Market-based instruments in agri-environmental governance: Case study of straw-burning control in Northeastern China

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Abstract:
Agri-environmental governance poses significant challenges in developing countries, often addressed through command-and-control policies and market-based instruments. Despite the importance of these policies, the interplay between them remains unexplored. In this paper, we leverage varied policies implemented across different provinces in Northeastern China to control straw burning, alongside the COVID-19 shock, as quasi-experiments to empirically examine the effects of market-based-instrument program (i.e., subsidies) on farmers' straw-burning behavior, given varying intensities of command-and-control policies (i.e., monitoring). Empirically, we collected satellite data on straw-burning spots and meteorological data at the county level from 2014 to 2020 and employed difference-in-difference and spatial regression discontinuity to conduct the analyses. The results indicate that, given stringent monitoring in place, subsidization offers limited additional effects on reducing straw burning. However, when stringent monitoring is not feasible during the COVID-19 period, subsidization can be effective in curbing the rebound of straw-burning behavior in the long term. This mitigated rebound effect is particularly pronounced in regions with severe COVID-19. These results highlight the resilience of market-based-instrument programs in maintaining governance outcomes over the long term, particularly when faced with unexpected external shocks.

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

JEL: G18, H23, Q18, Q53, Q58

Introduction

Agricultural production has been identified as a major cause of several environmental issues (Korontzi, et al., 2006, Wada, et al., 2010, Long, et al., 2021). 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]

Both policy groups have their respective advantages and disadvantages. CAC policies, such as monitoring and penalty, ensure stakeholders adhere to policy planning through extensive administrative control and mandatory enforcement, enabling timely and planned pollution mitigation (Yu, et al., 2024). However, their effectiveness depends on the feasibility of an accurate and real-time monitoring system, which can be labor-intensive for CAC enforcement and challenging to sustain over the long term (Stranlund, 1995, Shortle, et al., 2001, Cao and Ma, 2023). In comparison, despite limited controllability in pollution mitigation planning, MBIs, such as subsidies and emissions trading, are more economically sustainable for the long term. They can generate a positive reward mechanism encouraging polluting entities (e.g., factories, consumers, farmers) to voluntarily adopt more environmentally friendly technologies and practices, promoting engagement in long-term pollution mitigation efforts (Segerson, 1988, Xepapadeas, 2011, Blackman, et al., 2018).

Compared to CAC policies, MBIs play a more significant role in agri-environmental governance, especially in developing countries. First, agricultural pollution from farmers is scattered and challenging to regulate through CAC policies. Unlike factories, which centralize production and emissions at fixed locations, agricultural pollution is diffuse, characterized by

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.

non-point source emissions occurring irregularly across vast farmlands (Fan, et al., 2019). This spatial and temporal variability significantly increases enforcement costs for real-time monitoring, making CAC difficult to maintain. Second, farmers face various practical barriers to accessing alternative, non-polluting solutions. According to Mazaheri, et al. (2022), an MBI becomes effective when the benefits of adopting non-polluting solutions outweigh their associated costs. The underlying assumption is that alternatives are available to the polluting entities and that these solutions are cost-effective. However, meeting these conditions is particularly challenging for farmers in most developing countries due to limited access to financial resources (Poulton, et al., 2010, Fan, et al., 2013), technologies (Walter, et al., 2017) and to related knowledge (Ridley, 2004, Zhang, et al., 2016). Therefore, a subsidy program (as a core element of the MBIs) is necessary for farmers, as it reduces their barriers to adopting environmentally friendly, non-polluting practices while also lowering the monitoring costs (Smith, 2019).

Numerous studies have examined the standalone effectiveness of MBIs in environmental governance (see reviews on MBIs by Blackman, et al. (2018) and Mazaheri, et al. (2022)). However, their effectiveness when combined with CAC policies remains poorly understood, particularly in the context of agri-environmental governance. In practice, CAC and MBI policies may be combined based on the agri-environmental governance structure and the capacities of relevant agencies (Yu, et al., 2024). Given this practical reality, an ambiguous understanding of MBIs' effectiveness, when integrated with CAC policies, can lead to policy inefficiencies, causing policymakers to implement suboptimal policy mixes, misallocating public funds, and wasting regulatory resources. This, in turn, could hinder the achievement of pollution reduction targets at the lowest societal cost.

Leveraging well-timed panel data, this study investigates the effects of a MBI policy (i.e., subsidization) on controlling straw burning in Northeast China, conditional on varying intensities of CAC interventions. Straw burning is a typical case of agriculture-based non-point-source pollution (Theesfeld and Jelinek, 2017, Bhuvaneshwari, et al., 2019), 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 Northeast China. Two-thirds of straw-burning spots in China were located in this region in 2017 (Yin, et al., 2021).

To address straw burning, Northeast 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, Northeast China 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. Specifically, Heilongjiang substantially raised its subsidy, whereas neighboring provinces (i.e., Jilin) saw only a marginal increase. Such a quasi-experiment allows us to explore the effectiveness of MBI conditional to stringent CAC policies in Heilongjiang, using its neighboring province as a control group. Second, the outbreak of Coronavirus Disease 2019 (COVID-19) in the spring of 2020 greatly affected the implementation of stringent CAC measures in the field, rendering them infeasible in both Heilongjiang and its neighboring province. It allows us to examine the effectiveness of MBI conditional to weak CAC policies in Heilongjiang, compared to its neighboring province.

To isolate the effectiveness of MBIs from mixed policy interventions, we employed both difference-in-differences (DID) and spatial regression discontinuity (SRD) approaches for empirical estimation. We collected satellite-based data on monthly straw-burning spots and related meteorological data for all counties in Heilongjiang and its neighboring province for the period 2014 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 during periods of stringent straw-burning monitoring, subsidization in Heilongjiang yields only a limited additional reduction compared to its neighboring province. However, when weak monitoring during the COVID-19 outbreak triggered a significant rebound in straw burning in the control group, subsidies effectively mitigated this rebound. This mitigating effect was particularly pronounced in counties severely impacted by COVID-19.

Our study contributes to the extensive literature on MBIs in environmental governance by examining the effectiveness of combining MBIs with CAC policies in the agricultural sector. In previous reviews by Blackman, et al. (2018) and Mazaheri, et al. (2022)), the studies related to MBIs in environmental governance are centered on industrial sectors, such as steel, transport, and construction, and only focus on the effectiveness of MBIs themselves, without considering their interplay with other policies. Our study instead provides a theoretical framework and valuable evidence regarding the interplay of MBI with CAC measures in agri-environmental governance. Considering the unique characteristics of agriculture, the evidence provides valuable insights for policymakers designing environmental governance strategies with similar characteristics.

Our findings add to the existing body of research on straw-burning policies. Studies by He, et al. (2020), Cao and Ma (2023), and Nian (2023) have leveraged satellite-based data to provide valuable insights into the effectiveness of MBIs in China. Similarly, Garg, et al. (2024) and Dipoppa and Gulzar (2024) have examined straw-burning policies in South Asia, revealing the drives of straw burning and the role of local government incentives in regulatory efforts to control it. In comparison, our study employed similar data but provided a more comprehensive analysis by examining the interaction between MBIs and CAC. Moreover, our results extend the findings of Wang et al. (2021) and Sun et al. (2019) by highlighting the unsustainability of CAC. Considering the challenges associated with the prohibitive monitoring costs and sustainability of CAC measures over the long term (Van Rooij, 2006), the results imply that the integration of both CAC and MBI measures is needed to yield a more significant and long-lasting effect in straw-burning control and other similar agri-environmental governance in a developing country context.

The remainder of this paper is organized as follows. Section 2 provides an overview of straw-burning practices, including the evolution of agri-environmental policies and their implementation. In Section 3, we develop a theoretical framework to understand the potential joint effects of stringent monitoring and subsidization on farmers' straw-burning behavior. Section 4 outlines the data collection, and we present the empirical estimation strategy in

Section 5. Section 6 presents the empirical results, reporting the effectiveness of subsidization under both stringent and weak straw-burning monitoring conditions. Finally, Section 7 concludes the paper and discusses the policy implications of the results.

Institutional setting

2.1 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 Northeast 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 Northeast 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.

2.2 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.[3] In response to such top-down pressures, a stringent ban on straw burning control was promulgated in September 2018 in both Heilongjiang and Jilin.[4] 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 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 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

3 The central government policy was known as "*The Action of Straw Utilization in NE China*", issued by the Ministry of Agriculture (MA) (2017).
4 Details of policies from different levels of local governments in Heilongjiang and Jilin are shown in the online Appendix Table A1.

standards, committee members—particularly leaders with the chief responsibility—will be subject to administrative punishment. Under such a stringent CAC system, grassroots committees (i.e., 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.

2.3 MBIs with varying intensity

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).[5] 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. To check this variation, we analyzed temporal changes in straw utilization machinery data from the China Agricultural Machinery Yearbook (the China Agricultural Machinery Yearbook [CMIF], 2021). It highlights the disparity in subsidy intensity between Heilongjiang and Jilin after 2018 (Figure 2). In Heilongjiang, the number of straw-returning seeders, which are used for seeding on soil with returned straw, nearly doubled in 2018. In contrast, Jilin saw only a 13.36% increase (Panel A). 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% (Panel B).

5 The Northeast 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.

Additionally, a farm survey we conducted revealed the significance of this subsidy increase for farmers. The benefits of straw returning, such as improved soil fertility (enriching of soil organic matter) and reduced fertilizer usage (Wang, et al., 2018, Lv, et al., 2019, Yan, et al., 2019), have been advocated. However, implementing straw returning (or bailing) can be costly for farmers, considering its extended costs.[6] Field survey shows that the total investment in straw-returning machines—including straw-cleaning machines (15,000 yuan), straw-returning seeders (50,000 yuan), and straw-bailing machines (100,000 yuan)—can be nearly 165,000 yuan (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 (Appendix Table A2). Wang, 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 (Appendix Figure A1). 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.

[Insert Figure 1 here]

2.4 COVID-19 outbreak in spring 2020 weakening CAC

Stringent CAC policies were short-lived. 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 in the spring of 2020. This created unprecedented challenges for spring grain sowing, as farmers, typically clearing straw by mid-March for April planting, faced delays due to lockdown restrictions. As a result, they were forced to complete spring plowing under severe time constraints before the May rains. This urgency triggered a sharp increase in

6 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).

the proportion of straw-burning incidents occurring in April, increasing from about 30% to over 50% of total spring incidents in both Jilin and Heilongjiang provinces (Appendix Figure A2). Moreover, monitoring efforts were hampered as village committee staff were reassigned to enforce lockdown measures, reducing available manpower for straw-burning field checks. The survey we conducted during the spring of 2020 revealed how village committees responded to straw-burning monitoring activities amid lockdown policies.[7] 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 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.

In summary, we observed a significant change regarding CAC and MBIs (see 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. Lastly, the COVID-19 outbreak in the spring of 2020 further disrupted labor-intensive field inspections, leaving subsidy mechanisms as the primary policy tool in both regions. These policy variations

7 The ideal way to study the overall straw-burning monitoring situation during the COVID-19 period is through a large-scale farmer survey encompassing the entire Northeast China region. 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 appendix document.

enabled us to explore the effectiveness of MBIs under different intensities of CAC policy enforcement.

[Insert Table 1 here]

Theoretical framework

We develop a concise theoretical framework to illustrate how CAC and MBI policies affect farmers' agri-environmental choices, focusing on straw burning. 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, the main sustainable straw-utilization practice, 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.[8] Assume the service cost of straw-returning by local machinery cooperatives is constant at c ($c > 0$).[9] 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 (Liu, et al., 2019,

8 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.
9 Due to the nature of the field practice, cooperative charges a fixed service fee per hectare, irrespective of the actual amount of straw returned.

Krishna and Mkondiwa, 2023). 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 $i{v_1}^2$ ($i > 0$). 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 $\pi_a = jv_1 - i{v_1}^2$.

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 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:

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

$$\text{s.t. } v_1 + v_2 = 1 \quad (2)$$

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.

Given the policy context of straw-burning management in Northeast China, Figure 1 illustrates the impact of varying policy interventions in Heilongjiang and Jilin. Point “a” represents the straw-burning situation in both provinces before the policy intervention (2014-2018). Following the implementation of stringent straw-burning monitoring, Jilin’s status shifts from “a” to “b”, while Heilongjiang’s moves from “a” to “c”.[10] Thus, the subsidy effect under strict monitoring is represented by the gap “bc”. However, this effect is considerably smaller than the gap “ad”, which is the conditions in Jilin and Heilongjiang during spring 2020, due to the challenges of monitoring feasibility.

[Insert Figure 2 here]

10 Strictly speaking, Jilin’s status shifts slightly to the right of point “b” due to its increased marginal subsidization. However, to avoid introducing unnecessary labels in Figure 2, we simplify this by stating in the main text that it shifts to point “b.”

Data

The study focuses on the Heilongjiang (treatment group) and Jilin regions (control group), which encompass the primary plains of Northeast China (Figure 3). The research period spans from October 2014 to April 2020.

[Insert Figure 3 here]

4.1 Satellite data on straw burning

Straw burning, the primary outcome variable, can be detected using satellite remote sensing from the National Aeronautics and Space Administration (NASA). 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). [11] We collected satellite-tracked straw-burning data for four key months each year (March, April, October, and November), aggregating daily straw-burning incidents into monthly totals. Additionally, we define a straw-burning year as spanning from autumn (October-November) to the following spring (March-April), as both periods involve burning the same batch of straw residue. Grain production in Northeast China follows a single growing season from May to mid-October. Straw burning for land preparation typically occurs either between October and November after harvest or from early March to April of the following year before seeding.

[Insert Table 2 here]

4.2 Satellite data on $PM_{2.5}$ and grain-planting area

Monthly $PM_{2.5}$ data, another key outcome variable, were obtained from the National Tibetan Plateau Data Center of China (Wei and Li, 2023a, Wei and Li, 2023b). The temporal coverage of this dataset spans from 2000 to 2021. For this study, we extracted $PM_{2.5}$ data from

11 The satellite passes the local Northeast China 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.

2014 to 2020 for Jilin and Heilongjiang provinces. By integrating these spatial data with county boundary shapefiles, we calculated county-level monthly $PM_{2.5}$ during the straw-burning seasons (October, November, March, and April).

We also collected spatial grid-scale data on maize, wheat, and rice cultivation areas in Jilin and Heilongjiang provinces from the National Ecological Science Data Center. We aggregated the grid data into a county-level index representing the planting intensity of these three crops. The indices for maize, wheat, and rice were then summed to create a grain-planting area index. As the dataset is annual, it reflects the extent of grain cultivation prior to each straw-burning year. This index serves as an outcome variable and helps validate the assumptions underlying our empirical strategies.

4.3 Climate and COVID cases data

County-level monthly climate data, including temperature, precipitation, and wind speed, were incorporated as control variables. Daily meteorological records from the National Meteorological Information Center of China were averaged to derive monthly values. Additionally, we compiled the total number of COVID-19 cases reported before April 30th in 2020 from the National Health Commission's daily updates. Since the National Health Commission only published COVID-19 case data at the prefecture level, this dataset is available at the prefecture level and will be used in the subsequent heterogeneous analysis.

4.2 Summary Statistics

We present some descriptive statistics in Table 2. Although Jilin and Heilongjiang are spatially adjacent, there are still discernible distinctions in climate factors between them. Owing to its northern location, Heilongjiang 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, Figure 4 presents a spatial analysis of straw-burning spots by distance from the border before 2018 (The distance calculations are detailed in Appendix Figure A3). The results indicate that counties near the border exhibited similar trends, with minimal differences between treatment and control groups. In particular, counties within 100 km of the border displayed nearly identical patterns before the policy intervention. However, as the distance extended to the 100 – 150 km range, noticeable differences emerged, becoming more pronounced in counties located beyond 150 km from the border. This spatial pattern reflects the underlying distribution of grain-planting areas, as supported by a similar analysis using grain-planting data reported in Appendix Figure A4.[12] It also shows that counties near the border share comparable grain planting.

[Insert Table 2 here]

[Insert Figure 4 here]

12 We performed spatial analyses of grain-planting areas, including maize-, rice-, and wheat-planting distributions, as well as $PM_{2.5}$ concentrations, as presented in Appendix Figures A5 – A8.

