Mitigating agricultural fires with carrot or stick? Evidence from China

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Abstract

This paper examines the effects of biomass power plants (BPPs) on farmers' use of agricultural fires for land clearance in China from 2001 to 2019. We show that the entry of BPPs leads to a significant reduction of agricultural fires by -14%. Farmers near BPPs display stronger responses, resulting in a greater decrease in straw burning, particularly during high agricultural fire seasons. The notable decline in agricultural fires is likely driven by economic incentives provided by BPPs to farmers for collecting crop straw from their land. Additionally, straw-burning bans have limited effectiveness in reducing total agricultural fires, but they appear to reduce straw burning during nighttime, when the monitoring of agricultural fires is easier. We also provide evidence of significant improvements in local air quality, with associated health benefits that far exceed the monetized social benefits of carbon emission reductions.

Keywords: agricultural fire, environmental externality, straw burning, biomass power plant

JEL codes: H23, Q12, Q52, Q53

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1 Introduction

Technological advances have greatly improved monitoring of environmentally destructive behavior by large polluters. Many countries, including the US, China, and India, have built sophisticated high-frequency monitoring systems that focus on large firms and keep their emissions of air and water pollutants under close government surveillance. These systems directly reduce the manipulation of reported pollution by polluters and government officials (Karplus et al. 2018; Greenstone et al. 2022), and also help discipline polluters' environmentally destructive behavior and improve their environmental performance (Zhang et al. 2018; Zou 2021). However, environmental externalities from smaller contributors, especially from households, are much harder to monitor. Closely monitoring their behavior is highly costly due to the large number of potential contributors and their damaging practices usually continue regardless of government prohibitions (Aunan et al. 2019; Rao et al. 2021). How to effectively regulate their environmental externalities remains a challenge to governments.

This paper focuses on a specific environmental externality caused by rural residents, i.e., open agricultural burning. In many countries, including China, India, and Brazil, farmers use open fires to dispose of crop residues (straw stubble) as a cheap way to clear their land. The combustion of straw stubble generates substantial amounts of air pollutants, such as particulate matter and sulfur dioxides, and rapidly and severely worsens local air quality.[1] These air pollutants pose large risks to human physical and mental health by increasing mortality of infants and the elderly and damaging cognitive abilities (Rangel and Vogl 2019; He et al. 2020; Graff Zivin et al. 2020). This practice is therefore restricted or even strictly prohibited by many governments.[2] However, governments face high costs in closely monitoring agricultural fires. Remote sensors on satellites can capture hotspots caused by open burning from space, but real-time satellite monitoring is rarely available in most countries.[3] The delay in monitoring causes obstacles for government officials to arrive at fire sites promptly and find out (or prove) who sets the fires. Therefore, satellite monitoring is mostly used for ex-post evaluations of the severity of open burning, but cannot directly help governments strengthen enforcement. To better monitor agricultural fires,

[1] For example, in Punjab and Haryana of India, stubble burning accounts for 30% to 40% of air pollution in October and November. Source: https://www.reuters.com/world/india/india-struggles-put-out-crop-waste-fires-that-fuel-air-pollution-2021-11-11/.

[2] China has partially banned agricultural open burning since 1997. In the US, Oregon prohibited this practice in 2009, and many other states impose restrictions on farmers by requiring them to obtain permits for open burning.

[3] The US National Aeronautics and Space Administration (NASA) provides real-time monitoring on open burning, within one minute of satellite observation, but data are currently available only for the US and Canada. Source: https://wiki.earthdata.nasa.gov/pages/viewpage.action?pageId=258343755.

some local governments in China have recently installed real-time cameras with infrared sensors that can automatically detect open burning and store visual records for evidence.[4] However, such monitoring systems are highly costly and hence are not widely used.[5] Due to these obstacles in monitoring, the bans on agricultural open burning in many countries are impeded by weak enforcement.

This paper studies an alternative approach to solving this problem, namely through biomass power plants (BPPs). BPPs remunerate farmers for collecting crop straw from their land and use the acquired straw to generate electricity. The payments from BPPs for crop straw internalize the environmental costs of farmers' straw-burning practice à la Coase. The effectiveness of such payments in mitigating agricultural fires depends on whether they are sufficiently large to cover farmers' private costs of straw collection, which may vary substantially across different individuals. BPPs collect straw not only from farmers who would burn straw if not for the remuneration, but also from farmers who would dispose of straw in environmentally friendly ways, such as using straw as food for livestock or fertilizer for crops. These farmers may have lower private costs of collecting straw—otherwise they would have burned the straw to clear their land. These lower costs imply that the acquiring price of straw could still be lower than the straw-collecting costs of farmers who choose to use open burning to dispose of straw. Therefore, the payments from BPPs could fail to internalize the external environmental costs of open agricultural burning and so do not necessarily mitigate agricultural fires.

We use the entry of BPPs in China as a quasi-natural experiment to examine their impact on the occurrence of agricultural fires detected by satellites from 2001 to 2019. To address the challenge of endogenous site selection, we compare BPPs in operation to untreated BPPs, including those in the process of preparation and a small number in the withdrawal process. Typically, it takes an average of 3.5 years from business registration for BPPs in China to obtain government approvals, complete construction of plants and transmission lines, commence operations with electricity supply licenses. The lengthy establishment process, coupled with variations in the timing of business registrations, creates plant-specific differences in entry time. We explore these variations to uncover the causal impact of BPP entry on reducing agricultural

[4]Source: http://sthjt.gxzf.gov.cn/zwxx/qnyw/t5493486.shtml, http://env.people.com.cn/n1/2018/0822/c1010-30244953.html.

[5]For example, Shijiazhuang, a city in Hebei province of China, installed a monitoring system with 529 cameras for agricultural fires in farmland near railways and highways, with an annual cost around 30 million Chinese Yuan (CNY hereafter, 1 CNY$\approx$ 0.14 USD). Source: http://www.sjz.gov.cn/download.jsp?pathfile=/yjsgk/atm/1613639344654/20210222150033124.pdf.

fires.

We find that on average, the entry of a BPP statistically significantly reduces nearby agricultural fires by 14%, with larger reductions in regions closer to BPPs (as much as -23%) and in high agricultural fire seasons (-17%), i.e., the periods before sowing and after harvest. Our evidence suggests that economic incentives, provided by BPPs to acquire crop straw from farmers, are a likely channel for the significant reductions in agricultural fires. We find that the reductions are mostly driven by BPPs that are not financially constrained in remunerating farmers for straw collection and BPPs that are able to provide farmers higher payments due to receipt of production subsidies from government. BPPs with greater demand for crop straw, reflected by their electricity output and capacity utilization, also exhibit larger effects on reducing agricultural fires.

Additionally, we compare the impact of BPPs to that of straw-burning bans. We find that straw-burning bans in China have a much smaller effect on reducing agricultural fires compared to BPPs. Although the bans appear to significantly reduce agricultural fires at night when fires are easily visible from a long distance, the number of nighttime fires is only one-ninth of the number of daytime fires, resulting in limited overall reduction in total fires.

Finally, we show that BPP entry has a negligible effect on reducing vegetation cover but significantly improves air quality. Back-of-an-envelope calculations indicate that public health benefits due to reductions in agricultural fires well exceed the monetized social benefits of carbon emissions reductions from BPPs' generated electricity and even slightly exceed the private revenues of BPPs from electricity sales.

This paper contributes to several strands of literature. First, it is directly related to the literature on the rise and prevention of agricultural fires. Straw burning is a labor-saving practice used by farmers to clear their land so that their sowing and harvesting activities can be less labor-intensive (Garg et al. 2022). Hence, the opportunity cost of labor has a determining effect on the use of agricultural fires. For example, Behrer (2019) finds that an anti-poverty program in India significantly increased cropland fires because the program increases agricultural wages and induces farmers to dispose of crop residues with the labor-saving straw burning. Garg et al. (2022) show that access to rural roads also increases agricultural fires because it leads to reductions in the farm labor workforce. This paper contributes to the literature by showing that the entry of BPPs, which remunerate farmers for their labor costs of collecting straw, has a significant effect on reducing agricultural fires.

This paper is closely related with Nian (2023), who also examines the impact of BPP entry on agricultural fires in China. However, Nian (2023) adopts an "inner ring versus outer ring" strategy by comparing agricultural fires within 10 km of BPPs (including fires within 5 km of BPPs and fires between 5 and 10 km from BPPs) to fires between 10 and 15 km away from BPPs. This strategy not only requires additional assumptions beyond quasi-random variations in the timing of treatment (Pollmann 2023), but the chosen 10 km cutoff is substantially smaller than the industry's consensus on the operational radius of BPPs, potentially causing the outcomes in the outer ring to be influenced by the treatment.[6] In contrast, our paper compares agricultural fires near operational BPPs to fires near counterfactual locations where the treatment could have occurred. This type of approach typically relies on weaker identification assumptions and demonstrates high robustness against omitted variable biases (Borusyak and Hull 2020; Pollmann 2023).

In addition, our comprehensive data on BPPs, including information on their operations and financial status, allows us to closely investigate the underlying mechanisms behind the reduction in agricultural fires. We provide suggestive evidence that the observed reduction in agricultural fires is likely driven by economic incentives provided by BPPs to farmers. Previous studies have utilized randomized controlled trials and government programs to examine the effectiveness of economic incentives, such as payments for ecosystem services, in forest protection (Alix-Garcia et al. 2015; Jayachandran et al. 2017; Ferraro and Simorangkir 2020) and reducing agricultural fires (Edwards et al. 2020; Jack et al. 2022). In particular, Edwards et al. (2020) find that the economic incentives in their randomized field experiment seem too small to induce farmers to reduce agricultural fires. Jack et al. (2022) show that economic incentives with upfront payments significantly reduce crop residue burning whereas standard incentives with no upfront payments have null effect, possibly due to distrust of standard incentives. Consistently, we find larger reductions in agricultural fires around the BPPs that are able to provide farmers with greater economic incentives, namely the BPPs with production subsidies from the government and BPPs with higher electricity capacity utilization and output. Additionally, we observe a negligible effect for BPPs that do not fulfill their legal obligations regarding debt payoff, likely due to smaller economic incentives provided by these plants or farmers' lack of trust in their promise of payment.

[6] For instance, according to a newspaper report dated November 24, 2020 by the China Environment News, which is under the administration of the Ministry of Ecology and Environment, BPPs in China typically operate within a radius of no more than 100 km, which is ten times greater than the 10 km cutoff. Source: http://epaper.cenews.com.cn/html/2020-11/24/content_99720.htm.

This paper is also relevant to the literature on control of open burning. Fires are widely used for land clearing, and this practice generates not only air pollutants that damage human health but also substantial carbon emissions.[7] Balboni et al. (2021) discuss different policies to control forest fires set by firms in Indonesia and show that property rights reforms have a negligible effect on reducing fires, whereas increasing punishments for setting fires can reduce fires by up to 80%. Nevertheless, forest fires are usually much larger in scale than agricultural fires and are easier for governments to detect, whereas most agricultural fires in China are set by rural households rather than firms, suggesting difficulty for governments in monitoring their illegal behavior.

Furthermore, incomplete environmental regulation may improve compliance in emissions of regulated pollutants, but provoke types of polluting behavior that are less regulated, such as crop residue burning (Hernández-Cortés 2022). Ashraf et al. (2016) compare the effectiveness of subsidies and punishments in addressing externalities with a theoretical model and two cases from New York and Zambia. They show that when judicial strength is low, subsidies are more effective than fines because effective sanctions are impossible if inspectors cannot determine who is responsible for the externalities. The present paper echoes their findings by showing that BPPs significantly reduce straw burning activities that are hard to monitor, but punishment imposed by straw-burning bans has a limited effect except on straw burning at night, when inspectors can more easily identify fires.

Last, this paper is relevant to the literature on co-benefits of reducing carbon emissions (Fullerton and Karney 2018; Scovronick et al. 2019; Aldy et al. 2021). BPPs are thought to contribute to achieving net-zero carbon emissions, but are also controversial due to fears of deforestation (see Favero et al. 2020). However, China maintains strict regulation on forests and BPPs in China use agricultural residues as fuel. Accordingly, we find no effect of BPP entry on vegetation cover, but sizeable health benefits due to the reduction in agricultural fires.

The remainder of this paper proceeds as follows. Section 2 introduces agricultural fires and regulations on straw burning in China and also provides background on China's biomass power plants. Section 3 describes the empirical strategy. Section 4 presents the main results. Section 5 compares the effects of BPPs with those of straw burning bans. Section 6 discusses the benefits and costs of BPPs. Section 7 concludes.

[7] Hsiao (2021) shows that CO_2 emissions due to forest fires set by the palm oil industry in Indonesia and Malaysia accounted for 4.7% of global emissions from 1986 to 2016.

2 Background

2.1 Agricultural fires and regulations on straw burning

Wildfires in China mainly occur on farmland rather than woodland or grassland. In recent decades, rural households in China have switched from cooking and heating with wood and straw to more efficient alternatives such as electricity, natural gas, and coal (Tao et al. 2018). This energy transition by rural households is associated with increased agricultural fires as surplus agricultural waste is burned. Fires in farmland, detected by the Moderate Resolution Imaging Spectroradiometer (MODIS) fire product, increased by more than 120% from 2003 to 2019, and fires in woodland decreased by about 60% in the same period (see Figure 1).[8] In 2019, the number of agricultural fires recorded by the MODIS fire product was almost 2.5 times greater than the number of forest fires.

China has officially restricted straw burning for more than 20 years. The first straw burning ban was introduced in 1997, when the Ministry of Agriculture issued an administrative order prohibiting straw burning in the summer harvesting season. The administrative order was written into law in 2000 when the National People's Congress approved the amendment of the Atmospheric Pollution Prevention and Control Law. The law stipulates that straw burning is prohibited in areas that are densely populated or close to airports or arterial roads. At that time, mitigation of agricultural fires mainly relied on mandatory regulations such as these, and the regulations were temporarily strengthened around 2008 to improve Beijing's air quality during the Olympic Games (Chen et al. 2013; He et al. 2016).

However, despite these government regulations, agricultural fires continued increasing rapidly, especially after 2009 (see Figure 1). The surge in agricultural fires was halted when the central government promoted the utilization of crop straw in 2013. Local governments were ordered to use "carrot and stick" methods to reduce agricultural fires. They treated companies that recycle straw as the main contributors to reducing agricultural fires and supported them with preferential policies. They also enhanced the implementation of straw burning bans, and some provinces even passed legislation completely prohibiting straw burning across their entire jurisdiction.

[8]The substantial reduction in woodland fires detected by MODIS is consistent with the official statistics of China. According to China Statistical Yearbooks, the annual number of forest fires in China has reduced from 10,463 in 2003 to 2,345 in 2019. The Chinese government attributes this reduction to the substantial increase in resources allocated to forest fire prevention. From 2008 to 2015, the number of forest firefighters increased by 53.8% to 113,000 persons. Government expenditure on forest fire prevention amounted to 30 billion CNY (about 4.3 billion USD) during that period. (Source: National Forest Fire Prevention Plan (2016–2025), http://www.gov.cn/xinwen/2016-12/29/content_5154054.htm.)

Nowadays, farmers who burn crop straw illegally will be fined 500 to 2,000 CNY (about 70 to 300 USD) and may even be detained for five days or more, according to several Chinese laws.

2.2 Biomass power plants in China

Biomass power plants typically consume crop straw, animal waste, residential garbage, and wood to generate electricity. We focus on agricultural and forestry BPPs that use crop straw and wood as fuel. For convenience, we refer to these simply as BPPs throughout the paper.

The first BPP in our sample came into operation in 2006, and the biomass power sector began growing rapidly in 2009. In the decade from 2009 to 2019, the sector's installed capacity grew tenfold from 1,088 megawatts to 10,920 megawatts. The amount of electricity generated follows a similar trend, implying almost constant operating hours for biomass power plants' generators (4,405 hours on average in 2019). These operating hours are close to those of coal-fired power plants (4,376 hours in 2019) and are substantially higher than those for other renewable energy sources, such as hydropower (3,637 hours), wind power (1,938 hours), and solar power (1,097 hours).

Despite the biomass power sector's rapid growth in the last decade, establishing a BPP is a lengthy process. Figure D1 in the Online Appendix illustrates the main procedures involved. The process begins with the company registering the business with the Administration for Market Regulation, followed by obtaining approvals from at least six provincial-level government departments.[9] Each department typically has a maximum of 20 working days to review and make a decision on the company's application. Some departments also require the application to be published on their websites for an additional 20 days before granting approval. Furthermore, the company cannot directly submit applications to the provincial-level departments but must instead submit them to local authorities, who then forward them to the provincial governments after conducting initial reviews. As a result, this bureaucratic process often takes a minimum of 6 months. In cases where the application is denied by any department, the company must revise and resubmit it for reconsideration, further prolonging the process. Additionally, after obtaining approvals from the government departments, the company typically needs to purchase land use rights through land auctions organized by the Bureau of Planning and Natural Resources.

[9]Once completing business registration, the biomass power company submits a project proposal to the Provincial Development and Reform Commission (PDRC). The PDRC then provides the company with detailed instructions. The company must obtain approvals from the Department of Housing and Urban-Rural Development, the Department of Natural Resources, the Department of Water Resources, and the Department of Ecology and Environment.

This step can be a time-consuming process that may extend over several months or even years, particularly when it involves land acquisition from residents and the demolition of existing housing structures.

After completing all these procedures, the company goes to the Provincial Development and Reform Commission to apply for planning and construction permits for the project. During construction, the company must apply to the provincial power grid company for connection to the electricity grid, which then requests grid-planning institutes to design a power connection plan and hires construction forces to build transmission lines. After finishing plant and transmission line construction, the company must perform a trial run before starting project acceptance procedures, and after completing these procedures the company can finally apply to the Provincial Energy Administration for an electricity business license, which is a requisite for power plants to supply electricity to power grids.

