Hai Hong: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Kevin Chen:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition.

Conflict of interest

The authors declare no competing interests.

[50] See column (3) of Table 2 in their paper.

[51] 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.

[52] We do not use the estimate from He et al. (2020a) since they do not provide the average mortality rate, but their estimates on the effects of air pollution on mortality are similar to the ones obtained by Fan et al. (2020).

[53] The measure of mortality rate in Fan et al. (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.

[54] 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 et al. (2020) use data from DSP, their research periods differ: Ebenstein (2012) studies mortality rates during 1991–2000, while Fan et al. (2020) conduct their analysis during 2014 and 2015.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jdeveco.2026.103727.

Data availability

Data will be made available on request.

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