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Straw burning, $PM_{2.5}$, and death: Evidence from China

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ABSTRACT

This study uses satellite data to detect agricultural straw burning and estimates its impact on air pollution and health in China. We find that straw burning increases particulate matter pollution and causes people to die from cardiorespiratory diseases. We estimate that a 10 μg/m^3 increase in $PM_{2.5}$ increases mortality by 3.25%. Middle-aged and old people in rural areas are particularly sensitive to straw burning pollution. Exploratory analysis of China's programs to subsidize straw recycling suggests that extending these programs to all the straw burning regions would bring about a health benefit that is an order of magnitude larger than the cost.

1. Introduction

Farmers often burn agricultural straw residues from crops such as wheat, rice, maize, and cotton *in situ* after harvest. Straw burning is particularly prevalent in developing countries that rely heavily on agricultural production and is a major cause of seasonal air pollution (Andreae and Merlet, 2001; Gadde et al., 2009; Rangel and Vogl, 2019). However, effective regulations on straw burning are rare and the lack of scientific evidence on how straw burning affects people's health can make the government reluctant to design and enforce strict regulations. In this study, we estimate the impacts of straw burning on air pollution and mortality using data from China and try to quantify the potential benefits of China's recent efforts in straw recycling.

Our analysis is based on a novel panel dataset that assembles detailed information on straw burning, air pollution, and mortality in China. High-resolution satellite image data are used to identify the exact locations of straw burning in China from 2013 to 2015. Straw burning data are then linked to local air quality data collected from 1650 ground-level monitors. Death records from a quarter of the Chinese population are obtained from the Disease Surveillance Point system (DSPS) of China's Center for Disease Control and Prevention, which contains information on gender, age group, and cause of death at the county level for the same period.

With these data matched at the county level, we then estimate how straw burning affects air pollution and mortality. Our baseline results show that 10 additional straw fires within 50 km of a county center will lead to a 4.79 μg/m^3 (or 7.62%) increase in monthly fine particulate matter ($PM_{2.5}$, diameter $<$ 2.5 μm) and a 1.56% increase in all-cause mortality in Chinese counties. Using straw burning as an instrumental variable, we further estimate that a 10 μg/m^3 increase in monthly $PM_{2.5}$ can lead to a 3.25% increase in mortality. Heterogeneity analyses reveal that straw burning pollution primarily increases cardiorespiratory mortality, and has a strong impact on people over 40 in rural and poor areas, but has no statistically significant impact on younger people.

The key concern of our baseline IV estimate is that straw burning may affect human health through channels other than air pollution. For example, local governments may implement straw burning regulations that are endogenous to local population health. It is also possible that straw burning can create temporary income shocks to farmers, as the activity is associated with harvesting. To address these issues, we adopt two augmented IV strategies, which together lend additional credibility to our baseline finding. In our first augmented strategy, we use non-local

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straw burning to instrument local air pollution (conditional on local straw burning). Non-local straw burning is an appealing instrument for air pollution because the burning behaviors of non-local farmers are typically not subject to the local government's control. In the second strategy, we follow Rangel and Vogl (2019) and explore different wind patterns for identification. We separate straw burning from upwind and downwind areas and use the difference in the coefficients between upwind and downwind fires to isolate the pollution effect from the potential income effect. The identification relies on the fact that upwind and downwind straw fires have asymmetric impacts on air pollution, but have symmetric impacts on local people's income. In both exercises, we obtain estimates that are quantitatively similar IV to the baseline model, suggesting the endogeneity of straw burning is not a big concern in our research context.

Based on our findings, we then evaluate China's recent straw recycling policy, launched in 2016. We find that subsidizing straw recycling effectively improved air quality and the estimated health benefits could outweigh the costs by an order of magnitude. Specifically, using a Difference-in-Differences (DiD) approach, we show that the number of straw fires in subsidized provinces dramatically declined after the policy (by 153 a year), relative to the non-subsidized provinces, and this change brought down the annual average $PM_{2.5}$ concentration by 4.33 μg/m^3. These estimates imply that the straw recycling policy could have averted 18,900 pre-mature deaths annually in China.

We contribute to the literature in three ways. First, this paper adds to the emerging literature on the impacts of straw burning (e.g. Graff Zivin et al., 2019; Lai et al., 2018; Rangel and Vogl, 2019). In this thin line of literature, Rangel and Vogl (2019) are the first to link agricultural burning to health outcomes. Exploiting the interactions between wind patterns and sugarcane harvest fires in Brazil, they show that late-pregnancy exposure to upwind fires decreases birth weight, gestational length, and in-utero survival, but not early neonatal survival. Graff Zivin et al. (2019) adopt a similar approach and find that air pollution from agricultural fires lowers the cognitive performance of students in a high-stakes test in China. Lai et al. (2018) investigate how agricultural fire affects cognitive function among the Chinese people and show that more straw burning reduces old people's cognition and memory. Our main contributions beyond Rangel and Vogl (2019) are that (1) we are able to investigate the impacts of straw burning on mortality for different age groups, which helps highlight the most vulnerable people to straw burning pollution, and (2) we apply our estimates to assess a recent straw recycling policy implemented by the Chinese government.

Second, we find significant rural-urban heterogeneity in the air pollution effect. Due to data limitations, rural residents have largely been ignored in existing air pollution studies. Notable exceptions include Zhou et al. (2015) and Fan et al. (2020). In both studies, the authors find that air pollution effects are larger and statistically significant in rural areas, but small and statistically insignificant in urban areas. While our research context is different from the previous studies, we also find that straw burning and air pollution significantly increase the mortality of rural residents and poor residents, but not that of urban or rich residents. These results together suggest that better socio-economic conditions can mitigate the health damage of air pollution.

Finally, we show that China's recent straw-recycling subsidy significantly reduced straw burning activities, which provides important insights into designing effective straw burning regulations. Historically, the Chinese government relied on command-and-control regulations to reduce straw burning. Due to the high enforcement costs, however, these policies were not very successful. In contrast, providing subsidies to farmers and recycling companies immediately led to less burning and improvement in air quality. The incentive-based approach seems to outperform the command-and-control approaches in our research context. These findings can be referenced by other agrarian economies with similar agricultural burning issues.

The rest of this paper is structured as follows. Section 2 introduces the practice of straw burning in China and reviews the current literature. Section 3 describes the data on straw burning, deaths, pollution and weather, followed by an introduction on data compilation, a summary of key variables, and descriptive analyses. Section 4 discusses our empirical strategy. Section 5 reports the main findings. Discussions of caveats and robustness checks follow in Section 6. Section 7 explores a variety of heterogeneities in the health effects of straw burning pollution. Section 8 estimates the impact of the straw recycling policy and conducts an exploratory benefit-cost analysis. Section 9 concludes.

2. Background

2.1. Agriculture and straw management in China

China has the largest straw resource in the world. With a sown area of 0.11 billion *ha*, China produced 0.62 billion tons of grain in 2015,[1] accounting for 24% of the total grain output worldwide.[2] The major crops in China are maize, rice, and wheat. Rice is mainly planted in the south, while wheat is common in the northern and central regions. Maize is widely planted, with its main production area in northeastern China. Two-season planting is common in central, eastern and southern China but is rare in northern regions, which are colder and have a longer winter. As a result, straw production also varies over time and space.

China produces the largest amount of agricultural straw residues in the world. In 2012, nearly one billion tons of straw were produced, contributing to 18.5% of the global straw production. Straw consists of crop stubble and stalks. Crop stubble is usually left on the farmland after harvest and then burnt *in situ*. Stalks are longer and can be collected after being cut, but a large portion of them remain unrecycled (Shi et al., 2014). According to China's Ministry of Agriculture, 320 million tons of straw were not utilized in 2015, accounting for about 31% of the total straw produced nationwide.[3]

The straw burning seasons in China are from late May to late July and from late September to late November each year.[4] Farmers burn straw for several reasons. First, they need to clear their fields for the next round of cultivation, but straw does not decompose quickly. Second, fires kill pests, weeds, fungi and bacteria that can be harmful to new crops. Third, the ashes can fertilize the farmland. Finally, alternative measures (such as straw returning and straw recycling) require additional labor work that is not economically rewarding.

There are two primary ways of straw utilization: straw returning and straw recycling, both of which are time-consuming and labor-intensive. Straw returning, or soil incorporation, means to cut straw into smaller pieces and put them back into the farmland as fertilizer. However, the small pieces can make plowing inconvenient. Because the decomposition process takes time, straw returning often hinders crop growth in the short run. Straw recycling means re-using straw for other purposes, such as industrial materials, fuel and animal feed. Because each household owns only a small piece of farmland, the economy of scale of straw recycling cannot be easily realized. Burning straw after harvest thus is a common practice in China.

2.2. Straw burning and air pollution

Pollution from straw burning is a typical example of a negative externality. It originates from rural farms and can travel to distant regions. The impact of straw burning on air pollution has been discussed extensively in the science community, with a focus on measuring pollutant emissions, numerically modeling the transmission of emissions, and

[1] National Bureau of Statistics: http://www.stats.gov.cn/tjsj/zxfb/201512/t20151208_1286449.html.

[2] Food and Agricultural Organization, United Nations: http://www.fao.org/worldfoodsituation/csdb.

[3] http://www.moa.gov.cn/zwllm/zwdt/201605/t20160526_5151375.htm.

[4] There is no straw burning during growing seasons.

analyzing the physicochemical reactions of air pollutants (see Chen et al., 2017 for a recent review).

The substances emitted from straw burning include particulate matter (PM), volatile organic compounds, carbon dioxide, and other compounds known to be toxic (Andreae and Merlet, 2001). Straw burning emits a large amount of PM, which is dominated by submicron and fine particles. According to Zhang et al. (2016), the annual $PM_{2.5}$ emissions from open straw burning are about 1.036 million tons, accounting for 7.8% of total anthropogenic emissions of PM in China. In eastern China, straw burning emissions could contribute up to 56% of total emissions in the summer.

Straw burning emits little SO_2 and NO_x, which are common pollutants from other sources such as fossil fuels (Streets and Waldhoff, 2000). While straw burning also generates small amounts of CO and secondary O_3, these pollutants are generally less stable and persistent in the air than PM, and therefore straw burning is not considered a major contributor to these pollutants.[5] Weather conditions, such as temperature and humidity, can also affect the smoke's composition and the generation of other secondary pollutants.

PM emissions from straw burning can travel long distances, and critics sometimes blame straw burning for the large-scale and widespread haze episodes in China.[6] However, there is a lack of research that quantifies the impacts of straw burning on air quality at the national scale. Existing scientific studies that use numerical modeling to quantify the impacts of straw burning on air pollution tend to be applicable only to specific areas within a short period of time, in part due to the huge uncertainties in the emission inventories and the complex interactions between straw burning emissions and meteorological factors (Chen et al., 2017).

2.3. Air pollution, health, and straw burning regulations

A large number of economic studies have documented that air pollution can significantly damage human health, in both developed countries (e.g. Arceo et al., 2016; Chay and Greenstone, 2003; Currie and Neidell, 2005; Currie et al., 2014; Schlenker and Walker, 2015) and developing countries (e.g. Chen et al., 2013; Ebenstein et al., 2017; Fan et al., 2020; He et al., 2016). To identify the causal impact, previous studies typically focused on policies that directly affect air pollution levels (such as the Clean Air Act in the U.S.) or explore the sources of air pollution (such as cars, airplanes, and wildfires).

Until very recently, economists did not investigate pollution caused by straw burning. There are at least two empirical challenges. First, credible data on agricultural fires are not readily available. Second, isolating the pollution effect of straw burning can be challenging, as straw burning can be associated with local economic activities that may affect human health. Rangel and Vogl (2019) are the first to look into this issue; they utilize satellite data to overcome the data barrier and explore wind patterns to pin down the air pollution effect.[7] Given that almost all the developing countries and many developed countries are subject to such seasonal air pollution threats, there is a great need for additional evidence on how straw burning affects human health in a broader context and on how to design effective policies to control agricultural fires.