These procedures are not only lengthy but are also associated with high unpredictability due to rent-seeking by government officials. The energy sector of China is notorious for its corruption in project approvals, with government officials often abusing their power for personal gain. A notable example occurred in 2014 when 23 high-ranking officials in energy-related government departments and state-owned energy enterprises were arrested for bribery and corruption.[10] Among them was Tienan Liu, the former director of the National Energy Administration, who was convicted of accepting 35.6 million CNY in bribes to facilitate project approvals for energy companies.[11] Consequently, even if a biomass power company identifies a suitable location for electricity generation using crop straw, it may struggle to obtain government approval if it is unwilling or unable to bribe corrupted officials. Therefore, the successful acquisition of government approval and the duration of the approval process depend not only on following the required procedures but also on the company's connection with the authorities.

In some cases, high uncertainty could also arise from unforeseen events involving BPPs and third parties. For instance, in Shaanxi province, one BPP successfully obtained approval from the PDRC in 2008 but failed to complete factory construction by the end of 2022 due to a legal dispute with a construction company.[12] Similarly, in Sichuan province, a BPP faced financial difficulties during plant construction and was unable to fully remunerate the construction

[10]Source: https://datanews.caixin.com/2014-06-24/100682346.html.

[11]Source: http://www.xinhuanet.com//politics/2014-12/10/c_1113595801.htm.

[12]Source: http://sndrc.shaanxi.gov.cn/fgwj/2008nwj/1016307z2aQvy.htm, https://aiqicha.baidu.com/wenshu?wenshuId=b4bef5718228cc328dc9ff43648d62c29e8c038c.

company. Although the plant construction was completed, the BPP never went into operation.[13] Additionally, delays in the process can also be caused by grid companies. For instance, in another BPP case in Sichuan, the plant was ready for operation, but the grid company did not build transmission lines because the construction cost of transmission lines was considered to exceed the future revenues for the grid company.[14]

Consequently, the unpredictability associated with establishing biomass power plants is primarily determined by the relationship between BPPs and the government, as well as unforeseen incidents involving third parties. These factors are generally unrelated to the straw-burning activities of local farmers. Furthermore, in Section 3.3, we demonstrate that registered BPPs, both with and without electricity business licenses, exhibit similar characteristics in terms of local natural and economic conditions. These characteristics include factors such as nearby agricultural fire frequency, biomass resource availability, distances to major infrastructures, and county-level economic variables. Therefore, we draw upon the extensive procedures and uncertainties involved in the process from business registration to obtaining an electricity business license to identify the causal effect of BPP entry on agricultural fires.

3 Empirical design

3.1 Empirical specification

We use a staggered event-study design to exploit variations in timing of BPP entry. However, comparison of regions with and without BPPs would be susceptible to endogeneity problems due to the non-random site selection of power plants. For example, counties with severe agricultural fires generally have greater biomass resources and hence larger incentives to establish BPPs.

To overcome this problem, we exploit the lengthy process of establishing BPPs, as described in Section 2.2, and use as the untreated group plants that are in the process of preparation or withdrawal, i.e., plants that have registered their business but have not entered the market by the end of the sample period. The long duration and high unpredictability in establishing BPPs not only increases variation in the timing of BPP entry but also creates untreated units.[15] We use

[13] Source: https://aiqicha.baidu.com/nwenshu?wenshuId=5b96bdd3a83e55ba3b1b8cf523db7dc8337eb869.

[14] Source: http://finance.sina.com.cn/g/20090728/15096538746.shtml.

[15] The absence of untreated units would result in the under-identification problem of fully-dynamic models in the test for parallel trends (Borusyak et al. 2022). In robustness checks, we also exclude BPPs that are not in operation at the end of the sample period and find that the main results are robust to the exclusion of the untreated plants.

these variations to identify the effects of BPP entry on agricultural fires.

More specifically, we consider the following event-study specification:

$$Fire_{iym} = \beta Biomass_{iym} + \alpha X_{iym} + \gamma_{im} + \eta_{pym} + \epsilon_{iym} \tag{1}$$

where $Fire_{iym}$ is the frequency of agricultural fires surrounding plant i in year y and month m, $Biomass_{iym}$ is a dummy variable that equals one if plant i is in operation in year y and month m, and zero otherwise, X_{iym} is a set of weather control variables, including temperature, precipitation, wind speed, wind direction, and relative humidity, γ_{im} represents plant-month fixed effects, η_{pym} represents calendar-month-specific province-time fixed effects, and ϵ_{iym} is the error term.

Equation (1) is a standard staggered event-study design. $Biomass_{iym}$ compares the treated plant i to untreated plants (plants that have not come into operation by the end of the sample period), treated plants that are not yet in operation, and other treated plants that have come into operation (Goodman-Bacon 2021). This design is subject to the problems of negative weights (de Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021). We discuss the identification issues in detail in the Online Appendix A.

Although plants in operation and in the process of preparation or withdrawal could share similar characteristics regarding agricultural fires in their regions, we must still consider potential confounding factors occurring in parallel with BPP entries. We address this problem by controlling for calendar-month-specific province-time fixed effects η_{pym}. Controlling for time-varying province fixed effects means that our model uses within-province variations to identify the effects of BPP entry. The fixed effects absorb all variations at the province level and higher levels, such as seasonal variations in agricultural activities across different provinces of China, the subsidy policy for straw utilization in ten provinces discussed by He et al. (2020), and the straw burning bans discussed in Section 6. In addition, we control for month-specific plant fixed effects γ_{im} to allow for idiosyncratic seasonal patterns of agricultural fires surrounding each BPP.

There could also be other confounding factors at a more granular level. For example, in some counties, the local government might strengthen the enforcement of straw burning bans and at the same time provide favorable policies for straw utilization, which could promote the creation of BPPs. However, due to the long time required to establish BPPs, such policies are unlikely to be concurrent with the timing of BPP entries, and are more likely to occur before BPP entries. Therefore, they can be tested by estimating dynamic treatment effects with lags and leads.

To count agricultural fires surrounding each BPP, we must choose a radius. He et al. (2020) count the fire frequency within 50 km of the center of each county and note that the average county radius is 33 km (calculated based on the average county area). The impact of one BPP could span several nearby counties if straw supply from the county where the BPP is located cannot satisfy its demand for electricity generation. Because the actual operational scope of the BPPs is unobservable to us, we start the empirical analysis with a 10 km bin and count agricultural fires in rings with distance between $r - 10$ km and r km from each plant, where $r = 10, \ldots, 120$. The maximum distance of 120 km is slightly larger than the biomass power industry's consensus that BPPs collect straw within a distance of 100 km at most. The further a ring is from the BPP, the higher the transportation costs the BPP will face. Therefore, we expect that the impact of BPP entry decreases with distance from the plant.

We estimate equation (1) with ordinary least squares (OLS) and Conley spatial standard errors. To be conservative, we choose a large bandwidth for the Conley standard errors (600 km), which is five times the largest ring we consider. The robustness checks in the Online Appendix A consider alternative bandwidths (200, 500, and 1,000 km) for the Conley standard errors and also clustered standard errors at the plant level. Because the dependent variable, agricultural fire frequency, is a count variable, we also consider a Poisson regression for estimation in the robustness checks.

3.2 Data

The fire data we use are from the MODIS units aboard two satellites (Terra and Aqua). Each satellite scans the entire surface of the Earth every one to two days and passes over China twice a day. The exact timing of passing over China varies with scans and tracks, but is usually between 10 am and 3 pm, and between 9 pm and 2 am in China Standard Time (CST). NASA processes the satellite images and detects fires and other hotspots by thermal anomalies, based on both absolute detection when the fire strength is sufficient to detect and relative detection by comparison with backgrounds to account for variations in surface temperature and brightness. MODIS generally detects fires with a 1 km resolution, although under favorable observing conditions the resolution can be as small as 50 meters. NASA takes the routine resolution and reports the detected fires by the center coordinates of the 1 km pixels. For each power plant, we count the total number of fire pixels in a month within a certain distance from the plant as the frequency of fires surrounding the plant in that month. Because the MODIS fire data are available starting from 11 November

2000, we use 2001 to 2019 as our sample period.

Hotspots detected by MODIS include fires in cropland, forests, and grassland, as well as active volcanoes and static land hotspots. To differentiate agricultural fires from other types of hotspots, we use the global land cover type product (MCD12Q1) provided by NASA, which is also derived from MODIS images. This dataset provides yearly land type classifications for each 500 meter grid square globally from 2001 to 2019. We match every hotspot in the MODIS fire data to the closest grid square in the MCD12Q1 dataset and identify fires in cropland based on International Geosphere-Biosphere Programme classifications. To avoid the possible influence of fires on land type classifications, we use classifications for the previous year to identify agricultural fires.[16]

We obtain the list of registered companies in the biomass power industry from the Registration Information of Industrial and Commercial Enterprises. This dataset contains basic information about companies, including company name, unified social credit code, organization code, registered address, registration date, industry classification, and business scope. Based on company names and business scopes, we retain in our sample companies that generate electricity from direct combustion or gasification of agricultural and forestry waste, and exclude companies that generate electricity only from incineration or gasification of residential garbage and animal waste. In total, we identify 954 registered companies that use agricultural and forestry waste as fuel. To match MODIS fire pixels, we geocode companies by their registered address with *Gaode Maps*, developed by *AutoNavi*, which is a leading online map service provider in China.

To identify the plants that are in operation in the sample, we use the dataset from the National Energy Administration detailing power generation companies with electricity business licenses. The dataset includes company names, unified social credit codes, organization codes, and effective dates and expiration dates of their licenses. We match this dataset with the 954 registered companies by their unified social credit codes and organization codes, and we use the licenses' effective dates as the plants' operational dates. The earliest operation year of BPPs in the sample is 2006, and electricity business licenses have a 20 year duration. This long license duration eliminates the concern that some plants may have renewed their licenses, causing misidentification of their operational dates.

Among the 954 registered companies, 467 began production by the end of 2019. Within

[16]Land type classifications in the previous year are used to identify agricultural fires except for hotspots in 2001. We identify fires in cropland in 2001 based on the land type classifications of the same year because 2001 is the earliest full year available in the MCD12Q1 data.

the 487 untreated plants, only 43 canceled or revoked their business registration by the end of 2021, implying that most of the untreated plants are likely in the process of preparation rather than withdrawal. The average difference between their registered dates and operational dates is approximately 3 years and 6 months. Figure D2 in the Online Appendix shows the geographical distribution of the treated and untreated BPPs. Most of the BPPs are located in the east and middle of China, whereas some provinces in the middle and west appear to have a higher proportion of untreated plants. Due to the difference in spatial distributions of treated and untreated plants, comparison of plants across different provinces could be subject to omitted variable biases. This spatial pattern hence highlights the importance of using within-province variations to identify the effects of BPPs.

The control variables for monthly average weather conditions are obtained from the China Meteorological Administration. Data on characteristics of counties where the BPPs are located are taken from county statistical yearbooks.

We consider heterogeneous effects for plants with different liquidity constraints that affect their ability to offer farmers economic incentives for acquiring straw from their land, such as debtor judgments from the supreme court of China[17] and plants receiving the feed-in tariff subsidy disclosed by the Ministry of Finance and the State Grid Corporation. Additionally, we consider the influence of BPPs' demand for straw by comparing the heterogeneous effects of BPPs with different capacity for electricity generation. We use a dataset on national power plants from the China Electricity Council (CEC). This dataset covers national power plants with installed capacity above 6,000 kW from 2005 to 2018 and provides plant-level information on generation capacity, electricity generation, and capacity factors.

In order to understand how the entry of BPPs affects farmers' factor inputs in agricultural activities, we use the National Fixed Point Survey conducted by the Ministry of Agriculture on rural households. The survey includes household-level information for more than 20,000 households in 32 provinces from 2000 to 2015, including household income, capital (agricultural machines) and labor inputs for agricultural activities, and land inputs for different agricultural plants. We examine how the entry of BPPs changes rural households' agricultural inputs and income.

We also consider the effects of BPPs on vegetation cover. Following Asher and Novosad (2020), we use two vegetation indices, the normalized difference in vegetation index (NDVI)

[17]The supreme court of China discloses debtor judgments information on the Enforcement Information Disclosure Platform, http://zxgk.court.gov.cn/zhzxgk/.

and the enhanced vegetation index (EVI), to measure local vegetation cover. We use monthly vegetation indices from MODIS Terra with a 1 km resolution (the same size as fire pixels). Further, to examine the effects of BPPs on air pollution, we use annual data on $PM_{2.5}$ concentration provided by the Atmospheric Composition Analysis Group, which uses satellite data on Aerosol Optical Depth and the GEOS-Chem chemical transport model to estimate ground-level $PM_{2.5}$ concentration (van Donkelaar et al. 2019; Hammer et al. 2020).[18]

3.3 Summary statistics

The underlying intuition of our identification strategy is that the untreated plants share similar pre-treatment characteristics with the treated plants, and so can serve as plausible counterfactuals for the treated plants. To confirm this, we examine whether the operating plants are similar to untreated plants within the same province in the pre-treatment period in terms of their location choices.

Table 1 shows the summary statistics for variables in pre-treatment periods. The average monthly fire frequency within 100 km of treated BPPs is 37.317, slightly lower than the frequency around untreated BPPs (41.742). After controlling for province-specific time trends in agricultural fires, the p-value of the difference is 0.605, implying no significant difference in pre-treatment agricultural fires between treated and untreated plants.

The availability of biomass resources is a determining factor in site selection for BPPs. Table 1 shows that treated and untreated plants share very similar extents of vegetation cover (NDVI and EVI), implying that their location choices are similar in terms of biomass supply.

In addition, Table 1 shows pre-treatment economic characteristics of counties where the BPPs are located, including population, the value-added of the agriculture sector, industry sector, and service sector, aggregated power of agricultural machines, grain output, and vegetable (including fruits and flowers) output. The counties where treated BPPs are located have larger vegetable output than untreated counties, and the difference is significant at the 5% level. All other variables are very similar between the two groups, and their differences are not statistically significant. The two groups of plants also share similar time-invariant characteristics that may be correlated with agricultural fires, such as the distances to the nearest city center (the seat of city government), to the nearest national highway, and to the nearest airport.

[18] https://sites.wustl.edu/acag/datasets/surface-pm2-5/.

4 Empirical results

4.1 Main results

Figure 2 presents the coefficients on $Biomass_{iym}$ (circles) in equation (1) and their 95% confidence intervals (vertical lines) constructed from Conley spatial standard errors, where the outcome variables are fire frequency in rings binned by a 10 km radius.[19]

All coefficients within the 90 km radius are negative and statistically significant at the 1% level. The effect on agricultural fires in the closest ring is the largest (-23%), whereas fire frequency between 10 km and 40 km of BPPs decreases by more than 18% after BPP entry. The effect on agricultural fires in the rings between 40 km and 70 km is a reduction of about 14%, and the effect in the rings between 70 km and 90 km is a reduction of about 11%. These reductions within the 90 km radius indicate that farmers respond to the entry of BPPs and reduce their use of fires to dispose of straw and clear land.

The coefficients for rings beyond 90 km are not statistically significant at the 5% level, and their magnitudes are much smaller. The decreasing magnitudes by distance from the plants and non-significant effects beyond 90 km highlight the importance of BPPs' transaction costs in reducing agricultural fires. As the distance increases, BPPs bear greater search costs for crop residues and transportation costs to move straw from cropland to their plants. Crop residues are usually large in size but light in weight, creating high transportation costs per ton for crop straw.[20] The high transaction costs reduce the incentive for BPPs to collect straw from faraway cropland. Accordingly, BPP entry does not statistically significantly affect agricultural fires in distant regions, and farmers in those regions continue using fires for land clearing. This finding is consistent with the literature on the importance of transaction costs in the practice of payments for ecosystem services (Jack et al. 2008; Wunder et al. 2020).

Given the non-significant effect on agricultural fires more than 90 km from BPPs, we use the aggregated fire frequency within this distance as an outcome variable and re-estimate equation (1). Columns (1)–(3) of Table 2 present the estimation results. Column (1) considers standard two-way fixed effects without any additional controls. The coefficient implies a decrease of 9.27 fires per month after BPP entry relative to the control group. Column (2) uses variations

[19]Because the rings farther away from BPPs are larger in area, they tend to have more fire pixels. To compare the coefficients for different rings, we normalize the outcome variables in Figure 2 based on the average fire frequency in each ring. This normalization preserves the levels of statistical significance and allows us to directly interpret the coefficients as percentage changes in fire frequency.

[20]According to Zhao et al. (2017), transportation costs account for more than 20% of operational costs of BPPs.

within the same province for identification, by including province-calendar-month fixed effects that absorb any time-varying differences across provinces. It also includes plant-month fixed effects to absorb seasonal variations in nearby agricultural fires for each plant. Consequently, the coefficient in Column (2) is -5.075, which is much smaller than in Column (1), but remains statistically significant at the 1% level. Column (3) further controls for weather conditions. The effect of BPP entry decreases slightly compared with Column (2), but remains highly significant, and suggests that on average BPP entry mitigates agricultural fires within a 90 km radius by 4.863 fires per month, roughly a 14% decrease relative to the average fire frequency of 34.428.

Although the effects are highly statistically significant, the entry of one BPP only mitigates a small percentage of agricultural fires. This result may suggest that transaction costs hinder the economic incentive for farmers to reduce agricultural fires. However, as shown in Figure 2, even in areas close to BPPs, the entry of BPPs only reduces agricultural fires by about one quarter. Therefore, the quantity of straw collected from farmers who would otherwise burn it is relatively small compared to the substantial demand for straw by BPPs for electricity generation. Consequently, BPPs primarily collect straw from farmers who would have disposed it through alternative means. Most farmers who use fires to clear land would face higher private costs if they were to dispose of straw in an environmentally friendly manner. The entry of BPPs seems to only sufficiently offset such costs for a modest fraction of farmers.

Agricultural fires exhibit strong seasonal variation and closely follow sowing and harvesting activities. To show the seasonal variation in the impact of BPP entry on agricultural fires, we use fire frequency within 90 km as the outcome variable and estimate equation (1) for each month. Figure 3 shows the estimated coefficients (circles) and their 95% confidence intervals (vertical lines). The largest reductions occur in March, April, October, and November. Figure D3 in the Online Appendix demonstrates that these four months, along with June, have the largest agricultural fire frequencies, aligning with the seasonal patterns of sowing and harvest for major grain crops in China. The coefficients for the other months in Figure 3 are centered around zero and are of small magnitude, showing no statistical significance.

