Command-and-control and market-based instruments in agri-environmental governance:

Case study of straw-burning control in Northeastern China

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Abstract:
Agri-environmental governance is a formidable challenge in many developing countries, and non-point source pollution from agricultural production is a particular concern. Policies that address agri-environmental issues generally can be sorted into two broad groups: command-and-control policies and market-based instruments. The existing evidence on the effectiveness of these two policy types is mixed, and few studies have examined their joint effects. In this paper, we take straw-burning control in Northeastern China as a specific case to explore the evolution of its agri-environmental governance, and empirically examine the joint effects of its stringent monitoring-based command-and-control policies and subsidy-based market-based-instrument program on farmers' straw-burning behavior. Empirically, we collected satellite data on straw-burning spots and meteorological data at the county level from 2013 to 2020 and employed difference-in-difference and spatial regression discontinuity to conduct the analyses. The results indicate that stringent monitoring can be effective in reducing straw burnings in the field, while subsidization seems to yield an insignificant supplemental effect under strict monitoring conditions. However, when stringent monitoring cannot be effectively implemented to control straw-burning, subsidization can be effective in curbing the rebound of straw-burning behavior in the long term.

Keywords: command-and-control, market-based instruments, agri-environmental governance, difference-in-difference, regression discontinuity

JEL: G18, H23, Q18, Q53, Q58

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1 Introduction

Agricultural production has been identified as a major cause of several environmental issues (Korontzi, et al., 2006, Long, et al., 2021, Wada, et al., 2010). Different policies have been created to prohibit polluting activities and ensure a sustainable agricultural production mode (Blackman, et al., 2018, Smith, 2019). These policies generally can be sorted into two broad groups: command and control (CAC) policies, which are implemented with government administrative power (Gallego et al., 2013; Duflo et al., 2013);[1] and market-based instruments (MBIs), which are based on providing positive or negative economic incentives (Jin and Lin, 2014).[2]

The effectiveness of these two groups of policies in agri-environmental governance (AEG) is still controversial (Blackman, et al., 2018). Studies assessing the CAC policies show that the effectiveness of CAC in AEG relies on the feasibility of an accurate and in-time monitoring system (Cao and Ma, 2023, Shortle, et al., 2001, Stranlund, 1995). Complete and in-time information collection and command are necessary conditions to address the non-compliance problems (Choe, et al., 1999). Information asymmetry between government environmental agencies and (non-)complying farmers poses a challenge to applying CAC policies (Heyes, 2000). The challenge is more prominent in addressing non-point source (NPS) pollution among smallholders (Duflo, et al., 2013; Oliva, 2015). First, it is almost impossible to monitor NPS pollutants and track their origins. In air pollution, PM_{10} and $PM_{2.5}$ are

1 Studies on vehicle restrictions (Gallego, et al., 2013) and environmental audits (Duflo, et al., 2013) are based on the CAC policies.
2 Studies on ecological compensation (Hou et al., 2021) and the pollution levy (Jin and Lin, 2014) are based on the MBI instruments.

typical NPS pollutants with wide dispersion over a large area. In such cases, government environmental protection commands can hardly be implemented without an in-time and accurate monitoring system, and no effective control of the pollutants can be achieved (Bhuvaneshwari, et al., 2019). When there is an in-time accurate monitoring system, however, to what extent such a stringent CAC policy can effectively address the NPS pollution in AEG is still yet to be clarified. Second, from the time perspective, whether a stringent CAC policy with intensive monitoring can effectively reduce NPS pollution in the long run is another public concern. Previous literature examining the effectiveness of CAC policies primarily focuses on urban industry sectors and the NPS pollution in air and water in a short period (Greenstone and Hanna, 2014, Tanaka, 2015, Troncoso et al., 2012). For instance, Blackman, et al. (2018) reviewed 23 studies on CAC policies for the transport and energy industries in urban areas in developing countries. Limited evidence is available regarding AEG.

Meanwhile, proponents of providing subsidies in AEG argue that MBIs can be more economically sustainable. First, government subsidies and/or other types of MBIs can generate a positive reward mechanism encouraging polluting entities (e.g., factories, consumers, farmers) to voluntarily engage in more environmentally-friendly technologies and practices (Blackman, et al., 2018, Segerson, 1988, Xepapadeas, 2011). Second, an MBI could be more economically sustainable when the benefits of alternative non-polluting solutions are higher than their associated costs. For instance, Mazaheri, et al. (2022) reviewed the existing studies on the effectiveness of MBIs in environmental governance and found that high MBI incentives and low investment costs of alternative solutions were necessary conditions. The underlying assumption is that alternatives are available to the polluting entities and that these solutions are cost-effective. Farmers in most developing countries encounter various practical barriers to accessing alternative, non-polluting solutions. These barriers include financial constraints due to heavy initial investments (Fan, et al., 2013, Poulton, et al., 2010), limited access to the technologies (Walter, et al., 2017) and to related knowledge (Ridley, 2004, Zhang, et al., 2016). A subsidy program (as a core element of the MBIs) might provide farmers with a direct stimulus to engage in environmentally friendly, non-polluting practices (Smith, 2019).

In practice, both CAC and MBI measures might be employed interactively according to their AEG structure and different agencies' capacities. Only a few empirical studies, however, have examined the joint effects of CAC and MBI policies in reducing agri-environmental pollution.[3] Therefore, taking advantage of well-timed panel data, in this study, we examine the effects of a stringent CAC and an MBI policy jointly with an enhanced monitoring system on controlling straw burning in China. Specifically, we aim to examine the joint effects of a monitoring-based CAC system and a subsidy-based MBI program in reducing farmers' straw-burning behavior in Northeastern (NE) China. Straw burning is a typical case of agriculture-based NPS pollution (Bhuvaneshwari, et al., 2019, Theesfeld and Jelinek, 2017), contributing to air pollution such as PM_{10} and $PM_{2.5}$ concentrations (Guo, 2021, Lai, et al., 2022). Straw burning is a common practice among farmers to dispose of excess grain residues after harvesting, and it is most prevalent in NE China. Two-thirds of straw-burning spots in China were located in this region in 2017 (Yin, et al., 2021).

To address straw burning, NE China initiated a straw-burning management reform in 2018. This reform created two quasi-experiments to evaluate the effectiveness of CAC and MBI measures in reducing straw burning. First, in 2018, NE China

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3 The joint effects refer to the overall impacts or outcome when two or more policies, strategies, or interventions are implemented together.

enhanced CAC measures to reduce straw burnings by employing satellite images for monitoring. However, the increased subsidization for sustainable straw use through MBIs varied significantly across provinces. Heilongjiang substantially raised its subsidy, whereas neighboring province saw only a marginal increase. Such a quasi-experimental design allows us to explore the effectiveness of a structural transformation from a weak CAC to an enhanced CAC in the neighboring province, as well as the joint effects of an interactive CAC and MBI policy combination in Heilongjiang. Second, the outbreak of COVID-19 in early 2020 greatly affected the implementation of stringent CAC measures in the field, rendering them infeasible. It allows us to examine the long-term effect of MBI measures when stringent CAC measures were no longer feasible in the field.

To estimate the effectiveness of different types of AEG measures, we used both difference-in-difference (DID) and spatial regression discontinuity (SRD) approaches to conduct the empirical estimation. We collected satellite-based data on monthly straw-burning spots and related meteorological data for all counties in Heilongjiang and its neighboring prefectures for the period 2013 to 2020. Monthly satellite data on strawing burning provides us with a more accurate measurement of straw burning and has greatly reduced measurement errors in empirical analyses. The results show that stringent monitoring can effectively reduce straw burnings in the field, while subsidization yields a milder but longer-lasting effect. Such an effect is particularly significant when stringent monitoring cannot be effectively implemented in the field.

This study offers both theoretical and empirical contributions. On the theoretical front, we developed a theoretical framework to analyze the interplay of both CAC and MBI measures in AEG, with a specific focus on straw management in China. This theoretical framework greatly enhanced our understanding of the intricate mechanisms that jointly determined the effectiveness of CACs and MBIs. From the empirical perspective in AEG, the study provides valuable evidence regarding the interactive role of CAC and MBI measures, which are of great insights for policymakers in designing their AEG in NPS pollution management. Moreover, it reveals the long-term effectiveness of both CAC and MBIs measures in reducing NPS pollution. Considering the challenges associated with the prohibitive monitoring costs and sustainability of CAC measures over the long term, the results imply that the integration of both CAC and MBI measures is needed to yield a more significant and long-lasting effect in AEG governance in a developing country context.

The remainder of this paper is organized as follows. In Section 2, we develop a theoretical framework to understand the potential joint effects of stringent monitoring and subsidization on farmers' straw-burning behavior. Section 3 provides an overview of straw-burning practices, including the evolution of AEG policies and their implementation. Section 4 outlines the data collection, and we present the empirical estimation strategy in Section 5. Section 6 presents the empirical results, focusing on the joint effects of stringent monitoring and subsidization on farmers' straw burning prior to COVID-19. In Section 7, we show the long-term effectiveness of subsidization on straw burning, from conditional to weak monitoring during the COVID-19 period. Finally, Section 8 concludes the paper and discusses the results.

2 Theoretical Framework

We develop a theoretical framework to illustrate how CAC and MBIs affect farmers' agri-environmental choices, focusing on NPS pollution. In this framework, we delineate CAC as a proactive monitoring mechanism manifested through government agencies' field patrols that identify and penalize farmers' straw-burning behaviors. Simultaneously, MBIs are characterized as subsidies for straw-returning, providing direct economic incentives to encourage farmers to adopt sustainable practices. The pollution practice under consideration is straw burning.

Assume there are two options available to farmers to deal with excessive straws. One option (or the default option) is straw burning; while a more environmental option is straw returning, where the straw is reintroduced back into the field. Assume $v_1 \epsilon [0,1]$ is the proportion of straw returned per hectare, then $v_2 = 1 - v_1$ is the proportion of straw burned per hectare. Farmers' allocation decisions regarding the proportion between the two options are influenced by three key factors: the economic benefits derived from straw returning (π_e), the agronomic benefits from straw returning (π_a), and the costs associated with penalties imposed for straw burning (ρ_s).

First, the economic benefit (including profit) is derived from the farmer's receiving of straw-returning subsidies and the cost of the straw-returning service. The subsidy is proportional to the straw-returning proportion, denoted by sv_1 ($s > 0$). This indicates that local governments set up a standard subsidy program and introduced graded subsidies to encourage farmers to return more straw.[4] Assume the service cost

4 For example, Lishu county in Jilin province has implemented graded subsidies for straw returning proportion, with rates set at 30%, 50%, and 80% per hectare.

of straw-returning by local machinery cooperatives is constant at c $(c > 0)$.[5] The economic profit from the straw return can be calculated as $\pi_e = sv_1 - c$.

Second, the relationship between the agronomic profit from straw returning and the proportion of straw returning per hectare follows an inverse "U" shape (Krishna and Mkondiwa, 2023, Liu, et al., 2019). The agronomic benefit is a linear function represented by jv_1 $(j > 0)$. This indicates that returning more straw to the field can improve the soil quality. However, the agronomic cost is a nonlinear function represented by $iv_1{}^2$ $(i > 0)$. While a low proportion of straw returning is unlikely to result in significant issues, excessive amounts left in the field can lead to various problems, including insect and weed damage and hindered seed germination. Therefore, an optimal straw-returning proportion exists. Once this optimal point is surpassed, soil improvement benefits from straw returning will not be able to compensate for the yield loss due to excessive returning. Consequently, the agronomic profit from straw returning can be calculated as $\pi_a = jv_1 - iv_1{}^2$.

Farmers who burn straw might be subject to penalties determined by fines and the possibility of identification (piece of farmland and the ownership). To simplify the model, we assume the fine for burning straw is a fixed value of f $(f > 0)$, and the probability of being identified is further determined by monitoring intensity $m\epsilon[0,1]$, and the proportion of straw burning $v_2 = 1 - v_1$. Monitoring intensity is an external factor contingent upon the in-time monitoring conducted by government agencies. In comparison, the proportion of straw burning (v_2) is the factor determined by farmers. If farmers burn a small proportion of the straw, they are less likely to attract the attention of patrollers. By contrast, burning a large proportion of straw is more likely to be

5 Due to the nature of the field practice, cooperative charges a fixed service fee per hectare, irrespective of the actual amount of straw returned.

detected. Consequently, the probability of a farmer being identified for burning straw is a nonlinear function of the proportion of straw burning, and we can express the relationship as mv_2^2. Thus, the costs associated with penalties imposed for straw burning can be expressed by $\rho_s = fmv_2^2$.

Based on this framework, a farmer's total benefits from the straw allocation function can be represented as follows:

$$\pi = \pi_e + \pi_a + \rho_s = sv_1 - c + jv_1 - i{v_1}^2 - fmv_2^2 \tag{1}$$

$$\text{s.t. } v_1 + v_2 = 1 \tag{2}$$

Taking the first-order condition (F.O.C) on v_2 $(\frac{\partial \pi}{\partial v_2})$, we obtain the farmer's optimal proportion of straw burning, which is given by:

$$v_2^* = \frac{-s-j+2i}{2fm+2i} \quad (v_2^* \epsilon [0,1], m\epsilon[0,1], s\epsilon[0,(2i-j)]) \tag{3}$$

Equation (3) indicates that the optimal proportion of straw burning is jointly determined by the variables *s* and *m*, which represent two policy tools: subsidies for straw returning and monitoring of straw burning, respectively. The parameters i, j and f, which are all greater than zero, influence the effects of these variables on v_2^*. Notably, for v_2^* to be positive, the value of s must be less than $2i - j$.

Based on the equation (3), the effects of monitoring or subsidization can be expressed by their partial derivatives, as shown below:

$$\frac{\partial v_2^*}{\partial m} = -\frac{2f(2i-j-s)}{(2i+2fm)^2} < 0 \tag{4}$$

$$\frac{\partial v_2^*}{\partial s} = -\frac{1}{2i+2fm} < 0 \tag{5}$$

Proposition 1: *Enhanced CAC (i.e., in-time monitoring) and MBI (i.e., high subsidization) measures can mitigate farmers' activity in straw burning. Conversely, decreasing either CAC or MBI may exacerbate farmers' engagement in straw burning.*

Both equations (4) and (5) indicate that there were negative relationships. Increased (or decreased) monitoring (intensity) of straw burning or increased (or decreased) subsidization of straw returning will reduce (increase) the proportion of straw burning. We use Figure 1 to visually illustrate these relationships. As monitoring of straw burning increases from m_0 to m_1, given s_0, the optimal proportion of straw burning, v_2^*, decreases from point "a" to point "b". Similarly, an increase in the subsidies of straw returning from s_0 to s_1, given m_0, the optimal proportion of straw burning, v_2^*, decreases from point "a" to point "d".