[5] Existing evidence shows that the amount of CO generated by incomplete combustion during open straw burning is low (Zhang et al., 2013) and that the association between biomass burning and O_3 is also weak (Jaffe et al., 2013; Rangel and Vogl, 2019). O_3 in the troposphere is mainly contributed by vehicle and industrial processes, and the formation of O_3 is complex, depending on nonlinear interactions with temperature, solar radiation and other precursors.

[6] For example, Xinhua News: http://news.xinhuanet.com/politics/2015-10/20/c_1116884784.htm.

[7] Several associational studies in the public health literature also investigated the relationship between straw burning and health (e.g. Jacobs et al., 1997). Due to lack of convincing identification strategies, estimates from these studies can be biased (see Dominici et al., 2014) and we therefore do not discuss the details of these studies.

Conceptually, agricultural fires share a lot of similarities to wildfires. While little research can be found on agricultural fires, multiple studies have assessed the impacts of wildfires. For example, Jayachandran (2009) examines the effect of smoke (measured by aerosol from satellites) on early-life mortality during a big forest fire in Indonesia in 1997 and finds that the fire significantly worsened infant health in poor areas. Sheldon and Sankaran (2017) show that Indonesia's wildfire affected Singapore's air pollution and increased hospital admissions. Miller et al. (2017) use smoke plumes to identify pollution from wildfires in the U.S. and show that wildfires could affect PM concentrations and impair the health of the elderly in regions where background levels of air pollution are low. Other studies have shown that wildfires also have impacts on labor supply, housing prices, hospitalization and defensive (avoiding) expenditures (e.g. De Mendonça et al., 2004; Donovan et al., 2007; Moeltner et al., 2013; Richardson et al., 2012).

Unlike natural wildfires, however, agricultural fires are mostly anthropogenic. They occur more frequently than wildfires and spread across many countries and regions. Because a large proportion of the world's population still live in agricultural regions, the aggregate impact of straw burning can be orders of magnitude larger than that of wildfires. Therefore, estimating the impact of agricultural fires and identifying effective ways to control straw burning are of great policy relevance and urgency.

In the past two decades, the Chinese government tried a variety of policy instruments to control straw burning activities. The government historically relied on command-and-control regulations, and straw burning was officially banned in the 1990s. Some local governments required village leaders to patrol and do surveillance; some educated farmers through propaganda; and some applied administrative sanctions to local village leaders (such as dismissal or suspension) if villagers were found burning straw. Unfortunately, most of these regulations were too difficult and costly to implement. The reality is that rural households continued to burn straw regardless of various bans. For example, in our data, the number of straw fires actually increased significantly from 2012 to 2015.

Seeing that the command-and-control regulations were ineffective, starting in 2016, the central government turned to an incentive-based policy that provides subsidies to farmers and enterprises for straw recycling. As will be elaborated later in this paper, this subsidy seems effective and has significantly reduced straw burning.

3. Data

3.1. Straw burning data

Straw burning can be detected by remote sensing from satellites. In China, the Satellite Environment Center of the Ministry of Ecology and Environment (MEE) collects daily straw burning data from the moderate resolution imaging spectroradiometers (MODIS) of NASA's Satellites TERRA and AQUA. These satellites overpass China twice a day in the daytime (around 10:30 and 13:30 local time) and twice each night (around 22:30 and 1:30 local time) and report all fire pixels detected with 250, 500, or 1,000 m resolution (Kaufman et al., 1998). A fire point is identified when a thermal anomaly is detected within a pixel using a contextual algorithm that exploits the mid-infrared radiation from fires (Justice et al., 2002). Therefore, the burnt area can be much smaller than the satellite resolution. MODIS routinely detects both flaming and smoldering fires and the minimum area reported is about 50 square meters under good weather conditions. A large fire can be recorded as multiple fire points or pixels. Estimation of the burnt area is not recommended due to large uncertainties in modeling.[8]

The MEE checks the MODIS fire data and distinguishes straw burning from other types of fires (such as wildfires) based on geographical

[8] For details, see https://earthdata.nasa.gov/firms-faq.

information and land use. The measure of straw burning is consistent and comparable over time and across regions. Straw is burnt after harvesting and before planting. As China has two planting seasons, we also observe two burning seasons, one in summer and the other in late autumn and early winter.

One limitation of the satellite data is that it does not distinguish large straw fires from smaller ones. However, because each household is only allowed to lease a small piece of land in China, we believe the size of each straw fire is similar in size, especially within the same county.[9] Another limitation is that satellites capture this data only when they pass over the continent. Since straw burning may occur during non-overpassing periods and die out without thermal anomalies when satellites pass, the number of actually fires can be under-estimated. Thus, the precise interpretation of our regressions is that they estimate the effects of straw burning *detected by satellite* on air pollution and mortality.

3.2. Death data

Death data were collected from the Disease Surveillance Point System (DSPS) of the Chinese Center for Disease Control and Prevention (CDC). The DSPS was launched in the 1990s and collects the most comprehensive information on deaths in China. From 1991 to 2000, data were collected at 145 representative locations nationwide. From 2003, the system was expanded to cover 161 urban districts and rural counties. The DSPS was scaled up again in 2013 to cover 605 counties (283 rural counties and 322 urban districts) with a population of 0.34 billion, encompassing roughly a quarter of China's total population, making it highly representative for the whole country.[10]

In each DSP location, the local CDC is required to record and verify all deaths that occurred in hospitals or at home. Each death is registered in DSPS following a standard protocol. The death certificate contains detailed information on gender, age, and cause of death, allowing us to construct location-, gender-, and age-group specific cause-of-death mortality rates. The DSPS collects death records only for local residents, defined as those who have lived in a DSP location for at least 6 months in the past year.

In this study, we have access to all the death records (5 million) from 2013 to 2015. We use the logarithm of the number of deaths as the main dependent variable. Age-adjusted mortality rate (number of deaths per 100 thousand people) is also used as a robustness check. Since the population structure change is negligible during our sample period, the two measures yield similar estimates. Each cause of death is categorized as either cardiorespiratory or non-cardiorespiratory. Cardiorespiratory diseases include cardiac complaints, conventional respiratory diseases, cerebrovascular dysfunction (mostly stroke), tracheal and bronchial infections, and lung cancers. Other causes are grouped as non-cardiorespiratory. We expect that straw burning pollution has a larger impact on cardiorespiratory mortality than on non-cardiorespiratory mortality.

3.3. Pollution and weather data

Daily air quality data were collected from the records of 1650 local monitoring stations and were averaged by month. Concentrations of fine particulate matter ($PM_{2.5}$) were the key variable of interest, but data on PM_{10}, SO_2 and NO_2 were also collected.

Previous studies show that China's air quality data were sometimes manipulated because the central government attached high political stakes to local air quality (e.g., Ghanem and Zhang, 2014). However, this concern has been significantly alleviated in recent years because the Chinese government upgraded the air quality monitoring system to measure finer pollutants (such as $PM_{2.5}$) and at the same time automated the sampling and reporting process in 2013. Greenstone et al. (2019) show that the new monitoring system makes it very difficult to manipulate the air pollution data, which has significantly improved the data quality. In addition, we focus on burning in the summer season, during which the PM concentrations are relatively low.[11] Local officials have little incentives to manipulate such data, because the political assessment targets primarily the number of severely polluted days.

Daily weather conditions, including wind speed, wind direction, relative humidity, precipitation, and temperature, were collected from 403 meteorological stations. We then average them by month and match them with the DSP data. Wind can carry pollutants to other areas but also can disperse them. Strong wind helps fires spread. Higher humidity might discourage fires and result in less complete combustion. Rainfall and temperature may also affect farmers' burning decisions. We thus include all of them as control variables.

3.4. Data matching and summary statistics

We aggregate all the datasets to the monthly level for subsequent analysis, for three reasons. First, aggregating data to the monthly level creates more variation in the number of straw fires for each county.[12] Second, using monthly data can better capture the cumulative effect of air pollution in the medium run. As shown by many epidemiological studies and a few recent economic studies, the impact of air pollution tends to accumulate over time.[13] The reason is that prolonged exposure to air pollution can cause more complex cardiorespiratory diseases and increase the size of the affected population. Using daily data may significantly under-estimate the air pollution effect. In a robustness check, we also use the distributed lag models with up to 7-day lags of straw burning as independent variables to instrument $PM_{2.5}$ and find that the estimates are indeed smaller than the monthly estimates (Appendix Table A1). Third, a known issue when running regressions using daily data with many lagged dependent variables is that the estimated coefficients can be noisy and tend to oscillate. This is because air pollution levels are highly correlated in consecutive days, making it difficult to interpret specific coefficients (see Barwick et al., 2018). Further incorporating the instrumental variables in such models is even more challenging both technically and computationally.

We then merged different datasets into one panel at the county-month-year level from May 20 to July 20 each year from 2013 to 2015, during which straw burning data are monitored and verified by the MEE. The DSPS counties were first matched with the locations where air quality data were collected. If a county had no monitoring station within 50 km of its center, that county was dropped from our analysis. If a county had multiple monitoring stations within that range, the average concentrations across all of the stations were used. Counties for which no $PM_{2.5}$ data were reported for more than a year were also dropped. The

[9] For example, the average area of farmland leased per agricultural household is 5 *mu* or 0.0033 km^2 in China in 2015, which is smaller than the size of a fire pixel but is larger than the fire area that can be detected. Source: http://opinion.people.com.cn/n1/2017/0605/c1003-29316482.html.

[10] More details about the DSPS can be found in He et al. (2016) and Ebenstein et al. (2017).

[11] The air pollution levels are higher during the winter because China's winter heating system burns large amounts of coal. Given the relative low PM concentrations in summer, we may capture the health impact of PM at the lower tail.

[12] At the monthly level, the average number of straw fires in a county is about 2. For the daily data, we see a large number of zeros even during the burning seasons.

[13] See, for example, Barwick et al. (2018), Cheung et al. (forthcoming), Costa et al. (2017), Deryugina et al. (2019), Schwartz (2000), Zanobetti et al. (2002); Zanobetti and Schwartz (2008), Zeger et al. (1999).

weather data were matched with the DSPS data in a similar way. The total number of straw fires observed within 50 km of the geographic center of each county was then tabulated by month.[14] The average area of a Chinese county is 3363 km^2, covered by a radius of around 33 km. We choose 50 km as the main specification and explore other distances from 35 km to 100 km as robustness checks. The final balanced panel covered 107 urban districts and 102 rural counties, with at least one pollution monitoring site within 50 km from each county's center. In total, 390 out of the 605 DSPS counties were dropped due to lack of data on $PM_{2.5}$.

Table 1 reports descriptive statistics of the key variables, including the number of straw fires, air pollution concentrations, and the number of deaths. There were 2540 straw fires detected by the satellites during the period studied, an average of two fires within 50 km of each county's center. Straw fires were equally distributed along different wind directions, suggesting that wind patterns are largely random during the burning seasons. Both urban districts and rural counties had straw burning detected. The number of staw fires was lower in the urban districts. This is reasonable because the sown area is smaller in urban districts than in rural counties.

Panel B of Table 1 reports the summary statistics for air pollution and visibility (i.e., impaired visibility due to air pollution). The average $PM_{2.5}$ concentration during summer burning seasons was around 49 $\mu g/m^3$, which is significantly lower than other seasons. Rural counties have slightly higher $PM_{2.5}$ concentrations than urban districts during the summer burning seasons. We also observe rural SO_2 concentration is higher, likely because rural households burn more coal for cooking and heating than do urban households.