Therefore, we classify these five months (March, April, June, October, and November) as high agricultural fire seasons, and classify other months as low agricultural fire seasons. We then estimate equation (1) for the two groups of seasons separately, with fire frequency within the 90 km radius as the outcome variable. Columns (4)–(9) of Table 2 present the estimation results. For the high fire seasons, Column (6) controls for time-varying province fixed effects and weather conditions, and shows a coefficient of -11.192, significant at the 1% level, suggesting that BPP entry reduces fires by 17% (relative to the 64.286 average fire frequency) in high fire seasons. Coefficients for the low fire seasons in Columns (7)–(9) are much smaller (-0.428 in the last column) and not statistically significant, indicating that BPP entry has no effect in these seasons.

The validity of our event study design relies crucially on the parallel trend assumption. Sun and Abraham (2021) show that in the presence of heterogeneous treatment effects, tests of parallel trends in staggered event study designs with OLS can be contaminated by effects from multiple time periods. To deal with this issue, we examine the parallel trend assumption by using the method proposed by Borusyak et al. (2022) to estimate the following equation:

$$Fire^{90}_{iym} = \sum_{h=-k}^{h=-1} \tau_h \mathbb{I}[K_{iym} = h] + \alpha X_{iym} + \gamma_{im} + \eta_{pym} + \epsilon_{iym} \tag{2}$$

where $Fire^{90}_{iym}$ represents the agricultural fire frequency within a 90 km radius of BPP i in year y and month m, and $\mathbb{I}[K_{iym} = h]$ is the event indicator that equals one for observations h years before the onset of treatment. Other variables are defined as in equation (1).

We follow Borusyak et al. (2022) to use only untreated observations to estimate equation (2), with observations at least $k + 1$ years before the onset of treatment as the reference group. The choice of k directly affects the estimates on τ_h, and a particularly large k could result in a small reference group and low power of the joint test on τ_h. For robustness, we consider three different values for k, namely 5, 10, and 17. Figure 4 presents the pre-treatment coefficients, as well as the post-treatment coefficients obtained through an imputation procedure that is not influenced by the choice of k. All pre-treatment coefficients prior to BPP entry are centered around zero and not statistically significant. Notably, the pre-treatment coefficients for $k = 17$ have much wider confidence intervals compared with the coefficients for $k = 5$ and $k = 10$, possibly due to the relatively small reference group when $k = 17$ (i.e., observations 18 years before the onset of treatment). Meanwhile, all post-treatment estimates are negative and most are statistically significant at the 5% level.

One concern for Figure 4 is that BPP entry may cause a displacement effect on agricultural fires across different months and the effect may contaminate the examination of parallel trends when different months are pooled together, as in Figure 4. To address this concern, Figure D4 in the Online Appendix examines the parallel trend assumption for $k = 10$ by each month. For all months, most pre-treatment coefficients are small and not statistically significant. Moreover, most post-treatment coefficients in high fire seasons are negative and statistically significant, but the post-treatment coefficients in other months are not statistically significant, implying no displacement effect.[21]

We further follow Borusyak et al. (2022) to formally test for the existence of pre-trends. Specifically, we use an F-test to detect pre-trends for $k = 5, 10, 17$. For all months and for the five months in high fire seasons, Table 3 shows that all 18 F-statistics are quite small and have p-values larger than 0.1, except in April for $k = 17$ (p-value=0.081) when we have a relatively small reference group. Consequently, the results indicate no significant pre-trends during the pre-treatment years.

4.2 Robustness checks

We perform robustness checks for potential errors in measurement of agricultural fires in this section. In the Online Appendix A, we consider robustness checks for potential measurement errors in plant operation years and locations, as well as for the event-study design.

The MODIS fire product uses thermal anomalies to detect active fires. The algorithm is subject to false alarms caused by reflective surfaces and heated smoke plumes from non-fire sources. However, the fire product reports a confidence estimate, ranging from 0% to 100%, for each detected hotspot, and suggests that users exclude low-confidence hotspots (confidence levels lower than 30%) if they need to reduce potential false alarms. As a robustness test, we follow this suggestion and use hotspots with confidence levels above this threshold for estimations. Omitting low-confidence pixels causes the average number of fires within the 90 km radius to decline from 34.428 to 31.684 per month.

The thermal anomalies detected by MODIS may include hotspots other than vegetation fires, such as active volcanos and other static land sources of heat. In the main results, we use land type classifications to identify hotspots in cropland, which greatly alleviates this concern. To further assure the results are not biased by non-vegetation fires, as a robustness test we exclude all hotspots other than presumed vegetation fires, using the inferred hotspot type for each fire pixel provided by the MODIS fire product as well as the MCD12Q1 land type classifications. This process reduces the number of fires within the 90 km radius to 33.905 per month.

[21] Some post-treatment coefficients in June are positive but not statistically significant. Moreover, their magnitudes are not large enough to offset the reductions in other months, otherwise the coefficients in Column (3) of Table 2 would not be significantly negative.

MODIS is equipped on two satellites, Terra and Aqua, which were launched into space in 1999 and 2002. In theory, the two satellites could detect the same fire at different times if the fire occurs at the intersection of the two satellites' orbits, causing overestimation of fire frequency.[22] To avoid possible duplications in counting, we estimate equation (1) for hotspots detected by Terra and Aqua separately.[23]

The MODIS fire product routinely detects fires in 1 km pixels. Under favorable observing conditions, the spatial resolution can be much smaller (50 meters at the most accurate). To be conservative, we assume that all hotspots are detected at the 1 km resolution, and treat any hotspots within 1 km in the same day as the same fire. We apply the algorithm recursively and estimate equation (1) with the re-counted fire frequencies. The average fire frequency per month decreases to 29.032 after applying this algorithm.

Duplications in counting could also occur if a fire persists for more than one day and is detected by satellites on multiple days. As a robustness test, we follow Balboni et al. (2021) to recursively treat hotspots within 1 km in consecutive days as the same fire. This procedure reduces the average fire frequency per month slightly, to 33.024.

Using the six different samples, Figure 5 presents coefficients and 95% confidence intervals for fire frequency in 10 km binned rings from 0 to 120 km. The results are quite similar to Figure 2. Coefficients are negative and statistically significant for rings up to 90 km; beyond this distance coefficients are not statistically significant and center around zero. Additionally, conforming with Figure 2, the effects of BPP entry are generally decreasing in distance from the BPP.

4.3 Mechanisms

In this section, we explore potential mechanisms for the significant effects of BPP entry on reducing agricultural fires. Specifically, we investigate whether these effects are attributable to economic incentives provided by BPPs by examining heterogeneous effects among BPPs with varying abilities to compensate farmers for straw acquisition. We also consider whether the effects are driven by enhanced local enforcement aimed at protecting plant infrastructure, which we test by examining the impact of BPP entry on forest and grass fires. Additionally, we

[22]Terra normally passes over China between 10 am and 1 pm, and between 9 pm and 11 pm (CST), and Aqua normally passes over China between 11 am and 3 pm, and between 1 am and 4 am (CST).

[23]The average numbers of fires within the 90 km radius detected by Terra and Aqua are 19.102 and 18.338, respectively, per month from 2003 to 2019.

utilize a household-level dataset to investigate whether BPPs influence farmers' decisions on the allocation of their labor and capital inputs.

Economic incentives provided by BPPs. BPPs pay farmers to acquire straw from their land and use the collected straw to generate electricity. If farmers respond to these economic incentives and reduce straw burning, we should expect larger effects from BPPs that are able to provide greater incentives.

To examine this channel, we first consider heterogeneous effects of BPPs between judgment debtors, officially called Persons Subject to Forced Enforcement (PSFEs) and other BPPs. PSFEs are natural persons or legal persons that fail to perform obligations (usually paying off debts) ordered by law courts, and receive restricted access to administrative approval, government support and procurement, loans and financial markets, etc. Being listed as a PSFE indicates that the company lacks adequate liquidity to maintain normal operations. Because straw acquisition costs account for the majority of BPPs' operational costs (Zhao et al. 2017), the BPPs listed as PSFEs are more likely to have difficulties in providing farmers economic incentives to acquire straw. In addition, the lists of PSFEs are disclosed to the public by the Supreme People's Court of China. This public disclosure can directly harm the reputation of PSFE companies and provoke farmers' distrust of the ability or willingness of the BPPs listed as PSFEs to fulfill any pledged economic incentives. Consistent with this conjecture, Jack et al. (2022) show that trust may affect the effectiveness of economic incentives on reducing agricultural fires.

We separately estimate the effects of BPP entry on treated PSFE plants and treated plants never listed as PSFEs, and present the estimation results in Columns (1) and (2) of Table 4, respectively.[24] The coefficient for PSFE plants is 1.780 in high fire seasons and not statistically significant, whereas the coefficient for non-PSFE plants is -14.526, significant at the 1% level. The difference between the two coefficient is 16.306, and the standard error obtained via 100 bootstraps is 3.675, suggesting that the difference is statistically significant at the 1% level. Therefore, in line with our conjecture, PSFE plants experiencing financial liquidity difficulties have a noticeably smaller effect on agricultural fires compared to other plants. We note that the average fire frequencies in high fire seasons for PSFE plants (62.894) and non-PSFE plants (66.076) are similar, indicating that the difference in coefficients is not driven by differences in agricultural fire frequency around PSFE and non-PSFE plants. Farmers around PSFE plants do

[24] More than 80% of PSFE plants in the sample are treated plants. We include all untreated plants (plants not in operation by 2019) in both columns so that we compare each set of treated plants with the same set of untreated plants. We do this consistently in Table 4 because all plants receiving feed-in tariff subsidies by 2019 are treated plants.

not significantly reduce their straw burning, not because they use fewer fires to clear land, but it is more likely due to smaller economic incentives provided by PSFE plants or their lack of trust in the promise of payment from PSFE plants.

To promote renewable energy, China began providing a feed-in tariff subsidy to eligible power plants in 2006. The subsidy is not a lump-sum transfer but a form of production subsidy determined by annual electricity generation, so BPPs eligible for the subsidy should be able to provide farmers greater economic incentives to acquire more straw in order to increase their output and subsidy income. The government initially provided a fixed subsidy (0.25 CNY per kWh) to eligible BPPs. In 2010 the subsidy was changed to a fixed on-grid price (0.75 CNY per kWh), which is more than double the average on-grid price for BPPs without the subsidy (0.37 CNY per kWh in 2018). The straw-acquiring cost for BPPs not eligible for the feed-in tariff subsidy must be lower than 0.37 CNY per kWh to break even, whereas BPPs that receive the subsidy can pay up to twice as much to purchase straw while maintaining a positive cash flow.[25] To obtain this subsidy, power plants must apply to their provincial government, and the provincial government then submits applicant lists to the central government (after some preliminary reviews). The central government makes the final decision on whether to approve the application and announces lists of approved plants. We obtain these lists from the websites of the Ministry of Finance and the State Grid Corporation. By the end of 2019, about 60% of treated plants in our sample (271) received the feed-in tariff subsidy.

Columns (3) and (4) of Table 4 show the estimation results for treated plants with and without the feed-in tariff subsidy.[26] The coefficient for subsidized plants is -13.948 in the high fire seasons, significant at the 1% level, whereas the coefficient for plants without the subsidy (-3.181) is only 22.8% of the magnitude and not statistically significant. The difference between the two coefficients is statistically significant at the 10% level. Consistent with our expectation, BPPs that receive the feed-in tariff subsidy have much larger effects on reducing agricultural fires, implying that farmers are likely to respond more to the potentially greater economic incentives

[25] Without the subsidy, BPPs' payment for straw is generally less than 200 CNY per ton, but BPPs that receive the subsidy pay more than 300 CNY per ton. Source: https://e.chengdu.cn/html/2013-04/25/content_394366.htm.

[26] Table 4 compares plants that have received feed-in-tariff with plants that have never received it. We do not compare the same plants before and after they receive the subsidy. This is because plants that receive the subsidy are typically announced as eligible for feed-in-tariff within two years after they start operating, resulting in a relatively short pre-period to exploit this variation. In addition, once a BPP is deemed eligible for feed-in-tariff by the central government, its electricity production will be compensated for a duration of 15 years, starting from the moment it began grid-connected power generation. If a BPP was included in the provincial government's renewable energy projects development plan when it submitted the project proposal for government approval, it has a fairly high probability of receiving the feed-in-tariff. Consequently, it may provide farmers with significant economic incentives even before the official announcement of subsidy reception.

provided by BPPs that receive the production subsidy.

Another factor related to the size of economic incentives is the capacity scale of BPPs, because larger BPPs tend to have greater demand for straw and are likely to offer larger economic incentives to acquire straw. To examine this effect, we use the CEC dataset on national power plants and match our sample with this dataset. From the 467 plants in operation by 2019 per our main sample, we match 296 plants in the CEC dataset. We use the matched treated plants and untreated plants from the original sample for estimations. Columns (1) and (2) of Table 5 examine the heterogeneous effects of BPPs by nameplate generating capacity. The coefficients for BPPs with high and low capacity are -10.517 and -4.246, respectively, in high fire seasons. Nevertheless, neither coefficients are statistically significant due to large standard errors.

BPPs' nameplate capacity may be confounded by unobserved factors related to agricultural fires. To address this concern, Columns (3) and (4) of Table 5 show heterogeneous effects by capacity factors. A capacity factor is a unitless ratio of electricity generation to total capacity, and is likely to be more exogenous to agricultural fire frequency than installed capacity, because capacity factors are determined by local demand for electricity. The effect of BPPs with high capacity factors is quite large (-41.371) in high fire seasons, whereas the effect of BPPs with low capacity factors is only -1.906. The difference between the two coefficients (-39.465) is statistically significant at the 10% level, while the frequency of agricultural fires around BPPs with high and low capacity factors are quite similar (67.494 and 66.705, respectively). The BPPs with higher capacity factors are likely to use more straw to generate electricity and offer larger economic incentives for straw collection. Consistent with this, we observe much larger effects on reducing agricultural fires from the BPPs with higher capacity factors. Columns (5) and (6) provide further support for this channel by showing that BPPs with high annual electricity output have a larger effect (-48.276) in high fire seasons than BPPs with low output (-8.795), and the difference is also significant at the 10% level.

Local enforcement to protect plant infrastructure. Another potential explanation for the significant reduction in agricultural fires is that the entry of BPPs may strengthen local enforcement to protect plant infrastructure against fires.[27] If the observed reduction in agricultural fires is induced by local enforcement on fire prevention, we should expect significant reductions in nearby forest and grass fires, which are usually much more damaging than agricultural fires due to their greater burning intensity and larger burning area.

[27]We thank an anonymous referee for pointing out this potential channel.

Figure 6 shows the effects of the BPP entry on frequency of forest fires and grass fires in the rings binned by the 10 km radius. For both types of fires, all estimates for the rings within 50 km of BPPs are not statistically significant. For rings beyond 50 km from BPPs, two estimates for grass fires are negative and statistically significant but the other five estimates are not significant at the 5% level. Some coefficients for forest fires are even positive and statistically significant, although these have very small magnitudes. The results indicate that there is generally no reduction in the frequency of forest or grass fires around BPPs after they come into operation.

Moreover, if local enforcement is strengthened to protect plant infrastructure against fires, forest and grass fires closer to the plants should decrease more substantially than distant fires because closer fires are more likely to endanger plant infrastructure. Nevertheless, Figure 6 shows that most coefficients for forest fires remain flat as the distance from BPPs increases. The coefficients for grass fires in the eight rings between 10 km and 90 km also remain relatively flat, with a slightly larger effect for the ring between 50 km and 60 km from BPPs.

Factor reallocation. BPP entry may affect farmers through channels other than economic incentives for acquiring straw. BPPs directly create new jobs for plant operation and straw acquisition. They may also help local industrial development by attracting industrial firms and creating new jobs indirectly. Job creation has an ambiguous impact on agricultural fires. On one hand, farmers may decide to work for BPPs or other industrial firms as part-time workers, and so may reduce their labor input in agricultural activities. The reallocation of labor may induce farmers to use fires as a labor-saving method of clearing their land (Garg et al. 2022). On the other hand, farmers could reduce land input for growing crops or even completely move out of the agriculture sector, which could cause reductions in crop straw and agricultural fires.

To examine these effects, we use household-level data from the National Fixed Point Survey (NFPS) on rural households. We consider how the entry of a BPP within a 90 km radius of households in the NFPS dataset affects their labor, land, and other capital inputs. Table 6 shows the estimation results by the OLS estimators (Panel A) and Borusyak et al. (2022) estimators (Panel B). Column (1) shows the effects of BPPs on the total number of days used for agricultural activities. For both estimators, the effects of BPPs are quite small and not statistically significant, implying that the entry of BPPs does not significantly reduce farmers' labor input in agricultural activities. Column (2) shows the effects of BPPs on total crop planting areas in square meters. The coefficients are positive but not statistically significant, suggesting that the reduction in agricultural fires is not caused by a reduction in land input for growing crops. Instead, Columns

3 and 4 show a statistically significant increase in the area for planting grain crops for both estimators and a smaller decrease in the area for non-grain crops (non-significant for the OLS estimator but significant at the 10% level for the Borusyak et al. estimator). Grain crops are the major source of crop straw used by BPPs to generate electricity, and farmers appear to reallocate their land input towards grain crops that produce more straw, rather than other plants, possibly in response to the economic incentives provided by BPPs to acquire straw that increase the value of grain crops for farmers.

In order to collect straw more efficiently, farmers may also increase capital investment in agricultural machines. It is possible that these machines drive the reduction in agricultural fires. Column (5) shows the effects of BPP entry on machinery used for agricultural activities. The coefficients are quite small (less than 1% relative to the mean) and not statistically significant. Therefore, BPP entry has no significant effect on the capital investment in agricultural machines.