Empirical strategies

We employ the spatial regression discontinuity (SRD) and difference-in-difference (DID) design to examine the causal effect of subsidy on farmers' activity in straw burning. This approach, combining regression discontinuity with difference-in-differences, was previously utilized by Persson and Rossin-Slater (2024). They used the timing of policy implementation to create a discontinuity, examining whether this discontinuity of the outcome variable existed around the timing of the policy's introduction and comparing conditions before and after its implementation. In our study, we use the distance of counties from the border between Heilongjiang (treatment group) and Jilin (control group) as the source of discontinuity. [13] Following the algorithms proposed by Calonico, et al. (2014), we set the distance bandwidth to 142 km and focus on counties within this range for both the treatment and control groups to perform the subsequent analysis (Details on the bandwidth selection shown in Appendix Table A3).

5.1 SRD-DID design

Following Persson and Rossin-Slater (2024), the regression, which uses the distance to the border, d_i, as the running variable, can be expressed as follows:

$$Y_{imt} = \alpha + \beta_1 1[t = 2018] \times 1[d_i \geq 0] + \beta_2 1[t = 2019] \times 1[d_i \geq 0] + \beta_3 1[d_i \geq 0] + f(d) + 1[d_i \geq 0] \times f(d_i) + X'_{imt}\gamma + \theta_m + \varepsilon_{itm} \quad (7)$$

for each county *i* in the month *m* and period *t,* where we refer to each October through April as a separate period (e.g. October 2017 – April 2018, October 2018 – April 2019). Y_{imt} is the outcome variable, such as an indicator for straw-burning spots, the density of $PM_{2.5}$, and the grain-planting area. The dummy variable $1[t = 2018]$ is set to 1 for the period October 2018 – April 2019, 0 to otherwise. Similarly, the dummy variable $1[t = 2019]$ is set to 1 for the period from October 2019 to April 2020. The dummy variable $1[d \geq 0]$ is set to for counties

13 As illustrated in Figures 3 and 4, the treatment and control groups share a long border, with counties near the border showing more similar temporal trends in farmers' straw-burning activities. This observation underpins the integration of the SRD design into the DID framework, based on the assumption that counties closer to the border are more comparable than those farther away while also providing a sufficient sample size for robust estimation.

with a distance to the border greater than or equal to 0, representing the treatment group. $f(d)$ is a flexible function of the running variable, distance to the border, for which we use a polynomial in our main specifications and allow for it to have a different shape on opposite sides of the threshold in all periods. We also include fixed effects for every time period, θ_t. The vector X'_{imt} are control variables, including climate factors such as precipitation, wind speed, and temperature, as well as month-fixed effects to account for monthly variations that could influence the estimation. The ε_{itm} is the error term clustered at the county level.

The key coefficients of interest are β_1 and β_2. They represent the discontinuous dynamic changes in outcome variables between treatment and controlled groups during October 2018 – April 2019 and October 2019 – April 2020, respectively, relative to the analogous that observed prior to the policy implementation period (October 2014 – April 2018). In contrast, β_3, typically the primary focus in standard SRD models, serves as a control variable in our design, capturing the discontinuity in outcomes prior to policy implementation. Given the varying intensity of straw-burning monitoring after October 2018, the coefficients, β_1 and β_2, capture the effects of subsidies on outcomes under conditions of strict and relaxed monitoring, respectively. Additionally, the coefficients of $f(d)$ and $1[d_i \geq 0] \times f(d_i)$ describe the relationship between distance and outcome variables and capture differences in this relationship between the control and treatment groups, respectively.

5.2 DID design

We also utilize a standard DID design for the counties within the 142 km distance bandwidth to make a robustness check on SRD-DID estimates. The specification is defined as follows:

$$Y_{imt} = \alpha + \beta_1 1[t = 2018] \times 1[d_i \geq 0] + \beta_2 1[t = 2019] \times 1[d_i \geq 0] + X'_{imt}\gamma + \omega_i + \theta_t + \varepsilon_{itm} \tag{8}$$

where we incorporate the county-fixed effects, ω_i, in the specification. These county-fixed effects account for the variation in county distances from the border, which remains constant over time, absorbing the distance-related variation captured in equation (7). Other variables are the same as the equation (7).

The two specifications, SRD-DID and DID, each have their own advantages and limitations. The SRD-DID design can depict the changes in sharp discontinuity before and after the policy implementation and provides a detailed account of spatial factors influencing straw burning, such as the spatial distribution of grain-planting areas. However, it carries the risk of overfitting due to the running variable function $f(d)$. In contrast, the DID design is straightforward and easy to interpret but lacks the ability to capture nonlinear relationships between potential spatial factors and straw burning.

5.3 Identifying assumptions

The standard regression discontinuity design assumes that only the treatment variable changes discontinuously, while all other variables potentially influencing the outcomes of interest remain continuous functions of the assignment variable (Imbens and Lemieux, 2008). In our case, this assumption implies that farmers should not be able to strategically manipulate the grain-planting area.[14]

To assess the plausibility of the identifying assumption, we examine whether grain planting experienced any confounding shifts during the policy implementation period compared to the period prior to its implementation using equation (7). We report coefficients from SRD-DID models that use 0^{th} through 4^{th} order polynomials in the running variable, with the 0^{th} not considering $f(d)$. Table 3 presents the results, and we also report the Akaike Information Criterion (AIC) at the bottom of the table. The results are very stable across the different specifications. And importantly, we observe no significant discontinuities in the grain-planting area near the border following policy implementation, regardless of whether the analysis is conducted within the 142 km sample (Panel A) or the full sample (Panel B). Regarding the selection of polynomial order, the AIC value exhibits a noticeable decrease with the 2nd-order polynomial but remains stable from the 2nd to the 4th-order. To balance minimizing the AIC

14 Straws primarily originate from grain production in Northeast China.

and avoiding overfitting, we select the 3rd-order polynomial, even though its AIC is slightly higher than that of the 4th-order polynomial. Figure 5 further presents graphical evidence, following the common method (McCrary, 2008, Lee and Lemieux, 2010) . We divide the distance to the border into evenly spaced “bins” of 50 km each. Then, we calculated the mean value of the grain-planting area in each bin and constructed a 3rd-order fitted line. As shown in Figure 5, no observable discontinuity is evident, either the pre-policy period (2014 – 2017) or the post-policy period (2018 – 2019).

We also check for any discontinuities in the planting structure using equation 7, including the proportions of maize, rice, and wheat within the total grain-planting area. The results, presented in Appendix Table A4, reveal no significant discontinuities across the three outcomes. These findings are reassuring and suggest that differential policy selection is unlikely to bias the main estimates reported below.

[Insert Table 3 here]

[Insert Figure 5 here]

Result

6.1 Effects of subsidy on farmers' straw-burning activities

Graphical analysis. We begin by conducting a graphical analysis of the discontinuity in straw burning during each straw-burning period. Figure 6 presents a graphical SRD analysis, using 50 km bins to calculate the average number of straw-burning spots within each bin. This analysis illustrates the distribution of straw-burning spots relative to the border distance. Appendix Figure A9 provides a graphical analysis of the spatial distribution of straw-burning spots, offering a more intuitive interpretation of the results presented in Figure 6.

As shown in Figure 6, there is a clear jump in straw-burning spots near the border in the COVID year (autumn 2019 – spring 2020), but such a jump does not exist in the pre-policy period (autumn 2014 – spring 2017) and even in the first year of policy implementation (autumn 2018 – spring 2019). Specifically, straw-burning activity near the border remained stable during the pre-policy period. In contrast, when stricter monitoring was enforced in autumn 2018 – spring 2019, both sides of the border experienced a noticeable decline in straw burning. However, the treatment group (right side of the border), despite receiving higher subsidies, did not exhibit an additional reduction in straw burning. During the COVID-19 pandemic, when monitoring efforts were infeasible (autumn 2019 – spring 2020), straw burning substantially rebounded in the control group (left side of the border). Conversely, the treatment group experienced a much smaller rebound, resulting in a clear jump in straw-burning spots near the border. This pattern becomes even more pronounced when focusing on springtime straw burning, as illustrated in Figure 7.[15] Additionally, the relationship between distance and straw burning in both Figures 6 and 7 parallels the relationship between distance and grain-planting areas, with straw-burning activity being more concentrated near the border. These observed patterns in Figures 6 and 7 motivate the use of the SRD-DID approach to analyze dynamic changes in straw-burning discontinuity.

[Insert Figure 6 here]

15 The graphic analysis of straw burning in autumn is shown in Appendix Figure A10.

[Insert Figure 7 here]

Regression analysis. Table 4 presents the estimation results from the SRD-DID model (equation (7)) and the DID model (equation (8)) within 142 km distance bandwidth using different seasonal samples of straw-burning: the full sample, spring-only, and autumn-only straw-burning observations. To account for the specific nature of the outcome variable, we apply different estimation methods. Columns (1) and (3) report coefficients obtained using standard ordinary least squares (OLS) estimation, while columns (2) and (4) provide estimates based on a Poisson regression model, considering that the outcome variable, straw-burning spots, is a count variable. The model is clustered at the county level, and results with clustering at the prefecture-level are provided in Appendix Table A5.

In the overall sample, columns (1) and (3) of Panel A indicate no significant reduction in straw burning in the treatment group compared to the control group during the first year of policy implementation (autumn 2018 – spring 2019), when monitoring was strictly enforced. In contrast, during the COVID-19 period (autumn 2019 – spring 2020), when monitoring could not be effectively enforced, the treatment group experienced a significant reduction of approximately 14 straw-burning spots compared to the control group. Focusing specifically on springtime straw-burning activity (columns (1) and (3) of Panel B), the reduction was even more pronounced. In spring 2020, when COVID-19 disrupted monitoring efforts, the treatment group recorded about 25 fewer straw-burning spots than the control group. In comparison, columns (1) and (3) of Panel C show no significant difference in straw-burning spots between the treatment and control groups during autumn 2019. This finding supports the interpretation that the significant reduction observed in the overall sample (columns (1) and (3) of Panel A) is primarily driven by the disruption caused by COVID-19 in the spring of 2020. The above results suggest that while the subsidy has a limited impact on reducing straw burning when monitoring is strict, its effectiveness becomes significantly more pronounced when monitoring is weak.

Using the Poisson regression model, the results align with those from the OLS estimation, indicating that the subsidy's effect on reducing straw burning is significantly stronger under weak monitoring compared to stricter monitoring. The interpretation of coefficients of the Poisson regression model is different from that in OLS. For example, column (2) of Panel A indicates that, during the first year of policy implementation (autumn 2018 to spring 2019), the expected number of straw-burning spots in the treatment group was about 65.1% ($e^{-0.43}$) of the expected number in the control group. However, during the COVID-19 period (autumn 2019 to spring 2020), the expected number of straw-burning spots in the treatment group was only 32.8% ($e^{-1.11}$) of the expected number in the control group. This indicates a slight reduction in straw burning in the treatment group compared to the control group during the first year of policy implementation, but a much larger reduction during the COVID-19 period when monitoring was relaxed.

[Insert Table 4 here]

6.2 Effects of subsidy on air pollution

Graphical analysis. Figure 8 presents graphical analyses of $PM_{2.5}$ discontinuity during each straw-burning season. Notably, a $PM_{2.5}$ discontinuity (higher in the treatment group) was evident even before policy implementation (2014 – 2017), unlike the unclear discontinuity related to straw burning in Figure 6. In contrast, the discontinuity became less distinct when both control and treatment groups begin implementing straw-burning monitoring in autumn 2018 – spring 2019, accompanied by a reduction in $PM_{2.5}$ levels on both sides of the border. During the COVID-19 period (autumn 2019 – spring 2020), the variation in $PM_{2.5}$ levels, indicated by the width of the shaded area, showed a noticeable inflation in the control group (left side of the border), aligning with the straw-burning pattern depicted in Figure 6. This pattern becomes even more pronounced when focusing on springtime straw burning, as illustrated in Figure 9.[16]

[Insert Figure 8 here]

[Insert Figure 9 here]

16 The graphic analysis of $PM_{2.5}$ in autumn is shown in Appendix Figure A11.

Regression analysis. Table 5 presents a regression analysis of $PM_{2.5}$, following a similar design to the straw-burning model but excluding Poisson regression, as $PM_{2.5}$ is not a count variable. The results indicate a significant reduction in $PM_{2.5}$ (about 3.4 ug/m^3) in the treatment group only during spring 2020 compared to the control group, as shown in columns (1) and (2) of Panel B. In contrast, no significant changes were observed between the treatment and control groups during other periods. To ensure the robustness of our results, we apply the instrumental variable (IV) method. Specifically, we use the interaction term *Treat* × *Autumn 2019 – spring 2020* as an instrument for straw burning. The first-stage regression estimates the effect of this interaction on straw burning, followed by a second-stage regression estimating the impact of predicted straw burning on $PM_{2.5}$ (detailed methodology and results are provided in Appendix Table A7). Consistent with previous findings, the IV approach reveals a significant and positive impact of predicted straw burning on $PM_{2.5}$ only during spring, with no significant effects observed in other periods. This suggests that fluctuations in straw-burning activities closely correspond to similar changes in $PM_{2.5}$ in spring.

Additionally, we adjust the clustering level to the prefecture-level to test the results in Table 5 (see Appendix Table A6). This adjustment leads to substantially larger standard errors compared to those in Table 5, rendering the $PM_{2.5}$ reduction during spring 2020 statistically insignificant. In contrast, adjusting the clustering level does not produce similarly insignificant results when estimating its impact on straw burning (see Appendix Table A5). Combining these results, while the findings are somewhat sensitive to the clustering adjustment, the consistent evidence from both the regression and IV analyses supports the conclusion that reduced straw burning likely contributed to the observed $PM_{2.5}$ decline in spring 2020.

[Insert Table 5 here]

6.3 Heterogeneity analysis

COVID-19 cases. As indicated by the results, the discontinuity in straw burning between the control and treatment groups appears to be driven by the impact of COVID-19. To strengthen this analysis, we perform a heterogeneity analysis based on the monitoring costs associated with straw burning, measured by the total number of COVID-19 cases reported before April

30th. Following a similar analysis by Qi, et al. (2024), we use the second quantile threshold of 27 cases to classify the sample into low- and high-severity subsamples. We then re-estimate the SRD-DID model separately for these subsamples to evaluate the subsidy effects on straw burning. The results are presented in Panel A of Table 6, where columns (1) and (2) report findings for both autumn and spring samples, while columns (3) and (4) focus exclusively on spring samples.

Our findings suggest that the subsidy effects on straw burning were more pronounced in high-severity COVID-19 regions compared to low-severity regions. Notably, in spring 2020, the treatment group reported 61 fewer straw-burning spots, despite both the control and treatment groups experiencing severe COVID-19 outbreaks (columns (3) and (4) of Panel A). In contrast, this gap narrowed to only 14 spots where regions experienced COVID-19 severity relatively lower (columns (1) and (2) of Panel A). Combining these results with the previous graphical analysis (Figure 6), the findings suggest that the rebound in straw burning in the treatment group was significantly smaller than in the control group, even when both faced considerable challenges to straw-burning monitoring caused by severe COVID-19 conditions.

Maize proportion. Additionally, we conduct a heterogeneous analysis of monitoring costs, measured by the maize proportion in the grain-planting area. Compared to wheat and rice, maize generates significantly more straw in Northeast China, with a straw-to-grain ratio twice as high as that of the other two grain crops (Xing, et al., 2022). Therefore, counties with a higher maize proportion in their grain-planting areas face greater resistance from farmers against straw-burning bans, leading to higher monitoring costs. Following a similar approach to the COVID-19 case analysis, we use the second quantile threshold of 69% to classify the sample into low- and high-maize-proportion subsamples. The corresponding results are reported in Panel B of Table 6. Consistent with the findings in Panel A, the subsidy effects on straw burning are more pronounced in high-maize-proportion regions compared to low-proportion areas.

[Insert Table 6 here]

6.4 Robustness check

We conduct robustness checks across three dimensions. First, we adjust the polynomial order and distance bandwidth to assess the sensitivity of our results to these parameters. Second, we perform a parallel trend test to examine the pre-trends prior to policy implementation required by the DID models (Hou, et al., 2021, Chen, et al., 2022). Third, we present results using standard SRD specifications, following the setup from Wuepper, et al. (2020).