Panel C of Table 1 further summarizes the number of deaths by cause, age and gender. Around two-thirds of the total deaths are caused by cardiorespiratory diseases, and there are more deaths in rural areas compared with urban areas. Nearly 80% of the deaths are among people above 60 years old, and males account for around 58%. In addition, China has a relatively low infant mortality rate among countries at a similar development stage.[15]

The spatial distribution of straw burning and air quality is shown in Fig. 1. Panel A shows that most of the straw fires took place in Henan, Hebei, Shandong, Jiangsu and Anhui provinces in central China. Panel B shows the average $PM_{2.5}$ concentrations during the summer burning season in 2013–2015. We can observe a strong positive correlation between the number of straw fires and air pollution. In counties with more straw fires, $PM_{2.5}$ concentrations were higher.

4. Empirical strategy

4.1. Baseline model

We start by estimating the impact of straw burning on air quality using a fixed-effects model:

$$PM_{it} = \beta_0 + \beta_1 burning_{it} + X_{it}\theta + \tau_i + \pi_t + \xi_{it} \tag{1}$$

where PM_{it} denotes the $PM_{2.5}$ concentration in county i in month t; $burning_{it}$ is the total number of straw fires detected within 50 km of the center of county i in month t. X_{it} is a vector of weather variables: wind speed, wind direction, temperature, precipitation, and relative humidity.[16] τ_i are county fixed effects, and π_t are year and month fixed effects. ξ_{it} are errors. The county fixed effects control for time-invariant confounders specific to a county, such as its natural endowments, crop patterns and straw-burning culture. The year and month fixed effects further account for shocks common to all counties in a particular year or month. Standard errors are two-way clustered at county and month level to account for autocorrelations along these two dimensions.

We then estimate the impact of straw burning on health in a similar way:

$$Health_{it} = \alpha_0 + \alpha_1 burning_{it} + X_{it}\vartheta + \tau_i + \pi_t + \varepsilon_{it} \tag{2}$$

where $Health_{it}$ denotes the logarithm of the monthly number of deaths in county i in month t.

Equations (1) and (2) also provide the basis for estimating the impact of $PM_{2.5}$ on health. We focus on PM because we find that SO_2 and NO_2 were not significantly related to straw burning (see Appendix Table A2), which is consistent with the previous scientific evidence. PM can provoke pulmonary inflammatory response, alter cardiac autonomic function, and accelerate chronic obstructive pulmonary disease. We focus on $PM_{2.5}$ rather than PM_{10} because existing epidemiological evidence suggests that smaller particles pose a greater threat to human health than do larger ones (e.g., Zanobetti and Schwartz, 2009). $PM_{2.5}$ can penetrate deeper into the lungs and enter the bloodstream due to its small size, and can be quickly absorbed and create direct damage to the circulatory system (e.g., Godleski et al., 2000).

Specifically, the number of straw fires can be treated as the instrumental variable (IV) for $PM_{2.5}$, and Equation (1) can serve as the first stage. The second stage estimation uses the following equation:

$$Health_{it} = \gamma_0 + \gamma_1 \widehat{PM}_{it} + X_{it}\rho + \tau_i + \pi_t + \mu_{it} \tag{3}$$

where $\widehat{PM}_{it}$ is the predicted $PM_{2.5}$ concentrations from Equation (1). County fixed effects, year and month fixed effects, and weather conditions are all included as controls in both stages of IV.

4.2. Validity of the instrumental variable

In the baseline model, we control for county fixed effects, month and year fixed effects, and local weather conditions. Intuitively, the impact of straw burning is identified by changes in the number of straw fires within the same location across different harvesting seasons, holding weather conditions constant. At this level, whether we can treat straw burning variations as exogenous is debatable. Below, we discuss several possibilities that may invalidate the instrument, and provide solutions to each.

The first concern is that farmers' burning decisions may depend on air pollution levels. For example, is it possible that they reduce/increase straw burning activities if they observe high pollution? We believe this is highly unlikely. During our field trips, we interviewed farmers about their straw burning behaviors and very few of them acknowledged that burning straw is a major contribution to air pollution. In fact, farmers repeatedly stated that they had the right to burn straw and that such activities should not be regulated. This is also documented by multiple news articles.[17] In addition, in Appendix Table A3, we investigate whether pollution on the previous day affects current-day straw burning (=1 if there is at least one straw burning point) and find no statistically significant associations.

The second concern, which is more likely, is that straw burning can be affected by regulations that are endogenous to local pollution and health

[14] We use the geographic centers rather than administrative centers to calculate the number of straw fires. This is because straw fires take place in the farmlands and our results are primarily driven by rural areas. In rural areas, the majority of the population lives in the villages, which are far from the administrative center.

[15] See https://data.unicef.org/for more details.

[16] We follow Grange (2014) and measure monthly wind directions based on daily wind directions and speed using the vector decomposition method. See Grange (2014) for more details.

[17] For example, Xinhua News report that farmers believe straw burning is not a major contribution to regional air quality compared with industrial and vehicle emissions, and they think it is unfair to prohibit straw burning to improve urban air quality. For example: http://www.xinhuanet.com/energy/2015-10/22/c_1116898554.htm.

Table 1
Summary statistics during summer burning in 2013–2015.

VARIABLES	Obs.	Mean	S.D.	Min	Max		Urban	Rural
	(1)	(2)	(3)	(4)	(5)		(6)	(7)
Panel A: # of Straw Fires						Obs.	972	963
Total	1935	2.0	7.8	0	235		1.6	2.4
Local	1935	0.3	2.4	0	94		0.1	0.4
Non-local	1935	1.8	6.0	0	141		1.5	2.0
Upwind	1935	0.5	1.7	0	36		0.4	0.5
Downwind	1935	0.5	2.2	0	47		0.4	0.6
Vertical	1935	1.0	4.6	0	154		0.8	1.3
Panel B: Air Pollution								
$PM_{2.5}$ (μg/m^3)	1595	49.2	24.2	5.6	133.5		47.9	50.7
PM_{10} (μg/m^3)	1601	87.6	44.6	12.8	314.1		82.6	92.9
SO_2 (ppb)	1641	8.7	6.7	0.6	83.9		8.0	9.5
NO_2 (ppb)	1635	16.1	7.5	1.6	61.7		17.2	14.9
Visibility (km)	1935	14.2	6.1	1.6	30.0		14.7	13.7
Panel C: Number of Deaths (Monthly)								
<u>Cause</u>								
All causes	1935	189	141	5	1244		177	201
Cardiorespiratory	1935	114	87	1	812		107	120
Non-cardiorespiratory	1935	54	43	0	338		48	60
<u>Age</u>								
0	1935	1.4	1.9	0	20		1.3	1.4
1–4	1935	0.6	1.0	0	10		0.5	0.7
5–19	1935	1.3	1.7	0	16		1.0	1.5
20–39	1935	2.2	2.4	0	18		1.9	2.5
40–59	1935	31.0	23.5	1	189		28.7	33.2
60+	1935	149.2	114.4	5	1003		140.7	157.8
<u>Gender</u>								
Male	1935	109	81	3	734		102	117
Female	1935	80	62	2	601		76	84

Notes: Summary statistics of monthly straw burning, air pollution and number of deaths in 209 DSP counties are reported, including mean, standard deviation, minimum and maximum values. The summer burning period includes May.20th-July.20th in 2013–2015.

status. For example, governments that have strong incentives to improve local ambient air quality may also have strong incentives to provide better health care. If these efforts were correlated, we would overstate the impact of straw burning on population health. To address this possibility, we use non-local straw burning as the instrumental variable and estimate how burning outside a county's boundary affects its air pollution and health. Because the county government can only regulate straw burning within its jurisdiction, neighborhood counties' straw burning creates more exogenous variations in local air quality. To take into account the possibility that straw burning shocks to the economy may be spatially correlated, we control for the number of local straw fires when using the number of non-local straw fires as an instrument. As will be discussed in the next section, using non-local burning as the instrument generates almost identical estimates.

The third concern is that straw burning may be associated with temporary income shocks that also affect human health. For example, straw burning often takes place after harvesting, and harvesting can create positive income shocks to farmers. Were such temporary income increases important for health, we might under-estimate the air pollution effect.

We try to address this concern in two ways. First, income shocks should not affect different diseases in a way that coincides with the air pollution effect. Existing literature documents that air pollution primarily affects cardiorespiratory diseases and does not affect non-cardiorespiratory diseases, while the income effect does not follow this pattern. We analyze different causes of death and find that straw burning indeed only increases cardiorespiratory mortality, implying the air pollution effect is the channel. Second, we follow Rangel and Vogl (2019) and leverage wind directions to shut down the income channel, if there is any. Specifically, we define an upwind straw fire as being located within 45 degrees of the daily prevailing wind (fixed octants) calculated from a wind rose in Fig. 2. Straw fires in the opposite direction are defined as downwind ones. Presumably, upwind and downwind straw fires will contribute equally to any temporary income shocks (or any other economic shocks related to straw burning), but upwind straw fires would create a larger air pollution impact than downwind ones.

The idea can be formalized by the following model. First, health is determined by air pollution and income levels:

$$Health_{it} = \delta_0 + \delta_1 PM_{it} + \delta_2 Income_{it} + X_{it}\theta + \tau_i + \pi_t + \xi_{it} \tag{4}$$

where both PM_{it} and $Income_{it}$ are endogenous. We can observe air pollution but not income and our interest is to identify the impact of air pollution (δ_1) in this model.

Some straw fires occur upwind of the county center, and some occur downwind. We can separate the number of upwind straw fires ($Upwind_{it}$) from downwind straw fires ($Downwind_{it}$) and estimate how they affect pollution and income:

$$PM_{it} = \beta_0 + \beta_1 Upwind_{it} + \beta_2 Downwind_{it} + X_{it}\theta + \tau_i + \pi_t + u_{it} \tag{5}$$

$$Income_{it} = \alpha_0 + \alpha Upwind_{it} + \alpha Downwind_{it} + X_{it}\theta + \tau_i + \pi_t + v_{it} \tag{6}$$

In Equation (5), upwind straw fires and downwind straw fires affect air pollution asymmetrically. We expect upwind fires to have a larger impact on local air pollution than downwind ones, i.e. $\beta_1 > \beta_2$. In contrast, in Equation (6), upwind and downwind fires have the same impact on income, i.e., the coefficient of $Upwind_{it}$ is the same as the coefficient of $Downwind_{it}$. This is the key assumption of the model and we think it is a reasonable assumption because the impact of straw burning on income should not depend on wind direction.

Our data also allow us to estimate the following (reduced-form) equation:

$$Health_{it} = \gamma_0 + \gamma_1 Upwind_{it} + \gamma_2 Downwind_{it} + X_{it}\theta + \tau_i + \pi_t + w_{it} \tag{7}$$

Because we do not have data on transitory income (unobservable to researchers), we cannot estimate Equations (4) and (6). However, the following four coefficients can be estimated from the data: γ_1, γ_2, β_1, and β_2.