After identifying the individual effects of monitoring and subsidization, we then analyze their interaction effects. The interaction effects of monitoring and subsidization can be expressed with the second-order partial derivative as follows:

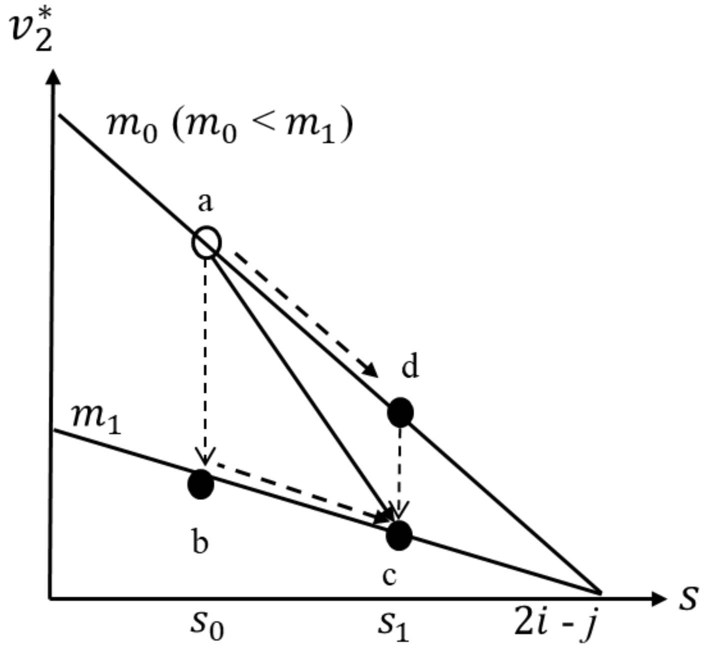
$$\frac{\partial {v_2^*}^2}{\partial s \partial m} = \frac{2f}{(2i+2fm)^2} > 0 \tag{6}$$

Proposition 2: The effect of MBI (i.e., subsidization) is conditional to the intensity of monitoring, and vice versa. *At high levels of monitoring, subsidies exhibit diminished effectiveness in mitigating farmers' straw burning incidence. Conversely, subsidies are more effective in influencing farmers' straw-burning behavior at lower monitoring levels.*

The positive relationship indicated by equation 6 suggests that the effect of subsidization on v_2^* becomes less negative (i.e., the rate of decrease in v_2^* with respect to s is reduced) as the level of monitoring m increases, and vice versa. This means there is a substitution effect between monitoring and subsidization. Although subsidization alone decreases v_2^*, higher monitoring reduces this decrease. The variation in the effect subsidization conditional to the monitoring intensity is reflected in the processes labeled as "ad" and "bc" in Figure 1. Specifically, the "bc" process reflects the negative effect of subsidization under high monitoring intensity (m_1). Notably, this negative effect is considerably smaller than the effect indicated by "ad," which represents the subsidization effect under low monitoring intensity (m_0). The underlying reason for this relationship is that once high monitoring intensity has been established and a significant proportion of straw burning has been replaced by straw returning, it becomes difficult for subsidies to encourage further transitions from straw burning to straw returning. This challenge is due to the negative agronomic consequences of excessive straw returning, which can lead to substantial output losses.

Finally, we analyze the joint effect of monitoring and subsidization. This joint effect is illustrated in the processes labeled as “ac” in Figure 1, indicating the outcome of both increased in monitoring and subsidization. This process can be divided into the process “ab” (monitoring effect conditional to s_0) and “bc” (subsidization effect conditional to m_1)). Due to the existence of positive interaction effects (equation 6), the joint effect of monitoring and subsidization on controlling straw burning is less than the sum of the effects of each policy when implemented independently.

Figure 1 The visual depiction of the theoretical framework



Note:
(a) The variable s represents the intensity of straw-returning subsidies.
(b) The variable v_2^* represents the optimal proportion of straw burning.
(c) The variable m represents the intensity of monitoring ($m_0 < m_1$).
(d) The i and j represent the costs and benefits associated with agronomy.
(e) The thin dotted line represents the monitoring effect
(f) The thick dotted line represents the subsidization effect
(g) The solid line represents the joint effects of monitoring and subsidization

3 Background of straw-burning control in NE China

3.1 Straw-burning management prior to 2018

Straw burning is a conventional practice among rural farmers in China to process excessive straws. Before autumn 2018, penalties for farmers' straw burnings in NE China included fines and administrative detention. However, the enforcement of these bans was inadequate, partially due to the absence of an effective monitoring system and a weak incentive from the local government. For instance, Hou et al. (2019) surveyed 480 maize farmers in NE China in 2013 and showed that 54.7% of villages had official bans on straw-burning control, while a limited effect on farmers' straw-burning activities was achieved.

3.2 A stringent CAC since 2018

In late 2017, the central government issued much more rigorous policies to pressure the local governments to curb straw-burning behaviors.[6] In response to such top-down pressures, a stringent ban on straw burning control was promulgated in September 2018, covering the entire NE China region.[7] A notable innovation in these bans was the introduction of a satellite-based monitoring system (called Chief-Responsibility-System, CRS). Farmers' straw-burning behaviors can be tracked immediately with satellite images.

Specifically, the CRS divided the NE provinces into five levels (e.g., provinces, prefectures, counties, townships, and blocks) and established straw-burning control committees at each level. Each committee comprised local government corresponding departmental leaders, including agriculture, environment, and police departments. With

6 The central government policy was known as "*The Action of Straw Utilization in NE China*", issued by the Ministry of Agriculture (MA) (2017).

7 Details policies from different levels of local governments in Heilongjiang and Jilin are shown in the online appendix Table A1.

the support of satellite images of straw burnings, the committee at each level coordinates different departments within its administrative area so that they can immediately identify where the observed straw burning is and who is responsible for it. The higher-level committee assesses the performance of the lower-level committee according to the actual number of straw-burning spots observed and tracked by the satellite. If the satellite detects straw-burning spots exceeding the pre-set tolerant standards, committee members—particularly leaders with the chief responsibility—will be subject to administrative punishment. Under such a stringent CAC system, lower-level committees (e.g., village committees) frequently conduct physical patrols to detect and prevent farmers' straw-burning behaviors. With such a system, quick and accurate straw-burning identification, responsibility attribution, and penalties could be immediately implemented, and the top-down CAC pressures could be strengthened.

3.3 Costs of straw returning in NE China

The benefits of straw returning, such as improved soil fertility (enriching of soil organic matter) and reduced fertilizer usage (Lv, et al., 2019, Wang, et al., 2018, Yan, et al., 2019), have been advocated. However, implementing straw returning (or bailing) can be costly for farmers, considering its extended costs.[8] Field survey shows that the total investment in straw-returning machines—including straw-cleaning machines (15,000 yuan), no-till seeders (50,000 yuan), and straw-bailing machines (100,000 yuan)—can be nearly 165,000 yuan (online appendix Table A2). Moreover, the technology of straw returning was still in its infancy, and only a limited proportion of straw could be effectively decomposed after it returned to the soil. When more than 50% of the straw returns, there might be a 5%–10% yield loss in the following harvest. Wang,

8 The extended costs in straw returning include smashing straws in the field, machineries for land deep tillage, and additional input of nitrogen (for the enzymes to decompose the straws).

et al. (2022) also demonstrated farmers' reluctance to return its excessive straws completely. The associated costs indicate that to promote straw returning effectively, a subsidy of nearly 800 yuan/ha to farmers (or farmers' willingness to accept straw returning, WTA) in Jilin and Heilongjiang might be a basic requirement to cover its related costs. In comparison, the subsidy intensities in both Heilongjiang and Jilin provinces before 2018 were quite low (300 yuan/ha in Heilongjiang and 375 yuan/ha in Jilin province). These subsidies were far from sufficient to promote straw returning among farmers.

3.4 Market-based instrument via machinery cooperatives

The stringent CAC policies might discourage farmers' straw-burning behavior; however, low subsidies provide no solution to that excess straw. Excessive straw in the field will threaten local grain production due to a low germination rate (Lv, et al., 2022). [9] To remove such excessive straws, the local government responded by increasing subsidies to promote straw returning and/or straw bailing (for electricity generation). In both Heilongjiang and Jilin provinces, we observed increases in subsidies for straw returning and straw bailing. However, the extent of subsidization varied greatly between Heilongjiang and Jilin province. The local government of Heilongjiang has doubled its straw subsidies, increasing from 300 yuan per hectare to 600 yuan per hectare. While in Jilin province it was only marginal, from 375 yuan per hectare to 450 yuan per hectare (online appendix Figure A1). The data for temporal changes in machinery for straw utilization (from the China Agricultural Machinery Yearbook; CMIF, 2021) reveals the differences in subsidy intensity between Heilongjiang and Jilin (online appendix Figure A2). In Heilongjiang, the number of no-

9 The NE China is one of China's main grain production regions, ensuring food security is one of the most important tasks for local government. Excessive straw in the field can cause seeds sowed on leafy straws rather than into the soil, which could significantly affect seed germination.

till seeders, which are used for seeding on soil with returned straw, nearly doubled in 2018. In contrast, Jilin saw only a 13.36% increase. Similarly, the number of straw-baling machines that bale the portion of straw that cannot be returned to the soil tripled in Heilongjiang, while Jilin experienced a more modest increase of 38.89%.

In terms of the subsidy approach, both provinces allocated such subsidies via local machinery cooperatives instead of directly subsidizing farmers, conditional on providing machinery services to farmers. After receiving subsidies, cooperatives provide straw returning or bailing services to farmers without charges. This indirect subsidization approach saves the local government's administrative costs, and cooperatives collect information on farmers' straw returns on behalf of the government and distribute the subsidies.[10] Monitoring cooperatives' misreporting of subsidies was more accountable to the government, which reduced the management cost of subsidization.

In summary, we observed a significant change in AEG in NE China regarding CAC and MBIs (Table 1). Prior to September 2018, there were weak CAC policies accompanied by a low MBI. The introduction of satellite-based monitoring with the CRS has fundamentally addressed the weak enforcement issue. Heilongjiang and Jilin both set strict performance indicators for evaluating village committees' monitoring efforts, specifying a limit of no more than 2-3 straw-burning spots per day. However, the increase in subsidies for straw returning (and bailing) between Heilongjiang and Jilin provinces varied significantly between Heilongjiang and Jilin provinces. Heilongjiang doubled its subsidy, whereas Jilin saw only a marginal increase. These

10 Management cost of subsidization via local cooperatives is much less than directly distributing subsides to farmers, since there were fewer cooperatives, and these cooperatives are more dedicated to building their brand and reputation in local machinery service market.

variations enabled us to explore the effectiveness of MBIs with a stringent CAC policy background.

Table 1. The policy comparison between Heilongjiang and Jilin

	Jilin Province		Heilongjiang Province	
	CAC	MBIs	CAC	MBIs
Prior Sep. 2018	Weak monitoring	375 yuan /ha	Weak monitoring	300 yuan/ha
After Sep. 2018	Satellite-based monitoring (2 spots/day)	450 yuan /ha	Satellite-based monitoring (3 spots/day)	600 yuan /ha

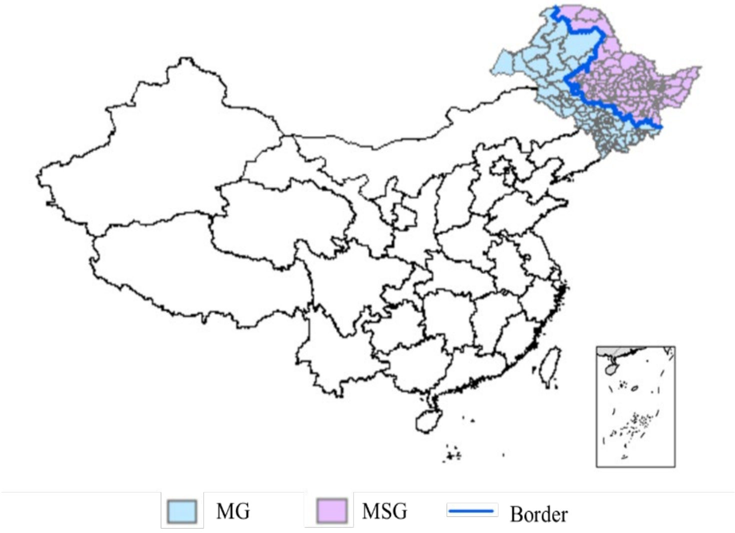
Note:
(a) The policy tool of CAC (command and control) is satellite-imaged-based monitoring of farmers' straw burning spots, encompassing the field identification of straw burning and the imposition of fines.
(b) The policy tool of MBIs (market-based instruments) is a straw-returning subsidy to farmers through cooperatives.
(c) Prior Sep. 2018, Northeastern (NE) China introduced a straw-burning ban that ostensibly prohibited farmers from engaging in straw-burning practices. However, the ban lacked effective monitoring instruments for enforcement.
(d) More details about the above policies, including their names and origins, are presented in the online appendix Table A1.

4 Data sources and summary statistics

We compile comprehensive county-level panel data on straw burning from 2013 to 2020 (for seven years) to conduct an empirical analysis. We select a total of 197 counties in Heilongjiang, Jilin, and two prefectures in Inner Mongolia to form the final sample size (as shown in Figure 2).[11] Specifically, we have 119 counties in Heilongjiang province, which has implemented strict monitoring CAC and a significant increase of subsidization for straw returning (and bailing) since September 2018. We use MSG (abbreviation of Monitoring plus Subsidization Group) to indicate this group of counties. In comparison, we collect data from 78 counties from Jinlin and neighboring counties in Inner Mongolia as a comparison group, which has also implemented strict monitoring CAC but a marginal increase of subsidization for straw returning (and bailing) since September 2018. To highlight the substantial disparity in subsidies between this comparison group and Heilongjiang, we simplify the policy changes for this group to only increase monitoring from September 2018. We use MG (abbreviation of Monitoring Group) to represent this comparison group.

11 We include 20 counties from two prefectures in Inner Mongolian, which are neighbouring to Heilongjiang border. Inner Mongolia's straw-returning subsidy strategy closely resembled that of Jilin, and despite the implementation of strict monitoring, no significant changes occurred in these areas around 2018. Therefore, the involvement of these two prefectures did not influence the analysis.

Figure 2. The geographic location of the research region



Note: (a) The MSG (monitoring plus subsidization group) encompasses 119 counties in Heilongjiang province.
(b) The MG (monitoring group) encompasses 78 counties in Jilin and two prefectures in inner Mongolia.

4.1 Satellite data on straw-burning in NE China

Straw burning can be detected using satellite remote sensing. NASA's TERRA and AQUA satellites collect moderate-resolution imaging spectroradiometers (MOD) and identify daily straw-burning data. These two satellites overpass China four times daily and report all fire pixels detected with a 1 km resolution provided as a gridded level-3 product in the Sinusoidal projection. We use MOD production from TERRA (MOD14A2), which monitors straw burning in the daytime (around 10:30 and 13:30 local time). [12]

We collect satellite-tracked straw-burning data for four months per year (including March, April, October, and November). Grain production in NE China has only one season (spread from May to mid-October), and the burning of straw for land preparation could be either early March to April (before seeding) or around October to November (after harvest). It's almost impossible to burn straws after November due to cold temperatures and the snowy weather. The dataset provides daily meteorological data. The monthly temperature, precipitation, and wind speed are calculated by averaging the daily values over a month. We integrate the straw-burning data with the climate data, creating a county-month-level dataset that spans the research period from October 2013 to April 2020. The interval, encompassing the months from the previous autumn (October and November) to the approaching spring season (March and April), is one straw-burning cycle. Despite spanning two seasons, this cycle involves burning the same batch of straw. The dataset comprises seven straw-burning cycles, incorporating 197 counties and 5,516 observations.

12 The satellite passes the local NE region two times during the day around 10:30 and 13:30 local time, and two times during the night around 22:30 and 1:30 local time. We do not consider MOD production from AQUA (MYD14A2) because AQUA overpasses China too late (around 22:30 and 1:30 local time) and is not suitable for our study.

4.2 Summary Statistics

We present some descriptive statistics in Table 2. Although the MG and MSG are spatially adjacent, there are still discernible distinctions in climate factors between them. Owing to its northern location, MSG experiences lower precipitation and temperatures and higher wind speeds in its counties. The differences in these three factors show that there might be other potential climate confounders that influence the estimates beyond our control.

Additionally, the straw burning in both MG and MSG counties is mainly located among grain production regions. The data for grain output per county (from the China County Statistical Yearbook; NBS, 2021) shows that the differences between MG and MSG counties have certain patterns. Counties with higher grain output are mostly concentrated on the border between MSG and MG regions (online appendix Figure A3), which are situated in flat plains—optimal for cultivating grains.[13] Additionally, the differences in grain output between MG and MSG widened as the distance from the border increased (online appendix A5). Counties within 100 km of the border exhibited a negligible difference in grain output between MG and MSG. However, as the distance extended to the range of 100~150 km, the difference became evident, and this difference continued to amplify in counties located beyond 150 kilometers to the border.