Finally, Column (6) shows the effects of BPPs on household income. If BPPs provide farmers economic incentives to reduce agricultural fires, we should observe that BPP entry is associated with an increase in farmers' income. For both estimators, the effects on household income exceed 3,600 CNY and are significant at the 1% level. The average household income in the sample is about 43,000 CNY, so on average, BPP entry is associated with an 8% increase in household income.

5 Comparison with straw-burning bans

China has officially restricted straw burning for several decades. In 2013, the central government enhanced regulation of straw burning in response to mounting pressure to improve air quality from the national anti-pollution campaign (see Greenstone et al. 2021, for a comprehensive review), and some provincial governments subsequently adopted legislation banning straw burning entirely.[28]

Table D1 in the Online Appendix summarizes the legislation and implementation dates. A total of 15 provinces passed legislation banning straw burning entirely and most started to implement this legislation before 2016. We add a dummy variable $StrawBan_{pym}$ to equation (1), denoting whether province p has implemented a complete ban effective in year y and month m. Variation in implementation of straw-burning bans is at the province level, so we cannot use

[28]Previous regulation generally targeted certain areas and periods, whereas the complete ban prohibits any straw burning in all areas of the province throughout the year.

within-province variations to identify the effects of straw-burning bans. We therefore relax the fixed effects in equation (1) to use plant-month and year-month fixed effects.

The effectiveness of regulation could be greatly affected by the cost of monitoring agricultural fires, and fires in the nighttime are much easier to spot. The straw-burning bans prohibit burning at all times, including the nighttime. To enforce the bans, government officials carry out some patrols at night, when fires can be detected easily with the naked eye, even from a long distance away. Before 2016, most night fires occurred in June. In our sample, for June in years before 2016, the average night fire frequency within the 90 km radius of BPPs is 45.672, whereas in other months before 2016, the average night fire frequency is only 0.522. However, after 2016, the average frequency of night fires in June declines to 0.916, which is even slightly smaller than the average frequency in other months (1.139).

Table 7 presents the results of Poisson and OLS regressions analyzing the effects of BPP entry and straw-burning bans on agricultural fires occurring at any time, in the daytime, and in the nighttime. Panel A shows the estimation results for fires at any time. The coefficients on $Biomass_{iym}$ estimated by both Poisson and OLS regressions consistently remain negative and highly significant for the full sample period and for high fire seasons. In contrast, the magnitudes of the coefficients on $StrawBan_{pym}$ are much smaller. While the OLS estimator for $StrawBan_{pym}$ in the full period (-4.182) is significantly at the 10% level, its magnitude is considerably smaller than the effect of BPP entry (-8.505). Moreover, the Poisson estimators for $StrawBan_{pym}$ are not significant for the full period and high fire seasons (-0.012 and -0.043), and even significantly positive during low fire seasons (0.075), suggesting the possible occurrence of inter-temporal displacement. These results indicate that complete bans on straw burning have a substantially smaller effect on agricultural fires compared to the effect of BPP entry.

Panels B and C of Table 7 present the effects of BPP entry and straw-burning bans on agricultural fires in the daytime and nighttime. For daytime fires in the full sample period and high fire seasons, both the Poisson and OLS estimators show negative and statistically significant coefficients on BPP entry at the 1% level. For nighttime fires, the effects remain negative but not statistically significant for the Poisson estimators. While the OLS coefficient on straw-burning bans is significantly negative for daytime fires in high fire seasons (-10.167), its magnitude is still much smaller than the effect of BPP entry (-19.130), and the Poisson coefficient remains not statistically significant in high fire seasons (-0.030) and significantly positive in low fire seasons (0.075).

On the other hand, the Poisson coefficients on straw-burning bans for nighttime fires are -0.291 and -0.328 for the full sample period and high fire seasons, both significant at the 1% level.[29] The coefficients suggest a roughly 30% decline in night fires due to the straw-burning bans. Therefore, although the bans appear to have little effect on mitigating agricultural fires during the daytime, they effectively reduce fires in the nighttime, when fires are easier to detect. Nevertheless, agricultural fires in the nighttime are much less frequent than fires in the daytime; the average fire frequency in the nighttime is only 3.618 for the full sample period, whereas the average frequency in the daytime is 30.810. Therefore, despite the significant effect on reducing nighttime fires, the straw-burning bans have a negligible effect on reducing total number of agricultural fires.

In the Online Appendix B, we further explore the inter-temporal displacement effects of the straw-burning bans on agricultural fires by estimating the effects by each month. Our findings indicate that the bans effectively reduce fires in June, September, and November, but fires rebound in other months. We show that this pattern appears to align with variations in the enforcement stringency of straw-burning bans.

6 Benefits and costs

6.1 Implications for air pollution and health

Reductions in fires due to BPP entry imply improvements in air quality, but the combustion of straw in BPPs' generators will also produce air pollutants, such as SO_2, NO_X, and $PM_{2.5}$. However, BPPs in China face strict regulation of emissions of air pollutants. They are required to install filters, such as dust collectors and desulfurizing and denitrifying facilities, to achieve emissions standards. Therefore, air pollutant emissions from BPPs should be considerably lower than emissions from open burning of the same quantity of straw in farmland. According to the emissions inventory for biomass burning compiled by the Ministry of Environmental Protection of China, open burning generates 6.79 grams of $PM_{2.5}$ and 6.93 grams of PM_{10} per kilogram of straw, whereas biomass steam boilers with standard wet dust collectors generate 0.48 grams of

[29]Interestingly, the OLS coefficients are positive but not statistically significant. Given that about 83% of the observations in the full sample period have no nighttime agricultural fires (and fire frequency is a count variable), it is more appropriate to model the heavy-tailed distribution using an exponential model rather than a linear model. In addition, the fixed-effects Poisson model demonstrates high robustness (Wooldridge 1999), even in the difference-in-differences setting (Wooldridge 2022). Therefore, we consider the results of the Poisson regression to be more reliable than those of OLS for nighttime fires.

$PM_{2.5}$ and 0.49 grams of PM_{10}. If they are equipped with highly efficient bag filters, $PM_{2.5}$ and PM_{10} emissions will be further reduced to 0.05 and 0.06 grams, about 0.8% of the emissions from open burning. Even biomass steam boilers without any filters generate 0.95 grams of $PM_{2.5}$ and 1.12 grams of PM_{10} per kilogram of straw, only 14% and 16% of the emissions from open burning, respectively. These estimates imply that for each unit reduction in agricultural fires due to BPP entry, particulate matter emitted from the fires is reduced by at least 84% even if no filters are installed by the BPPs.

We also provide empirical evidence of the improvements in air quality by using satellite-based annual data on $PM_{2.5}$ concentration from 2001 to 2018 to examine the effect of BPP entry on local $PM_{2.5}$ concentration. Panel A of Table 8 shows the OLS estimation results. We consider three different radii—30 km, 50 km, and 90 km—and calculate average concentrations within the radii. All coefficients on BPP entry are negative and statistically significant at the 5% level. BPP entry is associated with a 0.917 $\mu g/m^3$ reduction in average $PM_{2.5}$ concentration within the 30 km radius (Column (1)), about 2% of the average annual concentration. As a robustness test, we also use the estimation method proposed by Borusyak et al. (2022) and show the estimation results in Panel B of Table 8. Although the magnitudes of coefficients are slightly smaller, they are all statistically significant at the 1% level.

Figure D5 in the Online Appendix further shows the effects of BPPs on average concentration in the rings binned by a 10 km radius. Interestingly, although we observe no statistically significant reduction in agricultural fires beyond 90 km from BPPs (Figure 2), Figure D5 shows that the reduction in $PM_{2.5}$ concentration is statistically significant at the 5% level for rings up to 120 km to BPPs. This effect is most likely attributable to spatial spillover of air pollutants. The magnitudes of the coefficients in Figure D5 are also much more similar than those in Figure 2, suggesting that the pollutant concentrations in these rings are highly correlated.

The significant reduction in fire frequency and improvement in air quality imply large health benefits to rural residents. Column (3) of Table 2 suggests that the entry of one BPP reduces monthly agricultural fires by 4.863. Based on the estimated health damage caused by agricultural fires calculated by He et al. (2020),[30] and the average mortality at the county level,[31] the annual reduction in mortality due to the 467 plants in our sample amounts to 12,803 lives (4.836/10×0.0156×3,634×467). If we take the value of a statistical life of 2.92 million CNY, as

[30]He et al. (2020) find that an increase of 10 fires in the number of fires leads to a 1.56% increase in monthly deaths from all causes.

[31]The average annual mortality per county within the 90 km radius of a BPP was 3,634 in 2019, according to the China City Statistical Yearbook and county-level China Statistical Yearbook.

used by Fan et al. (2020) and He et al. (2020), the annual health benefits from the reduction in mortality are about 37 billion CNY.

Figure 7 illustrates that the health benefits resulting from improved air quality due to reduced agricultural burning are substantial, even in comparison to the social benefits derived from reducing carbon emissions. The biomass power sector generated 48.1 billion kWh of electricity in 2019. Because the Chinese government commits to purchasing all electricity generated by renewable energy sources including biomass, and more than 90% of thermal electricity in China is generated from coal during the sample period, we assume that all electricity generated by BPPs substitutes for electricity from coal-fired plants. Then the reduction in carbon emissions amounts to 28.379 million tons, which is a substantial decrease.[32] In fact, this reduction is more than twice the carbon emission reduction attributable to high-speed rail (Lin et al. 2021). Assuming a social cost of carbon in China of 26 USD per ton (Ricke et al. 2018), the reduction in carbon emissions can be valued at about 5 billion CNY. However, this value is only 14% of the monetized health benefits derived from reductions in agricultural fires. Therefore, in addition to the substantial benefits from reducing carbon emissions, BPPs in China deliver much greater health benefits by mitigating agricultural fires.[33]

Furthermore, Figure 7 shows that the health benefits to the public exceed BPPs' private revenues from selling the generated electricity. The National Administration of Energy disclosed that the average on-grid electricity price is 0.67799 CNY/kWh for BPPs in China in 2018.[34] Therefore, the total revenues from selling the 48.1 billion kWh of electricity amount to 33 billion CNY, which is about 10% smaller than the health benefits.

6.2 Costs of biomass power plants

Figure 7 also shows operational costs of BPPs, based on estimates from Zhao et al. (2017).[35] More than 60% of the costs are for acquiring straw (18 billion CNY), representing payments to farmers. BPPs' labor costs and other costs (including costs of transporting straw) are 2 billion

[32]The median of lifecycle carbon emission intensities of coal-fired and biomass-fired electricity are 820 and 230 g/kWh, respectively, according to Intergovernmental Panel on Climate Change (2015). The reduction in carbon emissions is 48.1$\times$(820-230)/1,000=28.379 million tons.

[33]The social cost of carbon is a contentious topic, with estimates ranging from dozens to hundreds of USD per ton. However, the large relative difference between the health benefits and benefits from reduction of carbon emissions implies that the two benefits would be equivalent only under a high estimate for the social cost of carbon (about 186 USD per ton).

[34]Source: http://www.nea.gov.cn/138530255_15729388881531n.pdf.

[35]Zhao et al. (2017) find that the straw cost for biomass power plants is 0.382 CNY/kWh, labor cost is 0.042 CNY/kWh, and other costs are 0.175 CNY/kWh.

CNY and 8 billion CNY, respectively. The total operational costs of BPPs amount to 28 billion CNY, leaving 5 billion annual profits from which to recover their investment costs.

A great concern about using biomass to generate electricity is that it could reduce forests and threaten biodiversity.[36] However, this criticism addresses use of forests for bioenergy, whereas BPPs in China mainly use agricultural waste as fuel. Furthermore, most forests in China are state owned or collectively owned, and the government has implemented strict regulation of woodland for several decades. Large-scale logging without government permission is strictly prohibited.[37]

Due to the nature of forest ownership and strict regulation, we expect the effects of BPP entry on loss of vegetation cover to be limited. To test this conjecture, we examine the effects of BPP entry on two vegetation indices (NDVI and EVI). Similar to Table 8, we consider three different radii (30, 50, and 90 km) and calculate the logarithms of average indices within the radii. Table 9 shows the estimation results. For both OLS estimators (Panel A) and Borusyak et al. (2022) estimators (Panel B), we find that the coefficients on BPP entry for NDVI and EVI are quite close to zero and none are statistically significantly negative. One coefficient is even statistically significantly positive, although small in magnitude (0.004). These results indicate that BPPs in China exert little influence on reducing local vegetation cover.

7 Conclusion

This paper provides empirical evidence of the effect of BPP entry on reducing agricultural fires, a prevalent method used by farmers in many countries to clear their land. Exploiting the entry of BPPs as a quasi-natural experiment, we show that BPPs have, on average, a statistically significant effect on reducing straw burning. Within a 90 km radius of a new BPP, agricultural fires reduce by 14%. Moreover, we find that farmers closer to BPPs exhibit a larger response (up to -23%), with the effect diminishing gradually as the distance from the BPP increases. This implies a critical role of BPPs' transaction costs in internalizing environmental externalities. The effects of BPP entry are also much stronger in months before sowing and after harvesting (-17%) than other months (-3%).

We show that the reduction in agricultural fires is likely induced by economic incentives

[36]Over 500 scientists wrote to the Presidents of the EU Commission, the US, and South Korea, and the Prime Minister of Japan in February 2021, urging the governments to stop subsidizing wood burning for electricity. Source: https://www.wwf.eu/?2128466%2F500-scientists-tell-EU-to-end-tree-burning-for-energy.

[37]According to the forest law of China, before cutting down more than two trees, even if the trees are on a farmer's own land, the farmer must submit a formal request to local government and obtain a forest logging permit.

provided by BPPs to farmers for acquiring straw from their land, because BPPs that are able to provide larger economic incentives to farmers exhibit greater effects on reducing nearby agricultural fires. We also show that farmers appear to respond to the economic incentives by allocating more land to growing grain crops, which produce more straw for BPPs to acquire.

We further compare the effects of BPPs with the effects of straw-burning bans. Agricultural fires are generally much smaller than forest fires and harder to monitor. We find that straw-burning bans have no overall effect on reducing agricultural fires. However, the bans appear to significantly reduce straw burning at night, when monitoring of agricultural fires is much easier than during the day.

Our back-of-an-envelope calculations indicate that public health benefits from improved air quality due to the reduction in agricultural fires are considerably larger than the monetized social benefits derived from carbon emission reductions achieved through the substitution of coal-fired electricity with electricity generated by BPPs. Moreover, these public health benefits are slightly larger than BPPs' private revenues from electricity sales. These substantial health benefits imply that BPPs, often recognized as (controversial) contributors to greenhouse gas emission reduction and climate change mitigation, play an even more significant role in reducing local air pollutants and improving human health. It is likely that similar health benefits exist in other approaches adopted by countries to reduce their greenhouse gas emissions.

At present, the opportunity cost of labor is rising rapidly in many developing countries. The rising labor cost could directly increase BPPs' straw-acquiring costs and aggravate their financial difficulties, especially under a regulated electricity price. Whether BPPs should, in future, be compensated more for the public health benefits they provide, or whether we should seek a more cost-effective way to control agricultural fires, merits further investigation.

References

Aldy, Joseph, Matthew J Kotchen, Mary Evans, Meredith Fowlie, Arik Levinson, and Karen Palmer (2021) "Cobenefits and regulatory impact analysis: Theory and evidence from federal air quality regulations," *Environmental and Energy Policy and the Economy*, 2 (1), 117–156.

Alix-Garcia, Jennifer M, Katharine RE Sims, and Patricia Yañez-Pagans (2015) "Only one tree from each seed? Environmental effectiveness and poverty alleviation in Mexico's Payments for Ecosystem Services Program," *American Economic Journal: Economic Policy*, 7 (4), 1–40.

Asher, Sam and Paul Novosad (2020) "Rural roads and local economic development," *American Economic Review*, 110 (3), 797–823.

Ashraf, Nava, Edward L Glaeser, and Giacomo AM Ponzetto (2016) "Infrastructure, incentives, and institutions," *American Economic Review*, 106 (5), 77–82.

Aunan, Kristin, Mette Halskov Hansen, Zhaohui Liu, and Shuxiao Wang (2019) "The hidden hazard of household air pollution in rural China," *Environmental Science & Policy*, 93, 27–33.

Balboni, Clare, Robin Burgess, and Benjamin A Olken (2021) "The origins and control of forest fires in the tropics," *Working paper*.

Behrer, A Patrick (2019) "Earth, wind and fire: The impact of anti-poverty efforts on Indian agriculture and air pollution," *Working paper*.

Borusyak, Kirill and Peter Hull (2020) "Non-random exposure to exogenous shocks: Theory and applications," *NBER working paper*, w27845.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess (2022) "Revisiting event study designs: Robust and efficient estimation," *Working paper*.

Chen, Yuyu, Ginger Zhe Jin, Naresh Kumar, and Guang Shi (2013) "The promise of Beijing: Evaluating the impact of the 2008 Olympic Games on air quality," *Journal of Environmental Economics and Management*, 66 (3), 424–443.

de Chaisemartin, Clément and Xavier d'Haultfoeuille (2020) "Two-way fixed effects estimators with heterogeneous treatment effects," *American Economic Review*, 110 (9), 2964–96.

Edwards, Ryan B, Walter P Falcon, Gracia Hadiwidjaja, Matthew M Higgins, Rosamond L Naylor, and Sudarno Sumarto (2020) "Fight re with nance: a randomized eld experiment to curtail land-clearing re in Indonesia," *Working paper*.

Fan, Maoyong, Guojun He, and Maigeng Zhou (2020) "The winter choke: Coal-fired heating, air pollution, and mortality in China," *Journal of Health Economics*, 71, 102316.

Favero, Alice, Adam Daigneault, and Brent Sohngen (2020) "Forests: Carbon sequestration, biomass energy, or both?" *Science Advances*, 6 (13), eaay6792.

Ferraro, Paul J and Rhita Simorangkir (2020) “Conditional cash transfers to alleviate poverty also reduced deforestation in Indonesia,” *Science Advances*, 6 (24), eaaz1298.

Fullerton, Don and Daniel H Karney (2018) “Multiple pollutants, co-benefits, and suboptimal environmental policies,” *Journal of Environmental Economics and Management*, 87, 52–71.