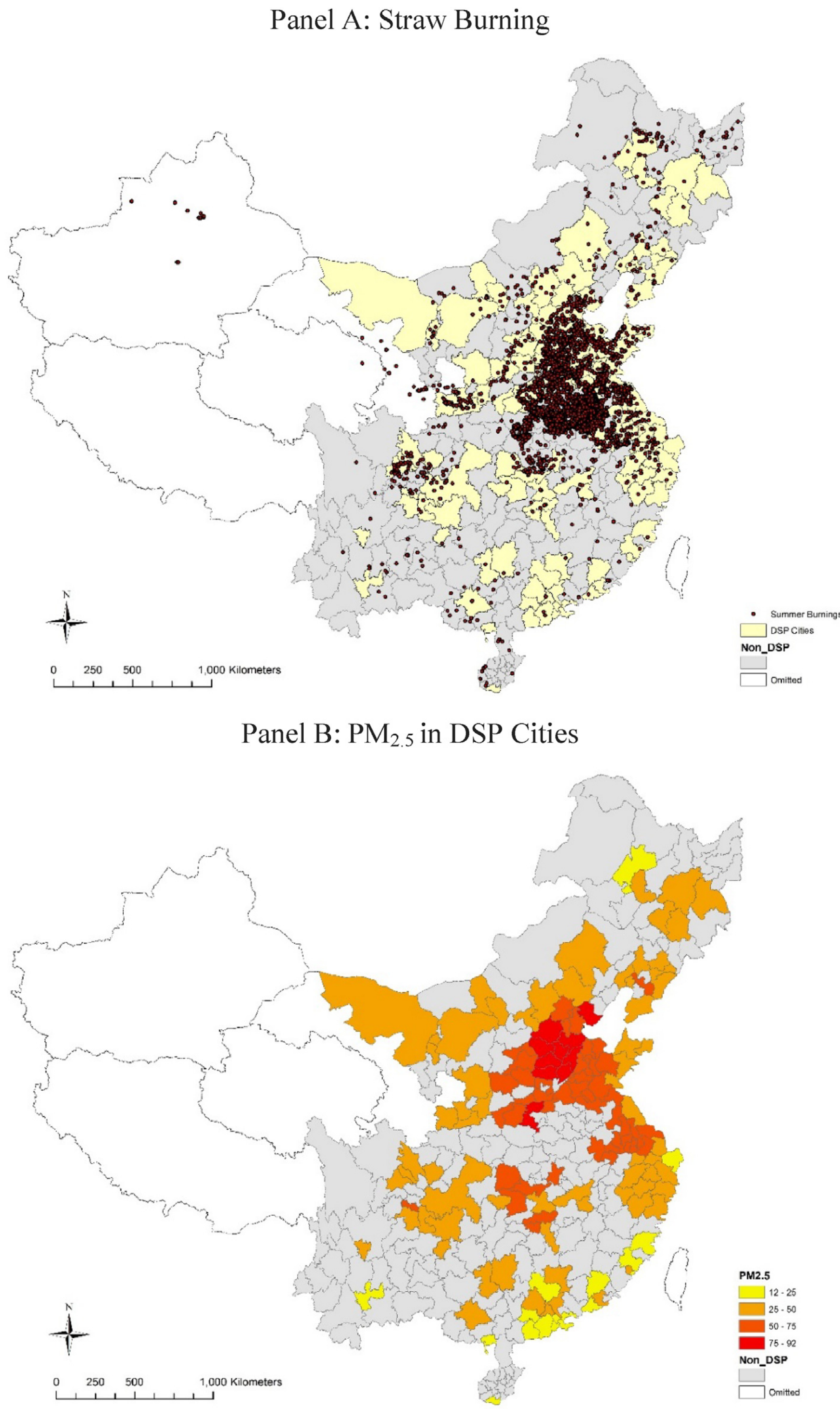

Fig. 1. Satellite Detected Straw Burning and $PM_{2.5}$ in Summer During 2013–2015. *Notes:* Colored polygons represent DSP (Disease Surveillance Point) cities used in the paper. Gray and white areas denote non-DSP cities. DSP counties are too small to see on the maps and thus are not plotted.

Based on Equations (4)–(7), we can derive the following Wald-type estimate:

$$\delta_1 = (\gamma_1 - \gamma_2) / (\beta_1 - \beta_2) \tag{8}$$

In other words, we can isolate the impact of air pollution on health using the four coefficients estimated from Equations (5) and (7). The estimation process proceeds as follows: (1) we first construct the number of upwind and downwind straw fires within 50 km of a county in a month; (2) we then estimate how upwind and downwind straw fires affect air pollution using Equation (5) and obtain $\widehat{\beta}_1$, and $\widehat{\beta}_2$; then estimate how upwind and downwind straw fires affect mortality using Equation (7) and obtain $\widehat{\gamma}_1$ and $\widehat{\gamma}_2$; (3) and finally calculate $\widehat{\delta}_1$ using Equation (8).

The final concern is that people may migrate to avoid air pollution

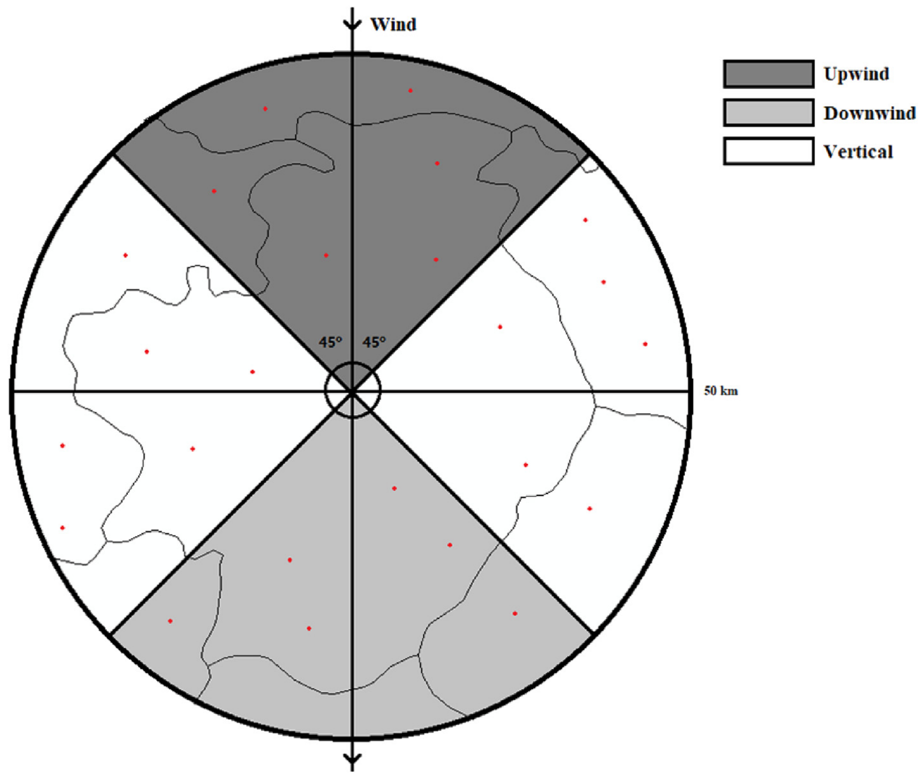

Fig. 2. Illustration of Straw Fires and Wind Direction. *Notes:* Each red dot represents a straw fire. The dark gray area includes upwind fires, the light gray area includes downwind fires, and the white area includes other (vertical) fires. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

exposure, which will cause potential misclassification of death counts in different areas.[18] However, we believe this concern can be significantly alleviated in our setting for four reasons. First, China's household registration system, i.e., *Hukou*, imposes significant costs for people to migrate both across different cities and between rural and urban areas within a city. Second, we focus on monthly variations in air pollution and mortality and control for time fixed effects in all regressions. Our findings will only be affected if people migrate in response to the number of straw fires month by month. This seems highly unlikely because the cost of frequent migration can be very high. Third, as mentioned, the DSP system collects death records only for local residents, those who have lived in a DSP location for at least 6 months in the past year. The death records for frequent migrants, if any, would not be recorded by the system. Finally and most importantly, as shown in Section 6.2, we find little evidence that individuals take avoidance behaviors against straw burning pollution in the summer, when the average $PM_{2.5}$ concentration is relatively low.

5. Baseline results

5.1. Straw burning and air pollution

Table 2 summarizes the regression results from Equation (1). We use $PM_{2.5}$ concentrations as the outcome variable (the results using the logarithm of $PM_{2.5}$ and other pollutants as the outcome variables are listed in Appendix Table A2). In Column (1), only the county fixed effects are included. Column (2) further controls for year and month fixed effects. Column (3) includes county, year and month fixed effects, as well as a set of weather controls. We cluster the standard errors at the county and month level (two-way clustering). Alternative ways of computing the standard errors, such as clustering at the county level only, do not affect the significance level.

Columns (1)–(3) show that 10 additional straw fires detected by satellite are associated with a 4.4–5.0 $\mu g/m^3$ increase in monthly $PM_{2.5}$ concentrations. In Column (4), we also include lagged number of straw fires in the regression. We find that previous month's straw fires do not affect current month's air pollution. This finding also helps rule out any lagged effects of straw burning on pollution at the monthly level.

Columns (5)–(6) compare the effects of straw burning on $PM_{2.5}$ in urban districts and rural counties. We find the impacts are similar in size. This is likely because all the locations in our sample (include the rural counties) are close to major cities where air quality information is available.

The F-statistics from Cragg-Donald (1993) tests for weak instruments show that straw burning is a strong instrument for $PM_{2.5}$. Note that adding year fixed effects, month fixed effects, and weather controls has negligible impact on the point estimate of the straw burning effect. This is encouraging, as it indicates that changes in straw burning are not correlated with these fixed effects and weather conditions.

5.2. Straw burning and death

In Panel A of Table 3, we report the relationship between straw burning and death. We focus on three measures: the logarithms of the total number of deaths in a month, cardiorespiratory deaths, and non-cardiorespiratory deaths.

After controlling for the county, month and year fixed effects and weather conditions, we find that a 10-point increase in the number of straw fires predicts a 1.56% increase in monthly deaths from all causes and a 1.82% increase in cardiorespiratory deaths. Both estimates are statistically significant. Straw burning has no significant impact on non-cardiorespiratory deaths. This finding is consistent with previous ones (e.g., Ebenstein et al., 2017; He et al., 2016) and suggests that air

[18] We thank a referee for bringing up this issue.

Table 2
Effects of monthly straw burning on $PM_{2.5}$ concentrations in summer.

	$PM_{2.5}$ (μg/m^3)				Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)
(per 10 points)	4.43***	5.03***	4.79***	4.61***	5.84***	3.76***
Straw Burning	(1.48)	(0.93)	(0.82)	(0.77)	(0.56)	(1.21)
	[0.80]	[0.72]	[0.68]	[0.83]	[1.06]	[0.89]
L1. Burning				−0.83		
				(1.17)		
				[0.99]		
Observations	1595	1595	1538	1538	806	732
F-statistics	6.0	417.6	16.2	20.2	28.0	11.2
R-squared	0.69	0.76	0.77	0.77	0.76	0.78
# Counties	215	215	209	209	107	102
County FE	Y	Y	Y	Y	Y	Y
Year FE		Y	Y	Y	Y	Y
Month FE		Y	Y	Y	Y	Y
Weather			Y	Y	Y	Y

Notes: Each column represents a separate regression. Columns (1)–(4) report the effects of 10 additional straw fires on monthly $PM_{2.5}$ concentrations. Columns (5)–(6) estimate the effects separately for urban districts and rural counties. Weather variables include wind speed, wind direction, precipitation, temperature, and relative humidity. Cragg-Donald F-statistics are reported. Standard errors in parentheses are two-way clustered at county and month level. Standard errors in brackets are clustered at county level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 3
Effects of straw burning and pollution on log # of death.