13 In the online supplementary document, we show the altitude of research counties in the online appendix Figure A6.

Table 2. Statistical description of variables and sample comparisons between two regions

	Full sample				Heilongjiang Province (MSG)		Jilin Province (MG)		Difference (5)-(7)	
	Mean	St. Dev	Min	Max	Mean	St. Err.	Mean	Std. Err.	Mean	Std. Err.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
# of observation	5,516				3,332		2,184		5,516	
# of counties	197				119		78		197	
Dependent variables										
Total value of straw-burning spots	10.88	[25.06]	0	311	12.48	(0.46)	8.43	(0.48)	4.05***	(0.69)
Climate variables										
Average value of precipitation, mm	22.32	[12.77]	0.83	100.59	21.94	(0.21)	22.91	(0.28)	-0.97*	(0.35)
Average value of temperature, Celsius	1.31	[6.01]	-20.91	11.70	0.94	(0.10)	1.90	(0.13)	-0.96***	(0.17)
Average value of wind speed, m/s	3.01	[0.67]	1.20	6.09	3.16	(0.01)	2.78	(0.01)	0.37***	(0.02)

Note:
(a) We have a total of 197 counties over the period of Oct. 2013 till Apr. 2020 (for 7 years).
(b) The straw burning mainly happened during March, April and October to November, which in total 4 months over a year. Thus, we have 5516 observations in our database.
(c) In the comparison group (Jilin Provinces), we have also included counties from two prefectures in Inner Mongolia. These two prefectures are neighboring Heilongjiang province and are exhibiting similar production conditions as the Heilongjiang and Jilin provinces.
(d) MSG = monitoring plus subsidization group; MG = monitoring group
(e) Data source: Author’s collection

5 Empirical Strategies

We employ a step-by-step approach to conduct empirical analyses to test our research propositions. First, we use the SRD design to mitigate the differences between MG and MSG, making these two regions comparable. Subsequently, we extend this baseline model to SRD–DID design to split the year-to-year change into the effects of monitoring and subsidization.

5.1 A SRD design

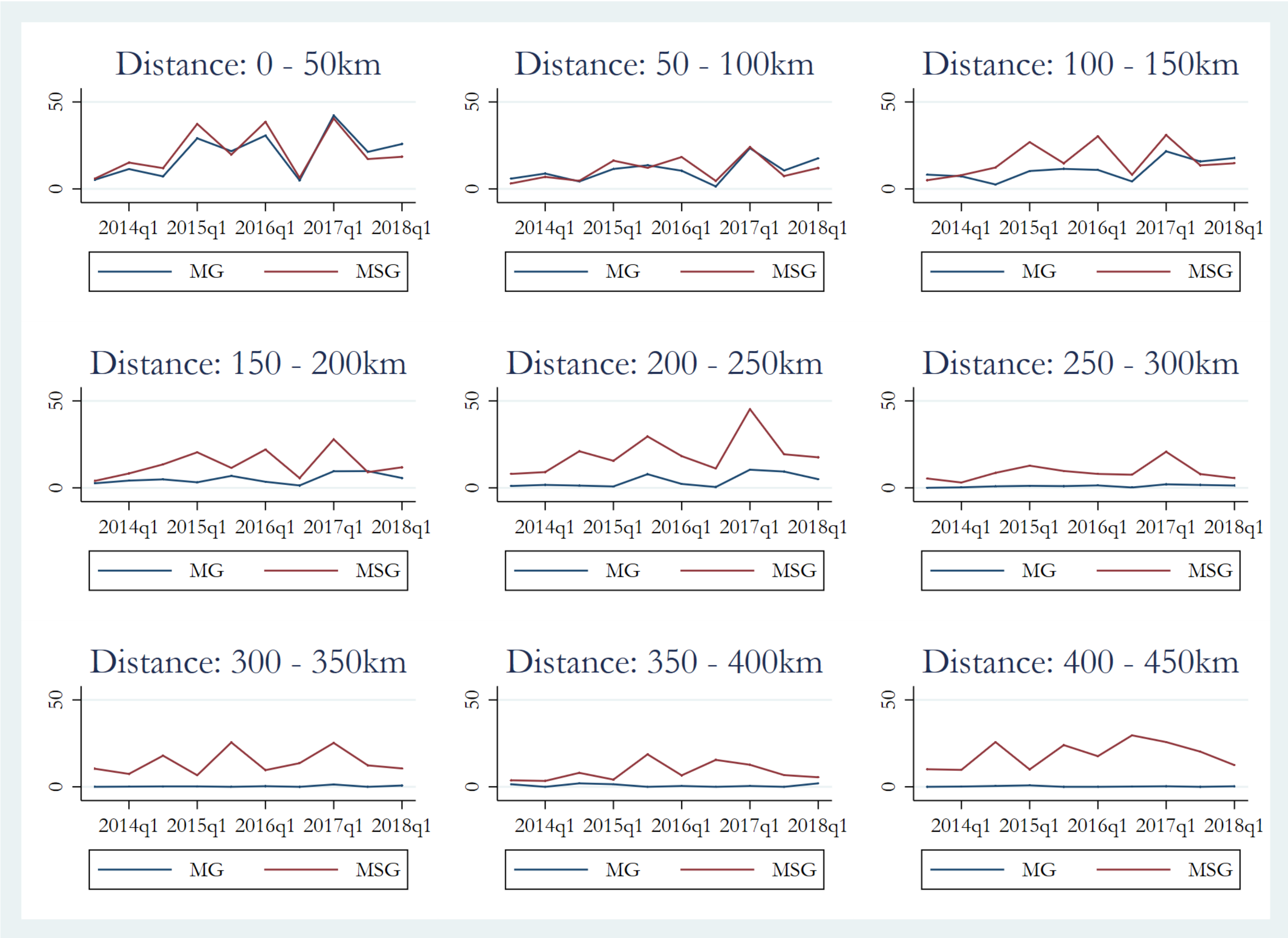
As demonstrated in the descriptive sections (Section 4.2), MSG and MG regions might not be comparable when considering all observations, especially when including the counties far away from the border. The SRD design assumes that the observed counties around the border are more comparable than those located farther apart (Chen, et al., 2013, Keele and Titiunik, 2015), thus when there is a proper bandwidth explored, a more comparable sample of counties between MSG and MG regions could be created. Therefore, the essence of the SRD design involves two key elements: (a) assessing the validity of this assumption, and (b) identifying the optimal distance-to-border bandwidth.

Our first step is to assess the validity of the comparability assumption. We utilize a 50 km to the border range as a window to illustrate the temporal changes in satellite-based straw-burning spots in the MG and MSG before the stringent monitoring CAC in Sep. 2018. As shown in Figure 3, counties within 100 km of the border exhibited a negligible difference in straw burning between MG and MSG (distance <100 km). However, as the distance extended beyond 100 km (distance > 100 km), the differences became increasingly noticeable and displayed a growing irregularity. Therefore, Figure

3 verifies the assumption that observations just to the left and right of a border are more comparable than those located farther apart.

The next step is the selection of the optimal bandwidth, the optimal maximum distance to the border. One criterion for selecting optimal bandwidth is that counties on both sides of the border, within this bandwidth, should have few differences in straw-burning spots before the monitoring implementation. The optimal bandwidth meeting the criterion for few differences is 100 km (Figure 3). However, counties within 100 km of the border represent only 35.53% of the total observations in our dataset, resulting in a significant data loss. We relax the criteria to enhance the statistical power, enabling a broader range of observations in the estimation process. The revised criteria allow differences in straw-burning spots between MG and MSG, yet these differences should remain consistent before the monitoring implementation.

Figure 3. Spatial and temporal analysis of straw-burning spots

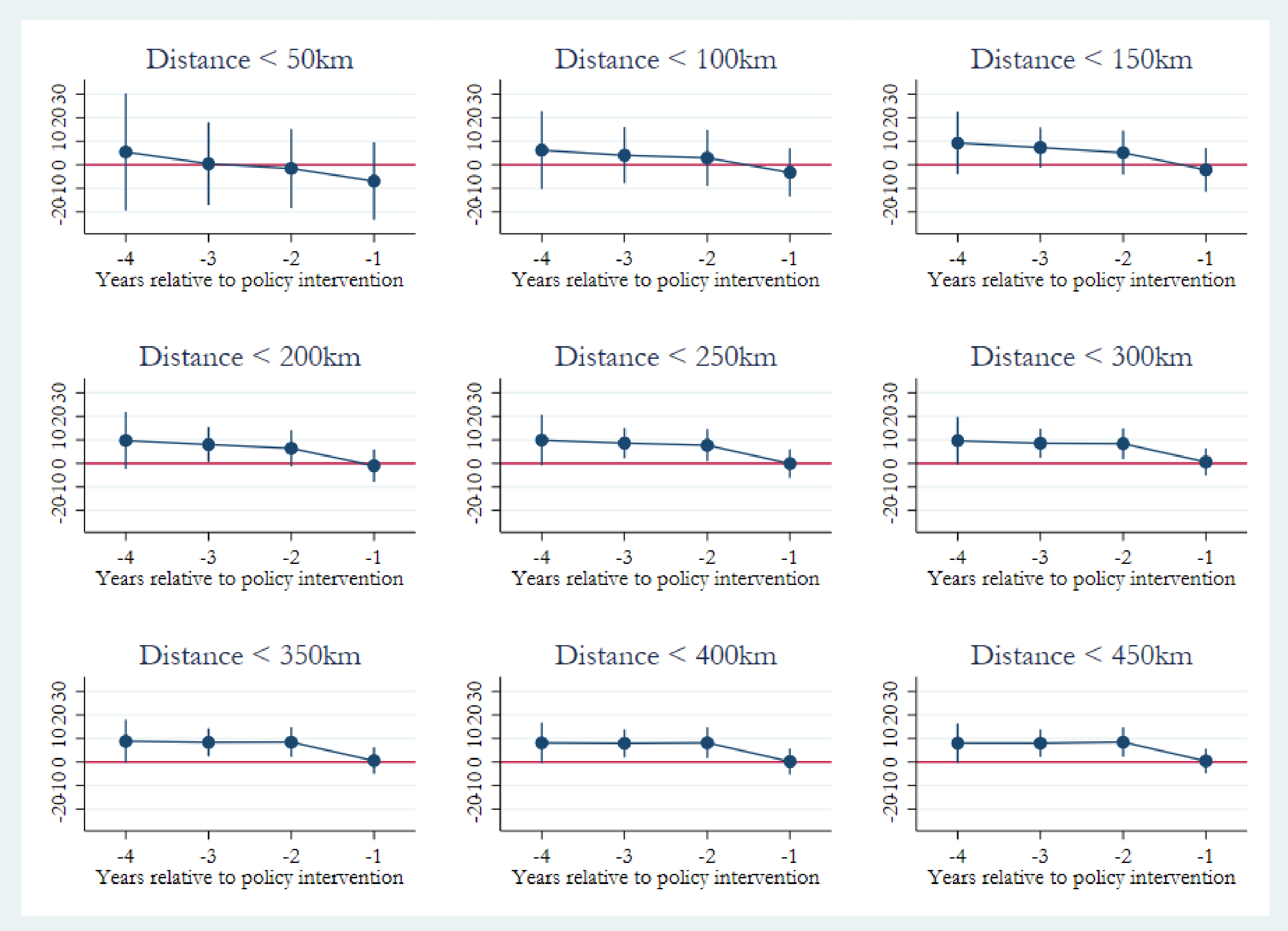


Note:
(a) The MSG (monitoring plus subsidization group) encompasses 119 counties in Heilongjiang, while the MG (monitoring group) encompasses 78 counties in Jilin and two prefectures in inner Mongolia.
(b) The horizontal axis denotes the straw-burning season, where the abbreviations "q1" and "q3" denote spring (March and April) and autumn (October and November), respectively.
(c) The vertical axis signifies the average value of straw-burning spots throughout the season.

To identify the optimal bandwidth based on the revised criteria, we employ the test on the parallel trend to statistically estimate the dynamic changes in the differences of straw-burning spots between MG and MSG, utilizing the data before the stringent monitoring CAC implementation (autumn 2013–spring 2018, a total of 3,940 observations). Figure 4 reports parallel trend tests across various bandwidth selections. The marked dot in the figure signifies these dynamic changes in straw-burning differences between MG and MSG relative to the baseline straw-burning circle[14], which is from autumn 2013 to spring 2014. When the confidence intervals of dots cover the value of zero, it indicates the straw-burning differences between MG and MSG in that specific circles are not statistically significant compared with the baseline circle. The horizontal axis represents the straw-burning circles prior to the implementation of monitoring. For instance, "-1" denotes the first circles before the monitoring implementation, corresponding to the period from autumn 2017 to spring 2018. Additionally, the baseline circle corresponds to the fifth circle before (i.e. autumn 2013-spring 2014), although it is not explicitly shown in the figure.

14 One straw-burning circle is from autumn of the previous year to spring of the next year.

Figure 4. Parallel-trend test



Note:

(a) The figure utilizes data spanning from autumn 2013 to spring 2018, encompassing a total of 3940 observations.

(b) We estimate the following specification:

$$Y_{imt} = \alpha + \sum_{k=4}^{1} \beta_k D_i \times T_k + X'_{imt}\gamma + \omega_i + \varphi_t + \theta_m + \varepsilon_{itm} .$$

where Y_{imt} is the straw-burning spots in county i, recorded in year t and month m. D_i is a dummy variable, which takes the value of 1 for counties in the MSG and 0 for counties in the MG. T_k is a dummy variable, which takes the value of 1 for kth circles before the monitoring implementation. We exclude the data for autumn 2013-spring 2014 as the baseline circle, corresponding to k = 5. Thus, the coefficient β_k denotes dynamic changes in straw-burning differences between MSG and MG relative to the baseline circle of autumn 2013-spring 2014. The vector X'_{imt} is a set of county-level climatic factors, including precipitation, wind speed, and temperature. The dummy variables ω_i, φ_t and θ_m denote the county, year, and month fixed effects, respectively.

(c) The confidence intervals are at 95% level, adjusted for prefecture-level clustering.

Figure 4 shows that counties within 150 km of the border demonstrate constant straw-burning differences between the MG and MSG before the monitoring implementation. Specifically, the confidence intervals for the four straw-burning circles, ranging from -4 to -1, consistently cover the value of zero in figures with a bandwidth of less than 150 km. Conversely, the confidence intervals extend beyond zero in figures with more than 150 km bandwidth. This indicates that as the bandwidth increases beyond 150 km, the observed variations in straw-burning differences become evident. Thus, we select the optimal bandwidth of 150 km on each side of the border.

5.2 A SRD-DID design

Choosing the optimal bandwidth of 150 km ensures comparability between counties in the MG and MSG. Building on this choice, we integrate the DID into the SRD to estimate the effect of monitoring and subsidization on straw burning. We estimate the following specifications:

$$Y_{imt} = \alpha + \beta_1 D_i + \beta_2 T_t + \beta_3 D_i \times T_t + \alpha_1 Z_i + \alpha_2 D_i \times Z_i + X'_{imt}\gamma + \theta_m + \varepsilon_{itm} \quad (7)$$

where Y_{imt} are the straw-burning spots in county *i* that are recorded in year *t* and month *m*. The DID design is characterized by the variables D_i, T_t, and $D \times T_t$. The variable D_i denotes a county i's status, which takes 1 for counties in the MSG and 0 for counties in the MG. Its coefficient β_1 measures the difference in straw-burning spots between the MG and MSG before the monitoring implementation. The period is denoted by T_t: T_t takes the value of 1 for the period after the monitoring implementation (autumn 2018 – spring 2019) and 0 for the baseline period before (autumn 2013 – spring 2018).

We are particularly interested in the coefficients β_2 and β_3. The coefficient β_2 measures the temporal changes in straw-burning spots in the MG compared with the baseline period. We assume that these temporal changes observed in the MG were exclusively influenced by the policy intervention[15] in autumn 2018, specifically, stringent monitoring. Thus, β_2 indicates the effect of monitoring on straw-burning spots. In comparison, the coefficient β_3 captures the additional temporal changes in straw burning in the MSG compared with that in the MG. Given that the MSG increased the subsidy substantially while the MG did not, β_3 indicates the effect of subsidization on straw-burning spots.

In addition to selecting optimal bandwidth, the SRD design is characterized by the variables Z_i and $D_i \times Z_i$. The variable Z_1 denotes the nearest distance from county i to the border (online appendix Figure A4). It captures the information about potential confounders that exhibit spatial distribution in relation to distance.

We follow the methodology of Wuepper, et al. (2020) by adopting a first-order linear relationship between distance and the straw-burning spots. The coefficients α_1 and α_2 serve distinct roles: α_1 indicates the correlation between straw burning and distance in the MG, while the coefficient α_2 indicates the difference in this correlation between the MSG and the MG. Together, these coefficients mitigate the influence of potential confounders spatially distributed in relation to distance.