Garg, Teevrat, Maulik Jagnani, and Hemant K Pullabhotla (2022) “Structural transformation and environmental externalities,” *Working paper*.

Goodman-Bacon, Andrew (2021) “Difference-in-differences with variation in treatment timing,” *Journal of Econometrics*, 225 (2), 254–277.

Graff Zivin, Joshua, Tong Liu, Yingquan Song, Qu Tang, and Peng Zhang (2020) “The unintended impacts of agricultural fires: Human capital in China,” *Journal of Development Economics*, 147, 102560.

Greenstone, Michael, Guojun He, Ruixue Jia, and Tong Liu (2022) “Can technology solve the principal-agent problem? Evidence from China’s war on air pollution,” *American Economic Review: Insights*, 4 (1), 54–70.

Greenstone, Michael, Guojun He, Shanjun Li, and Eric Yongchen Zou (2021) “China’s war on pollution: Evidence from the first 5 years,” *Review of Environmental Economics and Policy*, 15 (2), 281–299.

Hammer, Melanie S, Aaron van Donkelaar, Chi Li et al. (2020) “Global estimates and long-term trends of fine particulate matter concentrations (1998–2018),” *Environmental Science & Technology*, 54 (13), 7879–7890.

He, Guojun, Maoyong Fan, and Maigeng Zhou (2016) “The effect of air pollution on mortality in China: Evidence from the 2008 Beijing Olympic Games,” *Journal of Environmental Economics and Management*, 79, 18–39.

He, Guojun, Tong Liu, and Maigeng Zhou (2020) “Straw burning, PM2. 5, and death: Evidence from China,” *Journal of Development Economics*, 145, 102468.

Hernández-Cortés, Danae (2022) “The Distributional Consequences of Incomplete Regulation,” *Working paper*.

Hsiao, Allan (2021) "Coordination and commitment in international climate action: Evidence from palm oil," *Working paper*.

Intergovernmental Panel on Climate Change (2015) *Technology-specific Cost and Performance Parameters*, 1329–1356: Cambridge University Press.

Jack, B Kelsey, Seema Jayachandran, Namrata Kala, and Rohini Pande (2022) "Money (Not) to Burn: Payments for Ecosystem Services to Reduce Crop Residue Burning," *NBER working paper*, w30690.

Jack, B Kelsey, Carolyn Kousky, and Katharine RE Sims (2008) "Designing payments for ecosystem services: Lessons from previous experience with incentive-based mechanisms," *Proceedings of the national Academy of Sciences*, 105 (28), 9465–9470.

Jayachandran, Seema, Joost De Laat, Eric F Lambin, Charlotte Y Stanton, Robin Audy, and Nancy E Thomas (2017) "Cash for carbon: A randomized trial of payments for ecosystem services to reduce deforestation," *Science*, 357 (6348), 267–273.

Karplus, Valerie J, Shuang Zhang, and Douglas Almond (2018) "Quantifying coal power plant responses to tighter SO2 emissions standards in China," *Proceedings of the National Academy of Sciences*, 115 (27), 7004–7009.

Lin, Yatang, Yu Qin, Jing Wu, and Mandi Xu (2021) "Impact of high-speed rail on road traffic and greenhouse gas emissions," *Nature Climate Change*, 11 (11), 952–957.

Nian, Yongwei (2023) "Incentives, penalties, and rural air pollution: Evidence from satellite data," *Journal of Development Economics*, 161, 103049.

Pollmann, Michael (2023) "Causal Inference for Spatial Treatments," *Working paper*.

Rangel, Marcos A and Tom S Vogl (2019) "Agricultural fires and health at birth," *Review of Economics and Statistics*, 101 (4), 616–630.

Rao, Narasimha D, Gregor Kiesewetter, Jihoon Min, Shonali Pachauri, and Fabian Wagner (2021) "Household contributions to and impacts from air pollution in India," *Nature Sustainability*, 4 (10), 859–867.

Ricke, Katharine, Laurent Drouet, Ken Caldeira, and Massimo Tavoni (2018) "Country-level social cost of carbon," *Nature Climate Change*, 8 (10), 895–900.

Scovronick, Noah, Mark Budolfson, Francis Dennig et al. (2019) "The impact of human health co-benefits on evaluations of global climate policy," *Nature Communications*, 10 (1), 1–12.

Sun, Liyang and Sarah Abraham (2021) "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 225 (2), 175–199.

Tao, S, MY Ru, W Du et al. (2018) "Quantifying the rural residential energy transition in China from 1992 to 2012 through a representative national survey," *Nature Energy*, 3 (7), 567–573.

van Donkelaar, Aaron, Randall V Martin, Chi Li, and Richard T Burnett (2019) "Regional estimates of chemical composition of fine particulate matter using a combined geoscience-statistical method with information from satellites, models, and monitors," *Environmental Science & Technology*, 53 (5), 2595–2611.

Wooldridge, Jeffrey M (1999) "Distribution-free estimation of some nonlinear panel data models," *Journal of Econometrics*, 90 (1), 77–97.

——— (2022) "Simple approaches to nonlinear difference-in-differences with panel data," *Working paper*.

Wunder, Sven, Jan Börner, Driss Ezzine-de Blas, Sarah Feder, and Stefano Pagiola (2020) "Payments for environmental services: Past performance and pending potentials," *Annual Review of Resource Economics*, 12, 209–234.

Zhang, Bing, Xiaolan Chen, and Huanxiu Guo (2018) "Does central supervision enhance local environmental enforcement? Quasi-experimental evidence from China," *Journal of Public Economics*, 164, 70–90.

Zhao, Guiyu, Yanling Qi, and Yang Lv (2017) "Economic Benefit of Crop Straw Power Generation (in Chinese)," *Journal of Agriculture*, 7 (3), 86.

Zou, Eric Yongchen (2021) "Unwatched pollution: The effect of intermittent monitoring on air quality," *American Economic Review*, 111 (7), 2101–26.

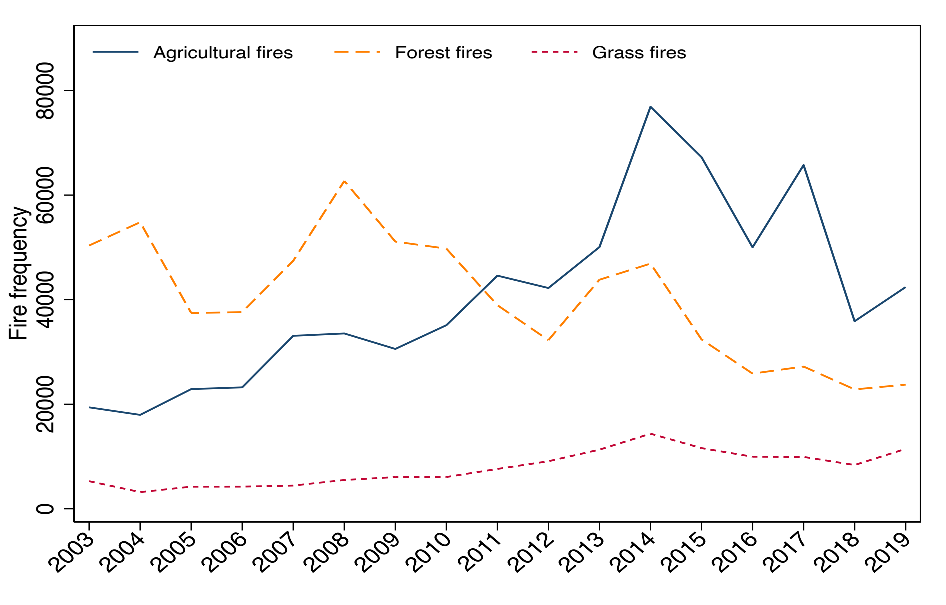


Figure 1: Frequency of agricultural fires, forest fires, and grass fires in China

Notes: Agricultural fires, forest fires, and grass fires are identified as hotspots detected by MODIS in farmland, forest, and grassland, respectively.

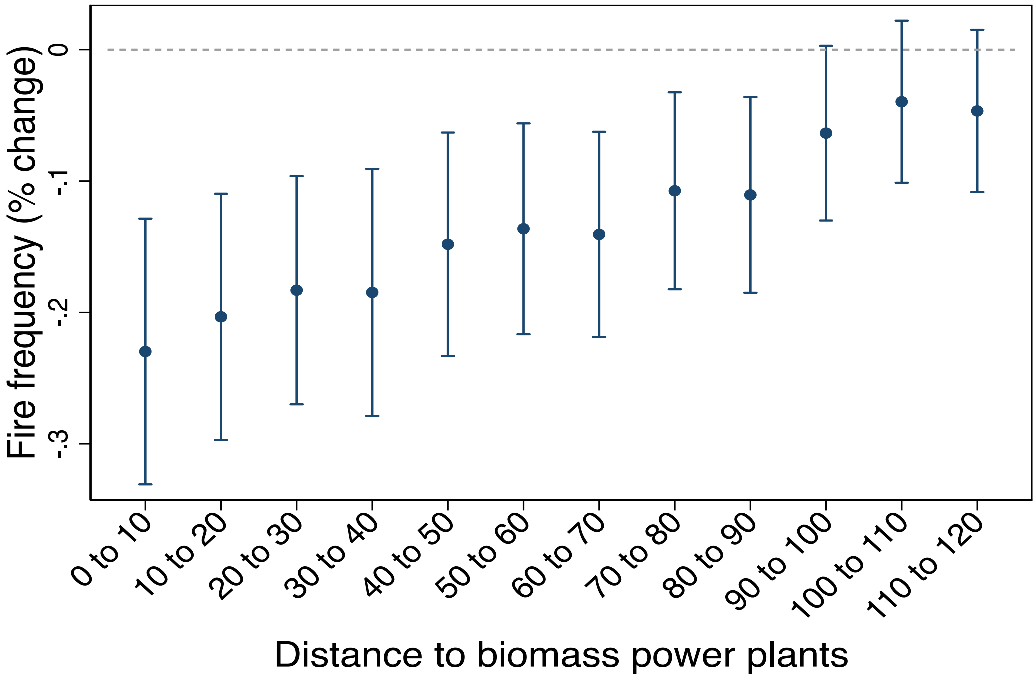


Figure 2: Effects of biomass power plants on fire frequency by distance

Notes: Circles represent point estimates and lines represent 95% confidence intervals.

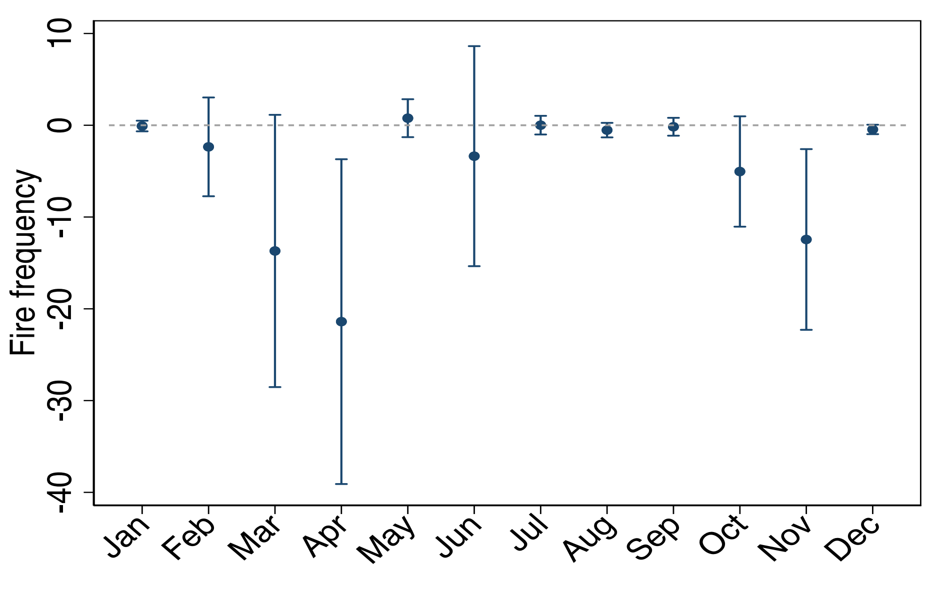
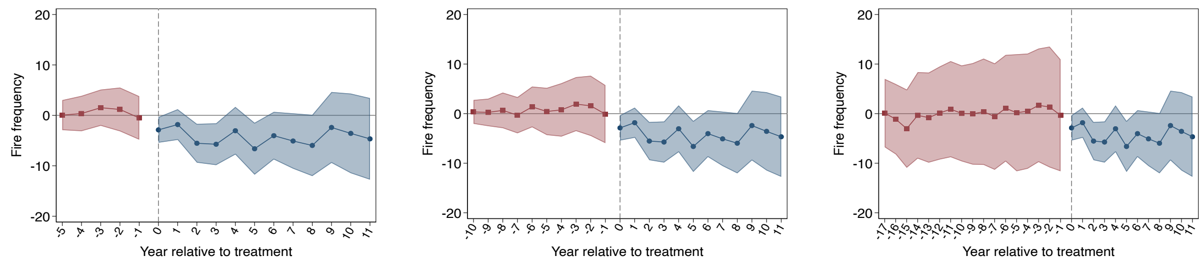


Figure 3: Effects on fire frequency within a 90 km radius by month

Notes: Circles represent point estimates and lines represent 95% confidence intervals.



(a) $k = 5$ (b) $k = 10$ (c) $k = 17$

Figure 4: Fire frequency before and after treatment

Notes: The dependent variables are the monthly frequency of fires within 90 km of BPPs. Square and circles represent point estimates and shaded areas represent 95% confidence intervals.

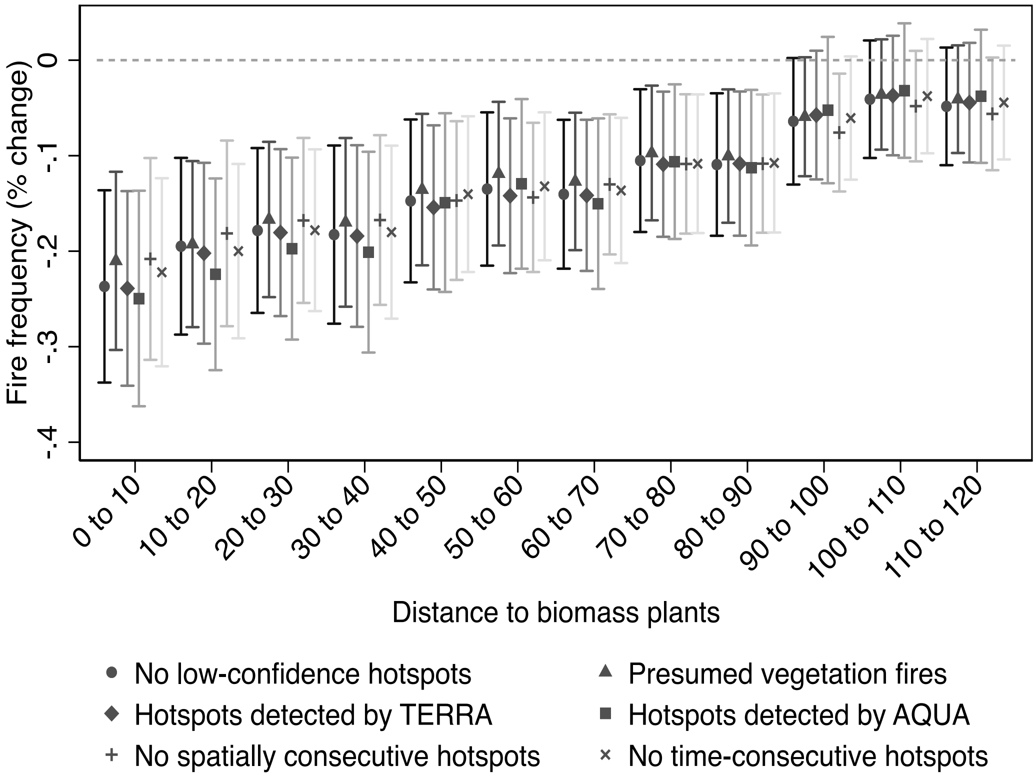


Figure 5: Robustness checks on measurement errors in fire pixels

Notes: The dependent variables are the monthly frequency of fires in the ten rings with distance between $r-10$ and r km from BPPs, where $r = 10, \ldots, 120$. Symbols represent point estimates and vertical lines represent 95% confidence intervals.

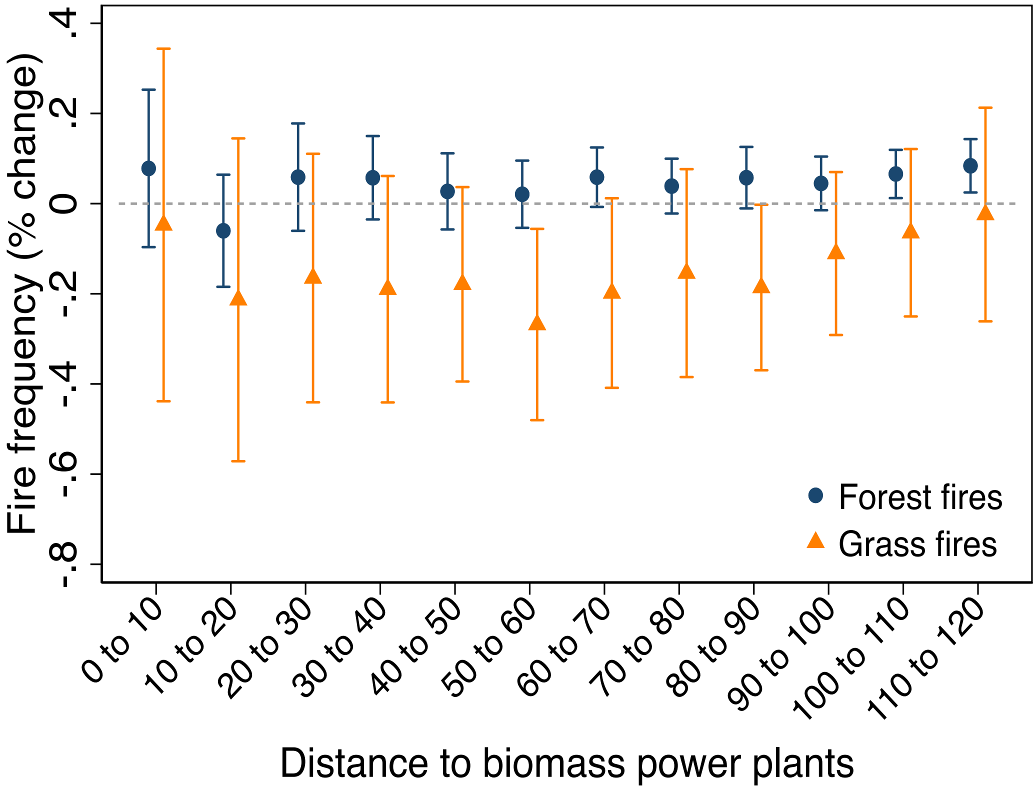


Figure 6: Effects of the entry of biomass power plants on forest and grass fires

Notes: The dependent variables are the monthly frequency of forest fires (circles) and grass fires (triangles) in the ten rings with distance between $r-10$ and r km from BPPs, where $r = 10, \ldots, 120$, and the vertical lines represent 95% confidence intervals.