Sensitivity analysis. We estimate equation (7) using polynomial functions of orders 0 through 4, with the corresponding results presented in Appendix Table A8. The findings indicate that the results remain stable across different polynomial orders and are consistent with those reported in Table 4. Second, we estimate equation (7) using various distance bandwidths, including 70 km, 200 km, 300 km, and the full sample presented in Appendix Table A9. The results reveal that the coefficient of *Treat* × *Autumn 2018 – spring 2019* is insignificant when using the 70 km bandwidth but becomes significant at 95% and even 99% confidence levels when the bandwidth exceeds 200 km. In contrast, the coefficient of *Treat* × *Autumn 2019 – spring 2020* remains consistently significant across bandwidth selections, aligning with the results reported in Table 4. These findings suggest that the significance of the estimated subsidy effect on straw burning is sensitive to the chosen bandwidth only under strict straw-burning monitoring (*Treat* × *Autumn 2018 – spring 2019*), but its magnitude remains lower than that observed under weak monitoring conditions, aligning with the results in Table 4.

Parallel trend test. Appendix Figure A12 displays the parallel trend test for straw burning, using two sample sets: Panel A shows results within a 142 km radius, while Panel B presents findings from the full sample.[17] The results indicate no evidence of a pre-trend before policy implementation in the 142 km sample. Additionally, the difference between the treatment and control groups during the first year after the policy (Autumn 2018 – Spring 2019) remains similar to the difference observed before the policy. However, this difference expands significantly in the subsequent year (Autumn 2018 – Spring 2020). These findings support the results reported in Table 4, indicating that the subsidy had a significant effect during the

17 We also report the parallel trend test for $PM_{2.5}$ in Appendix Figure A13.

COVID-19 year. However, when extending the analysis to the full sample, an observable pre-trend emerges prior to policy implementation. This suggests that selecting counties closer to the border provides a more comparable control group than including those farther away. Therefore, applying the SRD-DID approach is appropriate in this context.

Standard SRD estimates. We separately estimate the SRD model for each straw-burning season using triangular kernels. The results are reported in Appendix Table A10, with Panel A presenting the findings for a 0th-order polynomial (which does not account for the distance function) and Panel B showing the results for a 3rd-order polynomial of the distance function. In Panel A, where the distance function is not considered, the differences between the control and treatment groups are not statistically significant before policy implementation (2014–2017) or even during the first policy year, when straw-burning monitoring was strict (2018–2019). However, this gap becomes significant and considerably larger during the COVID-19 year (2019–2020), indicating a pronounced policy effect during that period. Conversely, when applying the 3rd-order polynomial of the distance function in Panel B, the differences between the treatment and control groups remain insignificant across all straw-burning seasons, including the COVID-19 year. Notably, the bandwidth varies across different years, suggesting that the relationship between distance and straw burning is unstable over time. Therefore, we argue that employing the SRD-DID approach is more suitable for our analysis.

Conclusion

Command and control (CAC) and market-based instruments (MBIs) policies are often employed together in agri-environmental governance, and MBIs are regarded as more sustainable. However, empirical studies examining the interplay of CAC and MBIs policies in reducing agri-environmental pollution are limited. This study uses the straw-burning control in Northeastern China as a case study. Leveraging well-timed panel data, this study investigates the effects of a MBI policy (i.e., subsidization) on controlling straw burning in Northeast China, conditional on varying intensities of CAC interventions. Our findings are as follows: First, during periods of stringent straw-burning monitoring, subsidization yielded only a marginal reduction in straw-burning activities compared to the control group, indicating limited MBI impact when regulatory enforcement was robust. Second, during the COVID-19 pandemic, when monitoring efforts were relaxed, straw burning significantly rebounded in the control group. However, this rebound was substantially mitigated in the treatment group receiving subsidies, suggesting that subsidies can play a crucial role when regulatory enforcement weakens. Third, the effectiveness of subsidies was more pronounced in regions with higher COVID-19 severity and greater maize proportions in grain-planting areas, where monitoring costs were higher, and farmers exhibited stronger resistance to straw-burning bans. Lastly, the subsidy-driven reduction in straw burning during the COVID-19 period resulted in a significant decline in $PM_{2.5}$ levels (about 3.4 ug/m^3). This finding highlights the potential environmental co-benefits of straw-burning governance.

In sum, the central insight for policy implications emerging from our findings is that MBIs demonstrate greater resilience in achieving governance outcomes compared to CAC policies. Our results indicate that MBIs demonstrate the function to sustain governance outcomes amidst unexpected disruptions over the long term, although these policies may not exhibit superior short-term effectiveness when CAC measures are strictly enforced, as CAC can efficiently achieve policy targets through direct regulation. This insight aligns with the principle of collective environmental governance, which highlights the MBI function in promoting public voluntary participation and balancing interests across multiple stakeholders

(Ansell, et al., 2008, Bodin, 2017). By fostering a more adaptive and cooperative relationship among muti-stakeholders, MBIs can more effectively coordinate motivations to take actions that flexibly address unexpected external shocks. Conversely, CAC policies demonstrate rigid fragility when mandatory force becomes infeasible due to external shocks. However, our results do not negate the role of CAC policies. Our findings show that a rebound in straw burning occurred in Heilongjiang (Figure 6), albeit to a lesser extent compared to neighboring provinces with weaker subsidy support. Therefore, we argue for the adoption of a hybrid policy framework for agri-environmental governance, as proposed by Smith (2019). He suggested that effective regulation and monitoring form the foundation of the policy framework, upon which comprehensive and targeted payment schemes are implemented to promote sustainable technologies as alternative approaches to pollution reduction.

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, 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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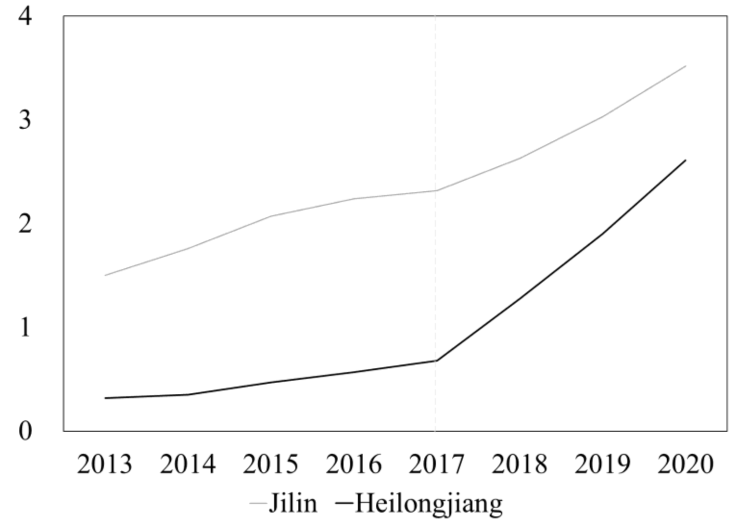
Panel A: Straw returning seeder, a thousand units



Panel B: Straw-baling machine, a thousand units

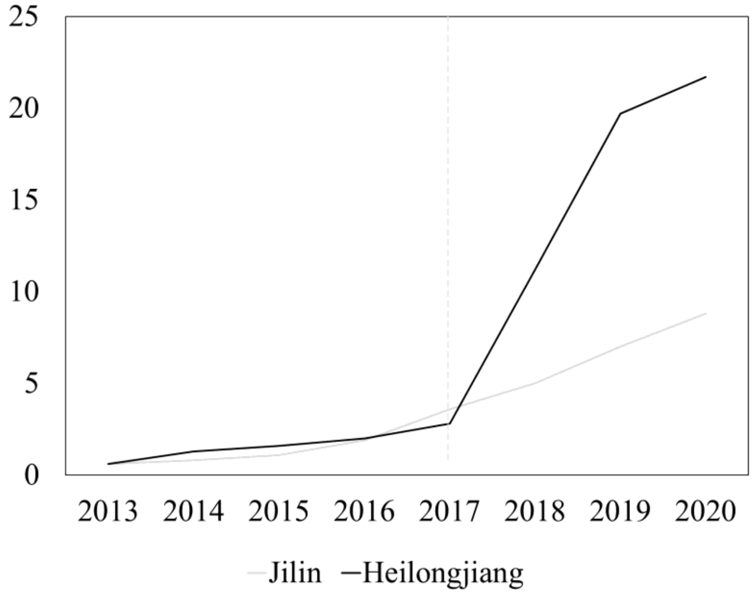


Figure 1. Temporal changes in straw-returning machines

Note:

(a) Data source: China Agricultural Machinery Yearbook (2014–2021). The yearbook provides data on the number of machines from the preceding year. For instance, the 2019 yearbook reports the number of machines for 2018.

(b) The dashed line represents the policy implementation year.

(c) Straw-returning seeders and straw-baling machines are the most expensive equipment used for straw-returning practices. Straw-returning seeders, also known as a no-till seeder, are designed to plant seeds directly into soil mixed with straw residues, with a price of approximately 50,000 yuan (about 7,000 USD). In contrast, a straw-baling machine compresses and packs straw that cannot be returned to the soil into bales, which can be transported and utilized by enterprises. The cost of a straw-baling machine is around 100,000 yuan (about 14,000 USD). More details about straw-returning costs are shown in Appendix Table A2.

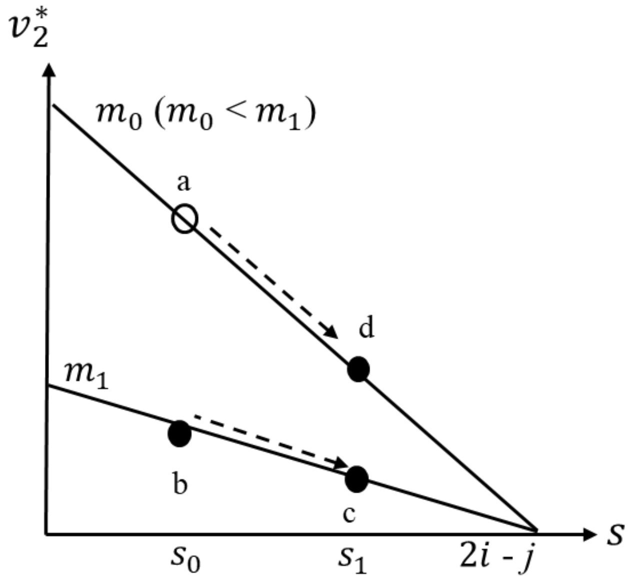


Figure 2. The visual depiction of the theoretical framework

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

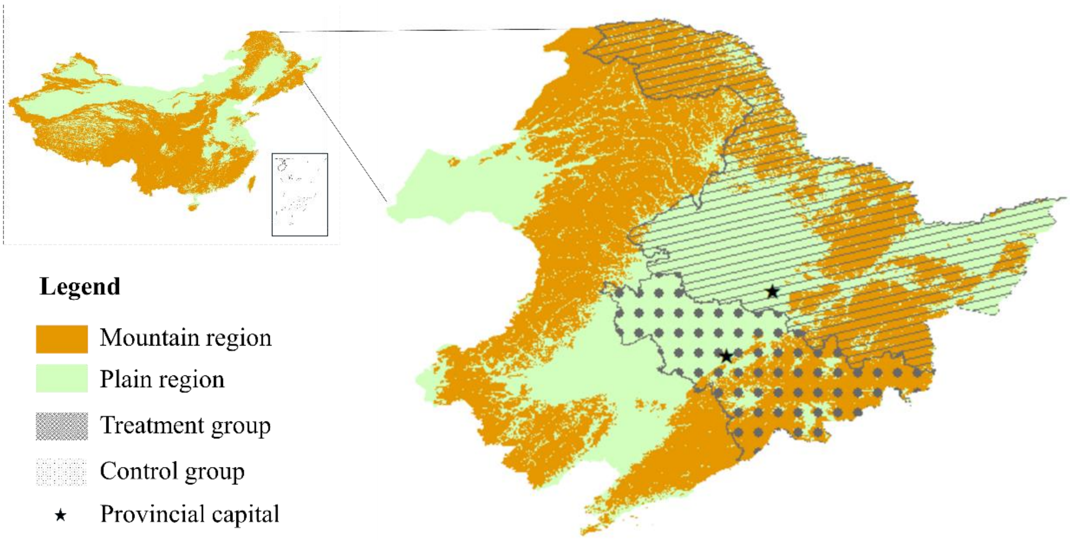


Figure 3. Northeast China and research regions

Note:
(a) The treatment group is Heilongjiang Province, while the control group is Jilin Province.

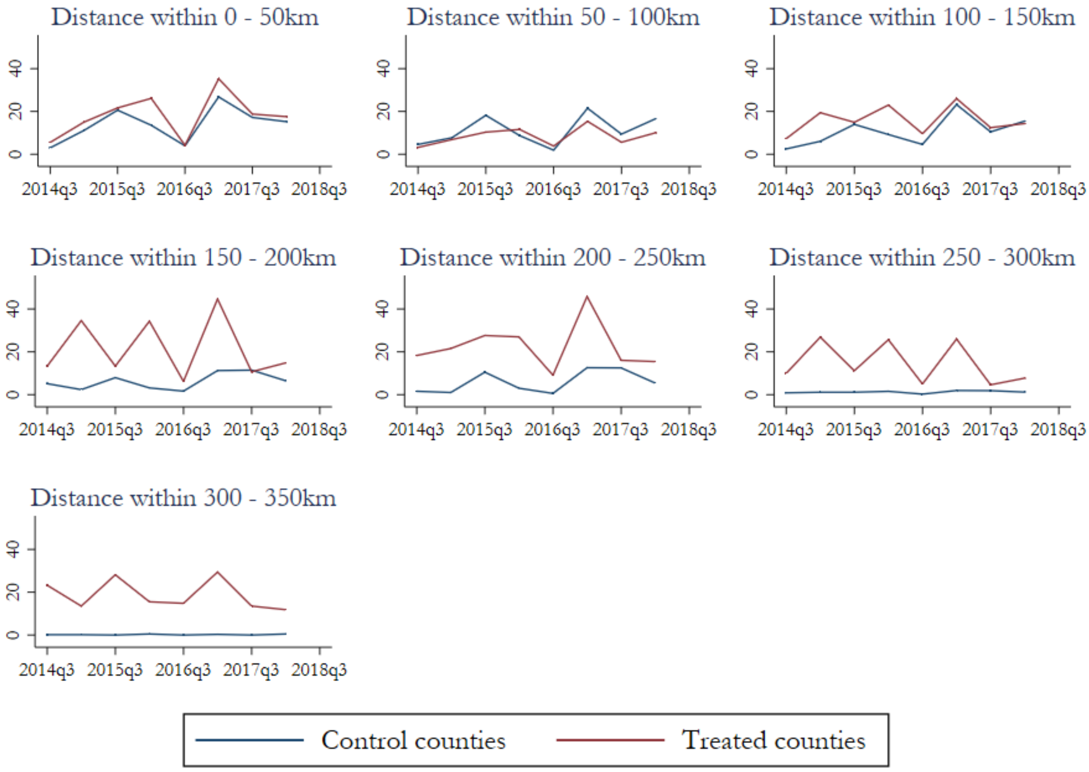
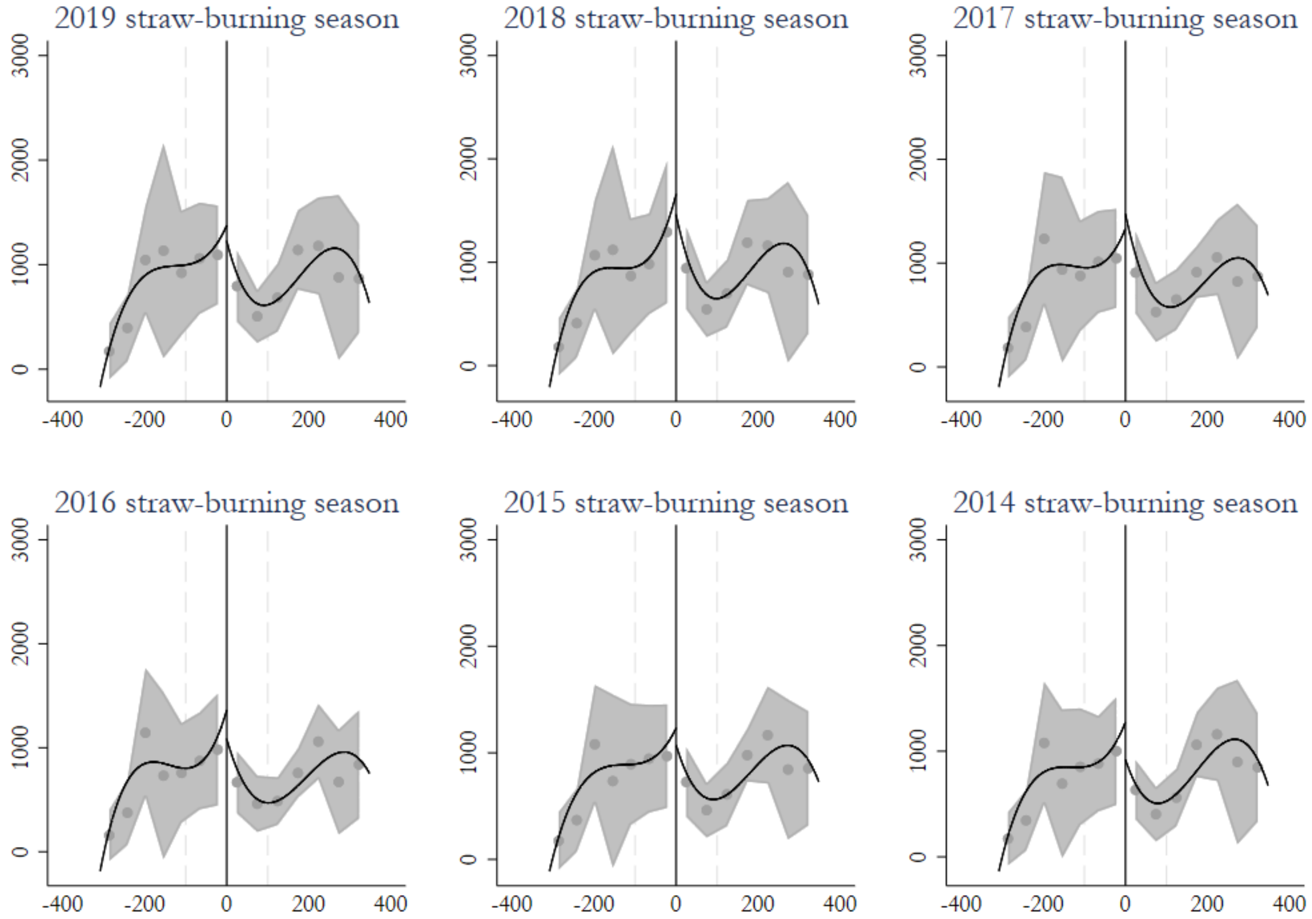