Additionally, given that observations just to the left and right of a border are more comparable than those located farther apart (Figure 3), we assign a higher weight for the estimation to counties near the border. The weight is calculated using a rectangular kernel as follows:

$$K = 1 - \left|\frac{distance}{bandwidth}\right| \quad K \in [0,1] \tag{8}$$

15 A limitation in our research design is the absence of a suitable control group for the MG concerning their policy intervention. There is a possibility that some non-policy confounders experienced significant changes in autumn 2018. To address this possibility, we assume that such changes did not occur, acknowledging this as a limitation in our approach.

Bandwidth is the optimal bandwidth, which is 150 km. The weight *K* approaches 1 as the distance to the border gets closer to 0, whereas the weight *K* gets closer to 0 as the distance to the border approaches the optimal bandwidth.

In terms of control variables, like equation (7), we control a set of county-level climatic factors X'_{imt}, precipitation, wind speed, and temperature. We also incorporate month-fixed effects θ_m, accounting for monthly fluctuations common to all counties. The ε_{itm} is the error term clustered at the prefecture level.

5.3 Robustness check

We employ two approaches to conduct robustness checks. The first approach is to employ the county fixed effect as a substitute for the variable, Z_i and $D_i \times Z_i$. The county fixed effect eliminates the influence of all potential confounders that vary across counties but remain constant over time, while the variable Z_i eliminates the influence of potential confounders distributed with spatial distance. Thus, the county fixed effect is a better choice in addressing the confounders that vary across counties but has limited function in addressing the confounders that vary over time. In comparison, the variable Z_i strikes a balance by addressing variations across both time and counties.

We estimate the following specification with the county fixed effect:

$$Y_{imt} = \alpha + \beta_1 D_i + \beta_2 T_t + \beta_3 D_i \times T_t + X'_{imt}\gamma + \omega_i + \theta_m + \varepsilon_{itm} \tag{9}$$

where ω_i is the county fixed effect. Given that the distance to the border is a factor that varies across the county but remains constant over time, both the variable Z_i and $D_i \times Z_i$ are absorbed by the county fixed effect. Equation (9) is estimated specifically for observations falling within the optimal bandwidth of 150 km. Other variables are the same as the equation (7).

Another approach is to adjust the optimal bandwidth and re-estimate the equation (7). This approach eliminates the concern about the sensitivity of the estimates to bandwidth selection. We adjust the optimal bandwidth of 150 km by increasing and decreasing it by 50 km, selecting 100 km and 200 km bandwidths, respectively. Then, we re-estimate the equation (7) and assess the sensitivity of the estimates to varying bandwidth selections.

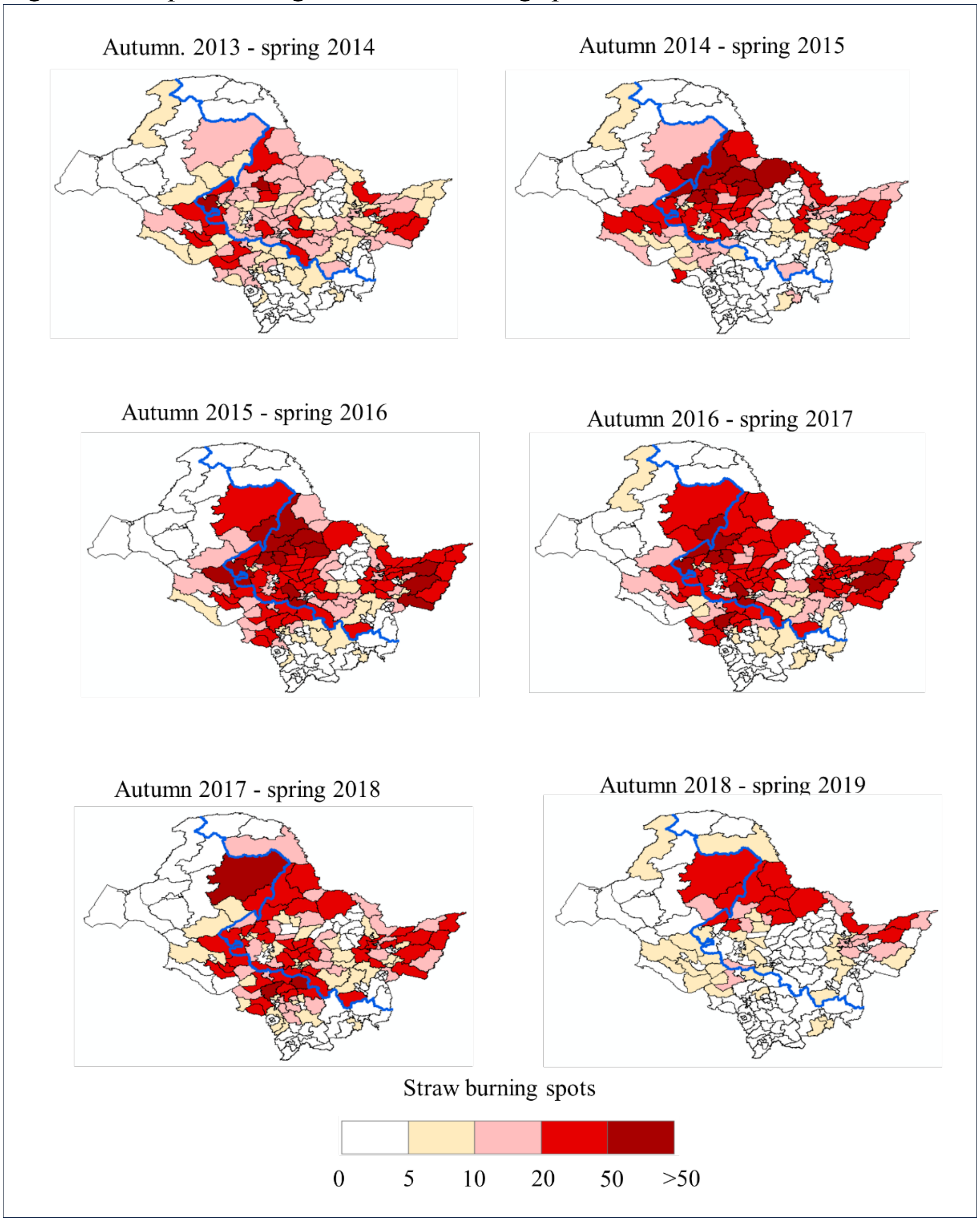
6 Results

6.1 The effect of policy intervention

First, we perform a graphical analysis to examine the temporal changes in straw burning within the MG and MSG. This analysis offers an intuitive overview of both groups' overall effect of policy intervention in autumn 2018. As shown in Figure 5, the straw-burning spots appear to be relatively modest from autumn 2013 to spring 2015. During this timeframe, most farmers used straw as a household fuel, resulting in limited demand for direct field burning. However, from autumn 2015 to spring 2018, there was a notable increase in farmers' straw-burning behaviors, resulting in a significant rise in straw-burning spots. Following the monitoring implementations (autumn 2018–spring 2019), there was a significant reduction in straw burning across all the territories of the MG and MSG, with only a few counties showing minimal change[16].

16 The counties showing minimal change may be attributed to the reluctance of prefecture-level governments to comply with directives from the provincial government, even though non-compliance may have adverse impact on their promotion.

Figure 5. Temporal changes in straw-burning spots



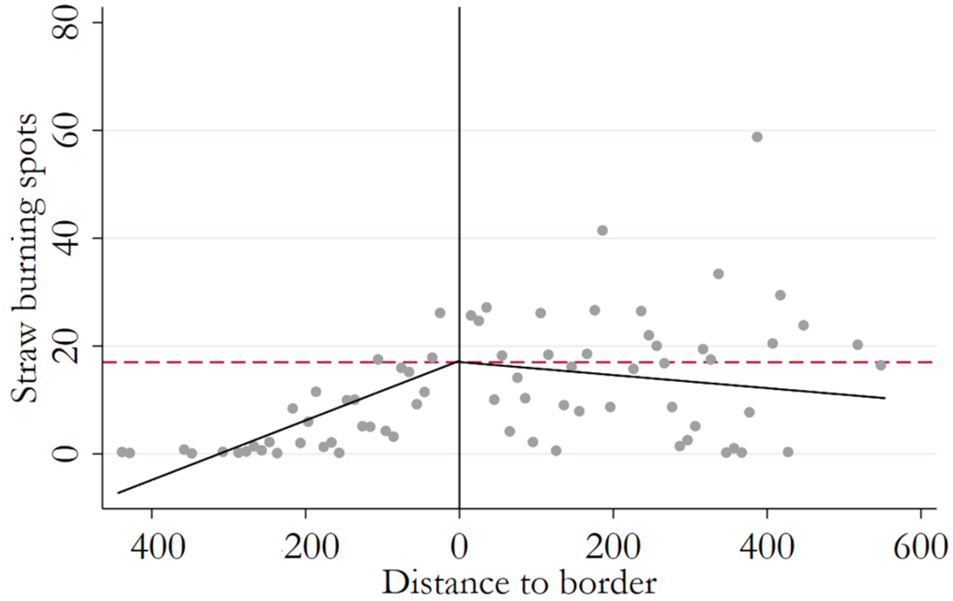
Note:
(a) The color in the figures represents the average value of straw-burning spots during a specific period.
(b) The blue line is the border between the MG and MSG. Counties situated to the right of the border fall within the MSG, while those on the left side belong to the MG.

We then employ graphical SRD to provide a more intuitive understanding of the overall effect of policy intervention in both the MG and MSG. To achieve this, we follow a common method (Lee and Lemieux, 2010), which divides the distance to the border into evenly spaced “bins” of 10 km each. Then, we calculated the mean value of straw-burning spots in each bin and constructed a fitted line. This approach allows us to visualize the distribution of straw burning with respect to distance. Figure 6 shows the fitted line as a slash, and the circle represents the average straw-burning spots within each 10 km distance bin. The vertical line (distance = 0) indicates the border, with observations on the left representing straw burning in the MG and those on the right representing straw burning in the MSG. The horizontal red line represents the intercept of the fitted line in the MG before the monitoring in place (MG) and serves as a benchmark for comparing the temporal changes in straw burning in the MG and MSG in autumn 2018–spring 2019. If the intercept of the fitted line is lower than that of the red line, it suggests that straw burning has been effectively controlled compared with its natural state without policy interventions.

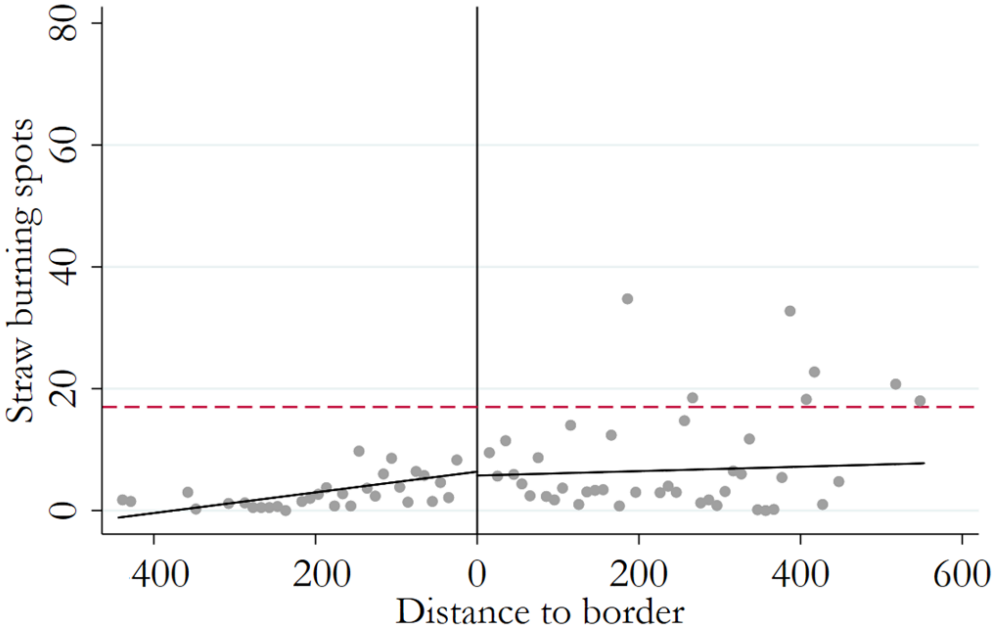
Figure 6 reveals that the MG and MSG experienced observable decreases in straw-burning spots after the policy intervention, especially in the counties near the border. Specifically, as shown in panel A, counties in both the MG and MSG near the border exhibited approximately 20 spots of straw burning during autumn 2013-spring. 2018. However, after the MG and MSG experienced the policy intervention during autumn 2018–spring 2019 (panel B), there were notable decreases in straw-burning spots in both the MG and MSG, especially the counties near the border.

Figure 6. The Spatial-Regression-Discontinuity (SRD) graphic analysis

Panel A: Autumn 2013 – Spring 2018



Panel B: Autumn 2018 – Spring 2019



Note:
(a) The circle represents the average value of straw-burning spots within uniformly distributed 10 km bins.
(b) The red line represents the straw-burning spots in the counties near the border in the period prior to the monitoring implementation (autumn 2013-spring 2018).
(c) The vertical line serves as the border, with the left side representing the MG and the right side representing the MSG.

The regression in Table 3 further statistically estimates the overall effect of policy intervention. The overall effects of policy intervention in the MG and MSG are captured by the coefficients of T in columns (1) and (2), respectively. Specifically, the coefficient of T in column (1) captures the temporal changes in straw burning in the MG following the implementation of the satellite-based monitoring system in September 2018, indicating the effectiveness of monitoring on controlling straw burning and representing the process of "ab" in the theoretical framework in Figure 1. Meanwhile, the coefficient of T in column (2) captures the temporal changes in straw burning in the MSG after the same period, indicating the joint effects of stringent monitoring combined with subsidization and representing the process of "ac" in Figure 1.

As shown in Table 3, the coefficients of T in columns (1) and (2) are -9.49 and -11.59, respectively, and are statistically significant at the 95% confidence level. After employing the county fixed effect, the coefficients of T in columns (4) and (5) are slightly different and still significant at the 95% confidence level. In the online appendix Table A3, we assess the robustness of the results by adjusting the bandwidth to 100 km and 200 km. The coeffects of T remain robust, indicating that the estimates are not sensitive to the choice of bandwidth. The coefficients of T in columns (1) and (2) reveal significant negative effects of the policy intervention in both the MG and MSG from autumn 2018 to spring 2019. This intervention resulted in a monthly reduction of satellite-based straw burning spots per county by 9.49 and 11.59, respectively. Given the mean values of 14.69 and 15.05 straw-burning spots in these regions before the policy intervention, the decrease of 9.49 and 11.59 spots represents a reduction of 64.6% (9.49/14.69) and 77% (11.59/15.05) in straw-burning spots. These findings suggest that the institutional innovation in September 2018, utilizing satellites to get information on farmers' straw-burning behaviors and implementing monitoring measures, successfully mitigated such activities in the MG and MSG. In addition, the negative effect in the MSG exceeded that in the MG by 2.10 spots. This suggests that stringent monitoring combined with subsidization might have a more pronounced effect on mitigating straw burning compared to the sole implementation of monitoring. These results support proposition 1 in the theoretical framework, underscoring the negative effect of monitoring and subsidization on farmers’ straw-burning behaviors.