	All-Cause		Cardiorespiratory		Non-Cardiorespiratory	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. The Impact of Straw Burning (Reduced-Form Estimates)						
Straw Burning	1.79**	1.56**	2.11**	1.82**	−0.72	−0.58
(per 10 points)	(0.92)	(0.80)	(0.98)	(0.81)	(0.86)	(0.96)
Panel B. $PM_{2.5}$ and Deaths (IV Estimates)						
$PM_{2.5}$	3.56***	3.25**	4.19***	3.80***	−1.43	−1.21
(per 10 μg/m^3)	(1.38)	(1.43)	(1.45)	(1.48)	(1.78)	(2.10)
Panel C. $PM_{2.5}$ and Deaths (OLS Estimates)						
$PM_{2.5}$	0.13	0.32	0.29	0.47	−0.46	−0.25
(per 10 μg/m^3)	(0.26)	(0.23)	(0.43)	(0.38)	(0.35)	(0.47)
Observations	1595	1538	1595	1538	1595	1538
# Counties	215	209	215	209	215	209
Fixed Effects	Y	Y	Y	Y	Y	Y
Weather		Y		Y		Y

Notes: Each column represents a separate regression. The reduced-form estimates, IV estimates, and OLS estimates are reported in Panels A, B, and C, respectively. Columns (1)–(2) examine the effects of pollution on percentage change in monthly all-cause mortality. Columns (3)–(4) and Columns (5)–(6) examine the effects on cardiorespiratory and non-cardiorespiratory mortality, respectively. Weather variables include wind speed, wind direction, precipitation, temperature, and relative humidity. Standard errors in parentheses are two-way clustered at county and month level. ***p < 0.01, **p < 0.05, *p < 0.1.

pollution is likely to be the causal factor for the excess mortality.

5.3. IV estimates on the impacts of $PM_{2.5}$ on deaths

We estimate the impact of fine particulate matter on monthly deaths using straw burning as the instrumental variable for air pollution. The results are reported in Panel B of Table 3. We find that a 10 μg/m^3 increase in $PM_{2.5}$ concentrations will lead to a 3.25% increase in all-cause deaths; again, the size of the coefficient is robust to the inclusion of weather conditions. Similarly, the mortality effect is driven primarily by cardiovascular and respiratory diseases, suggesting that air pollution is likely to be a causal factor.

For comparison, we also report the association between $PM_{2.5}$ and deaths, in Panel C of Table 3. We see that none of the coefficients is statistically significant at the conventional level. In addition, the OLS estimates are also substantially smaller than the IV estimates, suggesting that OLS estimates are downward biased.

The estimated coefficients using the IV approach were larger than associational estimates provided by public health and epidemiological studies in both developed and developing countries (e.g., Dockery et al., 1993; Samoli et al., 2008; Shang et al., 2013; Yin et al., 2017; Zanobetti and Schwartz, 2009; Zhou et al., 2015).[19] Our IV estimates are, however, quantitatively close to those of several recent studies using quasi-experimental approaches to estimate the health impacts of air pollution (e.g., Chen et al., 2013; Ebenstein et al., 2017; Fan et al., 2020; He et al., 2016). These results confirm that associational estimates can significantly under-estimate the air pollution effect.

6. Threats to baseline findings

In this section, we discuss multiple threats to our baseline IV results. We first estimate the health impact of air pollution using augmented instruments and compare them with the baseline results. Our analyses show that, while the simple IV (number of straw fires within 50 km of a county) is conceptually less appealing than the improved instruments, the estimates from the simple IV are quantitatively similar to the estimates from the improved instruments. In other words, the improved instruments do not really add much to our understanding of the straw burning impact. Second, we discuss how avoidance behaviors will affect our findings. In one exercise, we include the visibility variable in the model and do not find it having any impact. In another exercise, we examine how people search online for air filters and face masks and find that people do not respond to air pollution information during the summer. Our conclusion is that avoidance behavior is not a serious concern in our research context. Finally, we conduct a rich set of robustness checks and show that our findings are not affected by some decisions we make in the empirical analyses.

6.1. Results from augmented IVs

We report the regression results from the improved instruments in Tables 4 and 5. In Table 4, we use non-local straw burning as the instrumental variable for local air pollution, conditional on local burning. We report the first stage, reduced-form, and the IV estimates. We find

[19] For example, Shang et al. (2013) reviewed 33 studies in China and found that a 10 μg/m^3 increase in $PM_{2.5}$ increases total, respiratory, and cardiovascular mortality by 0.38%, 0.51%, and 0.44%, respectively. Zhou et al. (2015) have provided the only rural estimates of the impacts of outdoor air pollution, showing that each 10 μg/m^3 increase in $PM_{2.5}$ was associated with a 1.2% and a 0.55% increase in mortality risk in two Chinese counties.

Table 4
Leverage non-local straw burning to estimate the impact of pollution on death.

	First Stage ($Y=PM_{2.5}$)		Reduced-Form Estimates (Y = Log # of Deaths)		IV Estimates (Y = Log # of Deaths)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. First-Stage and Reduced-Form Estimates						
Non-local Burning	5.13***	4.96***	1.92*	1.62*		
(per 10 points)	(0.99)	(0.84)	(1.01)	(0.89)		
Local Burning	3.94*	2.91	0.01	0.47		
(per 10 points)	(2.24)	(1.99)	(2.15)	(2.17)		
Panel B. IV Estimates						
$PM_{2.5}$					3.75**	3.27**
(per 10 μg/m^3)					(1.53)	(1.54)
Observations	1595	1538	1595	1538	1595	1538
# Counties	215	209	215	209	215	209
Fixed Effects	Y	Y	Y	Y	Y	Y
Weather		Y		Y		Y

Notes: Each column represents a separate regression. Columns (1)–(2) estimate the effects of local and non-local straw fires on $PM_{2.5}$. Columns (3)–(4) estimate the effects of local and non-local straw fires on percentage changes in the number of deaths. Columns (5)–(6) reports the IV estimates. Weather variables include wind speed, wind direction, precipitation, temperature, and relative humidity. Standard errors in parentheses are two-way clustered at county and month level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 5
Leverage wind directions to estimate the impact of pollution on death.

	First Stage ($Y=PM_{2.5}$)		Reduced-Form Estimates (Y = Log # of Deaths)		IV Estimates (Y = Log # of Deaths)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. First-Stage and Reduced-Form Estimates						
Upwind Burning	12.76***	11.70***	5.79**	5.02*		
(per 10 points)	(3.79)	(2.53)	(2.87)	(3.01)		
Downwind Burning	4.09**	4.24***	2.04	1.68		
(per 10 points)	(1.28)	(1.18)	(2.98)	(2.87)		
Panel B. Wald Type Estimates						
$PM_{2.5}$					4.33	4.47
(per 10 μg/m^3)						
Observations	1595	1538	1595	1538	1595	1538
# Counties	215	209	215	209	215	209
Fixed Effects	Y	Y	Y	Y	Y	Y
Weather		Y		Y		Y

Notes: Each column represents a separate regression. Columns (1)–(2) examine the effects of upwind and downwind straw fires on $PM_{2.5}$ in a county. Columns (3)–(4) examine the effects of upwind and downwind straw fires on percentage changes in the number of deaths. Columns (5)–(6) report the Wald-Type estimates. Weather variables include wind speed, wind direction, precipitation, temperature, and relative humidity. Standard errors in parentheses are two-way clustered at county and month level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

that non-local burning is the primary contributor to the elevation in $PM_{2.5}$ concentrations in a given county, as shown in Columns (1) and (2). This is likely because over 88% of the total number of straw fires occurred within the 50-km radius of a county are non-local. A 10 μg/m^3 increase in $PM_{2.5}$ concentrations will increase mortality by 3.27%–3.75% (Columns (5) and (6)). These estimates are essentially the same as the baseline estimates in Table 3.

In Table 5, we summarize the results from estimating Equations (5), (7) and (8). In Columns (1) and (2), we see that upwind straw fires indeed have a larger impact on air quality than do downwind straw fires. In Columns (3) and (4), we find a similar pattern: upwind fires cause more people to die than do downwind fires. Both sets of results are robust to the inclusion of time-varying weather controls. In the last two columns, we estimate the impact of pollution on mortality using differences in the coefficients between upwind and downwind straw fires. We find that a 10 μg/m^3 increase in $PM_{2.5}$ concentrations will increase deaths by 4.47%. The estimates are slightly larger than those in Table 3, but the differences are statistically insignificant.[20]

Our interpretation of these results is that, although conceptually there are good reasons to worry about the endogeneity of straw burning, this concern matters very little in reality. In subsequent heterogeneity analysis, we thus focus on estimates from the baseline IV model. In addition, the baseline IV estimates are marginally more conservative than the alternative IV estimates, so when we use the baseline estimates to evaluate the potential gains from controlling straw burning, the benefit estimate would be interpreted as the lower bound.

6.2. Avoidance behavior

Avoidance or defensive behaviors can complicate the interpretations of the estimated impacts of air pollution. If people take measures to reduce exposure, such as reducing outdoor activities or using air filters, the true physiological impact of pollution will be under-estimated (e.g., Moretti and Neidell, 2011).

There are three reasons why we think avoidance behavior does not play an important role in our setting. First, we examine the visibility data and find that including visibility as a control in the regression has no impact on the air pollution effect (Panel A of Table 6). We also estimate the relationship between visibility and straw burning and find that straw burning does not significantly degrade visibility (Appendix Table A2).

Second, we use data in the summer season, when there are better meteorological conditions for pollutant dispersion, and the average $PM_{2.5}$ concentrations are relatively low. Pollution alerts are rarely triggered during the summer, so we expect that people undertake little avoidance behavior. To test this idea, we estimate the impact of straw burning on individuals' online searches for defensive equipment, using the Baidu Search Index. Baidu Search Index is analogous to Google Trends and tells us how many people search for certain keywords within a certain period of time in cities. Previous studies show that online search activities for "anti-$PM_{2.5}$ mask," "haze," "$PM_{2.5}$" and "Air Quality Index" (AQI) are very sensitive to air pollution and strongly correlated with online sales of defensive equipment (e.g., Liu et al., 2018). As reported in Panel B of Table 6, we find that straw burning does not affect any of these searches during the summer seasons on which we focus. In contrast, in the winter season when air quality is poorer, people are more likely to search more for these items when straw burning increases.[21]

Our conclusion is that the public is not quite aware of pollution in the summer, so our estimates are unlikely to be confounded by avoidance behaviors in a meaningful way.

6.3. Robustness checks

We conduct a variety of robustness checks to address some other issues related to our baseline findings. First, one reasonable concern about the satellite-detected straw burning data is that thick clouds may cover small fires, which will result in measurement errors in the explanatory variable. We thus directly include cloud coverage in the regression and check whether the estimates are affected. The results are reported in Column (3) of Appendix Table A4. We find that controlling for cloud coverage yields similar IV estimates, suggesting that the number of days

[20] The 95% confidence interval of the baseline estimate, 3.25%, is [0.45%, 6.06%], which contains all the point estimates in Tables 4 and 5.

[21] We also use data for "bottled water" as a placebo, and find that it is not related to short-run variations of pollution and straw burning for either summer or winter.

Table 6
Straw burning and avoidance behaviors.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. $PM_{2.5}$ and Deaths (IV Estimates): Controlling for Visibility (%)						
	All-Cause		Cardiorespiratory		Non-Cardiorespiratory	
$PM_{2.5}$	3.25**	3.30**	3.80***	3.87***	−1.21	−1.27
(per 10 $\mu g/m^3$*)*	(1.43)	(1.41)	(1.48)	(1.45)	(2.10)	(2.19)
Visibility	N	Y	N	Y	N	Y
Observations	1538	1538	1538	1538	1538	1538
# Counties	209	209	209	209	209	209
Panel B. Straw Burning and Online Search						
	Anti-$PM_{2.5}$ Mask	Haze	$PM_{2.5}$	AQI	Bottled Water	
Summer Burning	−0.26	−1.48	0.14	−10.70	1.57	/
	(7.24)	(3.09)	(1.35)	(6.52)	(4.59)	/
Winter Burning	15.30***	6.17**	5.21***	13.40***	0.76	/
	(4.60)	(2.47)	(1.22)	(1.43)	(2.34)	/
Observations	1383	1383	1383	1383	1383	/
# Cities	154	154	154	154	154	/

Notes: Each cell represents a separate regression. Panel A summarizes the IV estimates with/without visibility as control. In Panel B, dependent variables include Baidu Search Indices for anti-$PM_{2.5}$ mask, haze, $PM_{2.5}$, AQI and bottled water. We separately estimate the impact of straw burning on these outcomes for summer and winter. Location (county or city), month and year fixed effects, and weather conditions (wind speed, wind direction, temperature, precipitation, and relative humidity) are always controlled. Standard errors in parentheses are two-way clustered at county/city and month level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

with thick clouds is largely random, conditional on location and time fixed effects.[22]

Second, we control for SO_2 and NO_x in the regression and find that the $PM_{2.5}$ estimates remain robust. This finding suggests that changes in $PM_{2.5}$ concentrations, induced by straw burning, are indeed not correlated with changes in SO_2 and NO_x. The results are reported in Column (4) of Appendix Table A4.