Figure 4. Spatial and temporal analysis of straw-burning spots

Note:
(a) Data source: National Aeronautics and Space Administration of America.
(b) The treated counties are in Heilongjiang Province, while the control counties are in Jilin Province.
(c) Distance refers to the distance from counties to the border.
(d) 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.
(e) The vertical axis signifies the average value of straw-burning spots throughout the season.

Figure 5. The Spatial-Regression-Discontinuity (SRD) graphic analysis of grain-planting area



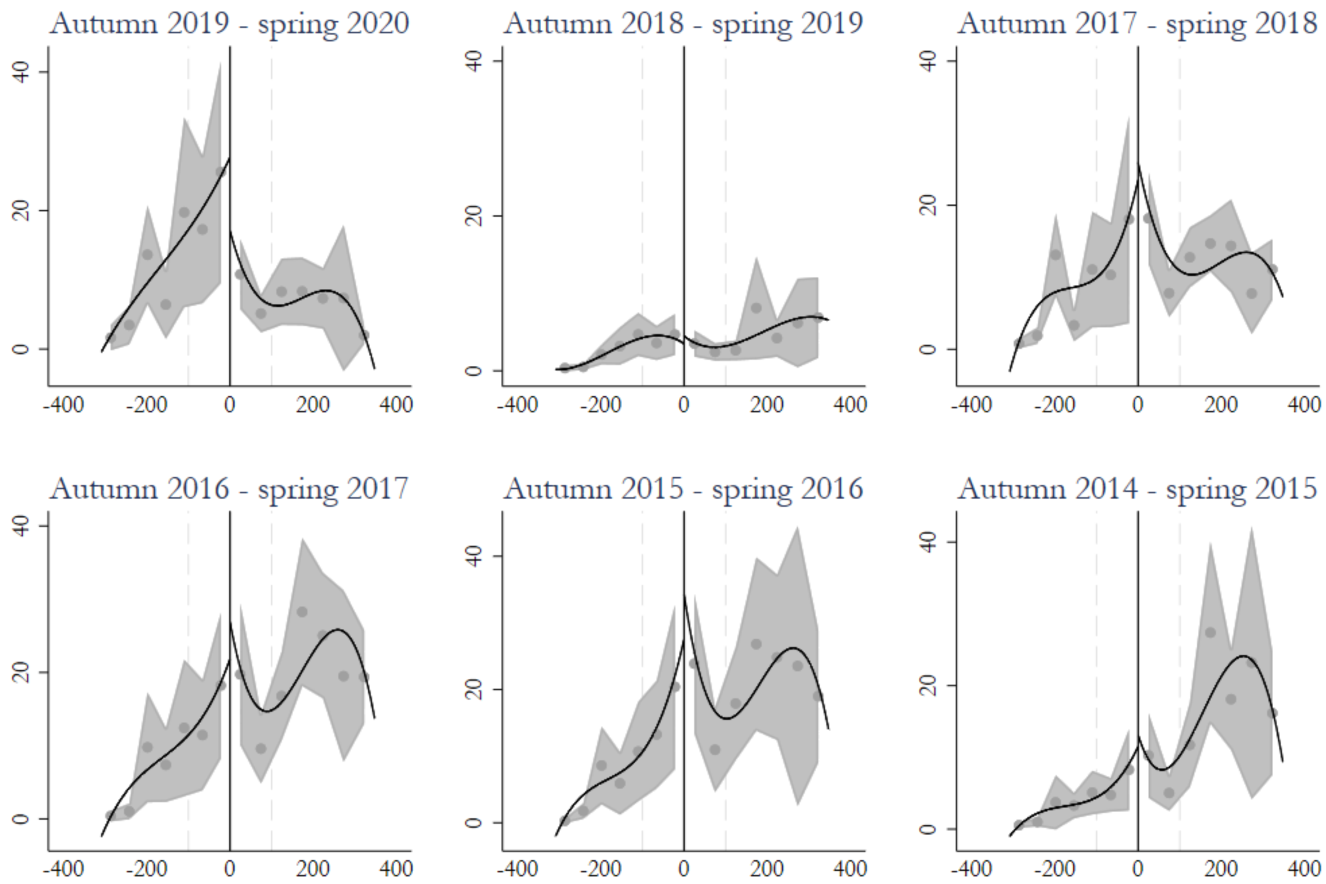
Note:

(a) The circle represents the average value of area grain planting area within uniformly distributed 50 km bins.

(b) The vertical line serves as the border, with the left side representing the control group (Jilin) and the right side representing the treatment group (Heilongjiang).

(c) The dashed line indicates the distance bandwidth of 142 km used in the subsequent estimations.

Figure 6. The Spatial-Regression-Discontinuity (SRD) graphic analysis of straw-burning spots



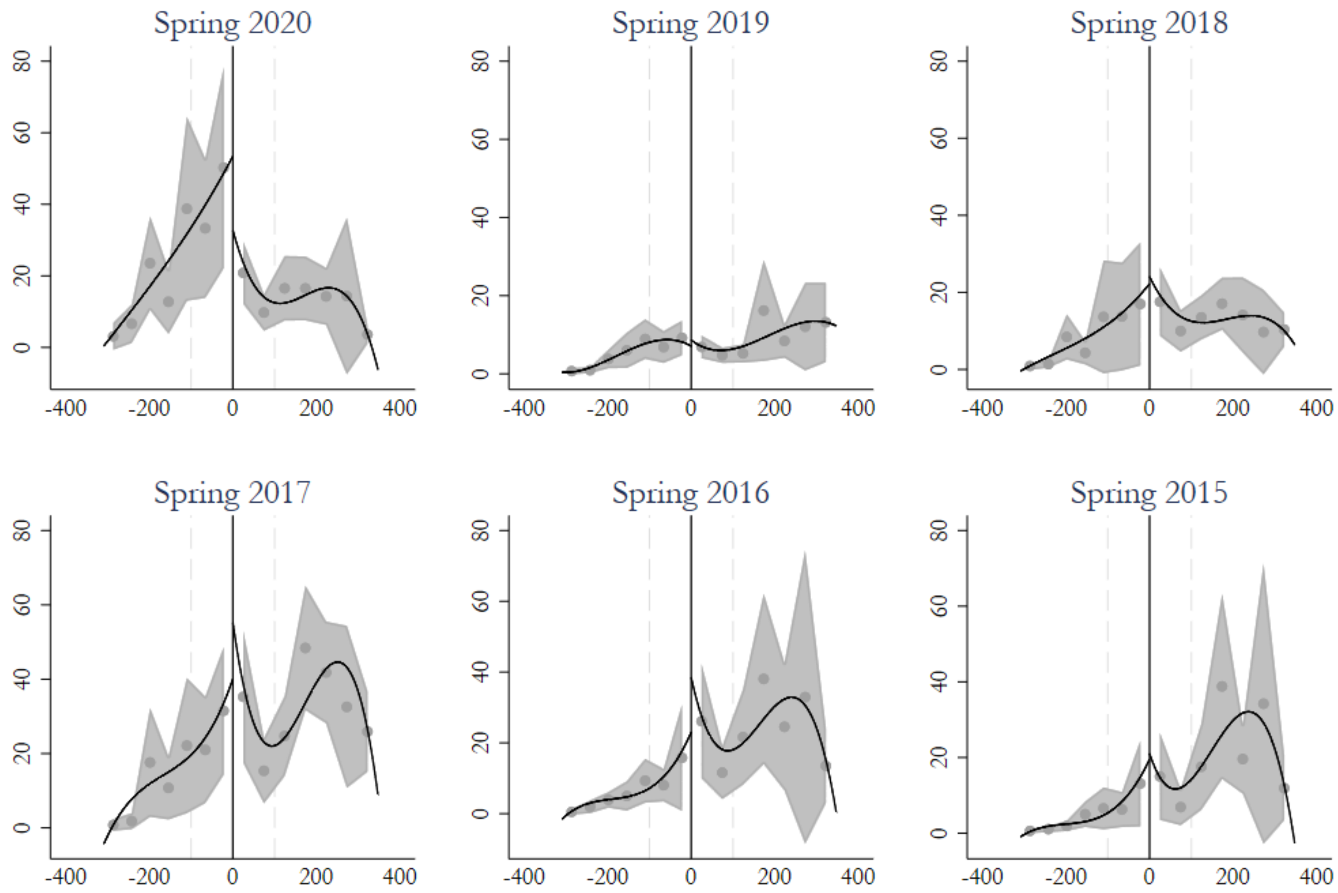
Note:

(a) The circle represents the average value of straw-burning spots within uniformly distributed 50 km bins.

(b) The vertical line serves as the border, with the left side representing the control group (Jilin) and the right side representing the treatment group (Heilongjiang).

(c) The dashed line indicates

Figure 7. The Spatial-Regression-Discontinuity (SRD) graphic analysis of straw-burning spots in spring

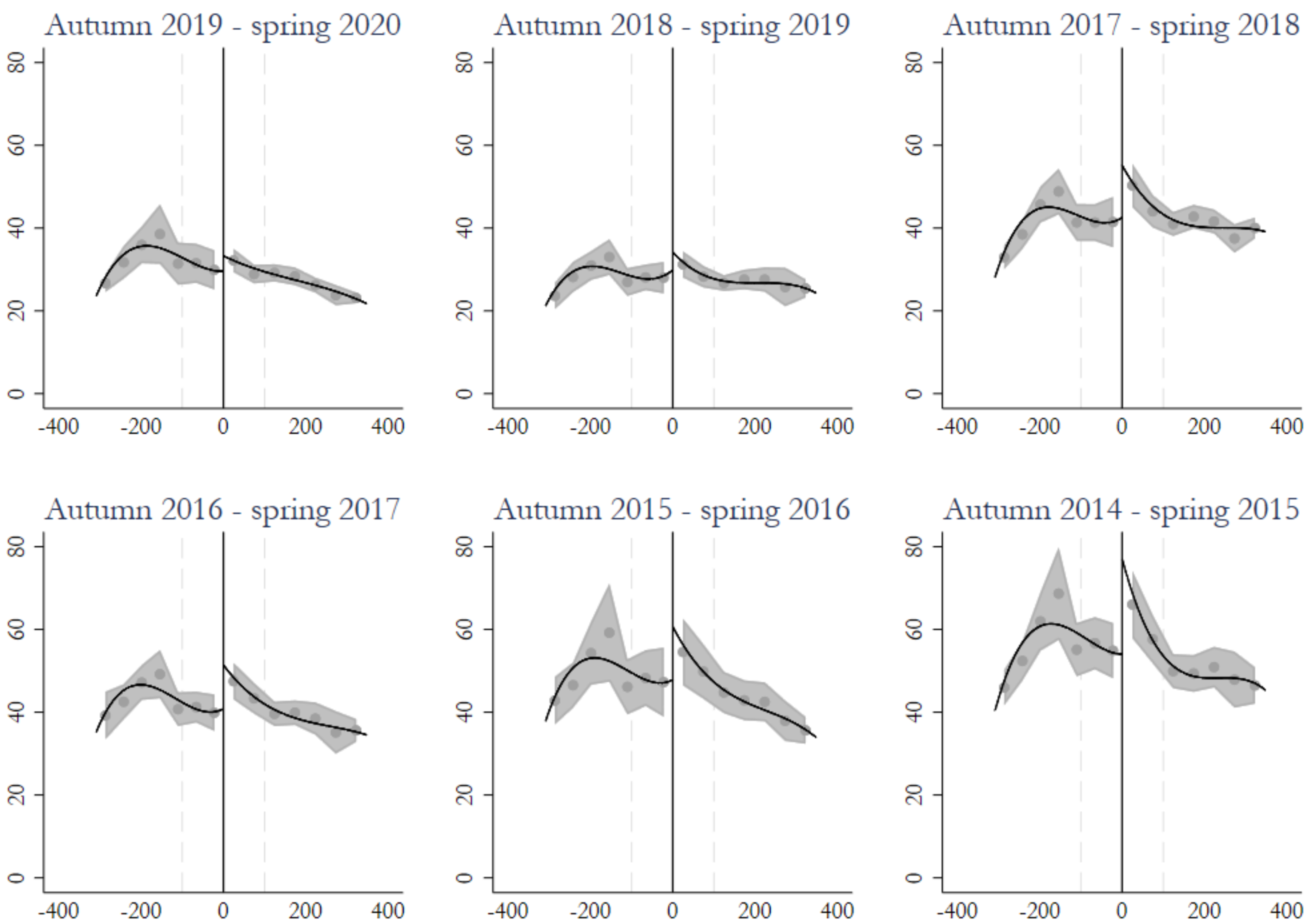


Note:

(a) The circle represents the average value of straw-burning spots within uniformly distributed 50 km bins.

(b) The vertical line serves as the border, with the left side representing the control group (Jilin) and the right side representing the treatment group (Heilongjiang).