Table 3. The effect of monitoring and subsidization on straw burning behaviors

	Estimates using distance to order			Estimates using county fixed effect		
	MG	MSG	DID	MG	MSG	DID
	(1)	(2)	(3)	(4)	(5)	(6)
T, 1 = autumn 2018 – spring 2019	-9.487**	-11.593**	-10.041**	-8.084**	-12.548**	-8.394***
	(3.622)	(3.356)	(3.418)	(2.816)	(4.030)	(2.786)
D × T			-1.325			-3.596
			(4.715)			(4.212)
D, 1 = counties in the MSG			0.150			
			(7.052)			
Distance variables						
Z, distance to the border	-0.086	-0.119**	-0.092			
	(0.064)	(0.041)	(0.058)			
D × Z			-0.029			
			(0.069)			
Climate variables						
Precipitation, mm	-0.313**	-0.290***	-0.313***	-0.049	-0.043	-0.046
	(0.091)	(0.057)	(0.051)	(0.087)	(0.053)	(0.045)
Temperature, celsius	-1.344***	-0.498	-0.811	0.342	1.135*	0.842*
	(0.115)	(0.892)	(0.573)	(0.535)	(0.559)	(0.405)
Wind speed, m/s	10.718***	6.290	7.739**	4.779	9.185**	7.530***
	(2.697)	(3.769)	(2.713)	(2.695)	(3.374)	(2.374)
Month fixed effect	Y	Y	Y	Y	Y	Y
County fixed effect	-	-	-	Y	Y	Y
Distance weight	Y	Y	Y	-	-	-
Observation	984	1,488	2,472	984	1,488	2,472
R^2	0.198	0.156	0.168	0.321	0.378	0.358

Note: (a) The independent variable is straw-burning spots, which is month-county level data.
(b) *D* takes the value of 1 for counties in Heilongjiang as MSG (monitoring plus subsidization group) and takes the value of 0 for the counties in Jilin and two prefectures in Inner Mongolia as MG (monitoring group).
(c) *T* takes the value of 1 for the period from autumn 2018 to spring 2019 and takes the value of 0 for the baseline period from autumn 2013 to spring 2018. The monthly number of straw-burning spots encompasses the data recorded for the months of March and April in spring as well as October and November in autumn.
(d) Z is the nearest distance from county *i* to the border.
(e) The optimal bandwidth we select is 150 km. We also respect the bandwidth as 100 km and 200 km, reporting the results in Table A3. The distance weight is calculated by the equation (8)
(f) Robust clustered-standard errors at the county level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

6.2 The effect of subsidization conditional to stringent monitoring

One interesting observation from the coefficients of T in columns (1) and (2) of Table 3 is that counties within the MSG were likely to experience a more pronounced reduction in straw-burning spots, specifically by 2.10 spots, compared with the MG. Considering that the MSG offered a more substantial subsidy to control straw burning, this further decrease in straw-burning spots reflects the subsidization effect conditional to stringent monitoring. This effect corresponds to the process of “bc” in Figure 1.

Subsequently, we examine the statistical significance of the additional reduction of subsidization. As shown in column (3) of Table 3, the additional reduction in straw-burning spots in the MSG during autumn 2018–spring 2019 did not achieve statistical significance. Specifically, the additional reduction is captured by the coefficient of $D_i \times T_t$ in column (3) of Table 3. This coefficient is -1.33 but not statistically significant. Including county fixed effects in column (6) also yields non-significant estimates. Furthermore, in the online appendix Table A3, we conduct a robustness check by adjusting the bandwidth and the coefficients of $D_i \times T_t$ remain non-significant. Furthermore, panel B of Figure 6 visually depicts the non-significant coefficient of $D_i \times T_t$ by examining the lack of discontinuity near the border. While both sides of the border witnessed a substantial reduction in straw-burning spots from autumn 2018 to spring 2019, the figure did not show a noticeable additional decrease on the right side of the border (MSG). Consequently, no apparent discontinuity occurred near the border. These results imply that the additional subsidy provided by the MSG government might have a small effect on mitigating straw burning under the conditions of stringent monitoring. Nevertheless, this effect exhibited substantial variation within the MSG, leading to statistical insignificance.

Regarding the control variables of Table 3, our findings indicate that precipitation and temperature had a significantly negative effect, whereas wind speed had a significantly positive effect. Notably, the effect of climate factors may lack economic meaning but is attributed to the limitation inherent in straw-burning data obtained from remote-sensing satellites. For example, the negative effect of precipitation may not be attributed to its role in inhibiting farmers from burning straw. Alternatively, this could be attributed to the difficulty in satellite detection posed by cloud cover during heavy rainfall, resulting in reduced detectability of straw burning.

7 The Long-term effect of subsidization conditional to weak monitoring

7.1 Background

Results in the above section indicate that subsidization had a limited effect on mitigating straw burning under stringent monitoring conditions. How does subsidization influence farmers' straw-burning behaviors when monitoring is less stringent? The outbreak of COVID-19 in spring 2020 has provided a quasi-natural experiment, offering an opportunity to interpret the effects of monitoring and subsidization further.

Until June 2020, the COVID-19 lockdown policy, restricting the movement of citizens and their physical contact, created a serious political challenge for straw burning control field checks. On the one hand, the lockdown policy created dramatic, unprecedented chaos in the spring sowing of grain. Farmers in the Heilongjiang and Jilin provinces typically begin clearing straw from fields around mid-March to ensure a smooth sowing process in April. However, farmers could not commence spring sowing until mid-April owing to the lockdown measures. This delay disrupted the usual timelines for grain production, placing farmers under immense pressure to rapidly complete a series of spring plowing operations before the arrival of the first spring rain in May. The temporal variations in the proportion of straw-burning spots in April relative to the total number of spots in spring highlight the disruptions in spring grain sowing (online appendix Figure A7). Before the spring of 2020, farmers primarily burned straw in March, with less than 40% of the total straw-burning incidents during the spring season occurring in April in both MG and MSG. However, due to lockdown measures in 2020, the proportion of straw-burning incidents in April increased significantly, especially in MSG, where nearly 80% of the incidents occurred in April. As a result, farmers had to rely on rapid and cost-effective methods for straw disposal, such as burning, in April 2020, considering the urgency of the sowing season. This significantly increased the pressure on village committees to monitor farmers' activity in straw burning.

On the other hand, monitoring straw burning at the farm level relied heavily on physical patrols, which placed significant demands on the manpower of village committees. However, during the lockdown period, most of the manpower within village committees was allocated to implementing lockdown policies. As a result, village committees were unable to allocate sufficient manpower to supervise the implementation of the straw-burning ban effectively. To investigate the impact of lockdown policies on the village committee's monitoring activities, we conducted a three-month field survey in Lishu County, Jilin Province, during the COVID-19 period. [17] Through field observations and semi-structured interviews with local authorities, we discovered that the tight spring planting schedule and a shortage of monitoring manpower led local government, village committees, and farmers to develop an

17 The ideal way to study the overall straw-burning monitoring situation during the COVID-19 period is through a large-scale farmer survey. However, due to lockdown policies, large-scale farmer surveys were not permitted. Instead, we conducted semi-structured interviews and field observations with village committee and local government officials to understand how local authorities addressed the challenges of infeasible straw-burning monitoring during the pandemic. Additional details regarding the semi-structured interviews and field observations are provided in the online supplementary document.

informal understanding regarding straw burning. To ease the pressure of straw burning monitoring, the local government and village committees arranged specific timeframes during which farmers were permitted to burn straw if necessary. Consequently, the outbreak of COVID-19 in spring 2020 created a brief period during which strict monitoring of straw burning was infeasible, allowing farmers to choose their own methods for straw disposal.

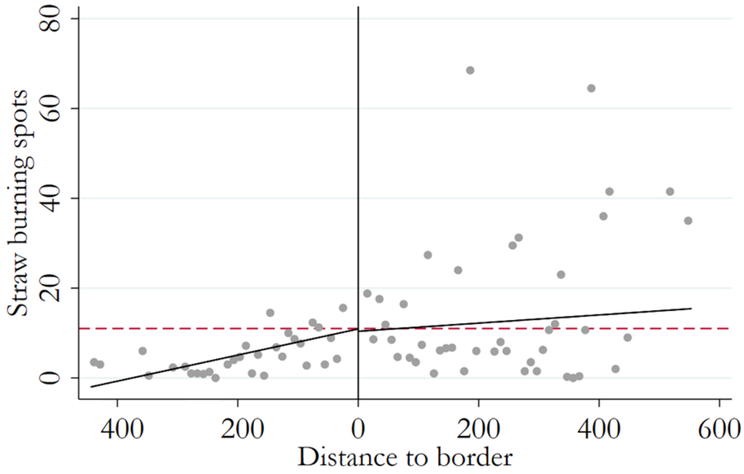
7.2 Regression result

Figure 7 presents the SRD graphic analysis, illustrating the effect of the infeasibility of monitoring during COVID-19 on straw-burning spots.[18] In both the MG and MSG, there was a rebound of straw-burning spots in spring 2020 (Panel B), contrasting with the prior circle subjected to stringent monitoring. Moreover, the figure indicates that the rebound of straw burning in MSG might be much smaller than in MG. This smaller rebound led to a significant discontinuity in straw-burning spots between the counties on each side of the border during COVID-19 (Panel B). By contrast, such a discontinuity was not observed in the previous spring (Panel A).

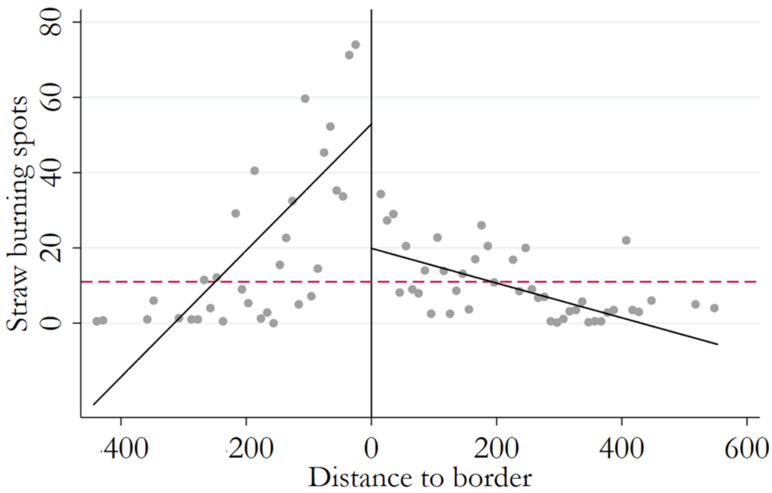
18 The temporal and spatical change in straw burning in the COVID-19 period is reported in the online appendix Figure A8.

Figure 7. The Spatial-Regression-Discontinuity (SRD) graphic analysis on weak monitoring

Panel A: Spring 2019



Panel B: Spring 2020



Note:
(a) The circle represents the average value of straw-burning spots within uniformly distributed 10 km bins.
(b) The red line represents the straw-burning spots in counties near the border during the period preceding the last spring before the COVID-19 period (spring 2019).
(c) The vertical line serves as the border, with the left side representing MG and the right side representing the MSG.
(d) The geographic analysis is shown in the online appendix Figure A8.

To test the significance of the above discontinuity, we continue to utilize the SRD-DID design, as presented in Table 4. In contrast to the earlier table in Table 3, the variable T now denotes the COVID-19 period, specifically March and April of 2020. The baseline period is the preceding spring (March and April of 2019), during which the MG and MSG implemented rigorous monitoring measures. As previously outlined, the bandwidth is 150 km. The standard errors are adjusted for prefecture-level clustering.

The first finding from Table 4 is that farmers' straw-burning behaviors rebounded in both the MG and MSG when monitoring became infeasible during COVID-19. Specifically, the coefficient of T in column (1) was 44.18 and significant at a 95% confidence level. It indicates that counties in the MG witnessed a dramatic increase in monthly straw-burning spots per county by 44.18 spots due to the infeasibility of monitoring. Regarding the MSG, the coefficient of T in column (2) is 5.05 but lacks statistical significance. However, when county fixed effects are included in column (5), this coefficient increases substantially to 9.28, although it remains statistically nonsignificant. Thus, the coefficients of T in columns (2) and (5) imply that counties in the MSG also experienced a resurgence in straw burning, although the magnitude of this rebound was small and did not reach statistical significance.

Another finding from Table 4 is that the subsidization significantly mitigated the rebound of farmers' straw-burning behaviors under conditions where monitoring was infeasible. Specifically, the variable, $D_i \times T_t$, in column (3) serves as a test, specifically examining whether the difference in the rebound between the MG and MSG during the COVID-19 period is statistically significant. The coefficient for this variable is -32.27, and it is significant at the 95% confidence level. It implies that the additional subsidy provided by the MSG government prevented the rebound of straw burning by 32.27

spots. We conducted a robustness check by adjusting the distance width, as shown in the online appendix Table A4, and the results remained consistent.

The comparison in the coefficients of $D \times T$ in Tables 3 and 4 support Proposition 2 in the theoretical framework, emphasizing that the impact of subsidization on straw burning is contingent on the intensity of monitoring. During the period of stringent monitoring from autumn 2018 to spring 2019, the additional subsidy provided by the MSG government only decreased straw-burning spots by 1.33 spots ("bc" in Figure 1), as shown in column (3) of Table 3. However, as the monitoring became impractical in the spring of 2020, the reduction in straw-burning spots attributable to the subsidy dramatically inflated to 32.27 spots ("ad" in Figure 1), as shown in column (3) of Table 4.

It is important to note that the variation in the effects of subsidization might also be attributed to the substantial improvement in the availability of straw utilization machinery. As discussed in Section 3.4, the subsidy provided by the MSG government significantly accelerated the development of such machinery (online appendix Figure A2). As a result, farmers in MSG had greater access to these machines compared to those in MG, offering them viable alternatives to burning straw during periods when monitoring was infeasible. This enhancement in machinery availability likely amplified the impact of the subsidies observed during this time.

Table 4. The long-term effect of subsidization conditional to weak monitoring

	Estimates using distance to order			Estimates using county fixed effect		
	MG	MSG	DID	MG	MSG	DID
	(1)	(2)	(3)	(4)	(5)	(6)
T, 1 = spring 2020	44.183**	5.053	38.547**	41.812**	9.279	34.719***
	(16.403)	(4.962)	(14.343)	(14.629)	(7.654)	(11.111)
D × T			-32.267**			-26.288**
			(14.817)			(10.771)
D, 1=MSG			-6.160			
			(9.977)			
Distance variables						
Z, distance to order, km	-0.162	-0.162*	-0.171			
	(0.131)	(0.070)	(0.137)			
D × Z			0.005			
			(0.147)			
Climate variables						
Precipitation, mm	-1.411	0.264	-0.202	-1.589	0.192	-0.123
	(1.347)	(0.285)	(0.534)	(1.440)	(0.165)	(0.450)
Temperature, celsius	-3.703	-1.503	-2.375	4.735	5.646	3.927
	(2.097)	(1.907)	(1.464)	(5.285)	(3.955)	(3.720)
Wind speed, m/s	21.169	14.623	21.572**	-52.630	-23.892	-22.718
	(15.240)	(10.701)	(7.449)	(37.520)	(23.239)	(24.013)
Month fixed effect	Y	Y	Y	Y	Y	Y
County fixed effect	-	-	-	Y	Y	Y
Distance weight	Y	Y	Y	-	-	-
Observation	164	248	412	164	248	412
R^2	0.275	0.039	0.179	0.574	0.349	0.470

Note:
(a) The independent variable is straw-burning spots, which is month-county level data.
(b) *D* takes the value of 1 for counties in Heilongjiang as MSG (monitoring plus subsidization group) and takes the value of 0 for the counties in Jilin and two prefectures in Inner Mongolia as MG (monitoring group).
(c) *T* takes the value of 1 for the period in spring 2020 and takes the value of 0 for the baseline period in spring 2019. The straw-burning season in spring includes two months, March and April.
(d) *Z* is the nearest distance from county *i* to the border.
(e) The optimal bandwidth we select is 150 km. We also respect the bandwidth as 100 km and 200 km, reporting the results in Table A4. The distance weight is calculated by the equation (8)
(f) Robust clustered-standard errors at the county level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

7.3 The impacts of policy intervention on air pollution

Finally, we provide a broader perspective on the social impacts of straw-burning governance. Estimates by He, et al. (2020) and Lai, et al. (2022) indicate that straw burning significantly increases concentrations of particulate matter with a diameter of 2.5 micrometers ($PM_{2.5}$, μg/m³). Thus, we evaluate the effects of the aforementioned policy interventions on $PM_{2.5}$ to reveal the social implications of straw-burning governance. The $PM_{2.5}$ data is sourced from the Atmospheric Composition Analysis Group (ACAG) at Washington University (2020) and covers the straw-burning seasons, specifically October and November in autumn and March and April in spring, from autumn 2013 to spring 2020. Figures A9 and A10 in the online appendix present the SRD graphical analysis of PM2.5, illustrating that the relationship between $PM_{2.5}$ and the distance to border is consistent with the relationship between that distance and straw burning. This consistency suggests that variations in $PM_{2.5}$ during the straw-burning season are attributable to changes in straw-burning activities. Consequently, the impact of policy interventions on $PM_{2.5}$ can be assessed through the temporal changes in $PM_{2.5}$ following the implementation of the policy, as estimated by the equation (7).