Third, instead of using the logarithm of the number of deaths as the outcome, we use the standardized mortality rate based on death and census data as an alternative outcome. The results are reported in Appendix Table A5. The standardized mortality rate is defined as the age-adjusted number of deaths per 100 thousand people.[23] We get consistent results using this alternative measure. If monthly straw burning increases by 10 points, all-cause and cardiorespiratory mortality rates will increase respectively by 1.71% and 1.91%. The IV estimates show that a 10 $\mu g/m^3$ increase in monthly $PM_{2.5}$ will lead to a 3.57% and a 4.00% increase in all-cause and cardiorespiratory mortality rates, respectively.

Fourth, we use the log of (1 + the number of straw fires) as the explanatory variable to estimate the effect of a percentage change in straw burning on mortality. The results are reported in Appendix Table A6. We find that a 10% increase in monthly straw burning in a county will increase all-cause deaths by 0.09%. The effect is driven primarily by extra deaths from cardiorespiratory diseases, consistent with the main findings.

Fifth, we include polynomial terms of the number of straw fires and weather conditions to explore whether there is any nonlinear effect of straw burning and weather. Appendix Table A7 represents the estimates with the quadratic term of straw burning. Straw burning's effect on deaths is slightly concave, with a turning point of around 40. Given that the average monthly number of straw fires in a county is 2 (with a standard deviation of 8) in our data, the health effect of straw burning can be well-approximated by a linear function. In addition, in Appendix Table A8, we follow Deschênes and Greenstone (2011) and use 5 temperature bins, namely (,15), [15,20), [20,25), [25,30), and [30), to control for temperature nonlinearly, and the estimates remain robust.

Sixth, we include the number of previous month's straw fires in the regression and try to examine potential lagged effects. The results are reported in Appendix Table A9. We see that the lagged burning variable is statistically insignificant in all regressions.

Seventh, in Appendix Table A10, we summarize the results using different matching distances between monitoring stations and counties. We find the results are quantitatively similar using alternative ways to match the DSP locations and air quality.

Finally, our main specification merges all data using the geometric county centers. Alternatively, we can match all data sets using the administrative centers. The results are reported in Appendix Table A11. We find a consistent impact of straw burning on all-cause deaths through cardiorespiratory diseases. The IV estimates are also similar in size to our baseline findings.

7. Heterogeneity

The health effects of burning straw can differ among subpopulations, as different individuals may have distinct exposures or physical responses to air pollution. We explore the health effects of straw burning by location, gender, and age in Table 7.

Panel A compares the relative health risk between urban districts and rural counties. We find that, although straw burning degrades both urban and rural air quality, residents in rural counties are more likely to be affected. Specifically, if the number of monthly straw fires increases by 10, all-cause mortality will increase by 2.52% in rural areas, but there is no significant relationship for the urban areas. The IV estimates of $PM_{2.5}$ are consistent with the reduced-form estimates using straw burning. Column (4) shows that a 6.69% increase in mortality is associated with a 10 $\mu g/m^3$ increase in $PM_{2.5}$ in rural areas, while there is no impact of pollution caused by straw burning on mortality in the urban areas. Panel B further distinguishes lower-income areas from higher-income areas based on the median GDP per capita in 2012.[24] We find a similar pattern: the health impact is concentrated in areas with lower incomes.

[22] Note that, if it was raining, there would be no measurement errors in straw burning because there is no burning on rainy days.

[23] We do not use the age-adjusted mortality results as the main outcome, for two reasons. First, population data for different age groups in different years need to be interpolated from the census data, which are only available every five years. So, conceptually it may increase inaccuracy in the health measure when we adjust the age structure. Second, as a practical matter, we use monthly changes in pollution/death within the same location for a given year for identification, so it does not matter whether we adjust the age structure (as it only rescales the outcome by population structure in a year).

[24] There are 42 urban districts and 66 rural counties in the lower-income group, and there are 66 urban districts and 41 rural counties in the higher-income group.

Table 7
Heterogeneous effects of straw burning pollution on death.

	Reduced-Form: # Straw Fires (per 10 points)		IV: $PM_{2.5}$ (per 10 μg/m^3)	
	(1)	(2)	(3)	(4)
Panel A: Urban vs. Rural				
Urban	0.42	0.12	0.67	0.20
	(0.52)	(0.39)	(0.85)	(0.69)
Rural	2.90**	2.52**	7.42***	6.69***
	(1.23)	(1.17)	(1.63)	(1.83)
Panel B: Rich vs Poor				
Urban	0.42	0.12	0.67	0.20
	(0.52)	(0.39)	(0.85)	(0.69)
Rural	2.90**	2.52**	7.42***	6.69***
	(1.23)	(1.17)	(1.63)	(1.83)
Panel B: Rich vs Poor				
Rich	0.30	0.11	0.67	0.27
	(0.66)	(0.69)	(1.50)	(1.71)
Poor	2.43**	2.15***	4.36***	3.95***
	(1.01)	(0.83)	(0.96)	(0.77)
Panel C: Male vs Female				
Female	1.80	1.40	3.58*	2.92
	(1.26)	(1.02)	(1.98)	(1.79)
Male	1.85**	1.74**	3.67***	3.64**
	(0.80)	(0.76)	(1.32)	(1.55)
Panel D: By Age Group				
60+	1.71**	1.53**	3.40***	3.20***
	(0.87)	(0.70)	(1.28)	(1.20)
40–59	3.27***	3.07**	6.50***	6.41**
	(1.27)	(1.41)	(1.87)	(2.66)
20–39	−0.23	−0.96	−0.46	−2.00
	(2.72)	(2.22)	(5.43)	(4.68)
5–19	3.56	2.29	7.08	4.78
	(2.16)	(2.42)	(4.77)	(5.67)
1–4	1.50	1.17	2.97	2.45
	(2.00)	(1.85)	(4.33)	(4.15)
0	1.80	2.62	3.77	6.17
	(2.14)	(2.08)	(4.60)	(5.33)
Fixed Effects	Y	Y	Y	Y
Weather		Y		Y

Notes: Each cell represents a separate regression. Columns (1)–(2) list the reduced-form estimates of the mortality effects of straw burning. Columns (3)–(4) report the IV estimates of $PM_{2.5}$. Panel A compares urban and rural areas. Panel B compares rich and poor areas separated by the median of GDP per capita in 2012. Panel C compares males with females. Panel D compares different age-groups. County, month, year fixed effects and weather conditions (wind speed, wind direction, temperature, precipitation, relative humidity) are controlled. Standard errors in parentheses are clustered by county and month. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

While this study is unable to pin down the exact channels through which the air pollution effect is mitigated in urban/richer areas, a growing line of literature suggests that the quality of medical services, availability of air pollution information, and defensive investment are possible factors. For example, Cheung et al. (2020) show that the impact of air pollution on mortality depends in part on whether the residents have immediate access to emergency services. When air pollution triggers a heart attack or an acute respiratory disease, immediate treatment is critical to save a patient's life. In Barwick et al. (2019), the researchers find that access to pollution information dramatically increased households' awareness about pollution and significantly reduced mortality caused by pollution. As air pollution information is largely unavailable in rural/poorer areas, it is not surprising that rural/poorer residents are more vulnerable to air pollution. Finally, as shown by Sun et al. (2017) and Ito and Zhang (2020), individuals' defensive investments in face masks and air filters depend not only on the air pollution level, but also on their income. Poor people are much less likely to invest in defensive equipment, which may significantly increase their exposure.

We are not alone in highlighting the significant urban-rural heterogeneity in the air pollution effect. Zhou et al. (2015) and Fan et al. (2020) observe similar patterns in their studies, while they use different identification strategies and focus on different research contexts. The sharp contrast between urban and rural areas indicates that previous studies, which focus mostly on urban residents, may understate the health cost of air pollution.

Panel C of Table 7 summarizes our findings by gender. We find that the mortality risk associated with straw burning is more significant for males.[25] This is generally consistent with the public health literature, as males in China are more likely to smoke and thus have compromised cardiorespiratory functions. Males are also more likely to work in the farmlands, which further increases their exposure to air pollution.

Panel D of Table 7 reports the results for different age groups: 0 (infants), those between 1 and 4, those between 5 and 19, those between 20 and 39, those between 40 and 59, and those above 60 years old. We find that a 10-point increase in the monthly number of straw fires was associated with a 1.53% increase in mortality for people above 60. Meanwhile, middle-aged people are also vulnerable to air pollution caused by straw burning. We estimate that, if the number of monthly straw fires increases by 10, the mortality risk for people between 40 and 59 will increase by 3.07%. This result is somewhat surprising, as existing literature typically finds that air pollution has a greater impact on the elderly (e.g., He et al., 2016; Fan et al., 2020). Our interpretation of these results is that, because rural middle-aged people are still a major labor force in the farmlands, their exposure to straw burning pollution can be greater than other groups. The ambient air pollution concentration in the county may understate this group's actual exposure to air pollution.

Straw burning does not significantly predict mortality among those below 40 years old, including infants. The null effect on the infant group also surprises us, as many studies show that infants are vulnerable to air pollution (e.g., Arceo et al., 2016; Chay and Greenstone, 2003; Currie and Neidell, 2005). Nevertheless, this result is consistent with Rangel and Vogl (2019), who show that air pollution from agricultural fires increases the likelihood of stillbirth but has no impact on infant mortality. Their argument is that infants at the highest risk for postnatal mortality might have been selected out before they were born, i.e., there may exist a survivor bias when studying infant mortality. As we do not have data for stillbirths or other measures of infant health, we are unable to further test this argument.[26]

The IV estimates show similar patterns. The effects of $PM_{2.5}$ are large and statistically significant for people over 40 years old. People below 40 are unlikely to die from air pollution caused by straw burning.

8. Straw recycling

In 2016, the central government of China enforced an incentive-based policy that subsidizes individuals and enterprises that recycled straw from the field.[27] The top 10 provinces with the most intensive straw burning activities each received 100 million Chinese yuan (around 14.2 million USD) in 2016 to recycle straw. These provinces are Henan, Anhui, Heilongjiang, Shandong, Jilin, Hebei, Jiangsu, Liaoning, Shanxi and Inner Mongolia. The subsidy's objective is to improve air quality by incentivizing farmers to recycle straw instead of burning it. The policy continued in 2017 the total amount of subsidy increased to 1.3 billion Chinese yuan (around 186 million USD).

We examine how this subsidy program affects straw burning using a

[25] We cannot reject the null hypothesis that the air pollution impact on males is greater than that on females.

[26] Nevertheless, the results for the infant group should be interpreted with caution. A known issue in the DSP reporting process is that infant deaths are more likely to be under-reported. While the Chinese CDC has been conducting retrospective surveys to determine under-reporting rates in different DSP locations, such adjustments are only available at the yearly level. It is unclear to use whether under-reporting of infant deaths differs across months.