Figure 8. The Spatial-Regression-Discontinuity (SRD) graphic analysis of $PM_{2.5}$



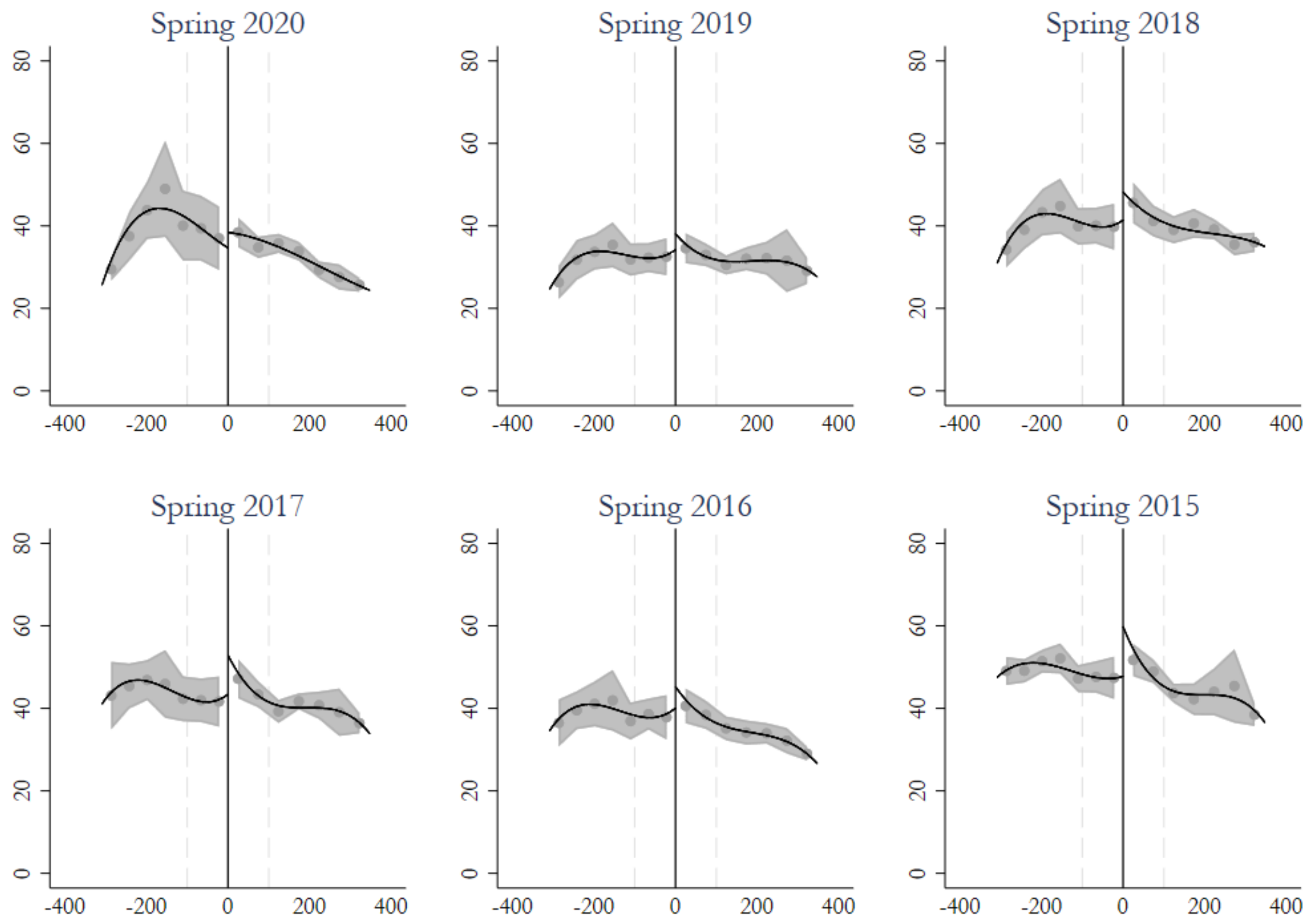
Note:

(a) The circle represents the average value of $PM_{2.5}$ [ug/m^3] within uniformly distributed 50 km bins.

(b) The vertical line serves as the border, with the left side representing the control group (Jilin) and the right side representing the treatment group (Heilongjiang).

(c) The dashed line indicates the distance bandwidth of 142 km used in the subsequent estimations.

Figure 9. The Spatial-Regression-Discontinuity (SRD) graphic analysis of $PM_{2.5}$ in spring



Note:

(a) The circle represents the average value of $PM_{2.5}$ [ug/m^3] within uniformly distributed 50 km bins.

(b) The vertical line serves as the border, with the left side representing the control group (Jilin) and the right side representing the treatment group (Heilongjiang).

(c) The dashed line indicates the distance bandwidth of 142 km

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
Jan. 2020–Apr. 2020 (COVID-19)	Weak monitoring	450 yuan /ha	Weak monitoring	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.
(e) Jan. 2020–Apr. 2020 marks the period of the lock-in policy due to COVID-19 during the straw-burning season.

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

	Full sample				Heilongjiang Province		Jilin Province		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	4,248				2,856		1,392		4,248	
# of counties	177				119		58		177	
Dependent variables										
Grain planting area index	792.20	[850.51]	0	4146	782.35	(31.90)	812.41	(45.47)	-30.06	(55.64)
Total value of straw-burning spots	11.62	[26.05]	0	311	13.37	(0.52)	8.03	(0.55)	5.34***	(0.85)
Average value of $PM_{2.5}$, ug/3	38.45	[18.09]	3.30	145.90	36.85	(0.33)	41.72	(0.49)	-4.87***	(0.58)
Climate variables										
Average value of precipitation, mm	22.06	[11.47]	0.83	75.61	21.07	(0.19)	24.10	(0.35)	-3.02***	(0.18)
Average value of temperature, Celsius	1.50	[5.84]	-20.91	11.30	0.75	(0.11)	3.05	(0.13)	-2.30***	(0.18)
Average value of wind speed, m/s	3.05	[0.62]	1.27	5.16	3.22	(0.01)	2.71	(0.01)	0.50***	(0.02)

Note:
(a) We have a total of 177 counties over the period of Oct. 2014 till Apr. 2020 (for 6 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 4,248 observations in our database.
(c) There are 76 counties (1,824 observations) located within a 142 km distance, including 45 counties (1,080 observations) in Heilongjiang and 31 counties (744 observations) in Jilin. The statistical summary of these counties is provided in the Appendix Table.
(d) Data source: Author’s collection

Table 3. SRD-DID analysis in the grain-planting area using different polynomials

	0^{th}	1^{st}	2^{nd}	3^{rd}	4^{th}
Sample within 142 km distance bandwidth					
Treat × 2018 straw-burning season	33.50	33.50	33.50	33.50	33.50
	(63.82)	(63.96)	(64.11)	(64.25)	(64.40)
Treat × 2019 straw-burning season	-25.29	-25.29	-25.29	-25.29	-25.29
	(42.76)	(42.85)	(42.95)	(43.05)	(43.14)
SRD variables	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
County number	76	76	76	76	76
Observation	456	456	456	456	456
AIC	7359.5	7357.4	7338.8	7338.1	7332.2
Full sample					
Treat × 2018 straw-burning season	9.81	9.81	9.81	9.81	9.81
	(51.83)	(51.88)	(51.93)	(51.98)	(52.03)
Treat × 2019 straw-burning season	-18.90	-18.90	-18.90	-18.90	-18.90
	(43.62)	(63.31)	(63.48)	(63.65)	(63.82)
SRD variables	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
County number	76	76	76	76	76
Observation	1062	1062	1062	1062	1062
AIC	17355.7	17328.5	17311.5	17308.2	17303.7

Note:
(a) The outcome variable is month-county straw-burning spots.
(b) *Treat* takes the value of 1 for counties in Heilongjiang (distance > 0) as the treatment group and takes the value of 0 for the counties in Jilin (distance < 0) as the control group.
(c) SRD (Spatial Regression Discontinuity) variables include *treat*, the distance function with a 1^{st} to 4^{th} order polynomial, and the interaction between *treat* and the distance function.
(d) The 2018 straw-burning season includes data from autumn 2018 to spring 2019, while the 2019 straw-burning season includes data from autumn 2019 to spring 2020. Spring refers to March and April, while autumn refers to October and November.
(e) AIC: Akaike Information Criterion
(f) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Effects of subsidy on straw-burning spots

	SRD-DID		DID	
	OLS	Poisson	OLS	Poisson
	(1)	(2)	(3)	(4)
Panel A. Sample in both autumn and spring				
Treat × Autumn 2019 – spring 2019	-3.62	-0.43**	-4.26	-0.53***
	(2.777)	(0.198)	(2.806)	(0.199)
Treat × Autumn 2019 – spring 2020	-14.31***	-1.11***	-14.27***	-1.11***
	(2.496)	(0.122)	(2.423)	(0.124)
SRD variables	Y	Y		
County fixed effect			Y	Y
Observation	1,824	1,824	1,824	1,824
R^2	0.178		0.340	
Panel B. Sample in spring				
Treat × Spring 2019	-3.75	-0.45**	-5.53*	-0.58***
	(3.050)	(0.186)	(3.206)	(0.184)
Treat × Spring 2020	-25.83***	-1.20***	-25.38***	-1.15***
	(5.741)	(0.163)	(5.551)	(0.165)
Climate factors	Y		Y	
SRD variables	Y	Y		
County fixed effect			Y	Y
Observation	912	912	912	912
R^2	0.212		0.467	
Panel C. Sample in autumn				
Treat × Autumn 2018	-0.97	-1.05*	-2.14	-1.10**
	(2.922)	(0.544)	(2.792)	(0.480)
Treat × Autumn 2019	-2.68	-0.94**	-4.01	-1.08**
	(2.876)	(0.477)	(3.069)	(0.532)
Climate factors	Y		Y	
SRD variables	Y	Y		
County fixed effect			Y	Y
Observation	912	912	912	912
R^2	0.165		0.362	

Note:

(a) The outcome variable is month-county straw-burning spots.

(b) *Treat* takes the value of 1 for counties in Heilongjiang (distance > 0) as treatment group and takes the value of 0 for the counties in Jilin (distance < 0) as control group.

(c) SRD (Spatial Regression Discontinuity) variables include *treat*, the distance function with a third-order polynomial, and the interaction between *treat* and the distance function. The distance bandwidth is 142 km.

(d) The climate variables include precipitation, temperature, and wind speed.

(e) Spring: March and April; Autumn: October and November

(d) We control climatic factors as well as year and month fixed effects in all models.

(f) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Effects of straw burning on $PM_{2.5}$

	SRD-DID	DID
	(1)	(2)
Panel A. Sample in both autumn and spring		
Treat × Autumn 2019 – spring 2019	0.55	1.17
	(1.586)	(1.719)
Treat × Autumn 2019 – spring 2020	-1.82	-0.86
	(1.581)	(1.757)
SRD variables	Y	
County fixed effect		Y
Observation	1,824	1,824
R^2	0.462	0.685
Panel B. Sample in spring		
Treat × Spring 2019	0.92	0.48
	(0.581)	(0.644)
Treat × Spring 2020	-3.43***	-3.30***
	(1.234)	(1.195)
SRD variables	Y	
County fixed effect		Y
Observation	912	912
R^2	0.367	0.735
Panel C. Sample in autumn		
Treat × Autumn 2018	-2.57	-0.95
	(3.087)	(3.052)
Treat × Autumn 2019	-2.09	-0.65
	(3.011)	(3.100)
SRD variables	Y	
County fixed effect		Y
Observation	912	912
R^2	0.589	0.811

Note:

(a) The outcome variable is month-county $PM_{2.5}$ [ug/m^3].
(b) *Treat* takes the value of 1 for counties in Heilongjiang (distance > 0) as treatment group and takes the value of 0 for the counties in Jilin (distance < 0) as control group.
(c) SRD (Spatial Regression Discontinuity) variables include *treat*, the distance function with a third-order polynomial, and the interaction between *treat* and the distance function. The distance bandwidth is 142 km.
(d) The climate variables include precipitation, temperature, and wind speed.
(e) Spring: March and April; Autumn: October and November
(d) We control climatic factors as well as year and month fixed effects in all models.
(f) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Heterogeneous analysis of subsidy effects on straw-burning spots

	Autumn and spring		Spring	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Panel A: COVID-19 cases				
Treat × Autumn 2018 and spring 2019	3.59	3.88	2.15	5.59
	(2.683)	(5.913)	(2.452)	(5.604)
Treat × Autumn 2019 and spring 2020	-6.36***	-29.71***	-14.33***	-61.82***
	(1.820)	(5.950)	(3.935)	(16.591)
Climate factors	Y	Y	Y	Y
SRD variables	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
Month fixed effect	Y	Y	Y	Y
Observation	792	1,032	396	516
R^2	0.211	0.231	0.292	0.307
Panel B: The proportion of maize planting area				
Treat × Autumn 2018 – spring 2019	-2.33	-4.44	-3.15	-6.92
	(3.465)	(4.529)	(3.421)	(5.117)
Treat × Autumn 2019 – spring 2020	-10.19**	-19.04***	-22.82*	-33.92***
	(4.458)	(4.939)	(12.152)	(8.230)
Climate factors	Y	Y	Y	Y
SRD variables	Y	Y	Y	Y
Year fixed effect	Y	Y	Y	Y
Month fixed effect	Y	Y	Y	Y
Observation	948	876	474	438
R^2	0.174	0.224	0.206	0.290

Note:

(a) The outcome variable is month-county straw-burning spots.

(b) *Treat* takes the value of 1 for counties in Heilongjiang (distance > 0) as treatment group and takes the value of 0 for the counties in Jilin (distance < 0) as control group.

(c) SRD (Spatial Regression Discontinuity) variables include *treat*, the distance function with a third-order polynomial, and the interaction between *treat* and the distance function. The distance bandwidth is 142 km.

(d) The climate variables include precipitation, temperature, and wind speed.

(e) Spring: March and April; Autumn: October and November

(f) We classify the sample into low- and high-severity COVID-19 subsamples based on the second quantile threshold of 27 reported cases. Similarly, we use the second quantile threshold of 69% to distinguish between low- and high-maize-proportion subsamples.

(g) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

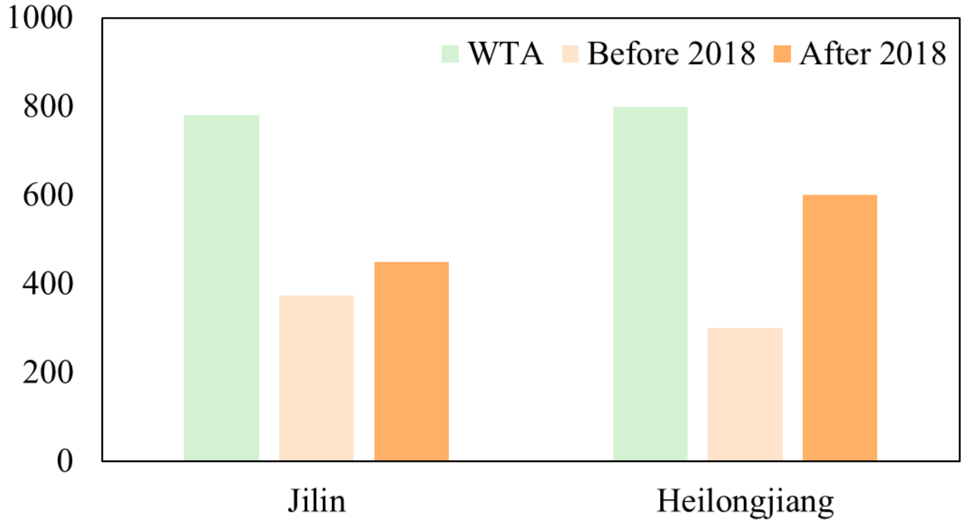
APPENDICES for

“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.

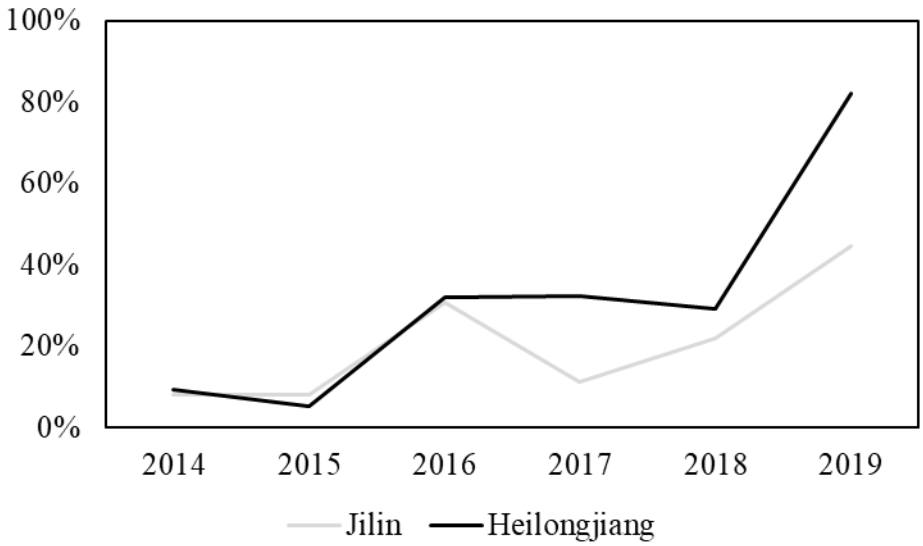
Appendix 1: Tables and figures

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. Proportion of satellite-based straw-burning spots in April relative to the total number of spots in spring



Note:
(a) Data source: National Aeronautics and Space Administration of America
(b) To enhance the comparability between Jilin and Heilongjiang, we focus on counties located near their shared border, specifically those within a 150 km radius of the border.