We use $PM_{2.5}$ as an independent variable to re-estimate the equation (7), with the results presented in Table 5. Columns (1) to (3) include data from autumn 2013 to spring 2019, consistent with Table 3, while columns (4) to (6) cover data including spring 2019 and spring 2020, consistent with Table 4. As shown in columns (1) and (2) of Table 5, the MSG experienced a greater reduction in $PM_{2.5}$ (μg/m³) compared to the MG following the implementation of stringent straw-burning monitoring. Specifically, the coefficients T in columns (1) and (2) are -18.86 and -22.19, respectively, indicating that $PM_{2.5}$ decreased by 18.86 μg/m³ in MG and 22.19 μg/m³ in MSG. It means the combination of monitoring and subsidization in MSG resulted in an extra reduction of

3.33 μg/m³, although this additional effect is not statistically significant, as evidenced by the coefficient of $D \times T$ in column (3).

In contrast, during the COVID-19 period, when monitoring was not feasible, both MG and MSG experienced a rebound in $PM_{2.5}$, with MG showing a more pronounced increase. The coefficients of T in columns (4) and (5) are 11.33 and 7.79, respectively, indicating that $PM_{2.5}$ rose by 11.33 μg/m³ in MG and 7.79 μg/m³ in MSG. Interestingly, Table 3 shows a significant difference in the number of straw-burning spots between the two groups, yet the difference in $PM_{2.5}$ was relatively modest, with a rebound of 3.54 μg/m³ greater in MG compared to MSG. This relatively small difference in $PM_{2.5}$ may be attributed to the mobile nature of air pollution. Although MSG did not see a significant rebound in straw burning, it was still influenced by the elevated pollution levels originating from MG due to their geographical proximity. This underscores the necessity for cross-regional coordination in air pollution control to prevent the inefficacy of individual regional governance efforts resulting from the inaction of neighboring areas.

Table 5. The effects of policy intervention on $PM_{2.5}$ (ug/m^3)

	Data: Autumn 2018−Spring 2019			Data: Spring 2019 and Spring 2020		
	(1)	(2)	(3)	(4)	(5)	(6)
T, 1 = autumn 2018 – spring 2019	-18.858***	-22.185***	-18.727***			
	(2.897)	(4.524)	(2.665)			
T, 1 = spring 2020				11.327***	7.789***	10.238***
				(1.909)	(1.765)	(1.920)
D × T			-3.205			-2.376
			(4.449)			(3.492)
D, 1=MSG			4.666			5.410
			(8.943)			(4.146)
Distance variables	Y	Y	Y	Y	Y	Y
Climate variables	Y	Y	Y	Y	Y	Y
Month fixed effect	Y	Y	Y	Y	Y	Y
Distance weight	Y	Y	Y	Y	Y	Y
Observation	984	1,488	2,472	164	248	412
R^2	0.340	0.383	0.362	0.291	0.437	0.310

Note:
(a) The independent variable is particulate matter with a diameter of 2.5 micrometers or less ($PM_{2.5}$, ug/m^3), which is month-county level data.
(b) The climate variables include precipitation, temperature, and wind speed
(c) The distance variables include distance to order (Z) and D × Z.
(d) The optimal bandwidth we select is 150 km. We also respect the bandwidth as 100 km and 200 km, reporting the results in Tables A5 and A6 in the online appendix, respectively. The distance weight is calculated by the equation (8)
(e) The Spatial-Regression-Discontinuity (SRD) graphic analysis of $PM_{2.5}$ is illustrated in Figures A9 and A10 in the online appendix.
(f) Robust clustered-standard errors at the county level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

8 Conclusion and discussion

Command and control (CAC) and market-based instruments (MBIs) policies are often employed together in agri-environmental governance (AEG). However, empirical studies evaluating the joint effects of CAC and MBIs policies in reducing agri-environmental pollution are limited. This study uses the straw-burning control in Northeastern (NE) China as a case study. Leveraging satellite-based panel data, we examine the effectiveness of a monitoring-based CAC system and a subsidy-based MBI program in reducing farmers' straw-burning behavior in NE China. Our findings are as follows:

First, the joint enhancement of both CAC measures (i.e., from weak to strict monitoring) and MBI measures (i.e., higher level subsidies) can improve the control of straw burning incidents compared to enhancing CAC measures alone, although the extent of improvement is limited. The combination of blocking (CAC) and dredging (MBIs) is the basic principle of straw burning, as well as other environmental governance principles in China (The State Council (SC), 2008). Our finding supports this principle, emphasizing that a balanced integration of mandatory and voluntary policies is crucial for effective governance of straw burning. Second, strict monitoring-based CAC can effectively control straw burning in the short term. However, this effectiveness may not be sustained over the long term, especially when external shocks (such as COVID-19 in this study) make monitoring infeasible. The justification for imposing strict straw-burning monitoring on farmers, particularly smallholders, continues to be a contentious issue in China. During the 2024 National People's Congress, some representatives even proposed gradually easing straw-burning bans, citing production challenges—such as pest infestations, disease outbreaks, and seedling shortages—stemming from the imperfect technology of straw returning.[19] Therefore, considering these agronomic issues, the sole implementation of CAC, despite its effectiveness, may overlook the welfare of farmers, who are a vulnerable group. Third, MBI policies (i.e. subsidization) can substantially mitigate the rebound in straw-burning behavior when external shocks (like COVID-19 in this study) disrupt straw-burning monitoring, although they are less effective in controlling straw burning under strict monitoring conditions. This finding provides empirical evidence supporting the long-term effectiveness of MBI policies in managing straw burning and other similar environmental issues.

Our findings contribute to the existing research by He, et al. (2020), Cao and Ma (2023), Nian (2023), and Hou, et al. (2019) by offering a new perspective on the effectiveness of MBI. They found that MBIs—including subsidies, biomass power plants, and machine availability—can effectively control straw burning in China. In contrast, our finding suggests that the effectiveness of subsidization on straw burning is contingent upon the level of monitoring, with limited impact observed under stringent monitoring conditions. Consequently, once monitoring measures have been implemented, further reductions in straw burning become less effective through subsidization. Moreover, our findings build on the studies by Wang et al. (2021) and Sun et al. (2019) by highlighting the unsustainability of CAC. While their research demonstrated the effectiveness of stringent CAC measures, particularly through the Chief Responsibility System (CRS), in controlling straw burning, our findings suggest that such practices lead to a resurgence in straw burning when monitoring becomes infeasible. This underscores the labor-intensive nature of monitoring, which is unsustainable at high intensity over the long term (Van Rooij, 2006).

19 See news (in Chinese) from the website: https://www.thepaper.cn/newsDetail_forward_26574529

This study carries significant policy implications, underscoring the importance of integrating both CAC and MBI approaches in AEG. While CAC measures can rapidly drive the transition of farmers from a pollution-intensive equilibrium to a high-level equilibrium based on sustainable practices in the short term, relying solely on CAC is insufficient to sustain this shift. Long-term maintenance of a high-level equilibrium requires the reinforcement of MBIs, which establish conditions that allow farmers to adopt sustainable practices at economically viable costs (Hou, et al., 2021, Piñeiro, et al., 2020). As farmers progressively adopt sustainable technologies, maintaining a high-level equilibrium is likely to become more stable. Additionally, this study emphasizes the role of technology in AEG. On the one hand, enhancing CAC measures necessitates the use of monitoring technologies, such as satellite imagery and drones, to address the information asymmetry between regulators and those regulated (Kloppenburg, et al., 2022, Lovett, et al., 2007). On the other hand, the effectiveness of MBIs depends on the application of sustainable technologies, such as straw returning and other conservation agriculture practices, which help reduce the abatement costs associated with pollution emissions (Smith, 2019).

The limitations of our work are as follows: First, the study lacks micro-level data to analyze how farmers manage straw that cannot be burned due to enhanced CAC measures. While the macro-level data used in this study provides accurate measurements and supports long-term dynamic analysis, it lacks detailed information about individual farmer practices. Future research could offer new empirical insights by incorporating micro-level data. Second, defining the evolution of Jilin's policies as a single enhancement of monitoring groups involves a risk of oversimplification. Jilin also marginally increased subsidies (Table 1), so the temporal changes in straw-burning spots estimated by our model may reflect the combined effects of both subsidies and monitoring, rather than monitoring alone. Consequently, a more precise way to interpret the comparison between Heilongjiang and Jilin is that it reflects the impact of additional subsidies in Heilongjiang on straw burning. However, despite its accuracy, this expression is overly verbose. To maintain conciseness, we retain the original representation. Third, the evidence about the infeasibility of straw-burning monitoring during COVID-19 primarily comes from field observations and semi-structured interviews in individual cases, which may take the risk of not fully capturing the overall situation of our study region. However, given that Jilin and Heilongjiang share similar resources and cultural backgrounds, the challenges and solutions observed in the individual case are representative of other regions as well. Thus, while this approach has limitations, we think it is acceptable for reflecting the broader regions to some extent.

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APPENDICES for

“Command-and-control and market-based instruments in agri-environmental governance: Case study of straw-burning control in Northeastern China”

Note: The material contained herein is supplementary to the article named in the title and published in the *American Journal of Agricultural Economics*.

Tables

Table A1. The CAC and MBI policies in Heilongjiang and Jilin

PROVINCES	TIME	DOCUMENTS		REFERENCE
CAC and MBIs Prior September 2018				
CAC measures				
Jilin	Sep-2017	Emergency notice from the Jilin Provincial Joint Conference Office on Air Pollution Prevention and Control on the ban on straw burning in the autumn of 2017	People' government	http://hjj.changchun.gov.cn/ywdt/zwdt/gnyw/201710/t20171020_1001529.html
Heilongjiang	Sep-2017	Inspection plan for banning wild burning of straw in the province in the spring of 2017 to improve atmospheric environmental quality	Agriculture committee	http://www.zgjgxh.com/news/show.php?itemid=2147
MBIs				
Jilin	Sep-2016	2016 Jilin Province Mechanized Conservation Tillage Technical Operation Subsidy Implementation Plan	Agriculture committee	https://www.tuliu.com/read-23122.html
Heilongjiang	Jul-2016	Notice on the implementation of the 2016 Heilongjiang Province Mechanized Straw Return Subsidy Work	Agriculture committee	https://www.sohu.com/a/131896274_679550
CAC and MBIs After September 2018				
CAC measures				
Jilin	Sep-2018	Measures for accountability for the straw burning ban in Jilin Province	People' government	http://jlau.ihwrm.com/index/article/articleinfo.html?doc_id=2556706
Heilongjiang	Sep-2018	Interim regulations on rewards and penalties for the work of banning open burning of straw	People' government	https://www.waizi.org.cn/policy/48454.html
MBIs				
Jilin	Sep-2018	Implementation Opinions on Accelerating the Promotion of Straw Covering and Returning Conservation Tillage Technology to Promote the "Green Growth" of Farmland Quality Cultivation and Ecological Farming Benefits	Agriculture committee	http://www.njhs.moa.gov.cn/gzdt/201810/t20181018_6315295.htm
Heilongjiang	Sep-2018	Notice on Implementation Opinions of Heilongjiang Province Corn Straw Subsidy for Deep Loosing and Burying and Returning to Field Operations	People' government	https://m.nongji360.com/view/100080

Note:
(a) CAC = command-and-control; MBI = market-based instrument

Table A2. Straw-returning costs

	Cost (Yuan/ha)	Occurrence probability	Expected cost
1. Visible cost			
1.1 Fixed cost			
Machine investment, yuan	164789.66	100%	164789.66
Maintenance, yuan/year	2298.01	100%	2298.01
1.2 Marginal cost			
Labor, yuan per ha, yuan/ha	50.87	100%	50.87
Fuel, yuan per ha, yuan/ha	152.21	100%	152.21
2. Invisible cost			
Pest damage	262.16	23.64%	61.98
Weed damage	301.94	29.30%	88.47
Seeds not germinating	2050.48	24.28%	497.88

Note:
(a) In 2021, we conducted surveys involving 79 cooperatives and 279 farmers in Lishu County, situated in Jilin Province. More details regarding the research design are show in the following section.
(b) The fixed and marginal costs are calculated using cooperatives' survey.
(c) The invisible cost is from farmers' survey.
(d) The occurrence probability is calculated by the proportion of farmers who reported damage.

Table A3. The Robustness check on SRD-DID estimates

	Bandwidth < 100 km			Bandwidth < 200 km		
	MG	MSG	DID	MG	MSG	DID
	(1)	(2)	(3)	(4)	(5)	(6)
T: 1 = autumn 2018 – spring 2019	-10.71**	-12.78**	-12.00**	-8.45**	-10.84***	-8.91***
	(4.05)	(3.72)	(4.02)	(2.92)	(3.10)	(2.75)
D × T			-0.345			-1.803
			(5.418)			(4.027)
D, 1 = Heilongjiang			-0.861			-0.889
			(8.118)			(6.667)
Distance variables						
Z, distance to order	-0.181	-0.225**	-0.201*	-0.082*	-0.078	-0.086**
	(0.106)	(0.068)	(0.105)	(0.041)	(0.043)	(0.039)
D × Z			-0.024			0.003
			(0.123)			(0.058)
Climate variables	Y	Y	Y	Y	Y	Y
Month fixed effect	Y	Y	Y	Y	Y	Y
Distance weight	Y	Y	Y	Y	Y	Y
Observation	600	1,080	1,680	1,272	1,776	3,048
R^2	0.221	0.177	0.187	0.190	0.143	0.157

Note:
(a) The independent variable is straw-burning spots, which is month-county level data.
(b) *D* takes the value of 1 for counties in Heilongjiang as MSG (monitoring plus subsidization group) and takes the value of 0 for the counties in Jilin and two prefectures in Inner Mongolia as MG (monitoring group).
(c) *T* takes the value of 1 for the period from autumn 2018 to spring 2019 and takes the value of 0 for the baseline period from autumn 2013 to spring 2018. The monthly number of straw-burning spots encompasses the data recorded for the months of March and April in spring as well as October and November in autumn.
(d) Z is the near distance from the county *i* to the border.
(e) The distance weight is calculated by the equation (8)
(f) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A4. The Robustness check on the effect of weak monitoring

	Bandwidth < 100 km			Bandwidth < 200 km		
	MG	MSG	DID	MG	MSG	DID
	(1)	(2)	(3)	(4)	(5)	(6)
T, 1 = spring 2020	36.26*	3.61	34.40**	33.61***	2.75	28.67***
	(16.05)	(4.68)	(14.15)	(8.54)	(6.76)	(7.79)
D × T			-30.45*			-24.26**
			(15.12)			(9.03)
D, 1=Heilongjiang			-10.96			-8.90
			(9.41)			(8.62)
Distance variables						
Z, distance to the border	-0.24	-0.25***	-0.28*	-0.16*	-0.05	-0.17**
	(0.133)	(0.05)	(0.13)	(0.08)	(0.06)	(0.08)
D × Z			0.03			0.11
			(0.14)			(0.10)
Climate variables	Y	Y	Y	Y	Y	Y
Month fixed effect	Y	Y	Y	Y	Y	Y
Distance weight	Y	Y	Y	Y	Y	Y
Observation	100	180	280	212	296	508
R^2	0.32	0.10	0.23	0.26	0.02	0.15

Note:
(a) The independent variable is straw-burning spots, which is month-county level data.
(b) *D* takes the value of 1 for counties in Heilongjiang as MSG (monitoring plus subsidization group) and takes the value of 0 for the counties in Jilin and two prefectures in Inner Mongolia as MG (monitoring group).
(c) *T* takes the value of 1 for the period in spring 2020 and takes the value of 0 for the baseline period in spring 2019. The straw-burning season in spring includes two months, March and April.
(d) *Z* is the nearest distance from county *i* to the border.
(e) The distance weight is calculated by the equation (8)
(f) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A5. The Robustness check on policies' effects on $PM_{2.5}$ (Distance<100 km)