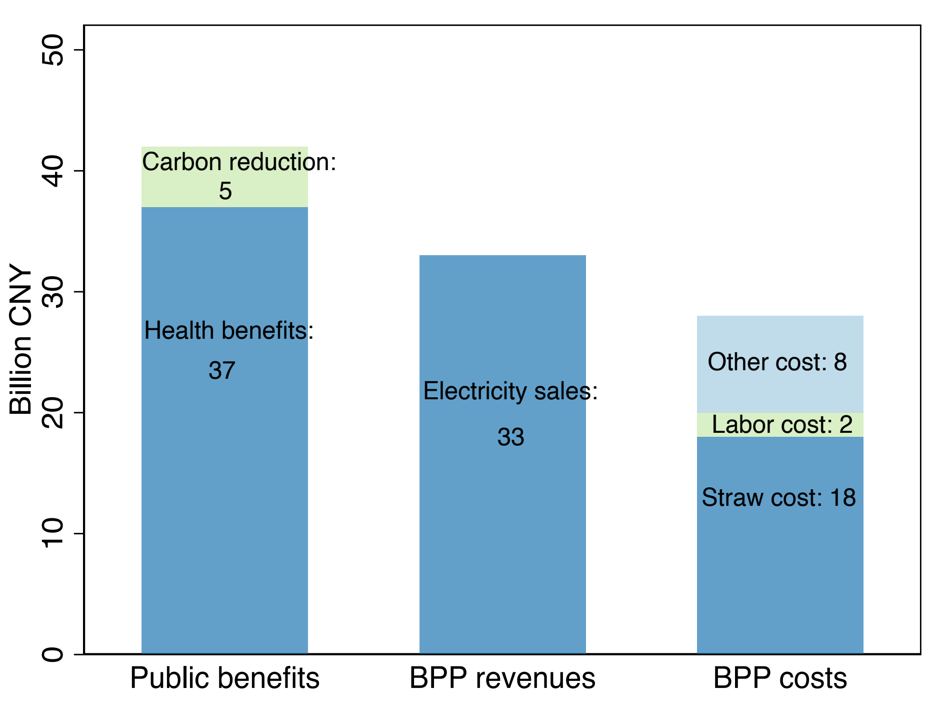


Figure 7: Annual benefits and costs of biomass power plants

Table 1: Summary statistics for pre-treatment characteristics

	Treated			Untreated			t-statistics	P-value
	N	Mean	Std	N	Mean	Std		
Fire frequency	72,163	37.317	169.175	111,036	41.742	178.546	0.517	0.605
NDVI	72,163	0.471	0.194	111,036	0.474	0.215	-1.097	0.273
EVI	72,163	0.288	0.141	111,036	0.287	0.152	-0.941	0.347
Population	4,266	0.719	0.391	5,776	0.650	0.384	0.157	0.875
Agriculture GDP	4,935	2.260	1.799	6,986	2.569	2.142	0.446	0.656
Industry GDP	4,947	5.632	8.126	7,012	5.609	9.118	1.335	0.182
Service GDP	4,803	3.788	5.288	6,755	4.711	9.815	-0.239	0.811
Agricultural machinery	3,444	0.539	0.774	4,992	0.583	2.837	-1.292	0.197
Grain output	5,125	0.667	0.845	7,225	0.795	0.979	0.434	0.665
Vegetable output	5,125	0.339	0.801	7,225	0.255	0.479	2.139	0.033
Distance to city center	467	57.391	48.691	487	67.403	61.282	-0.966	0.334
Distance to highways	467	17.041	27.692	487	16.557	23.238	1.454	0.146
Distance to airports	467	62.777	31.931	487	63.739	35.771	0.930	0.353

Notes: Fire frequency is the monthly frequency of agricultural fires within distance 100 km from BPPs. NDVI and EVI are monthly vegetation indices within distance 100 km from BPPs. Population is the county-level annual population (million). Agriculture GDP is the county-level annual value-added of the agriculture sector (billion CNY). Industry GDP is the county-level annual value-added of the industry sector (billion CNY). Service GDP is the county-level annual value-added of the service sector (billion CNY). Agricultural machinery is the county-level annual power of agricultural machines (gigawatt). Grain output is the county-level annual output of grains (million tons). Vegetable output is the county-level annual output of vegetables and flowers (million tons). Distance to city center is the distance from BPPs to the seats of city governments (km). Distance to highways is the distance from BPPs to the nearest national highways (km). Distance to airports is the distance from BPPs to the nearest airports (km). The t-statistics and p-values are constructed after controlling for province-year-month fixed effects for monthly variables, province-year fixed effects for annual variables, and province fixed effects for time-invariant variables.

Table 2: Effects of the entry of biomass power plants on agricultural fire frequency

	Full sample			High fire seasons			Low fire seasons		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Biomass	-9.270***	-5.075***	-4.836***	-23.372***	-11.471***	-11.192***	0.899	-0.504	-0.428
	(2.621)	(1.370)	(1.326)	(5.774)	(3.200)	(3.106)	(1.107)	(0.484)	(0.470)
Plant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	No	No	Yes	No	No	Yes	No	No
Plant-month	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Province-year-month	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Weather controls	No	No	Yes	No	No	Yes	No	No	Yes
Number of plants	954	954	954	954	954	954	954	954	954
Mean of dep. var	34.428	34.428	34.428	64.286	64.286	64.286	13.101	13.101	13.101
R-squared	0.168	0.709	0.710	0.197	0.700	0.701	0.204	0.705	0.706
Observations	217,512	216,828	216,828	90,630	90,345	90,345	126,882	126,483	126,483

Notes: The dependent variables in Columns (1)–(3), (4)–(6), and (7)–(9) are the monthly frequency of agricultural fires within the 90 km radius of BPPs for all months, for the high fire seasons (March, April, June, October, November), and for the low fire seasons (the rest of months), respectively. Biomass_{iym} is a dummy variable that equals one if plant i is in operation in year y and month m, and zero otherwise. Weather control variables include monthly average temperature, wind speed, relative humidity, and total precipitation. Conley spatial standard errors are in brackets. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: F-tests for pre-treatment trends

	All months	March	April	June	October	November
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: $k = 5$			
F-stat	0.466	1.100	0.789	0.345	0.645	0.611
P-value	0.802	0.359	0.558	0.886	0.665	0.692
			Panel B: $k = 10$			
F-stat	0.318	0.999	1.376	0.581	1.207	0.747
P-value	0.977	0.442	0.186	0.830	0.282	0.680
			Panel C: $k = 17$			
F-stat	1.158	0.854	1.518	0.902	1.067	0.740
P-value	0.293	0.630	0.081	0.572	0.382	0.763

Notes: The F-tests proposed by Borusyak et al. (2022) are used to test for pre-trends.

Table 4: Heterogeneous effects by financial conditions

	Judgement debtors		Feed-in tariff	
	Yes	No	Yes	No
	(1)	(2)	(3)	(4)
	Panel A: High fire seasons			
Biomass	1.780	-14.526***	-13.948***	-3.181
	(3.780)	(3.604)	(3.516)	(3.596)
Number of plants	592	849	758	683
Mean of dep. var	62.894	66.076	62.122	67.706
Observations	56,145	80,275	71,915	64,505
Difference	16.306*** (3.675)		-10.767* (4.119)	
	Panel B: Low fire seasons			
Biomass	-0.272	-0.458	-0.707	-0.099
	(0.480)	(0.571)	(0.567)	(0.583)
Number of plants	592	849	758	683
Mean of dep. var	12.344	13.066	12.829	12.703
Observations	78,603	112,385	100,681	90,307
Difference	0.186 (0.616)		-0.607 (0.665)	

Notes: The dependent variables in Panel A and Panel B are the monthly frequency of fires within the 90 km radius of BPPs in the high fire seasons and in the low fire seasons, respectively. Columns (1) and (2) represent delinquent plants and non-delinquent plants. Columns (3) and (4) represent plants that do and do not receive feed-in tariff subsidies. All untreated plants are included in the regressions. Biomass$_{iym}$ is a dummy variable that equals one if plant i is in operation in year y and month m, and zero otherwise. Weather control variables include monthly average temperature, wind speed, relative humidity, and total precipitation. Fixed effects are at the plant-month level and province-year-month level. Conley spatial standard errors are in brackets. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Heterogeneous effects by power generation characteristics

	Nameplate capacity		Capacity factor		Electricity output	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: High fire seasons			
Biomass	-10.517	-4.246	-41.371**	-1.906	-48.276**	-8.795
	(12.535)	(7.487)	(18.446)	(7.608)	(19.873)	(6.832)
Number of plants	650	627	694	731	673	722
Mean of dep. var	67.824	65.746	67.494	66.705	67.853	66.055
Observations	49,840	50,335	49,895	49,865	49,760	49,710
Difference	-6.272 (15.151)		-39.465* (21.044)		-39.481* (21.294)	
			Panel B: Low fire seasons			
Biomass	0.371	-0.721	-1.150	-0.864	-1.809**	0.474
	(0.857)	(1.063)	(0.790)	(1.131)	(0.871)	(1.206)
Number of plants	650	627	694	731	673	722
Mean of dep. var	12.615	12.753	12.761	12.546	12.693	12.594
Observations	69,776	70,469	69,853	69,811	69,664	69,594
Difference	1.092 (1.240)		-0.286 (1.407)		-2.283* (1.208)	

Notes: The dependent variables in Panel A and Panel B are the monthly frequency of agricultural fires within the 90 km radius of BPPs in the high fire seasons and in the low fire seasons, respectively. Columns (1) and (2) represent biomass power plants with high and low nameplate capacity. Columns (3) and (4) represent biomass power plants with high and low capacity factors. Columns (5) and (6) represent biomass power plants with high and low electricity generation. All untreated plants are included in the regressions. Biomass$_{iym}$ is a dummy variable that equals one if plant i is in operation in year y and month m, and zero otherwise. Weather control variables include monthly average temperature, wind speed, relative humidity, and total precipitation. Fixed effects are at the plant-month level and province-year-month level. Conley spatial standard errors are in brackets. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Effects of the entry of biomass power plants on rural households

	Labor input	Planting area	Grain area	Non-grain area	Capital input	Income
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: OLS estimates			
Biomass	-0.019	145.765	162.111*	-22.289	108.791	3,673.900***
	(1.965)	(127.928)	(94.171)	(64.862)	(449.368)	(868.774)
Number of HH	15,812	16,471	16,468	16,465	14,199	16,463
Mean of dep. var	58	4,995	3,622	1,227	11,283	43,667
Observations	126,232	145,289	145,250	145,195	112,689	145,525
			Panel B: Borusyak et al. (2022) estimates			
Biomass	-0.327	81.832	112.936**	-46.517*	155.484	3,953.136***
	(0.849)	(63.384)	(53.121)	(25.033)	(396.586)	(563.592)
Number of HH	16,283	17,049	17,046	17,043	15,125	17,037
Mean of dep. var	58	5,001	3,627	1,228	11,295	43,617
Observations	126,703	145,867	145,828	145,773	113,615	146,099

Notes: The dependent variables in Columns (1)–(6) are labor input on agricultural activities (days), planting area (square meters), planting area of grains (square meters), planting area of non-grain crops (square meters), agricultural machinery (CNY), and annual household income (CNY). Biomass$_{iy}$ is a dummy variable that equals one if household i is surrounded by an operating biomass power plant within 90 km in year y, and zero otherwise. Fixed effects are at the household level and household type-year level. Conley spatial standard errors (Panel A) and clustered standard errors at the household level (Panel B) are in brackets. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Comparison with the effect of straw-burning bans

	Poisson			OLS		
	Full	High	Low	Full	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: All fires			
Biomass	-0.154***	-0.189***	-0.063**	-8.505***	-21.006***	0.710
	(0.031)	(0.038)	(0.030)	(2.124)	(4.768)	(0.621)
StrawBans	-0.012	-0.043	0.075**	-4.182*	-8.621	-0.244
	(0.031)	(0.041)	(0.029)	(2.313)	(5.323)	(0.732)
Mean of dep. var	34.428	64.286	13.101	34.428	64.286	13.101
Observations	217,512	90,630	126,882	217,512	90,630	126,882
			Panel B: Daytime fires			
Biomass	-0.162***	-0.202***	-0.066**	-7.657***	-19.130***	0.804
	(0.032)	(0.040)	(0.029)	(1.959)	(4.365)	(0.601)
StrawBans	-0.001	-0.030	0.075***	-4.681**	-10.167**	-0.100
	(0.031)	(0.040)	(0.029)	(1.966)	(4.434)	(0.698)
Mean of dep. var	30.810	56.208	12.668	30.810	56.208	12.668
Observations	217,512	90,630	126,882	217,512	90,630	126,882
			Panel C: Nighttime fires			
Biomass	-0.077	-0.083	-0.034	-0.849**	-1.876*	-0.094
	(0.058)	(0.058)	(0.090)	(0.418)	(0.997)	(0.058)
StrawBans	-0.291***	-0.328***	-0.037	0.498	1.546	-0.144*
	(0.057)	(0.059)	(0.102)	(0.572)	(1.384)	(0.080)
Mean of dep. var	3.618	8.078	0.432	3.618	8.078	0.432
Observations	217,512	90,630	126,882	217,512	90,630	126,882

Notes: The dependent variables in Panels A, B, C are the monthly frequency of all agricultural fires, daytime fires, and night time fires within the 90 km radius of BPPs for all months (Columns (1) and (4)), for the high fire seasons (Columns (2) and (5)), and for the low fire seasons (Columns (3) and (6)), respectively. Biomass$_{iym}$ is a dummy variable that equals one if plant i is in operation in year y and month m, and zero otherwise. Strawbans$_{pym}$ is a dummy variable that equals one if province p completely bans straw burning in year y and month m, and zero otherwise. Weather control variables include monthly average temperature, wind speed, relative humidity, and total precipitation. Fixed effects are at the plant-month level and year-month level. Standard errors are clustered at the plant level. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Effects of the entry of biomass power plants on $PM_{2.5}$

	$r \leq 30$	$r \leq 50$	$r \leq 90$
	(1)	(2)	(3)
	Panel A: OLS estimates		
Biomass	-0.917**	-0.891**	-0.837**
	(0.397)	(0.393)	(0.381)
Number of plants	954	954	954
Mean of dep. var	46.714	45.974	45.051
Observations	17,172	17,172	17,172
	Panel B: Borusyak et al. (2022) estimates		
Biomass	-0.853***	-0.832***	-0.778***
	(0.314)	(0.309)	(0.296)
Number of plants	954	954	954
Mean of dep. var	46.714	45.974	45.051
Observations	17,172	17,172	17,172

Notes: The dependent variables in Columns (1) –(3) are the annual average $PM_{2.5}$ concentrations within 30, 50, and 90 km to BPPs, respectively. Biomass_{iy} is a dummy variable that equals one if plant i is in operation in year y, and zero otherwise. Weather control variables include annual average temperature, wind speed, relative humidity, and total precipitation. Fixed effects are at the plant level and year level. Conley spatial standard errors (Panel A) and clustered standard errors at the plant level (Panel B) are in brackets. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Effects of the entry of biomass power plants on vegetation indices

	NDVI			EVI		
	$r \leq 30$	$r \leq 50$	$r \leq 90$	$r \leq 30$	$r \leq 50$	$r \leq 90$
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: OLS estimates					
Biomass	0.001	0.002	0.004**	-0.003	-0.002	0.000
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of plants	954	954	954	954	954	954
Mean of dep. var	-0.927	-0.909	-0.887	-1.432	-1.420	-1.406
Observations	216,695	216,749	216,808	216,666	216,718	216,792
	Panel B: Borusyak et al. (2022) estimates					
Biomass	0.000	0.001	0.003	-0.004	-0.003	-0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Number of plants	954	954	954	954	954	954
Mean of dep. var	-0.927	-0.909	-0.887	-1.432	-1.420	-1.406
Observations	217,361	217,415	217,474	217,332	217,384	217,458

Notes: The dependent variables in Panel A and Panel B are monthly average vegetation indices (NDVI for Columns (1)–(3) and EVI for Columns (4)–(6)) for the high fire seasons and for the low fire seasons, respectively. Columns (1) and (4) represent average indices within 30 km of BPPs. Columns (2) and (5) represent average indices within 50 km of BPPs. Columns (3) and (6) represent average indices within 90 km of BPPs. Biomass$_{iym}$ is a dummy variable that equals one if plant i is in operation in year y and month m, and zero otherwise. Weather control variables include monthly average temperature, wind speed, relative humidity, and total precipitation. Fixed effects are at the plant-month level and province-year-month level. Conley spatial standard errors (Panel A) and clustered standard errors at the plant level (Panel B) are in brackets. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Online Appendix for "Mitigating agricultural fires with carrot or stick? Evidence from China"

A Additional Robustness Checks

Measurement errors in plant operation years and locations. In the main results we use electricity business license information to identify the year when each plant began operating. For robustness, we alternatively identify the years when operations began by using the CEC dataset. For the match 296 treated plants from the CEC dataset, we use the first year each plant is reported in the dataset as its year of beginning operating. The original and alternative operating years have similar means (2013.373 and 2012.334). We retain the matched plants and untreated plants from the original sample and re-estimate equation (1). The results are shown in Figure D6, and the coefficients (denoted by circles) and 95% confidence intervals (vertical lines) conform with our main results.