Figure A3. The distance to the border

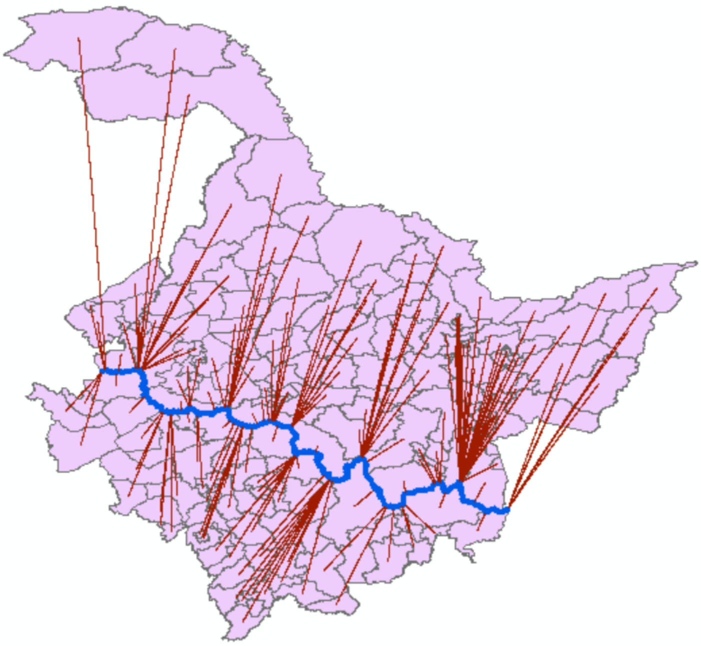
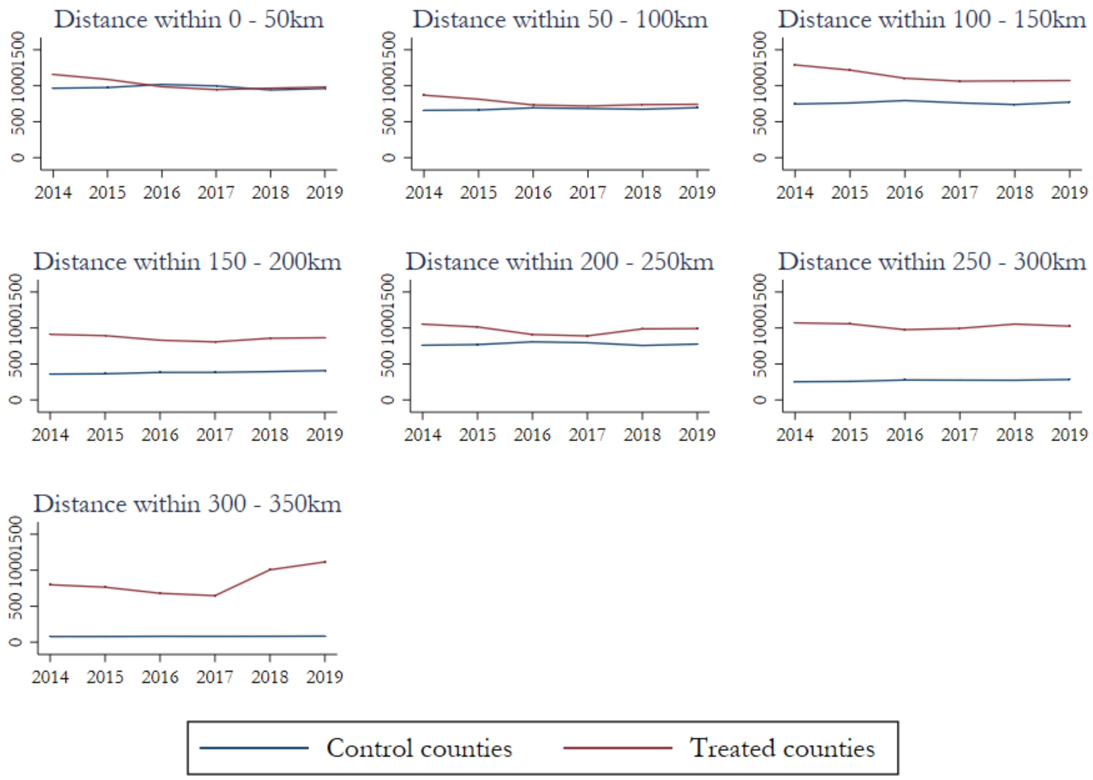
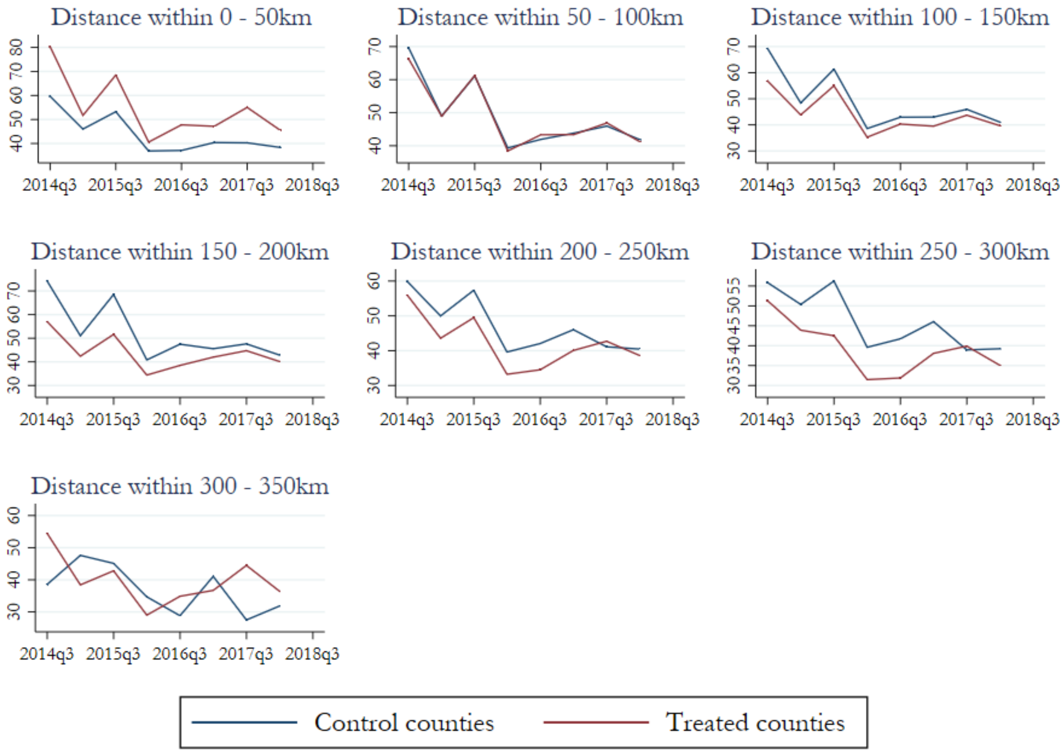


Figure A4. Spatial and temporal analysis of grain-planting area index



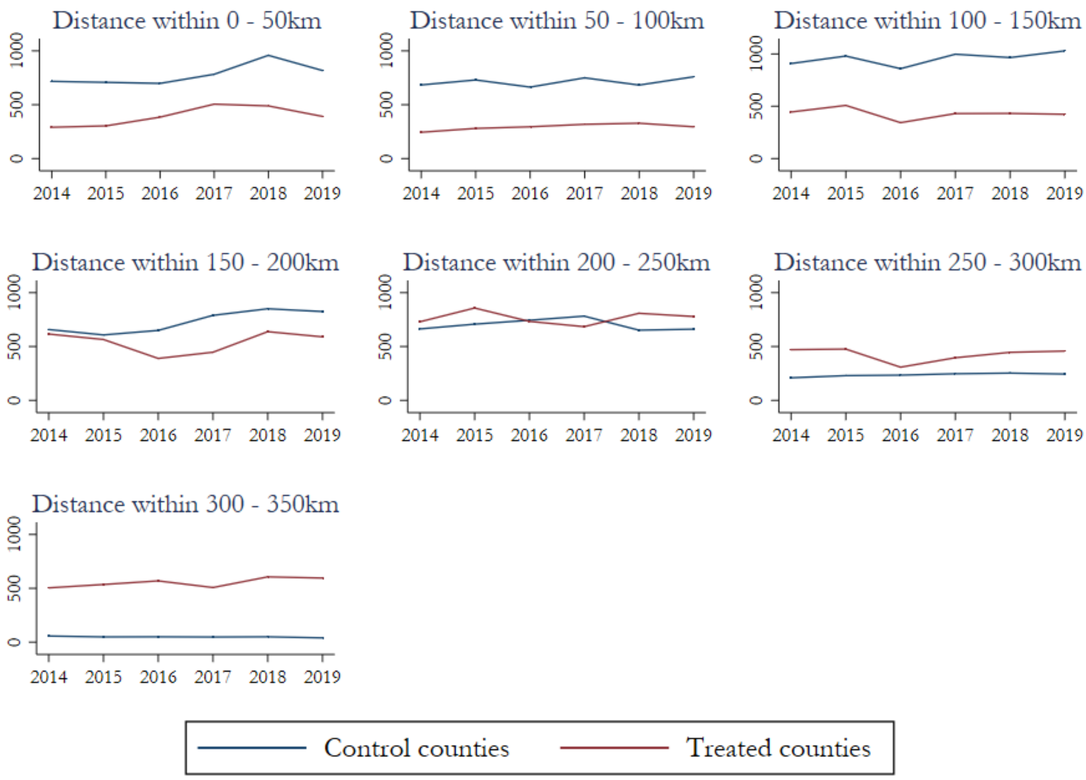
Note:
(a) Data source: the National Meteorological Information Center of China
(b) The treated counties are in Heilongjiang Province, while the controlled counties are in Jilin Province.

Figure A5. Spatial and temporal analysis of $PM_{2.5}$



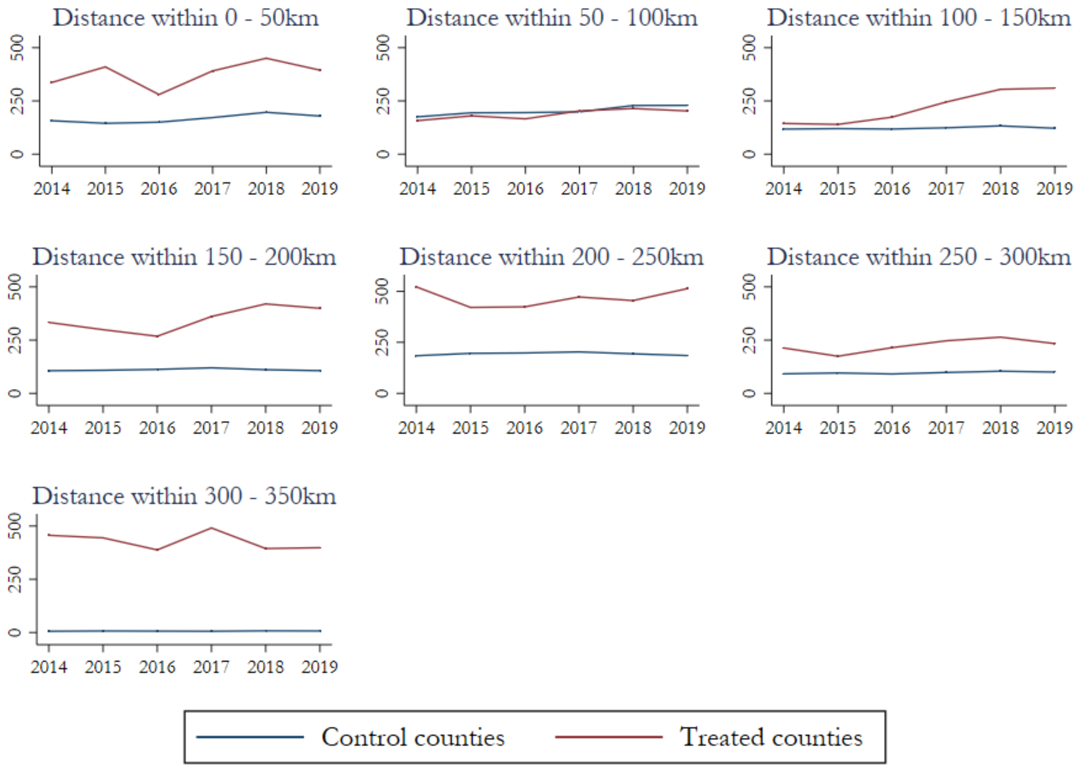
Note:
(a) Data source: the National Tibetan Plateau Data Center of China
(b) The treated counties are in Heilongjiang Province, while the controlled counties are in Jilin Province.
(c) Distance refers to the distance from counties to the border.
(d) The horizontal axis denotes the straw-burning season, where the abbreviations “q1” and “q3” denote spring (March and April) and autumn (October and November), respectively.
(e) The vertical axis signifies the average value of $PM_{2.5}$ [ug/m^3] throughout the season.

Figure A6. Spatial and temporal analysis of maize-planting area index



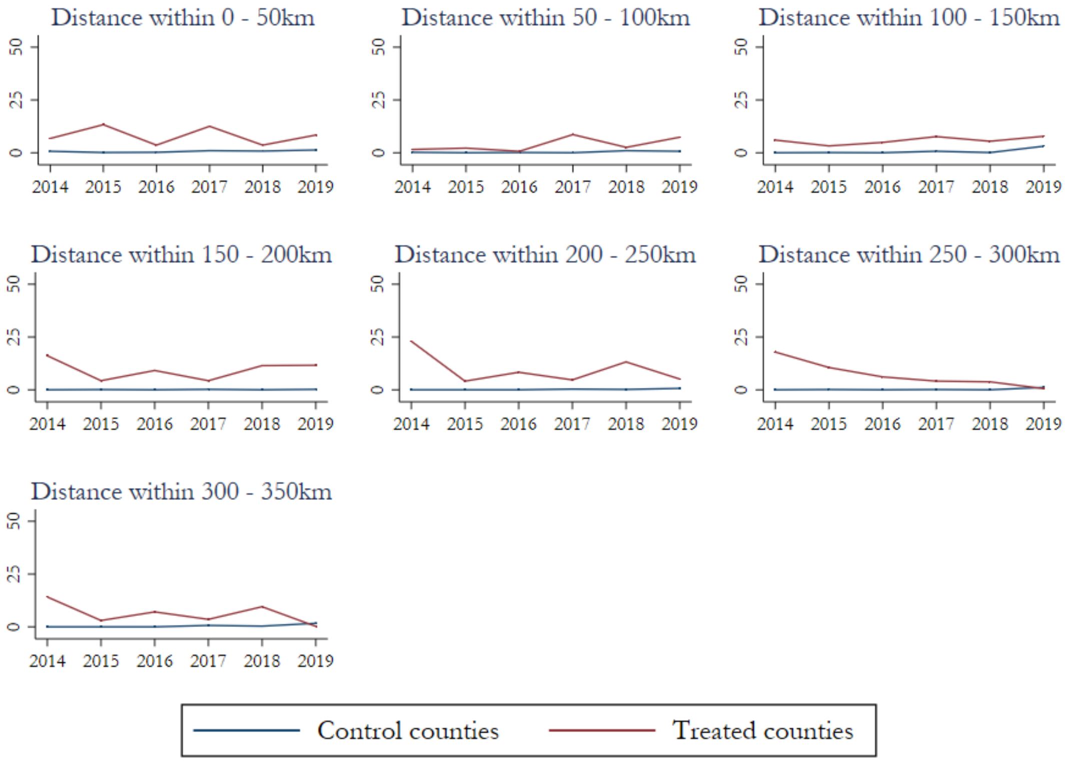
Note:
(a) Data source: the National Meteorological Information Center of China
(b) The treated counties are in Heilongjiang Province, while the controlled counties are in Jilin Province.