	Estimates using distance to order			Estimates using county fixed effect		
	MG	MSG	DID	MG	MSG	DID
	(1)	(2)	(3)	(4)	(5)	(6)
T, 1 = autumn 2018 – spring 2019	-9.487**	-11.593**	-10.041**	-8.084**	-12.548**	-8.394***
	(3.622)	(3.356)	(3.418)	(2.816)	(4.030)	(2.786)
D × T			-1.325			-3.596
			(4.715)			(4.212)
D, 1 = counties in the MSG			0.150			
			(7.052)			
Distance variables						
Z, distance to border	-0.086	-0.119**	-0.092			
	(0.064)	(0.041)	(0.058)			
D × Z			-0.029			
			(0.069)			
Climate variables						
Precipitation, mm	-0.313**	-0.290***	-0.313***	-0.049	-0.043	-0.046
	(0.091)	(0.057)	(0.051)	(0.087)	(0.053)	(0.045)
Temperature, celsius	-1.344***	-0.498	-0.811	0.342	1.135*	0.842*
	(0.115)	(0.892)	(0.573)	(0.535)	(0.559)	(0.405)
Wind speed, m/s	10.718***	6.290	7.739**	4.779	9.185**	7.530***
	(2.697)	(3.769)	(2.713)	(2.695)	(3.374)	(2.374)
Month fixed effect	Y	Y	Y	Y	Y	Y
County fixed effect	-	-	-	Y	Y	Y
Distance weight	Y	Y	Y	-	-	-
Observation	984	1,488	2,472	984	1,488	2,472
R^2	0.198	0.156	0.168	0.321	0.378	0.358

Note: (a) The independent variable is straw-burning spots, which is month-county level data.
(b) *D* takes the value of 1 for counties in Heilongjiang as MSG (monitoring plus subsidization group) and takes the value of 0 for the counties in Jilin and two prefectures in Inner Mongolia as MG (monitoring group).
(c) *T* takes the value of 1 for the period from autumn 2018 to spring 2019 and takes the value of 0 for the baseline period from autumn 2013 to spring 2018. The monthly number of straw-burning spots encompasses the data recorded for the months of March and April in spring as well as October and November in autumn.
(d) Z is the nearest distance from county *i* to the border.
(e) The optimal bandwidth we select is 150 km. We also respect the bandwidth as 100 km and 200 km, reporting the results in Table A3. The distance weight is calculated by the equation (8)
(f) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

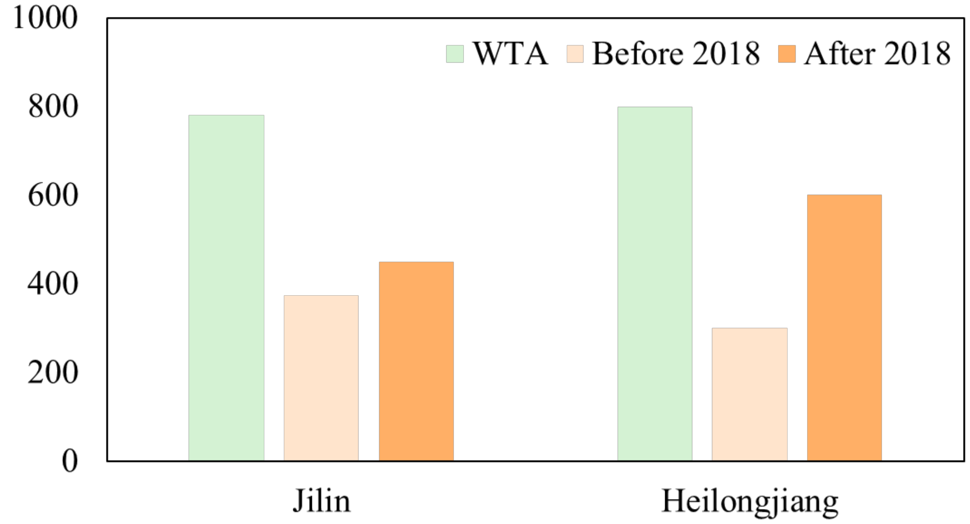
Table A6. The Robustness check on policies' effects on $PM_{2.5}$ (Distance<200 km)

	Data: Autumn 2018-Spring 2019			Data: Spring 2019 and Spring 2020		
	(1)	(2)	(3)	(4)	(5)	(6)
T, 1 = autumn 2018 – spring 2019	-18.88***	-21.79***	-18.74***			
	(3.080)	(4.239)	(2.816)			
T, 1 = spring 2020				11.66***	6.86***	10.50***
				(1.831)	(1.535)	(2.132)
D × T			-2.904			-3.611
			(4.290)			(3.252)
D, 1=MSG			6.408			6.517
			(8.638)			(3.802)
Distance variables	Y	Y	Y	Y	Y	Y
Climate variables	Y	Y	Y	Y	Y	Y
Month fixed effect	Y	Y	Y	Y	Y	Y
Distance weight	Y	Y	Y	Y	Y	Y
Observation	1,272	1,776	3,048	212	296	508
R^2	0.351	0.379	0.362	0.307	0.402	0.294

Note:
(a) The independent variable is particulate matter with a diameter of 2.5 micrometers or less ($PM_{2.5}$, ug/m^3), which is month-county level data.
(b) The climate variables include precipitation, temperature, and wind speed
(c) The distance variables include distance to order (Z) and D × Z.
(d) The bandwidth we select is 200 km. The distance weight is calculated by the equation (8)
(e) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Figures

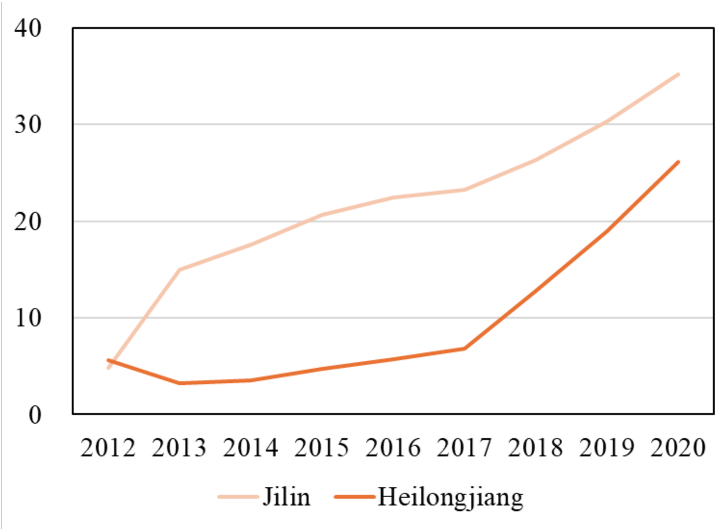
Figure A1. Straw-returning study (yuan/ha)



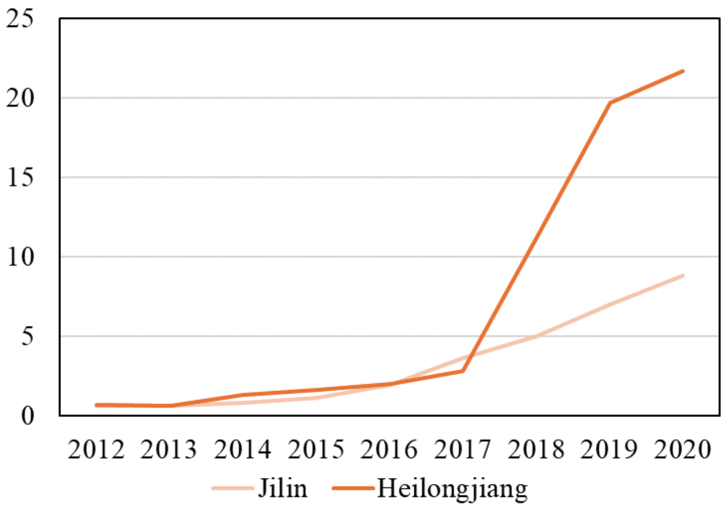
Note:
(a) WTA represents the farmer’s willingness to accept the subsidy for the adoption of straw returning. This data comes from Wang, et al. (2023). “Innovative incentives can sustainably enhance the achievement of straw burning control in China.” Science of The Total Environment. This paper made a meta-analysis on the farmer’s willingness to accept the subsidy for the adoption of straw returning in 12 provinces in China.
(b) Details of subsidy policies are provided in Table A1.

Figure A2. Temporal changes in straw-returning machines

Panel A: no-till seeder, a thousand units

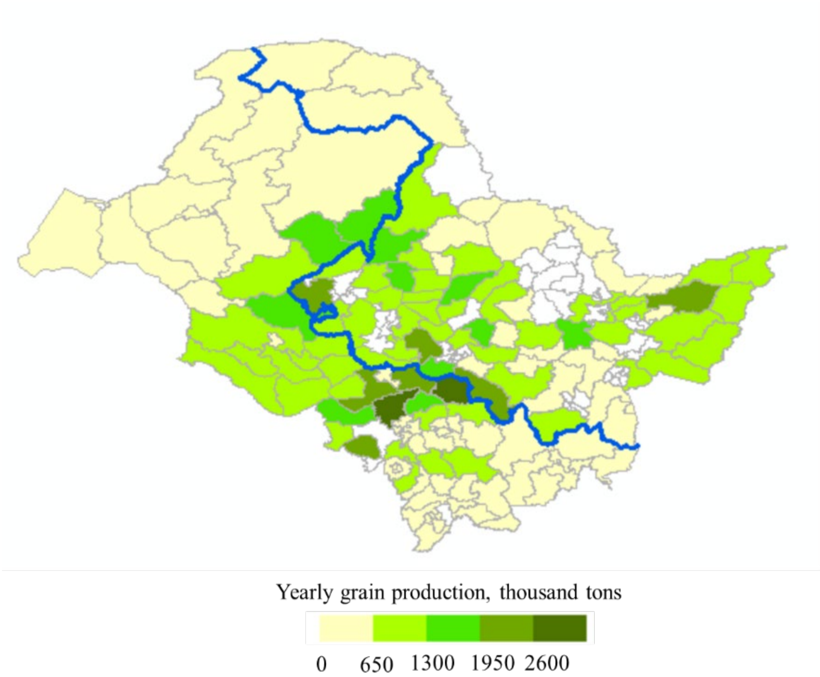


Panel B: straw-baling machine, a thousand units



Note:
(a) Data source: China Agricultural Machinery Yearbook (2013-2021)

Figure A3. Spatial distribution of grain output



Note:
(a) The grain output presented in the figure represents the average value for the years 2013 to 2020.
(b) Counties depicted in white signify the presence of missing values.
(c) Data source: China County Statistical Yearbook from 2014 to 2021

Figure A4. The distance to the border

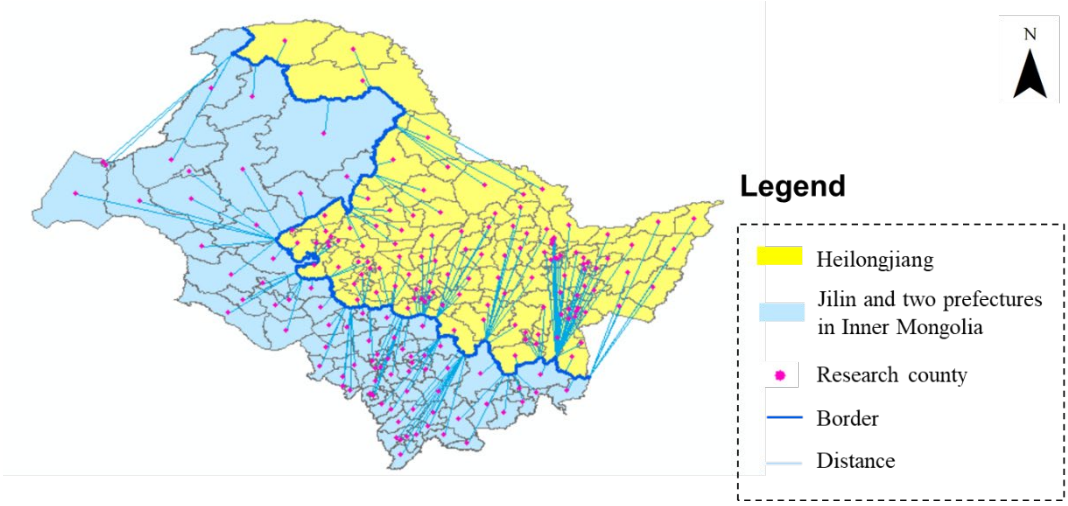
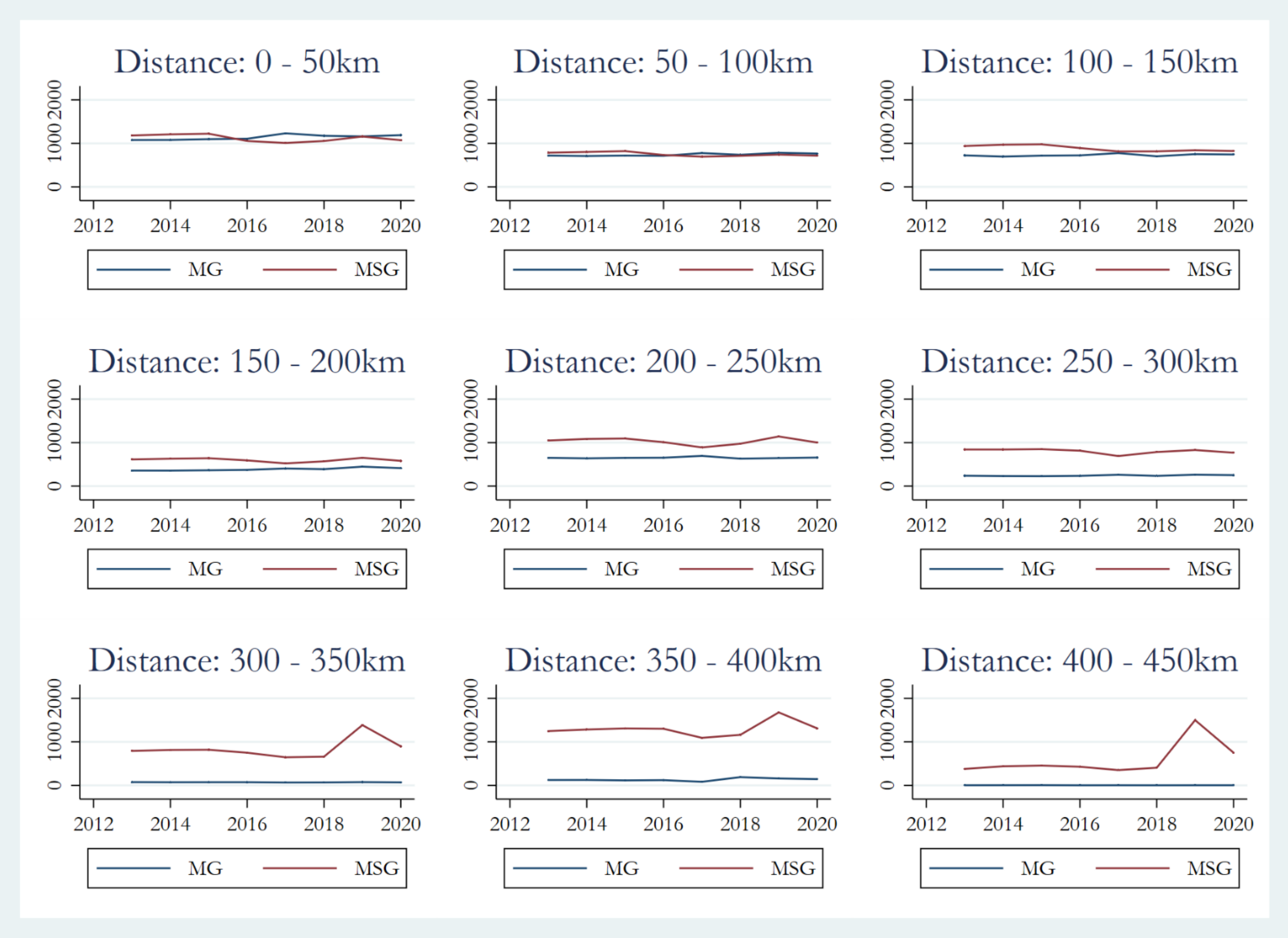


Figure A5. Spatial and temporal analysis of grain output



Note:
(a) The MSG (monitoring plus subsidization group) encompasses 119 counties in Heilongjiang, while the MG (monitoring group) encompasses 78 counties in Jilin and two prefectures in inner Mongolia.
(b) The horizontal axis denotes the year, while the vertical axis signifies the grain output measured in thousand tons.