[27] http://nys.mof.gov.cn/zhengfuxinxi/czpjZhengCeFaBu_2_2/201606/t20160603_2311988.html.

Difference-in-Differences (DiD) approach:

$$Y_{it} = \alpha + \beta^* subsidy_{it} + \gamma^* X_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (7)$$

where Y_{it} is the number of burning points or the PM concentrations in province i in year t. Each "year" is defined by the two straw burning seasons, from May 20 to July 20 and from September 20 to November 20, a total of 124 days. $subsidy_{it}$ is a dummy variable equal to 1 if province i received a subsidy in year t. X_{it} is a vector of meteorological conditions, including wind speed, wind direction, temperature, relative humidity, and precipitation. μ_i and π_t control for province and year fixed effects. β is the key parameter of interest. It estimates the effect of straw recycling subsidy on the number of straw fires or air quality.

The identifying assumption of the above model is that the treated provinces and untreated provinces should follow a parallel trend before 2016. To formally test the parallel trend assumption, we use an event-study approach following Jacobson et al. (1993) and estimate the difference in the number of straw fires between the two groups before and after 2016. We use 2015 as the reference year and compare the changes in the number of straw burning points between the two groups in other years relative to 2015. The estimates are plotted in Panel A of Fig. 3. While we observe a slight downward trend before 2015, none of the coefficients before 2015 are statistically significant. After the program was introduced, i.e., for 2016, we see a dramatic decline in the number of straw fires in the subsidized provinces. The effect remained positive and statistically significant in 2017. The corresponding event-study regression results are reported in Appendix Table A12.

Table 8 summarizes the regression results. Column (1) reports the baseline DiD result, where only province and year fixed effects are included. Column (2) further controls for weather conditions. In Column (3), we add a time trend that allows the treated provinces to evolve differently from the control provinces. This specification aims to address the concern that the treated and control provinces may not completely follow a parallel trend before 2016, as illustrated by the slight downward trend in Fig. 3. In Column (4), we further control for a set of province-specific time trends, allowing each province to have a different trend. With this most restrictive specification, we find that the annual number of straw fires in the subsidized provinces on average dropped by 153 since 2016 compared with provinces without subsidies. The less demanding specifications in Columns (1) to (3) generate slightly larger but quantitatively similar estimates. In Column (5), we use the logarithm of the number of straw fires as the outcome variable and find that the number of straw fires decreased by 28.8% ($e^{-0.339}$-1).

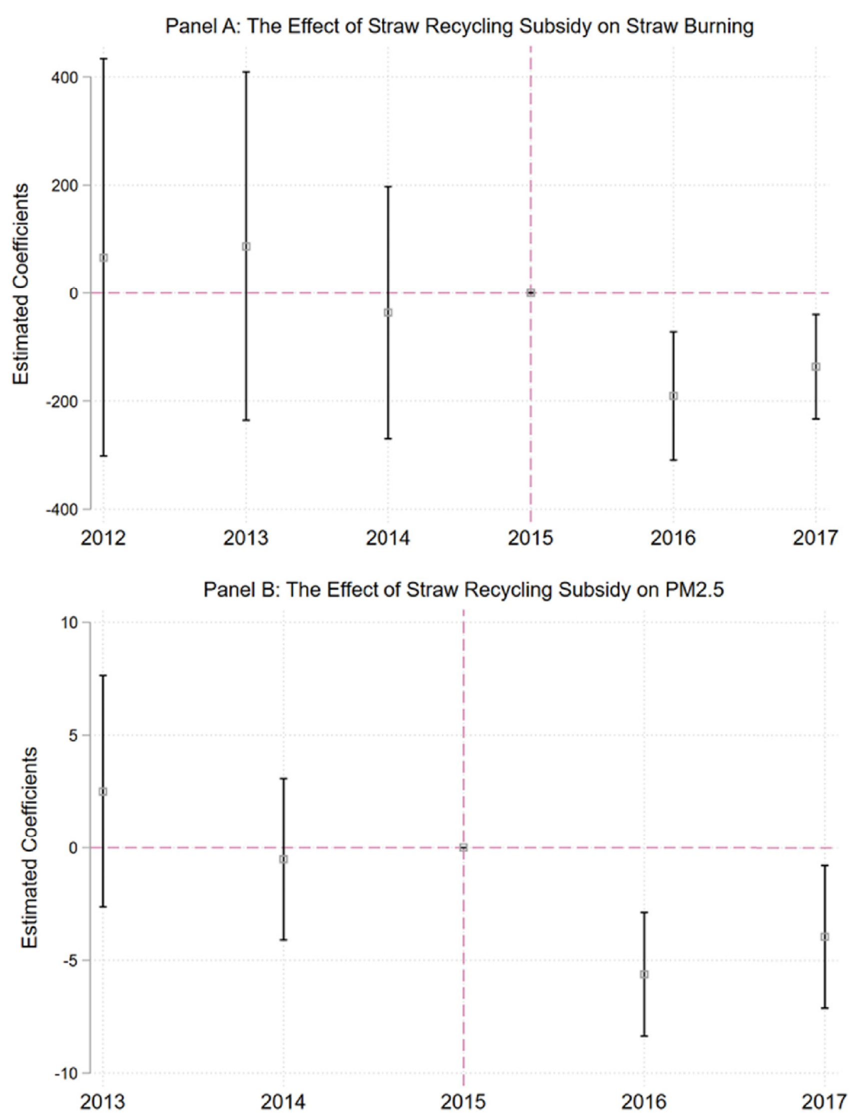

Fig. 3. Test for Parallel Pre-Trends in Straw Burning and $PM_{2.5}$. *Notes:* The upper figure in Panel A plots the impacts of straw recycling subsidy on the number of straw fires based on an event-study analysis following the methods of Jacobson et al. (1993). The lower figure in Panel B plots the impacts of straw recycling subsidy on $PM_{2.5}$. The year 2015 (one year before the subsidy) is chosen as the reference.

Table 8
Straw recycling subsidy and air quality.

VARIABLES	# of Straw Fires				Log(1+Burning)	$PM_{2.5}$	PM_{10}	SO_2	NO_2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Subsidy	−193.5***	−188.5***	−196.7***	−152.9***	−0.339*	−4.33**	−9.87***	0.03	−0.33
	(17.6)	(42.4)	(41.4)	(40.2)	(0.196)	(1.75)	(3.35)	(0.67)	(0.52)
Observations	186	186	186	186	186	155	186	186	186
R-squared	0.58	0.70	0.70	0.94	0.95	0.96	0.87	0.85	0.90
# Provinces	31	31	31	31	31	31	31	31	31
Province FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Weather		Y	Y	Y	Y	Y	Y	Y	Y
Treatment Trend			Y						
Provincial Trend				Y	Y	Y	Y	Y	Y

Notes: Each column represents a separate regression. Columns (1)–(4) list the effect of straw recycling subsidy on the number of straw fires in a province during straw burning seasons in a year. Column (5) uses the logarithm of the number straw fires as the dependent variable. Columns (6)–(9) report the effects of the straw recycling subsidy on air pollutants including $PM_{2.5}$, PM_{10}, SO_2, and NO_2. Province and year fixed effects are always controlled. Weather conditions include wind speed, wind direction, temperature, precipitation, relative humidity. Standard errors in parentheses are clustered by province and year. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

In Panel B of Fig. 3, we repeat the event-study analysis for $PM_{2.5}$. We focus on 2013 to 2017, as $PM_{2.5}$ was not monitored in most parts of China before 2013. We expect that the changes in $PM_{2.5}$ levels would follow the same pattern as changes in straw fires because straw burning primarily emits particulates. Indeed, we observe that the $PM_{2.5}$ levels fell significantly in 2016, and this reduction remained statistically significant in 2017, implying that straw burning reduction causally improved air quality. In Column (6) of Table 8, we report the impact of straw recycling subsidy on $PM_{2.5}$ using the most restrictive specification. We find that straw burning subsidy decreased the $PM_{2.5}$ concentrations in the treated provinces by 4.33 μg/m^3 during the straw burning seasons. Column (7) further reports the results for PM_{10} for comparison. The subsidy reduced PM_{10} concentrations by 9.87 μg/m^3. In Columns (8) and (9), we find no impact of the subsidy on the concentrations of SO_2 nor NO_2. This is in line with the scientific literature and further enhances the credibility of our findings.[28]

The significant drops in both straw burning and $PM_{2.5}$ have important implications for public health in China. We can conduct a back-of-the-envelope calculation to compare the benefits and costs of the policy. The mortality rate of the 10 treated provinces was 6.41 per thousand in 2015, and the total population of the 10 provinces was 614.2 million. To simplify the calculation, assuming that the incidence of deaths is equally distributed throughout the year, so the total number of deaths during the straw burning seasons would have been around 1.34 million in 2015. According to the IV estimate in Section 5.3, a 10 μg/m^3 change in $PM_{2.5}$ predicts a 3.25% change in mortality. That implies that a 4.33 μg/m^3 reduction in mean $PM_{2.5}$ concentrations during the burning seasons would bring down the mortality rate by 1.41%, equivalent to averting roughly 18,900 premature deaths annually.[29] Note that in this calculation, we assume that the subsidies affect individuals' health only through its impacts on straw burning pollution. We cannot fully rule out the possibility that the subsidy may directly improve health through the income channel, as farmers' budget constraints can be relieved by the subsidy.

We can monetize the health benefit using the value of statistical life (VSL). Since straw burning has a negligible effect on urban residents, the cost of premature death is estimated for rural residents only. Fan et al. (2020) suggested using 2.92 million Chinese yuan (about 440,000 USD) as the VSL for a typical Chinese rural resident. The health benefit from reduced mortality is estimated to be about 55 billion Chinese yuan (around 7.85 billion USD).

For the cost estimate, we look at three components: (1) the total amount of subsidy, (2) additional work to enforce the policy and encourage farmers to recycle straw, and (3) potential changes in agricultural production. The first component is straightforward: the government provided 1 billion Chinese yuan (142 million USD) in 2016 and 1.3 billion Chinese yuan (186 million USD) in 2017 to encourage farmers to recycle straw. The second cost component is more difficult to estimate, as we do not have data on how much additional work is needed to implement the policy. However, we believe the additional administrative cost did not exceed 1 billion yuan in 2016 and did not exceed 1.3 billion yuan in 2017. This is because, if the additional work alone had been more costly than the total amount of subsidy, the policy would not have been implemented. Adding these two components together, the upper-bound of the policy's cost would be less than 2.6 billion Chinese yuan each year (1.3 billion direct subsidies + 1.3 billion for additional administrative work).

To estimate the third cost component, we examine whether the subsidy affects the total yield of agriculture and total grain output (the most important type of crop output in China). The concern here is that if individuals were incentivized to engage more in agricultural production (because of the higher value of agriculture), the cost of the policy could be unintendedly larger. However, as reported in Appendix Table A13, we find that the subsidy does not affect agricultural output. Given this, we conclude that the third cost component should be small in magnitude, and therefore we leave it out of our cost calculation.

If we compare the benefit of controlling straw burning (55 billion Chinese yuan or 18,900 averted deaths) with the cost of subsidizing straw recycling (at most 2.6 billion Chinese yuan per year), we see that the benefit from reduced mortality alone is an order of magnitude larger than the cost. To put these numbers in another way, it costs at most 137,600 Chinese yuan (19,700 USD) to avert a premature death when the government subsidizes straw recycling. While these calculations are coarse, the significant difference in their magnitudes suggests that there would be significant welfare gains from controlling straw burning.