Figure A7. Spatial and temporal analysis of rice-planting area index



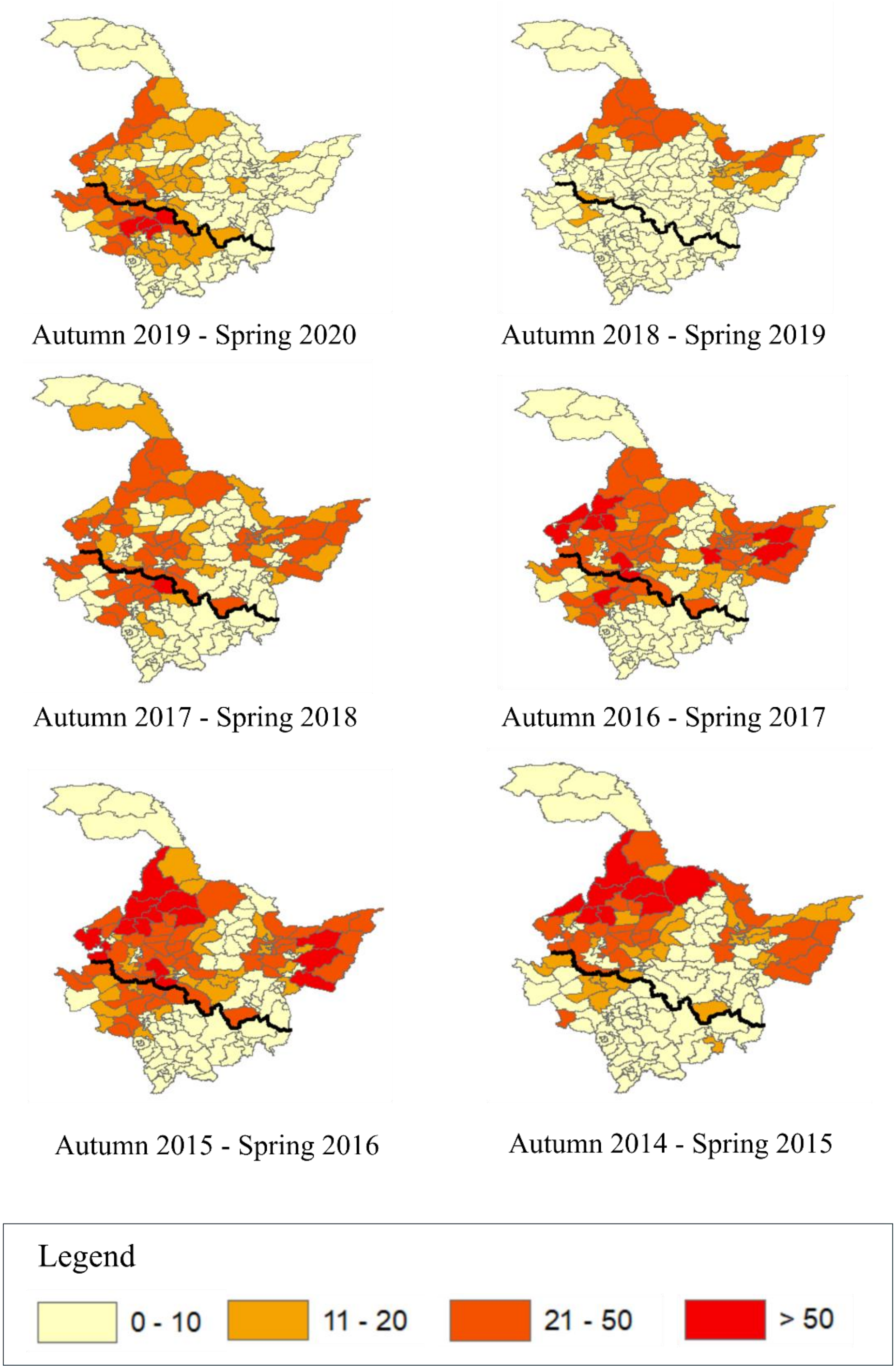
Note:
(a) Data source: the National Meteorological Information Center of China
(b) The treated counties are in Heilongjiang Province, while the controlled counties are in Jilin Province.

Figure A8. Spatial and temporal analysis of wheat-planting area index



Note:
(a) Data source: the National Meteorological Information Center of China
(b) The treated counties are in Heilongjiang Province, while the controlled counties are in Jilin Province.

Figure A9. Spatial distribution of straw-burning spots



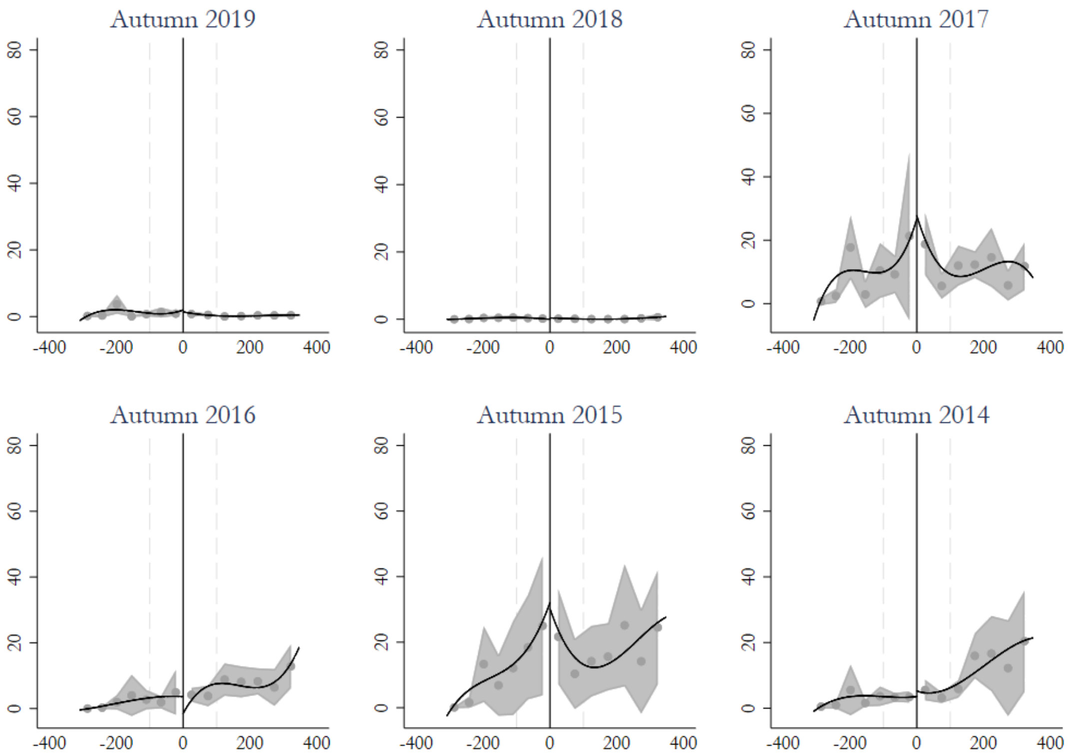
Note:

(a) Data source: National Aeronautics and Space Administration of America

(b) The color in the figures represents the average value of straw-burning spots during a specific period.

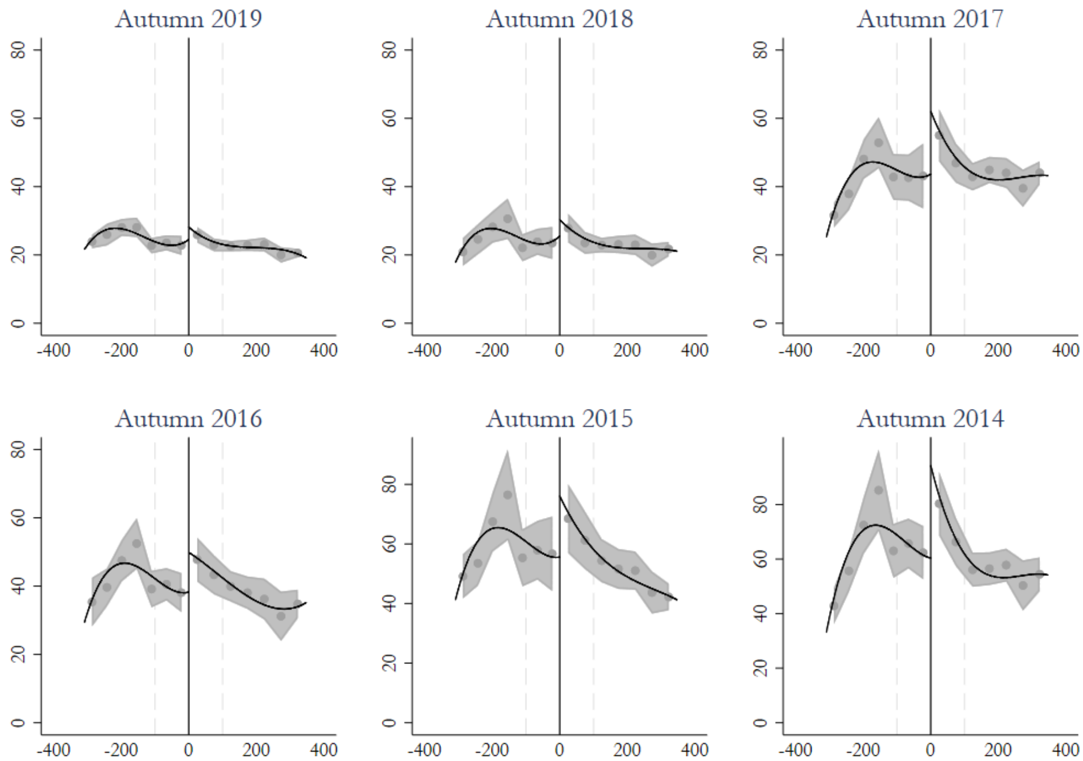
(c) The black line is the border between the Heilongjiang and Jilin. Counties situated to the right of the border fall within the Heilongjiang, while those on the left side belong to the Jilin.

Figure A10. The Spatial-Regression-Discontinuity (SRD) graphic analysis of straw-burning spots in autumn



Note:
(a) The circle represents the average value of straw-burning spots within uniformly distributed 50 km bins.
(b) The vertical line serves as the border, with the left side representing the control counties (Jilin) and the right side representing the treatment counties (Heilongjiang).
(c) The dashed line indicates the distance bandwidth of 142 km used in the subsequent estimations.
(d) The shaded area represents the 95% confidence interval.

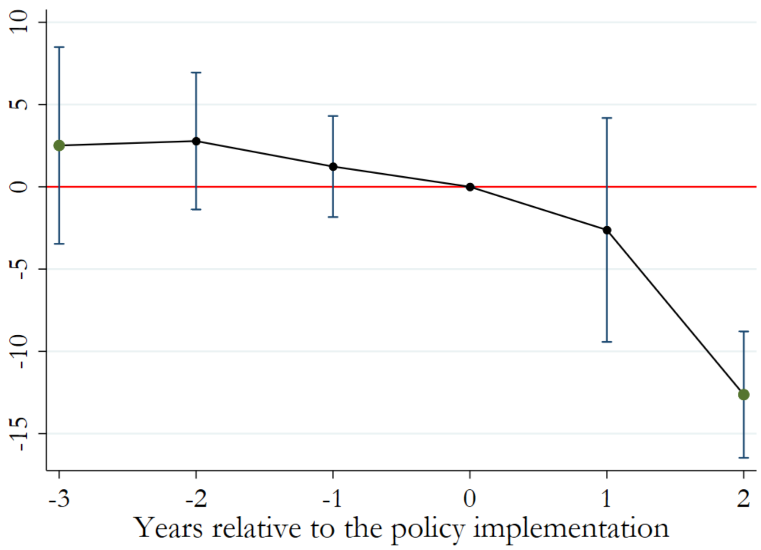
Figure A11. The Spatial-Regression-Discontinuity (SRD) graphic analysis of $PM_{2.5}$ in autumn



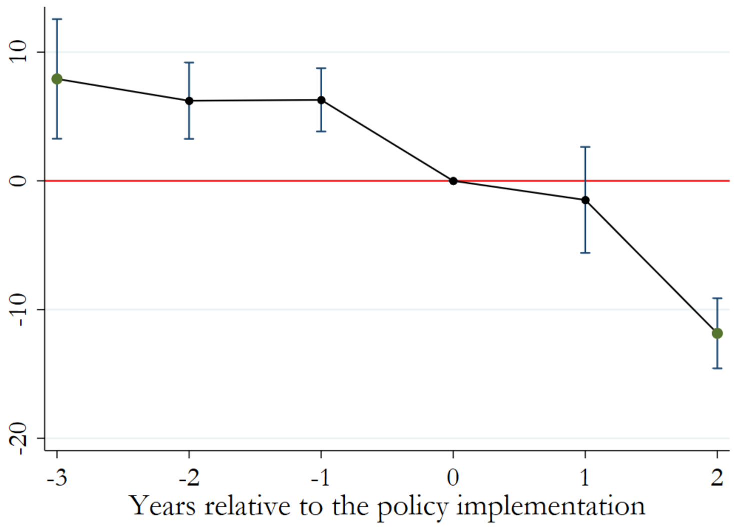
Note:
(a) The circle represents the average value of $PM_{2.5}$ [ug/m^3] within uniformly distributed 50 km bins.
(b) The vertical line serves as the border, with the left side representing the control counties (Jilin) and the right side representing the treatment counties (Heilongjiang).
(c) The dashed line indicates the distance bandwidth of 142 km used in the subsequent estimations.
(d) The shaded area represents the 95% confidence interval.

Figure A12. Parallel-trend test for straw burning

Panel A: Sample within 142 km distance



Panel B: Full sample



Note:

(a) Panel A reports the parallel-trend test for straw-burning spots using the data within 142 km distance bandwidth, while Panel B reports the parallel-trend test for straw-burning spots using the data using the full sample.

(b) We estimate the following specification:

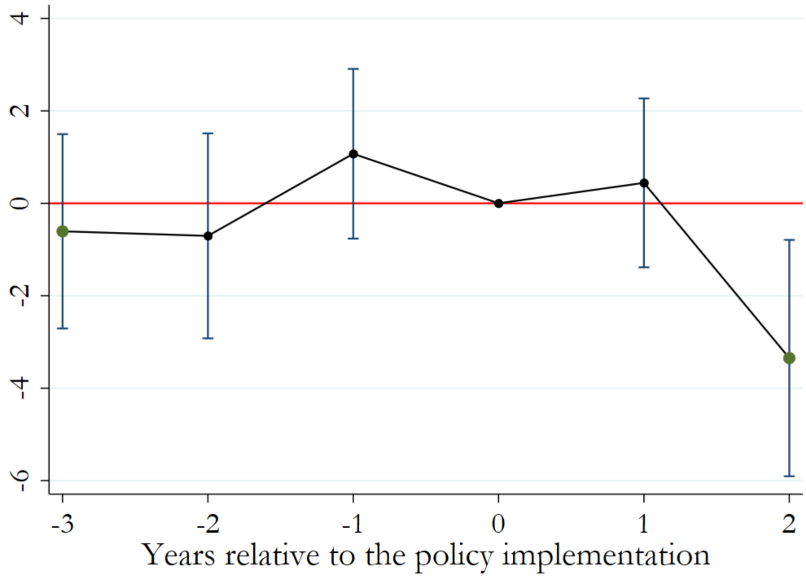
$$Y_{imt} = \alpha + \sum_{k=-3}^{0} \beta_k D_i \times 1(t = T_k) + \sum_{k=1}^{2} \beta_k D_i \times 1(t = T_k) + X'_{imt}\gamma + \omega_i + \theta_t + \varepsilon_{itm}$$

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 Heilongjiang and 0 for counties in Jilin. The coefficient β_k denotes dynamic changes in straw-burning differences between Heilongjiang and Jilin relative to the baseline straw-burning year, autumn 2017 – spring 2018 ("0" in the horizontal axis). The vector X'_{imt} is a set of month-specific dummy variables and county-level climatic factors, including precipitation, wind speed, and temperature. The dummy variables ω_i and θ_t denote the county and year fixed effects, respectively.