Figure A6. The altitude of research counties

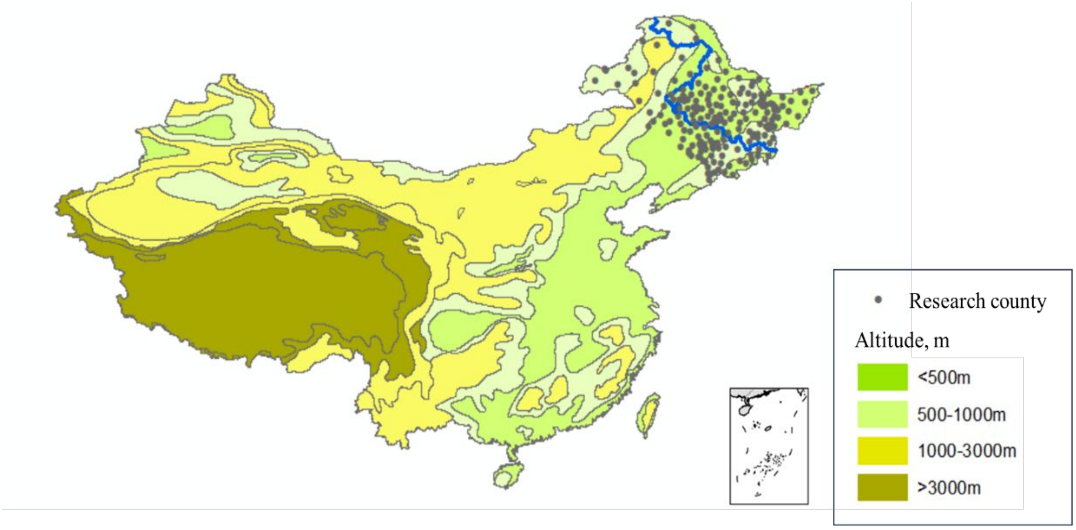


Figure A7. Proportion of straw-burning spots in April relative to the total number of spots in spring

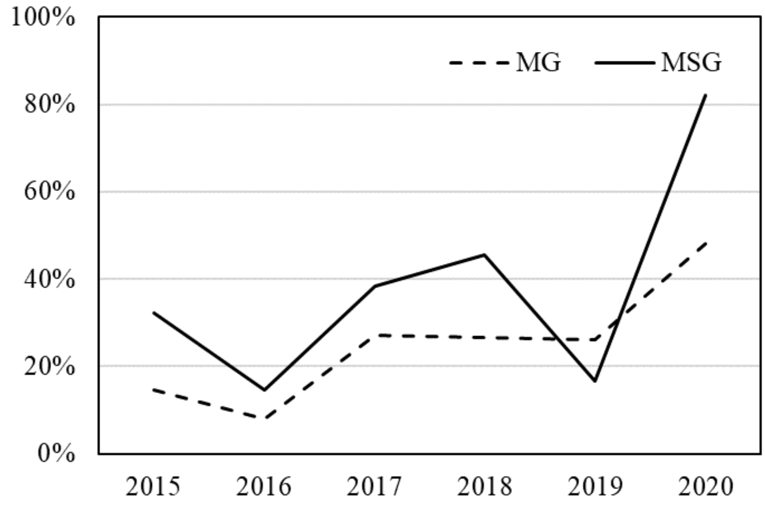
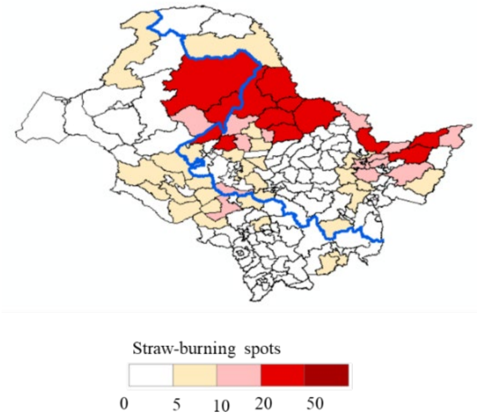
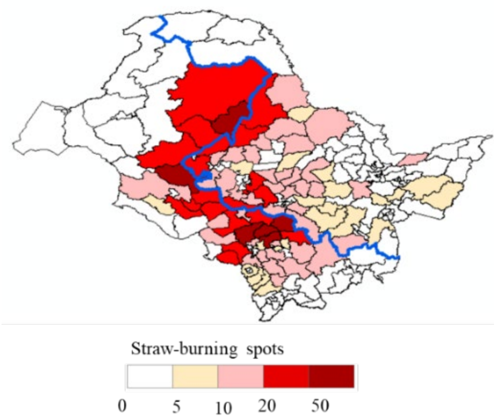


Figure A8. Temporal change in straw burning in the COVID-19 period

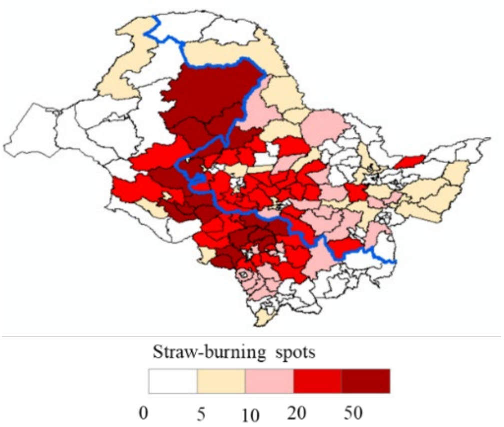
Panel A: Autumn 2018 - spring 2019



Panel B-1: Autumn 2019 - spring 2020



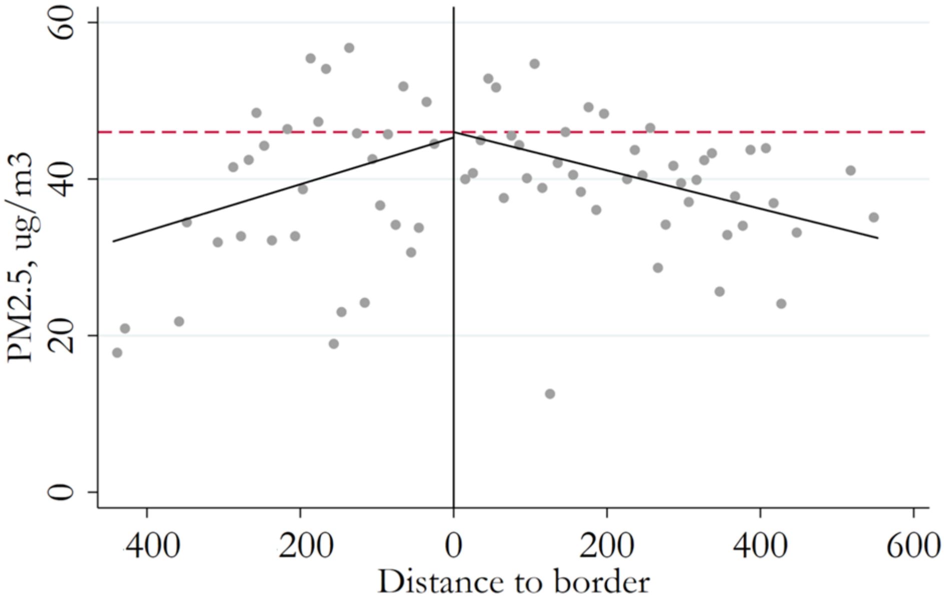
Panel B-2: Spring 2020



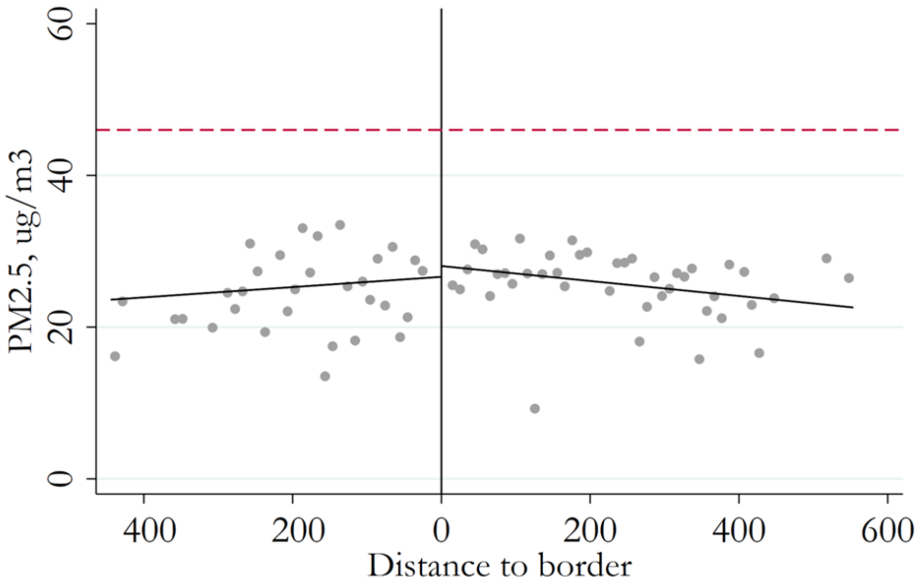
Note:
(a) The color in the figures represent the average value of straw-burning spots during the specific period.
(b) The blue line is the border between the MG and MSG. Counties situated to the right of the border fall within the MSG, while those on the left side belong to the MG.

Figure A9. The Spatial-Regression-Discontinuity (SRD) graphic analysis of $PM_{2.5}$

Panel A: Autumn 2013 – Spring 2018



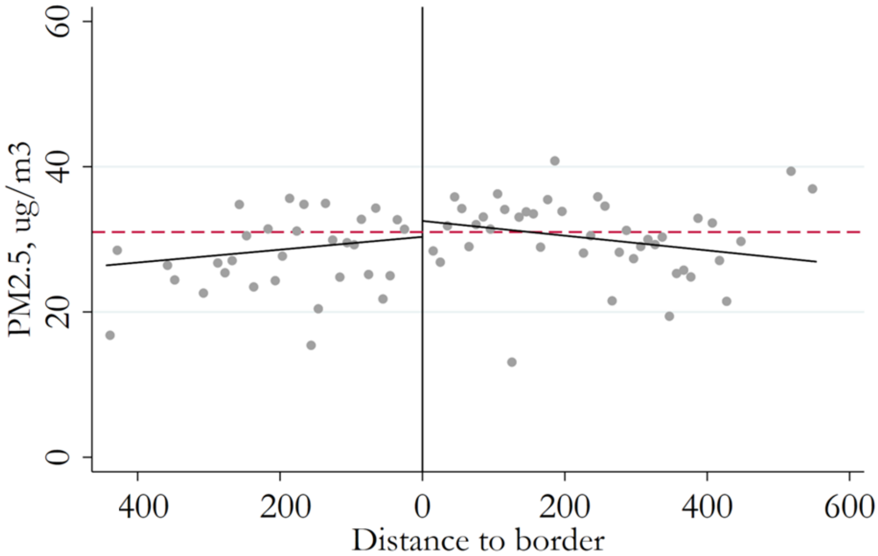
Panel B: Autumn 2018 – Spring 2019



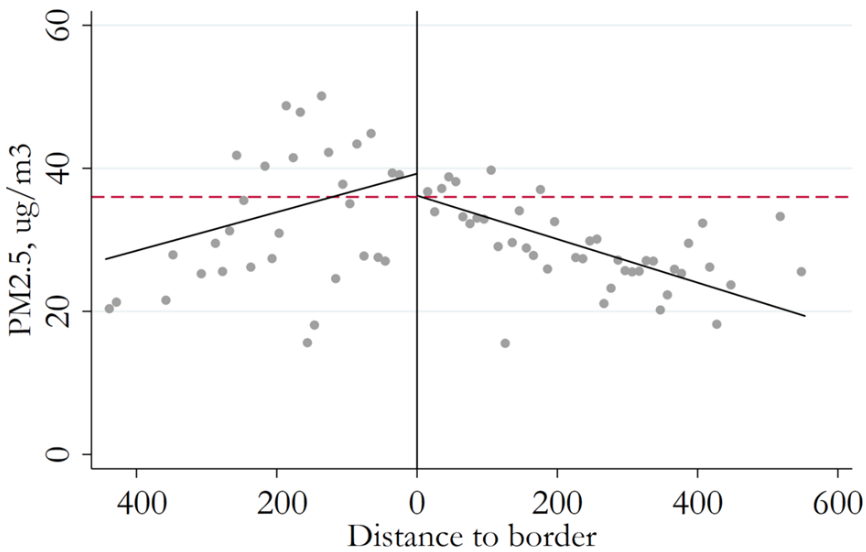
Note:
(a) The circle represents the average value of $PM_{2.5}$ within uniformly distributed 10 km bins.
(b) The red line represents $PM_{2.5}$ in the counties near the border in the period prior to the monitoring implementation (autumn 2013-spring 2018).
(c) The vertical line serves as the border, with the left side representing the MG and the right side representing the MSG.

Figure A10. The Spatial-Regression-Discontinuity (SRD) graphic analysis of $PM_{2.5}$ on weak monitoring

Panel A: Spring 2019



Panel B: Spring 2020



Note:

(a) The circle represents the average value of $PM_{2.5}$ within uniformly distributed 10 km bins.

(b) The red line represents $PM_{2.5}$ in counties near the border during the period preceding the last spring before the COVID-19 period (spring 2019).

(c) The vertical line serves as the border, with the left side representing MG and the right side representing the MSG.

Research design for the case study in Lishu county

We conducted field research in Lishu County to examine how local authorities addressed the challenges of straw-burning monitoring during the COVID-19 pandemic. Located in Jilin Province, Lishu County dedicates approximately 87% of its arable land to maize cultivation. We selected Lishu County for this study because it is the birthplace of straw-return technology in Northeast China, making it highly representative for examining straw-burning management practices.

The research was conducted in two rounds. The first round took place from early April 2020 to early June 2020. We resided at the Lishu Experimental Station, located in a farming village about 10 kilometers from the county center, to closely observe farmers' straw-burning practices during the pandemic. Our study employed a qualitative approach, incorporating semi-structured interviews and field observations. We conducted semi-structured interviews with key stakeholders, including 10 farmers, 5 members of village committees, and 3 local government officials from the agricultural departments. Due to the lockdown policy, our scope of action was constrained. As a result, the stakeholders we interviewed were all residents of villages near the experimental station, except the local government officials. The interviews with farmers explored their methods for evading straw-burning monitoring and changes in monitoring practices. For village committees, we investigated their monitoring approaches and the impact of COVID-19 on these strategies. Interviews with local government officials focused on how the local government adapted its monitoring plan during the pandemic. In addition to interviews, we utilized our time living in the village to closely observe farmers' straw-burning methods and the responses of village committees to these practices. This provided valuable insights into the practical challenges and responses related to straw-burning monitoring during COVID-19. We also attended several conferences on straw utilization to observe and assess the local government's responses and strategies.

In the first round of research, we observed that the village committee devoted substantial manpower to enforcing the lockdown policy. This effort included tracking residents returning from other areas, monitoring key roads, and preventing unauthorized individuals from entering the village. Consequently, the committee was unable to conduct regular physical patrols to monitor straw burning. Due to the challenges of effectively monitoring straw burning and the urgency of the spring planting season, local authorities and the village committee chose not to enforce a strict ban on straw burning. They established specific times when farmers could burn straw if necessary. Most farmers complied with these designated times and adhered to the relevant regulations. However, field observations revealed that some farmers continued to burn straw clandestinely. There were two primary methods for this covert burning: (1) Burning in enclosed structures: Farmers sometimes transported straw to cement sheds with roofs and burned it there. This method was less detectable by satellite imagery, and the village committee generally overlooked small-scale burning in this approach. (2) Nighttime Burning: Farmers also burned straw during the evening hours (between 7 p.m. and 9 p.m.), a time when monitoring was less stringent.

The second round of research was conducted from December 2021 to January 2022, after the COVID period. During this phase, we carried out a large-scale survey to statistically assess the costs associated with the primary alternative to straw burning, which is straw returning. The respondents include cooperatives and farmers. The sampling methods are as follows: The surveyed area covers 18 townships in Lishu County (see Figure A8). The local agricultural extension departments in each township assisted us in selecting 4 to 5 cooperatives of a certain scale. Subsequently, cooperative managers, who were interviewed, aided in contacting 4-6 farmers served by their respective cooperatives. Following the exclusion of invalid data, the sample comprised 79 cooperatives and 279 farmers. The main findings from the second-round survey are reported in Figure A2.

Figure A11. Spatial distribution of large-scale survey in Lishu County