In the main results, we use the registered address of each plant to geocode its location. However, a plant's operating location could differ from its registered address. To reduce measurement errors in plant locations, we search for each BPP's full name in an online map service and obtain its geographical coordinates.[1] This procedure returns geographical coordinates for 328 plants, more than 96% of which are already operating or under construction. To examine whether the locations differ meaningfully from registered addresses, we calculate the distance between each pair of locations. More than 90% of the 328 plants have a distance between the two locations of less than 10 km, and the median distance is only 1.969 km. We replace the original geographical coordinates of the 328 plants in our sample with the new coordinates, re-calculate fire frequency around the new coordinates, and re-estimate equation (1). The results are shown in Figure D6, where triangles and vertical lines denote coefficients and 95% confidence intervals, respectively. Consistent with our main results, we find that the effect of BPP entry decreases in distance from the plant and the effect is not statistically significant beyond a 90 km radius.

Robustness checks for empirical design. We use a staggered event study design to examine the effects of BPP entry on agricultural fires. However, this design could be subject to the problem

[1]This test assumes that search results for BPPs' full names in the online map service are likely to show their factory address rather than their registered address.

of negative weights (de Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021). To evaluate whether negative weights pose a threat to the empirical design, we use the program "twowayfeweights" proposed by de Chaisemartin and d'Haultfoeuille (2020) to estimate the weights attached to the two-way fixed effects OLS regression. We find that among the total 34,262 average treatment effects on the treated (ATTs), only 51 ATTs receive negative weights, and the sum of the negative weights is -0.00004. Therefore, the very small proportion of negative weights is highly unlikely to cause a meaningful bias to our estimations.

Given that agricultural fire frequency is a count variable, Table D2 employs Poisson regression to estimate equation (1). Consistent with the main results, the effects of BPP entry demonstrate negative and substantial magnitudes for all months (-0.094) and high fire seasons (-0.113), while they are notably smaller for low fire seasons (-0.036).

We use Conley spatial standard errors with a 600 km distance cutoff in the main results. For robustness, Table D3 considers three alternative distance cutoffs (200, 500, and 1,000 km) for Conley standard errors and also clustered standard errors at the plant level. Although the greater distance cutoff yields larger standard errors, all the Conley spatial standard errors, as well as the clustered standard errors, suggest a 1% significance level for agricultural fires in all months and high fire seasons, and non-significant results for low fire seasons.

The main results use BPPs in the process of preparation or withdrawal by the end of the sample period as the untreated group. For robustness, Table D4 excludes the untreated plants and uses treated and not-yet-treated plants for estimations. The effects of BPP entry are -4.829 and -11.457 for all months and for high fire seasons, respectively, quite similar to the results in Table 2 (-4.836 and -11.192), and the results remain significant at the 1% level. The effect for low fire seasons is only 0.048 and is not statistically significant.

B Inter-temporal Displacement Effects of Straw-burning Bans

To further understand the potential inter-temporal displacement of agricultural fires resulting from the straw-burning bans, we estimate the effects by month using Poisson regression. Figure D7 shows the coefficients (triangles) and 95% confidence intervals (vertical lines). The largest reductions in agricultural fires occur in June, September, and November. The bans lead to reductions of over 15% in agricultural fires during these three months.

To enforce the fire bans, government officials carry out patrols, and these are usually more frequent in high straw-burning months. To show how the stringency of enforcement of straw-burning bans varies during the year, we use the Baidu Index (the Chinese version of Google Trends) of "straw-burning ban" as a proxy for enforcement stringency. We use the daily news index measuring the number of articles about straw-burning bans in media news. Most news articles on straw-burning bans are about how government officials are implementing the bans at present, and a higher index indicates greater stress on the implementation of the bans. The Baidu index is available from July 2017 onward, so we calculate the monthly average index based on daily index data from 2018 to 2020.[2] The circles in Figure D7 represent the average index for each month. The substantial reductions in agricultural fires in June, September, and November closely align with the peaks of the index, because the magnitudes of the index in these three months are among the largest six months of the year.[3] This pattern suggests that the straw burning bans appear to reduce agricultural fires when enforcement of the bans is strictest.

In contrast, except for the coefficient in April (-0.007), the coefficients in other months in Figure D7 are positive, with the coefficients for May and December being particularly statistically significant. These positive coefficients imply that while the straw-burning bans reduce fires in certain months, fire frequency rebounds in other months. The timing of these rebounds also largely coincides with the Baidu Index, which shows drastic declines in May, August, and December. Despite reducing fires during periods of strict enforcement, farmers may opt to postpone straw burning if they lack alternative disposal methods or if the costs of environmentally friendly straw disposal are prohibitively high. This inter-temporal displacement may explain the

[2]We exclude one week in December (12 December to 19 December) because many governments report annual summaries of their performance in reducing straw burning during this week, causing an artificial increase in news index scores.

[3]The variation of the Baidu index from 2018 to 2020 does not appear to coincide with the monthly variation of agricultural fire frequency during that period. For example, fire frequencies in July and October are relatively low from 2018 to 2020, and the 3 months with the highest fire frequency are April, March, and February, which account for 57% of agricultural fires during that period. Therefore, the peaks of the Baidu index do not necessarily pick up the times of the years when agricultural fires are most prevalent.

subsequent increase in fire frequency. Consequently, straw burning bans may prove ineffective in reducing overall agricultural fires if enforcement is not consistently stringent throughout the year.

C Comparison with Other Incentive

Another environmentally-friendly way of disposing of straw, as an alternative to using it to generate electricity, is to pulverize the straw and bury it on farmland. Ideally, the straw will decompose into organic matter and provide nutrients to the soil. However, the decomposition process usually takes a long time and un-decomposed straw could obstruct the germination of new crops.[4] Hence, some farmers are reluctant to implement this practice. To incentivize farmers, in 2006 the central government began funding provincial governments to select some counties as pilots and distribute straw decomposing agents to local farmers for free.

To identify the counties that provide straw decomposing agents, we collect announcements of government procurement of straw decomposing agents from 2002 onwards from the China Government Procurement website.[5] We identify 303 counties that purchased straw decomposing agents during the sample period. To match the county list with plant-level observations, we use a dummy variable $FreeAgent_{iy}$ to denote whether plant i is in or surrounded by (within a 90 km radius) any counties that purchase straw decomposing agents in year y.

We add $FreeAgent_{iy}$ to equation (1) and present the estimation results in Table D5. Coefficients on BPP entry for the full period and high fire seasons remain negative and statistically significant, with magnitudes similar to those in Table 2. The coefficient on $FreeAgent_{iy}$ is small (-1.564) and not statistically significant in Column (3), indicating that providing famers free straw decomposing agents have no significant effects on reducing overall agricultural fires. The coefficient for high fire seasons is significantly negative at the 10% level in Column (6), but the magnitude (-4.595) is considerably smaller than the coefficient on BPP entry (-11.245). Providing farmers free straw decomposition agents reduce fire frequency by 4.595 per month in high fire seasons, which is only 40% of the effect of BPP entry. Furthermore, the coefficient on $FreeAgent_{iy}$ is positive (0.660) but not statistically significant for low fire seasons in Column (9). These results imply that providing free agents can reduce agricultural fires to some extent, particularly in high fire seasons. However, the impact is limited, possibly because economic incentives of free agents eliminate the cost to farmers of products for accelerating straw decomposition but do not compensate for the labor costs associated with collecting and pulverizing straw.

[4]Some anecdotal accounts claim that when there is un-decomposed straw in the land, farmers need to sow wheat seed in double the quantities needed in land not covered by straw. Source: http://m.news.cctv.com/2017/11/19/ARTIs7COovS72upulljUdUav171119.shtml.

[5]http://www.ccgp.gov.cn/.

D Tables and Figures

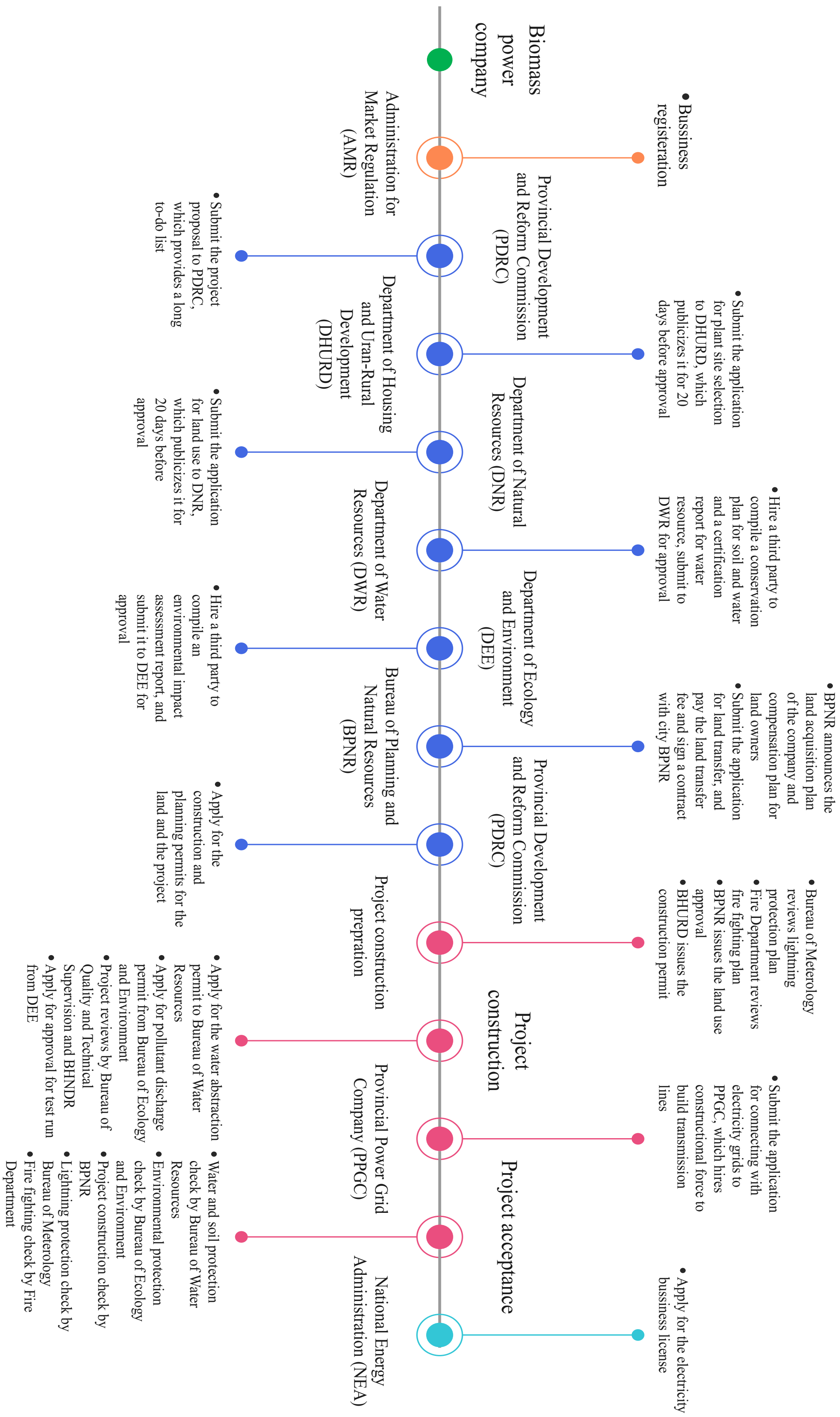


Figure D1: Procedures for establishing a biomass power plant in China

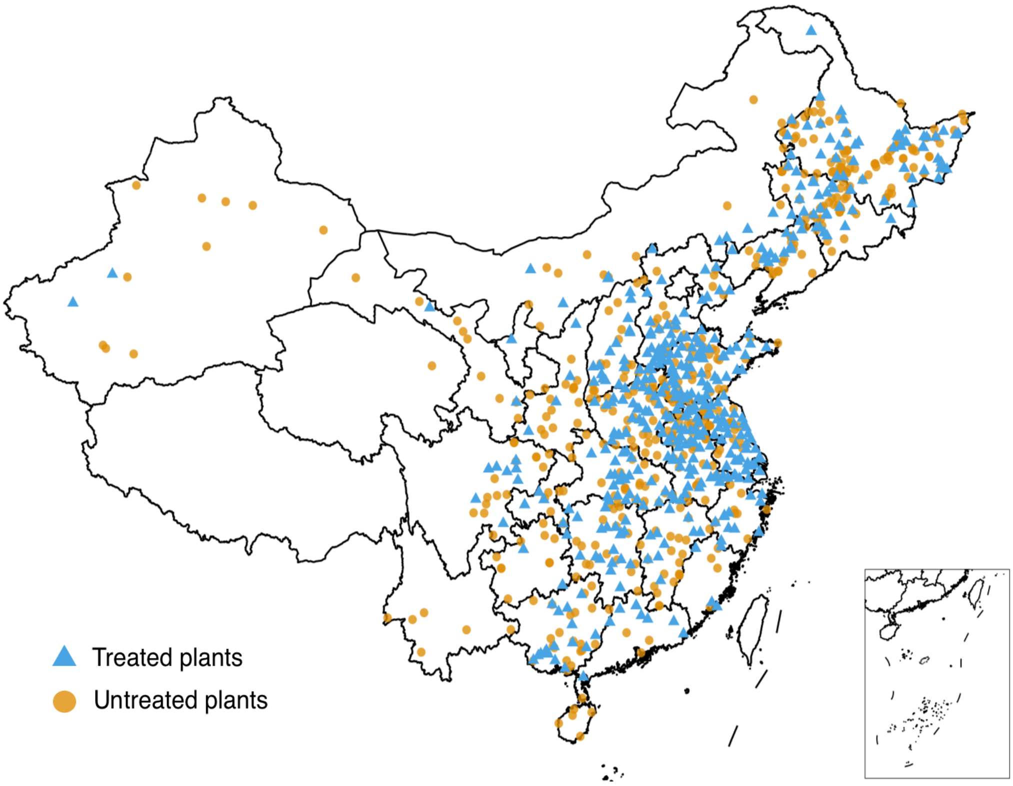


Figure D2: Geographical distribution of biomass power plants

Notes: Triangles represent treated plants and circles represent untreated plants.

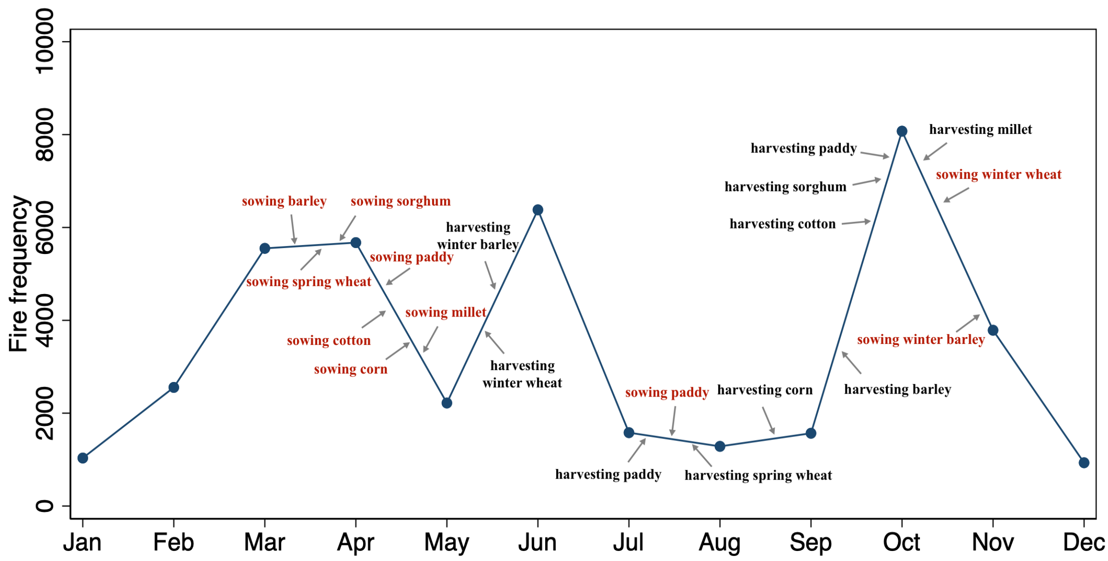
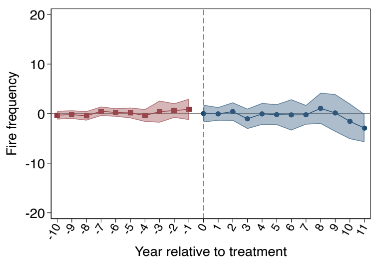
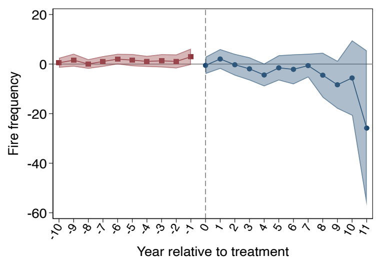


Figure D3: Monthly fire frequency and agricultural sowing and harvesting activities

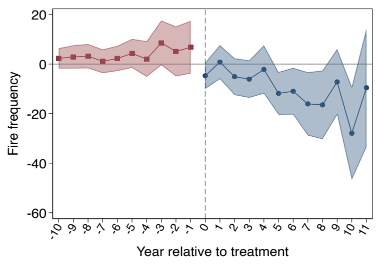
Notes: The monthly fire frequency is the average monthly agricultural fire frequency from 2003 to 2019.