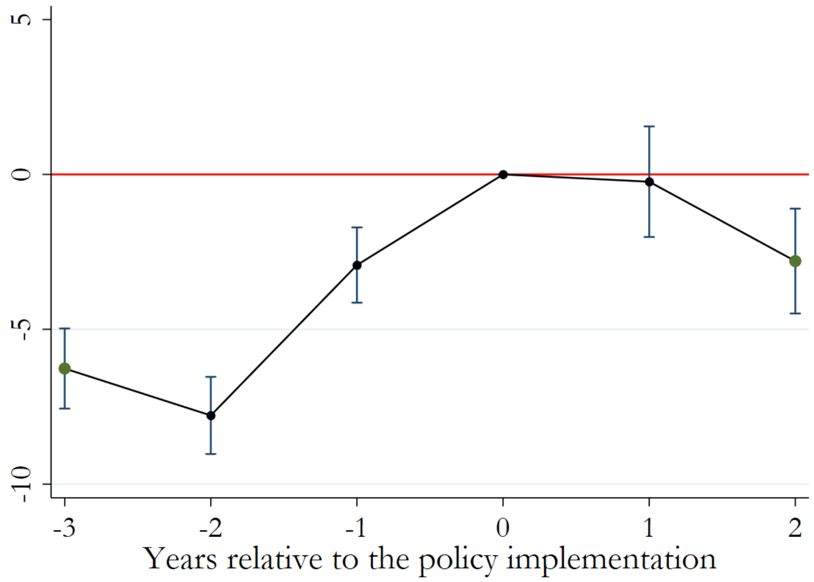
(c) The confidence intervals are at 95% level, adjusted for county-level clustering.

Figure A13. Parallel-trend test for $PM_{2.5}$

Panel A: Sample within 142 km distance



Pane B: Full sample



Note:

(a) Panel A reports the parallel-trend test for straw-burning spots using the data within 142 km distance bandwidth, while Panel B reports the parallel-trend test for straw-burning spots using the data using the full sample. The model specification follows the structure shown in Figure A12.

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

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	April-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	Jilin Province Mechanized Conservation Tillage Technical Operation Subsidy Implementation Plan	Agriculture committee	http://www.jlnongji.cn/1449/http://www.zgjgxh.com/news/show.php?itemid=21471467/2017-05-23/100438.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	Occurrence probability	Expected cost
1. Visible cost			
1.1 Fixed cost, yuan			
Machine investment, yuan	165,000	100%	164789.66
No-till seeder	50,000		
Strip tiller	15,000		
Straw-baling machine	100,000		
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 the 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 selection of optimal distance bandwidth using different optimal bandwidth algorithms

	MSE	MSE-2	MSE-Sum	Min-MSE	Med-MSE	CER	CER-2	CER-Sum	Min-CER	Med-CER
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Left bandwidth, km	141.50	131.13	121.63	121.63	131.13	98.27	91.07	84.47	84.47	91.07
Right bandwidth, km	141.50	176.49	121.63	121.63	141.50	98.27	122.57	84.47	84.47	98.27
County number	76	84	66	66	73	48	45	42	42	47

Note:

(a) We use data from the year prior to the policy implementation, specifically from autumn 2017 to spring 2018.

(b) The optimal bandwidth algorithms are: (1) one common mean squared error (MSE)-optimal bandwidth selector for both sides of the cutoff; (2) two different MSE-optimal bandwidth selectors (below and above the cutoff); (3) one common MSE-optimal bandwidth selector for the sum of regression estimates (as opposed to difference thereof); (4) minimum of (1) and (3); (5) median of (1), (2), and (3) for each side of the cutoff separately; (6) one common coverage error rate (CER)-optimal bandwidth selector; (7) two different CER-optimal bandwidth selectors (below and above the cutoff); (8) one common CER-optimal bandwidth selector for the sum of regression estimates (as opposed to difference thereof); (9) minimum of (6) and (8); (10) median of (6), (7), and (8) for each side of the cutoff separately.

Table A4. Discontinuity analysis across different grain types

	Maize proportion	Wheat proportion	Rice proportion
	(1)	(2)	(3)
Treat × 2018 straw-burning season	0.00	0.00	0.00
	(0.030)	(0.030)	(0.030)
Treat × 2019 straw-burning season	-0.03	-0.03	-0.03
	(0.031)	(0.031)	(0.031)
SRD variables	Y	Y	Y
Year fixed effects	Y	Y	Y
County number	456	456	456
Observation	0.289	0.289	0.289

Note:
(a) The outcome variable is the proportion of maize, wheat, and rice in total grain-planting area, measured at the year-county level.
(b) *Treat* takes the value of 1 for counties in Heilongjiang (distance > 0) as treatment group and takes the value of 0 for the counties in Jilin (distance < 0) as control group.
(c) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A5. Effects of subsidy on straw-burning spots with prefecture-level cluster

	SRD-DID		DID	
	OLS	Poisson	OLS	Poisson
	(1)	(2)	(3)	(4)
Panel A. Sample in both autumn and spring				
Treat × Autumn 2018 – Spring 2019	-3.62	-0.43	-4.26	-0.53
	(4.500)	(0.318)	(4.337)	(0.324)
Treat × Autumn 2019 – Spring 2020	-14.31***	-1.11***	-14.27***	-1.11***
	(4.498)	(0.145)	(4.225)	(0.162)
SRD variables	Y	Y		
County fixed effect			Y	Y
N	1,824	1,824	1,824	1,824
R^2	0.178		0.340	
Panel B. Sample in spring				
Treat × Spring 2019	-3.75	-0.45	-5.53	-0.58**
	(4.215)	(0.281)	(4.536)	(0.284)
Treat × Spring 2020	-25.83**	-1.20***	-25.38**	-1.15***
	(11.047)	(0.181)	(10.435)	(0.192)
SRD variables	Y	Y		
County fixed effect			Y	Y
N	912	912	912	912
R^2	0.212		0.467	
Panel C. Sample in autumn				
Treat × Autumn 2018	-0.97	-1.05	-2.14	-1.10*
	(4.266)	(0.642)	(3.752)	(0.604)
Treat × Autumn 2019	-2.68	-0.94	-4.01	-1.08
	(4.240)	(0.734)	(4.477)	(0.797)
SRD variables	Y	Y		
County fixed effect			Y	Y
Observation	912	912	912	912
R^2	0.165		0.362	

Note:

(a) The outcome variable is month-county straw-burning spots.

(b) *Treat* takes the value of 1 for counties in Heilongjiang (distance > 0) as treated group and takes the value of 0 for the counties in Jilin (distance < 0) as control group.

(c) SRD (Spatial Regression Discontinuity) variables include *treat*, the distance function with a third-order polynomial, and the interaction between *treat* and the distance function. The distance bandwidth is 142 km.

(d) We control climatic factors as well as year and month fixed effects in all models. The climate variables include precipitation, temperature, and wind speed.

(e) Spring: March and April; Autumn: October and November

(d) We control climatic factors as well as year and month fixed effects in all models.

(f) Robust clustered-standard errors at the prefecture-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A6. Effects of subsidy on $PM_{2.5}$ with prefecture-level cluster

	SRD-DID	DID
	(1)	(2)
Panel A. Sample in both autumn and spring		
Treat × Autumn 2018 – Spring 2019	0.55	1.17
	(4.416)	(4.755)
Treat × Autumn 2019 – Spring 2020	-1.82	-0.86
	(4.635)	(5.112)
SRD variables	Y	
County fixed effect		Y
N	1,824	1,824
R^2	0.462	0.685
Panel B. Sample in spring		
Treat × Spring 2019	0.92	0.48
	(1.341)	(1.535)
Treat × Spring 2020	-3.43	-3.30
	(3.252)	(3.158)
SRD variables	Y	
County fixed effect		Y
N	912	912
R^2	0.367	0.735
Panel C. Sample in autumn		
Treat × Autumn 2018	-2.57	-0.95
	(8.570)	(8.529)
Treat × Autumn 2019	-2.09	-0.65
	(8.257)	(8.573)
SRD variables	Y	
County fixed effect		Y
Observation	912	912
R^2	0.589	0.811

Note:

(a) The outcome variable is month-county level $PM_{2.5}$ [ug/m^3].

(b) *Treat* takes the value of 1 for counties in Heilongjiang (distance > 0) as treatment group and takes the value of 0 for the counties in Jilin (distance < 0) as control group.

(c) SRD (Spatial Regression Discontinuity) variables include *treat*, the distance function with a third-order polynomial, and the interaction between *treat* and the distance function. The distance bandwidth is 142 km.

(d) The climate variables include precipitation, temperature, and wind speed.

(e) Spring: March and April; Autumn: October and November

(d) We control climatic factors as well as year and month fixed effects in all models.

(f) Robust clustered-standard errors at the prefecture-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A7. Effects of straw burning on $PM_{2.5}$ using Instrument Variable (IV) method

	Autumn and spring		Spring	
	(1)	(2)	(3)	(4)
Predicted straw-burning spots	0.14	0.08	0.15***	0.14***
	(0.101)	(0.110)	(0.053)	(0.052)
Climate factors	Y		Y	
Distance	Y	Y		
County fixed effect			Y	Y
Observation	1,824	1,824	912	912
R^2	0.463	0.160	0.365	0.097
Kleibergen-Paap LM statistic	20.22	21.38	14.43	14.51
Cragg-Donald Wald F statistic	22.84	27.66	29.80	41.36

Note:

(a) We utilize a two-stage least squares (2SLS) approach to investigate the causal effect of straw burning on $PM_{2.5}$ levels. The instrumental variable employed is the interaction between the treatment indicator and the policy year during the 2019 straw-burning season. The first-stage regression is specified as follows:

$$Fire_{imt} = \alpha + \beta_1 1[t = 2019] \times 1[d \geq 0] + \beta_2 1[d \geq 0] + f(d) + 1[d \geq 0] \times f(d) + X'_{imt}\gamma + \theta_m + \varepsilon_{itm}$$

where $Fire_{imt}$ 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 Heilongjiang and 0 for counties in the Jilin. T_t is a dummy variable, which takes the value of 1 for years in Autumn 2019 and Spring 2020. The term $f(d-c)$ denotes a flexible function of the running variable, the distance to the border, modeled as a cubic polynomial. The vector X'_{imt} is a set of county-level climatic factors, including precipitation, wind speed, and temperature. The dummy variables φ_t and θ_m denote the year, and month fixed effects, respectively. The second-stage regression is expressed as:

$$PM_{imt} = \alpha + \delta_1 \widehat{Fire}_{imt} + \delta_2 1[d \geq 0] + f(d) + 1[d \geq 0] \times f(d) + X'_{imt}\gamma + \theta_m + \varepsilon_{itm}$$

where PM_{imt} is the straw-burning spots in county *i*, recorded in year *t* and month *m*. $Fire_{imt}$ denotes the predicted straw-burning spots from the first-stage regression. All other variables are defined as in the first-stage regression.

(b) The distance bandwidth is 120 km.

(c) We report the results in second-stage regression.

(e) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A8. Sensitivity analysis of subsidy effects on straw burning using different polynomial order functions

	0th	1st	2nd	4th
	(1)	(2)	(3)	(4)
Panel A. Sample in both Autumn and Spring				
Treat × Autumn 2018 – Spring 2019	-3.63	-3.56	-3.53	-3.62
	(2.792)	(2.759)	(2.769)	(2.779)
Treat × Autumn 2019 – Spring 2020	-14.28***	-14.21***	-14.17***	-14.31***
	(2.493)	(2.475)	(2.491)	(2.505)
SRD variables	Y	Y		
County fixed effect			Y	Y
N	1,824	1,824	1,824	1,824
R^2	0.153	0.159	0.171	0.178
Panel B. Sample in Spring				
Subsidy × Spring 2019	-3.72	-3.66	-3.63	-3.80
	(3.042)	(3.020)	(3.041)	(3.078)
Subsidy × Spring 2020	-25.85***	-25.79***	-25.74***	-25.81***
	(5.712)	(5.714)	(5.720)	(5.756)
SRD variables	Y	Y		
County fixed effect			Y	Y
N	912	912	912	912
R^2	0.175	0.183	0.199	0.213
Panel C. Sample in Autumn				
Subsidy × Autumn 2018	-1.10	-0.95	-0.90	-1.02
	(2.962)	(2.915)	(2.922)	(2.908)
Subsidy × Autumn 2019	-2.63	-2.58	-2.55	-2.76
	(2.849)	(2.844)	(2.867)	(2.852)
SRD variables	Y	Y		
County fixed effect			Y	Y
Observation	912	912	912	912
R^2	0.147	0.151	0.160	0.167

Note:
(a) The outcome variable is month-county straw-burning spots.
(b) *Treat* takes the value of 1 for counties in Heilongjiang (distance > 0) as treated group and takes the value of 0 for the counties in Jilin (distance < 0) as control group.
(c) SRD (Spatial Regression Discontinuity) variables include *treat*, the distance function with a third-order polynomial, and the interaction between *treat* and the distance function. The distance bandwidth is 142 km.
(d) We control climatic factors as well as year and month fixed effects in all models. The climate variables include precipitation, temperature, and wind speed.
(e) Spring: March and April; Autumn: October and November
(f) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A9. Sensitivity analysis of subsidy effects on straw burning using different distance bandwidth

	70 km	200 km	300 km	Full sample
	(1)	(2)	(3)	(4)
Panel A. Sample in both Autumn and Spring				
Treat × Autumn 2018 – Spring 2019	-4.67	-4.53**	-6.66***	-5.14***
	(4.445)	(2.256)	(1.973)	(1.733)
Treat × Autumn 2019 – Spring 2020	-13.47***	-13.75***	-13.89***	-15.88***
	(3.494)	(2.137)	(1.774)	(1.837)
SRD variables	Y	Y		
County fixed effect			Y	Y
N	768	2,472	3,240	4,248
R^2	0.223	0.171	0.167	0.124
Panel B. Sample in Spring				
Subsidy × Spring 2019	-5.69	-4.76*	-6.50***	-5.14***
	(4.391)	(2.442)	(2.163)	(1.733)
Subsidy × Spring 2020	-23.40**	-24.22***	-22.07***	-15.88***
	(9.057)	(4.709)	(3.720)	(1.837)
SRD variables	Y	Y		
County fixed effect			Y	Y
N	384	1,236	1,620	4,248
R^2	0.276	0.205	0.191	0.124
Panel C. Sample in Autumn				
Subsidy × Autumn 2018	-1.99	-1.02	-3.42*	-5.14***
	(4.879)	(2.363)	(2.050)	(1.733)
Subsidy × Autumn 2019	-3.61	-3.33	-5.81***	-15.88***
	(4.705)	(2.286)	(2.019)	(1.837)
SRD variables	Y	Y		
County fixed effect			Y	Y
Observation	384	1,236	1,620	4,248
R^2	0.234	0.152	0.168	0.124

Note:

(a) The outcome variable is month-county straw-burning spots.

(b) *Treat* takes the value of 1 for counties in Heilongjiang (distance > 0) as treated group and takes the value of 0 for the counties in Jilin (distance < 0) as control group.

(c) SRD (Spatial Regression Discontinuity) variables include *treat*, the distance function with a third-order polynomial, and the interaction between *treat* and the distance function.

(d) We control climatic factors as well as year and month fixed effects in all models. The climate variables include precipitation, temperature, and wind speed.

(e) Spring: March and April; Autumn: October and November

(f) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A10. Temporal variations in SRD estimates for straw-burning spots

	2014-2015 (1)	2015-2016 (2)	2016-2017 (3)	2017-2018 (4)	2018-2019 (5)	2019-2020 (6)
0^{th} level						
SRD estimate	1.77	10.73	8.15	-1.04	1.16	-11.478*
	(8.37)	(13.15)	(11.58)	(8.57)	(2.45)	(6.64)
Left BW, km	35.83	39.83	43.59	54.31	43.16	76.78
Right BW, km	35.83	39.83	43.59	54.31	43.16	76.78
Observation	32	52	68	100	68	152
3^{rd} level						
SRD estimate	-31.67	-21.55	-1.75	12.79	4.51	-12.68
	(36.21)	(53.59)	(50.41)	(40.76)	(10.90)	(36.63)
Left BW, km	116.82	129.33	132.31	141.50	140.88	142.9
Right BW, km	116.82	129.33	132.31	141.50	140.88	142.9
Observation	252	272	278	296	304	304

Note:
(a) The outcome variable is month-county straw-burning spots.
(b) The optimal distance bandwidths (BW) are determined using algorithms based on the common mean squared error (MSE) criterion.
(c) Robust clustered-standard errors at the county-level are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Appendix 2: 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. 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 Table A2.