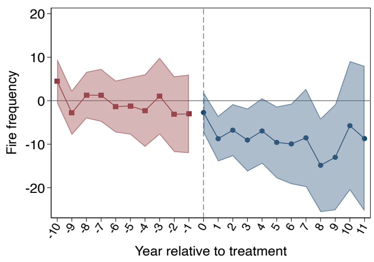
(a) January



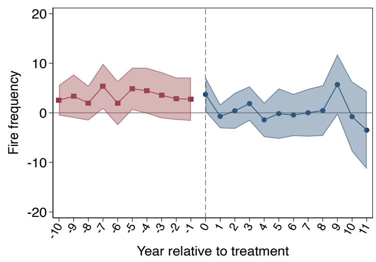
(b) February



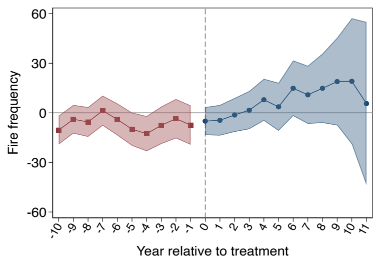
(c) March



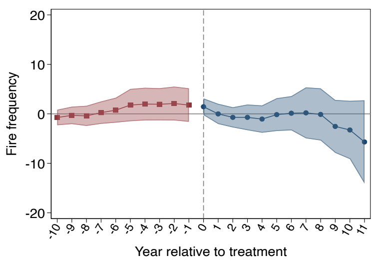
(d) April



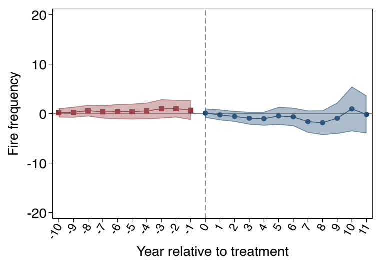
(e) May



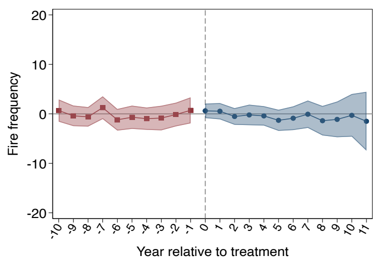
(f) June



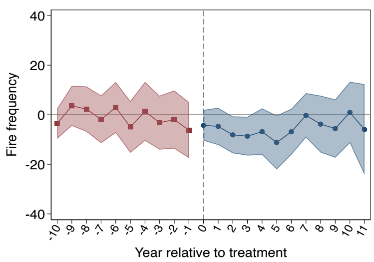
(g) July



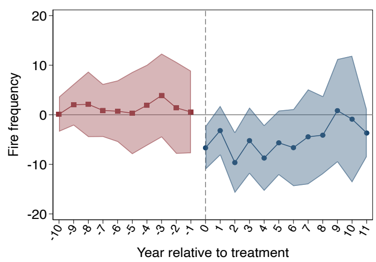
(h) August



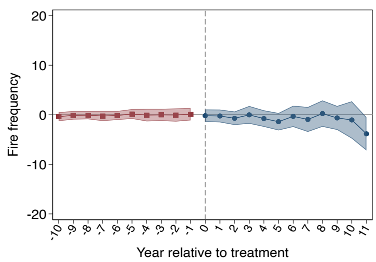
(i) September



(j) October



(k) November



(l) December

Figure D4: Fire frequency before and after treatment for each month

Notes: The dependent variables are the monthly frequency of fires within 90 km of BPPs. Square and circles represent point estimates and shaded areas represent 95% confidence intervals.

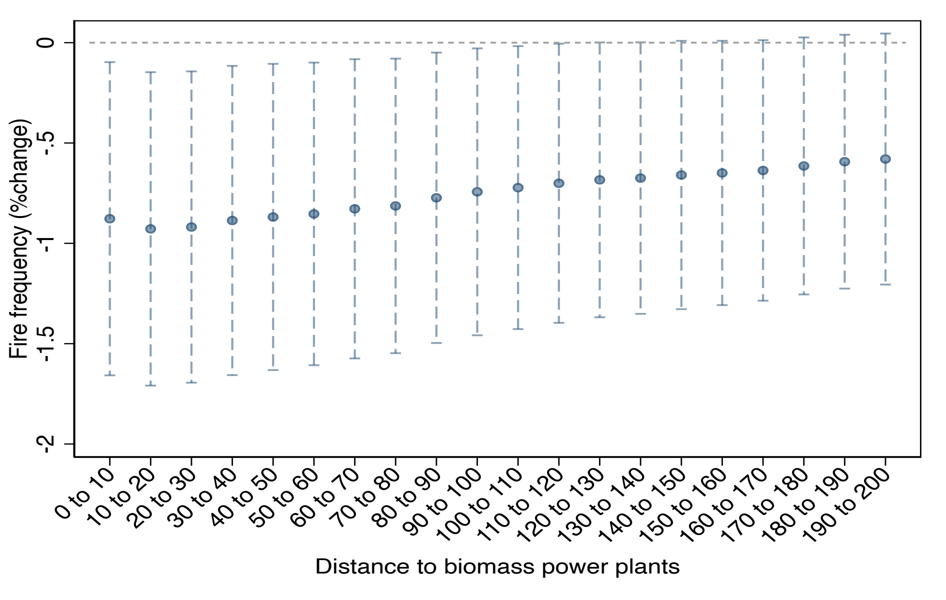


Figure D5: Effects of biomass power plants on $PM_{2.5}$ concentration by distance

Notes: The dependent variables are annual average $PM_{2.5}$ concentration in rings binned by a 10 km radius. Circles represent point estimates and vertical lines represent 95% confidence intervals.

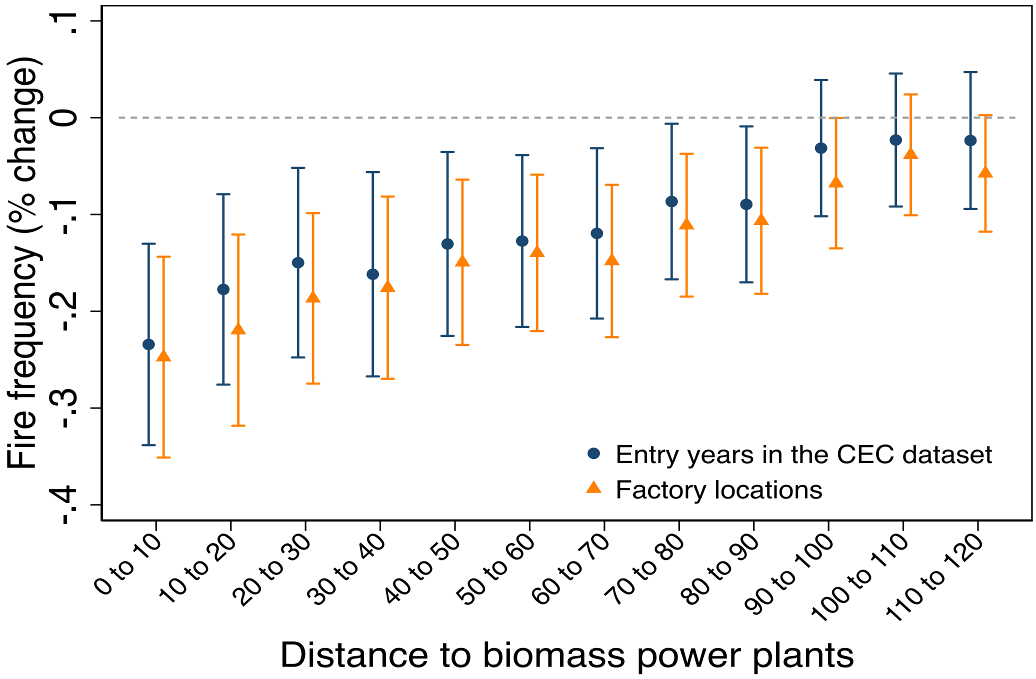


Figure D6: Robustness checks on measurement errors in entry years and factory locations

Notes: The dependent variables are the monthly frequency of fires in the ten rings with distance between $r - 10$ and r km from BPPs, where $r = 10, \ldots, 120$. Circles and triangles represent point estimates and vertical lines represent 95% confidence intervals.

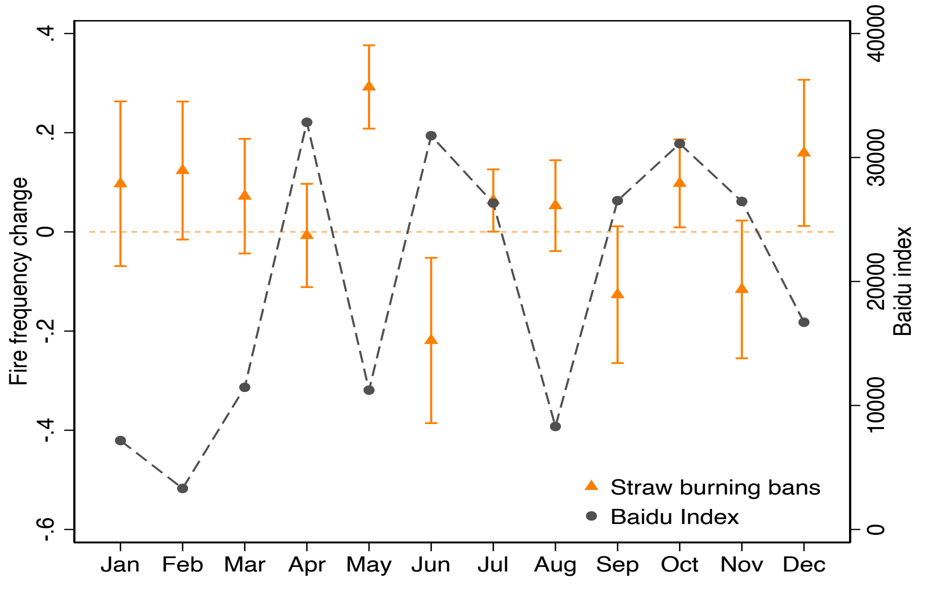


Figure D7: Effect of straw-burning bans by month

Notes: The dependent variables are the monthly frequency of fires within 90 km of BPPs. Triangles represent point estimates and vertical lines represent 95% confidence intervals. The dashed line represents the monthly average Baidu index for straw-burning bans.

Table D1: Legislation on complete straw burning bans

Province	Implementation Date	Legislation
Beijing	March 2014	Air Pollution Prevention and Control Regulations of Beijing
Fujian	January 2014	Detailed Rules for the Implementation of the Action Plan for Air Pollution Prevention and Control of Fujian Province
Hebei	June 2015	Decision of the Standing Committee of the Hebei Provincial People's Congress on Promoting the Comprehensive Utilization of Crop Straws and Banning Open Burning
Henan	June 2018	Notice of the General Office of the People's Government of Henan Province on Strengthening the Banning and Comprehensive Utilization of Crop Straw
Hubei	May 2015	Decision of the People's Congress of Hubei Province on the Prohibition of Open Burning and Comprehensive Utilization of Crop Straw
Hunan	December 2013	Detailed Rules for the Implementation of the Air Pollution Prevention and Control Action Plan of Hunan Province
Inner Mongolia	October 2015	Notice of the General Office of the People's Government of Inner Mongolia on Effectively Strengthening the Banning of Straw Burning
Jiangsu	June 2009	Decision of the Standing Committee of the Jiangsu Provincial People's Congress on Promoting the Comprehensive Utilization of Crop Straw
Jiangxi	December 2017	Decision of the Standing Committee of the People's Congress of Jiangxi Province on the Prohibition of Open Burning and Comprehensive Utilization of Crop Straw
Jilin	December 2013	Detailed Rules for the Implementation of the Air Pollution Prevention and Control Action Plan of Jilin Province
Shandong	December 2017	2013-2020 Air Pollution Prevention and Control Plan Phase II Action Plan (2016-2017) of Shandong Province
Shanghai	October 2014	Regulations on the Prevention and Control of Air Pollution of Shanghai
Shanxi	October 2013	Air Pollution Prevention and Control Action Plan of Shanxi Province
Tianjin	October 2013	Tianjin Clean Air Action Plan
Zhejiang	July 2016	Regulations on the Prevention and Control of Air Pollution of Zhejiang Province

Table D2: Robustness checks: Poisson regression

	Full sample			High fire seasons			Low fire seasons		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Biomass	-0.245***	-0.099***	-0.094***	-0.334***	-0.119***	-0.113***	-0.036	-0.042*	-0.036*
	(0.051)	(0.025)	(0.025)	(0.067)	(0.031)	(0.030)	(0.035)	(0.022)	(0.021)
Plant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	No	No	Yes	No	No	Yes	No	No
Plant-month	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Province-year-month	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Weather controls	No	No	Yes	No	No	Yes	No	No	Yes
Number of plants	953	950	950	953	950	950	952	949	949
Mean of dep. var	34.464	36.805	36.805	64.354	66.677	66.677	13.128	14.295	14.295
Observations	217,284	203,091	203,091	90,535	87,272	87,272	126,616	115,819	115,819

Notes: The dependent variables in Columns (1)–(3), (4)–(6), and (7)–(9) are the monthly frequency of fires within the 90 km radius of BPPs for all months, for the high fire seasons, and for the low fire seasons, respectively. Biomass_{iym} is a dummy variable that equals one if plant i is in operation in year y and month m, and zero otherwise. Weather control variables include monthly average temperature, wind speed, relative humidity, and total precipitation. Standard errors are clustered at the plant level. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table D3: Robustness checks: alternative radii for Conley spatial standard errors

	Full sample			High fire seasons			Low fire seasons		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Coefficient	-9.270	-5.075	-4.836	-23.372	-11.471	-11.192	0.899	-0.504	-0.428
Cutoff=200	(2.148)***	(1.071)***	(1.041)***	(4.869)***	(2.504)***	(2.444)***	(0.736)	(0.346)	(0.341)
Cutoff=500	(2.586)***	(1.294)***	(1.254)***	(5.712)***	(3.019)***	(2.934)***	(1.093)	(0.458)	(0.447)
Cutoff=1000	(2.622)***	(1.514)***	(1.468)***	(5.776)***	(3.552)***	(3.454)***	(1.120)	(0.525)	(0.509)
Clustered std	(2.142)***	(1.502)***	(1.495)***	(4.900)***	(3.356)***	(3.346)***	(0.655)	(0.475)	(0.474)
Plant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	No	No	Yes	No	No	Yes	No	No
Plant-month	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Province-year-month	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Weather controls	No	No	Yes	No	No	Yes	No	No	Yes
Number of plants	954	954	954	954	954	954	954	954	954
Mean of dep. var	34.428	34.428	34.428	64.286	64.286	64.286	13.101	13.101	13.101
Observations	217,512	216,828	216,828	90,630	90,345	90,345	126,882	126,483	126,483

Notes: The dependent variables in Columns (1)–(3), (4)–(6), and (7)–(9) are the monthly frequency of agricultural fires within the 90 km radius of BPPs for all months, for the high fire seasons (March, April, June, October, November), and for the low fire seasons (the rest of months), respectively. Biomass$_{iym}$ is a dummy variable that equals one if plant i is in operation in year y and month m, and zero otherwise. Weather control variables include monthly average temperature, wind speed, relative humidity, and total precipitation.

Table D4: Robustness checks: excluding all untreated plants by 2019

	Full sample			High fire seasons			Low fire seasons		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Biomass	-5.568**	-4.847***	-4.829***	-13.237**	-11.728***	-11.457***	0.064	0.074	0.048
	(2.262)	(1.594)	(1.569)	(5.258)	(3.775)	(3.722)	(0.511)	(0.344)	(0.344)
Plant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	No	No	Yes	No	No	Yes	No	No
Plant-month	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Province-year-month	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Weather controls	No	No	Yes	No	No	Yes	No	No	Yes
Number of plants	467	467	467	467	467	467	467	467	467
Mean of dep. var	34.403	34.403	34.403	62.796	62.796	62.796	14.123	14.123	14.123
Observations	106,476	105,792	105,792	44,365	44,080	44,080	62,111	61,712	61,712

Notes: The dependent variables in Columns (1)–(3), (4)–(6), and (7)–(9) are the monthly frequency of agricultural fires within the 90 km radius of BPPs for all months, for the high fire seasons (March, April, June, October, November), and for the low fire seasons (the rest of months), respectively. Biomass$_{iym}$ is a dummy variable that equals one if plant i is in operation in year y and month m, and zero otherwise. Weather control variables include monthly average temperature, wind speed, relative humidity, and total precipitation. Conley spatial standard errors are in brackets. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table D5: Comparison with the effect of providing free straw decomposing agents

	Full sample			High fire seasons			Low fire seasons		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Biomass	-9.076***	-5.089***	-4.854***	-22.669***	-11.517***	-11.245***	0.730	-0.495	-0.420
	(2.137)	(1.502)	(1.496)	(4.865)	(3.357)	(3.348)	(0.625)	(0.474)	(0.473)
FreeAgent	-9.015***	-1.251	-1.564	-32.660***	-4.088	-4.595*	7.873***	0.779	0.660
	(1.464)	(1.115)	(1.116)	(3.580)	(2.520)	(2.522)	(0.486)	(0.519)	(0.519)
Plant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month	Yes	No	No	Yes	No	No	Yes	No	No
Plant-month	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Province-year-month	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Weather controls	No	No	Yes	No	No	Yes	No	No	Yes
Number of plants	954	954	954	954	954	954	954	954	954
Mean of dep. var	34.428	34.473	34.473	64.286	64.410	64.410	13.101	13.090	13.090
Observations	217,512	216,828	216,828	90,630	90,345	90,345	126,882	126,483	126,483

Notes: The dependent variables in Columns (1)–(3), (4)–(6), and (7)–(9) are the monthly frequency of fires within the 90 km radius of BPPs for all months, for the high fire seasons, and for the low fire seasons, respectively. Biomass_{iym} is a dummy variable that equals one if plant i is in operation in year y and month m, and zero otherwise. FreeAgents_{iy} is a dummy variable that equals one if plant i is in or surrounded by (within a 90 km radius) counties that purchase straw decomposing agents in year y, and zero otherwise. Weather control variables include monthly average temperature, wind speed, relative humidity, and total precipitation. Standard errors are clustered at the plant level. *, **, and *** indicate statistical significance at the 1%, 5%, and 10% levels, respectively.