Note that improved air quality would also reduce morbidity, help individuals save on defensive expenditures on air filters and facial masks, increase labor productivity, and bring about co-benefits for the climate. Existing studies show that the benefits along these dimensions are also substantial (e.g., Barwick et al., 2018; Chang et al., 2019; Ito and Zhang,

[28] As a set of placebo tests, we run the same set of regressions using air pollution measures during the non-burning seasons. We find no difference in air quality between the subsidized provinces and the non-subsidized provinces during the non-burning seasons, as reported in Appendix Table A13 (Columns (1) to (4)). This alleviates the concern that other agricultural or pollution policies targeted at the subsidized provinces may confound the DiD estimates, or that the two groups of provinces are systematically different in other ways. In fact, we are unaware of any other policy in company with the straw-recycling subsidy that was applied to the same set of provinces in 2016.

[29] The mortality data in 2016 are unavailable for use in this project. Hence, the time windows for mortality estimation and policy evaluation are different.

2020; Zhang and Mu, 2018). Were these benefits also considered, we expect the gain from controlling straw burning to be even greater.

9. Conclusions

This paper investigates the impacts of agricultural straw burning on air pollution and mortality in China. We estimate that a 10-point increase in the number of straw burns detected by satellites in a county in a month will lead to a 7.62% increase in monthly $PM_{2.5}$ concentrations and a 1.56% increase in deaths. Straw burning primarily causes people to die from cardiorespiratory diseases. Using straw burning as an instrument for $PM_{2.5}$, we further estimate that a 10 μg/m^3 change in $PM_{2.5}$ will cause a 3.25% change in mortality and 3.80% change in cardiorespiratory mortality, which are similar in magnitude to previous estimates on the impacts of air pollution in China. Using alternative instruments (non-local straw burning and wind directions) generates quantitatively similar estimates, supporting the causal interpretation of our findings.

The health impacts of straw burning are highly heterogeneous. Specifically, the effects are greater in rural and poor areas than in urban and rich areas, suggesting better socio-economic conditions can mitigate the impact of air pollution on mortality. Straw burning mainly impairs the health of middle-aged and elderly people, so those who are more vulnerable and are more intensively exposed to the straw burning smoke are more likely to die due to straw burning.

Overall, these findings highlight the large health cost of straw burning and the need for more effective regulatory efforts. Exploiting China's straw recycling policy, we further show that providing subsidies to farmers and enterprises incentivized them to recycle straw, which significantly reduced air pollution caused by straw burning. Our exploratory analysis suggests that the benefits of subsidizing straw recycling are substantially larger than the costs. Other countries that facing similar problems may consider adopting similar policies.

Note that in this study we are only able to quantify the short-term health impacts of straw burning pollution on mortality. Presumably, accumulated exposure to air pollution would cause larger health damages to individuals (e.g. Ebenstein et al., 2017). That implies, the potential benefits from controlling straw burning would be even greater if the straw recycling can be sustained. Future research is warranted to better understand the welfare implications of these regulations in the long run.

Author statement

Guojun He: Methodology, Writing, Supervision, Funding acquisition. **Tong Liu:** Data curation, Methodology, Formal analysis, Writing. **Maigeng Zhou:** Resources, Data curation.

Declaration of competing interest

None.

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Appendix

Table A1
Effects of Air Pollution on Death using Daily Data.

VARIABLES	(1) All-Cause	(2) Cardiorespiratory	(3) Non-Cardiorespiratory
$PM_{2.5}$ *(per* 10 μg/m^3*)*	1.89**	2.59***	−0.97
	(0.94)	(0.89)	(1.16)
Observations	25,217	25,217	25,217
# Counties	209	209	209
County FE	Y	Y	Y
Week-of-Year FE	Y	Y	Y
Day-of-Week FE	Y	Y	Y
Weather	Y	Y	Y

Notes: Each cell represents a separate regression using a distributed lag model with 7-days of straw burning as an instrument for daily $PM_{2.5}$. Weather conditions include wind speed, wind direction, temperature, precipitation, relative humidity. Standard errors in parentheses are clustered by county and date. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A2
Effects of Straw Burning on Different Pollutants.

VARIABLES	(1) $PM_{2.5}$	(2) PM_{10}	(3) SO_2	(4) NO_2	(5) Visibility
Straw Burning *(per 10 points)*	7.62***	4.70***	−1.04	1.23	−0.07
	(0.84)	(0.65)	(2.50)	(1.45)	(0.77)
Observations	1538	1429	1467	1461	1538
R-squared	0.823	0.377	0.220	0.144	0.386

(*continued on next column*)

Table A2 (*continued*)

VARIABLES	(1)	(2)	(3)	(4)	(5)
	$PM_{2.5}$	PM_{10}	SO_2	NO_2	Visibility
# Counties	209	203	204	204	209
County FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Weather	Y	Y	Y	Y	Y

Notes: Each column lists results from a separate regression. Columns (1)–(4) report the effects of 10 additional straw fires on monthly $PM_{2.5}$, PM_{10}, SO_2 and NO_2 in counties. Column (5) reports the effects on monthly visibility. Weather includes wind speed, wind direction, precipitation, temperature, relative humidity. Standard errors in parentheses are two-way clustered at county and month level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A3
Straw Burning Decision.

VARIABLES	(1)	(2)	(3)
	Burning	Burning	Burning
L1.$PM_{2.5}$	0.00014*	0.00012	0.00012
	(0.00008)	(0.00008)	(0.00008)
L1.SO_2	−0.000004	−0.00012	−0.00011
	(0.00030)	(0.00030)	(0.00030)
L1.NO_2	0.00005	0.00011	0.00007
	(0.00021)	(0.00021)	(0.00022)
wind speed	0.00067	0.00105	0.00020
	(0.00089)	(0.00092)	(0.00094)
precipitation	0.00003	0.00004	0.00002
	(0.00004)	(0.00005)	(0.00005)
temperature	0.00157**	0.00145*	0.00184**
	(0.00068)	(0.00077)	(0.00076)
relative humidity	−0.00177***	−0.00180***	−0.00162***
	(0.00016)	(0.00016)	(0.00016)
Observations	27,178	27,178	27,178
R-squared	0.073	0.077	0.106
# Counties	204	204	204
Wind Direction	Y	Y	Y
County FE	Y	Y	Y
Week FE	Y	Y	
Week-of-Year FE		Y	
Day FE			Y

Notes: Each column represents a separate regression of straw burning decision (=1 if there is at least one burning point within a county) on air pollution of previous day and weather conditions (wind speed, wind direction, precipitation, temperature, and relative humidity). L1 denotes air pollutants on the previous day. Standard errors in parentheses are clustered by county. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A4
Effects of $PM_{2.5}$ on Log # of Death.

VARIABLES	IV				OLS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. All-Cause Mortality								
$PM_{2.5}$ (*per* 10 μg/m^3)	3.56***	3.25**	3.16**	3.17***	0.13	0.32	0.33	0.25
	(1.38)	(1.43)	(1.44)	(1.20)	(0.26)	(0.23)	(0.23)	(0.29)
Panel B. Cardiorespiratory Mortality								
$PM_{2.5}$ (*per* 10 μg/m^3)	4.19***	3.80***	3.69**	3.87***	0.29	0.47	0.52	0.39
	(1.45)	(1.48)	(1.48)	(1.21)	(0.43)	(0.38)	(0.38)	(0.43)
Panel C. Non-Cardiorespiratory Mortality								
$PM_{2.5}$ (*per* 10 μg/m^3)	−1.43	−1.21	−1.27	−1.11	−0.46	−0.25	−0.24	−0.24
	(1.78)	(2.10)	(2.13)	(2.03)	(0.35)	(0.47)	(0.48)	(0.41)
# Counties	215	209	208	203	215	209	208	203
Kleibergen-Paap F-Statistics	19.6	22.5	15.7	11.6				
Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Weather		Y	Y	Y		Y	Y	Y
Cloud			Y	Y			Y	Y
SO_2, NO_2				Y				Y

Notes: Each cell represents a separate regression. Columns (1)–(4) report IV estimates of effects of $PM_{2.5}$ on mortality, and Columns (5)–(8) report the OLS estimates. County, month and year fixed effects, weather conditions (wind speed, wind direction, temperature, precipitation, relative humidity), cloud coverage, SO_2 and NO_2 are controlled one by one. Standard errors in parentheses are two-way clustered at county and month level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A5
Effects of Straw Burning and $PM_{2.5}$ on Mortality Rate.

VARIABLES	(1) All-Cause Mortality Rate (log)	(2) Cardiorespiratory Mortality Rate (log)	(3) Non-Cardiorespiratory Mortality Rate (log)
Panel A: Reduced Form			
Straw Burning *(per 10 points)*	1.71*	1.91*	1.13
	(0.95)	(1.09)	(0.82)
Panel B: IV and OLS			
IV: $PM_{2.5}$ *(per* 10 μg/m^3*)*	3.57**	4.00**	2.37
	(1.78)	(2.00)	(1.55)
OLS: $PM_{2.5}$ *(per* 10 μg/m^3*)*	0.45**	0.67*	0.22
	(0.20)	(0.34)	(0.43)
Observations	1538	1538	1538
# Counties	209	209	209

Notes: Each cell represents a separate regression. Panel A lists the reduced-form estimates of straw burning's effects on age-adjusted mortality rate (log). Panel B presents the IV and OLS estimates of the effects of $PM_{2.5}$ on age-adjusted mortality rate. County, month, year fixed effects and weather conditions (wind speed, wind direction, temperature, precipitation, relative humidity) are controlled. Standard errors in parentheses are two-way clustered at county and month level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A6
Effect of Straw Burning (log) on Death.

VARIABLES	All-Cause		Cardiorespiratory		Non-Cardiorespiratory	
	(1)	(2)	(3)	(4)	(5)	(6)
Straw Burning *(per 10%)*	0.11**	0.09**	0.11**	0.09***	0.03	0.06
	(0.05)	(0.04)	(0.05)	(0.03)	(0.11)	(0.12)
Observations	1595	1538	1595	1538	1595	1538
# Counties	215	209	215	209	215	209
Fixed Effects	Y	Y	Y	Y	Y	Y
Weather		Y		Y		Y

Notes: Each column represents a separate regression. Columns (1)–(2) examine the effects of a 10% increase in straw fires on the percentage change in monthly all-cause mortality within a county. Columns (3)–(4) and Columns (5)–(6) examine the effects of straw burning on cardiorespiratory and non-cardiorespiratory mortality, respectively. Weather variables include wind speed, wind direction, precipitation, temperature, relative humidity. Standard errors in parentheses are two-way clustered at county and month level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A7
Nonlinear Effects of Straw Burning on Death.

VARIABLES	All-Cause		Cardiorespiratory		Non-Cardiorespiratory	
	(1)	(2)	(3)	(4)	(5)	(6)
(per 10 points)						
Straw Burning	3.71***	3.37***	4.50***	4.00***	1.82	2.42
	(1.37)	(1.15)	(1.34)	(1.10)	(1.68)	(1.75)
Straw Burning2	−0.04***	−0.04***	−0.05***	−0.05***	−0.05***	−0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Observations	1595	1538	1595	1538	1595	1538
R-squared	0.89	0.893	0.842	0.844	0.782	0.784
# Counties	215	209	215	209	215	209
Fixed Effects	Y	Y	Y	Y	Y	Y
Weather		Y		Y		Y

Notes: Each column represents a separate regression. Columns (1)–(2) list effects of 10 additional straw fires on percentage change in monthly all-cause mortality within a county. Columns (3)–(4) and Columns (5)–(6) examine the effects of straw burning on cardiorespiratory and non-cardiorespiratory mortality, respectively. Weather variables include wind speed, wind direction, precipitation, temperature and relative humidity. Standard errors in parentheses are two-way clustered at county and month level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A8
Effects of Straw Burning and $PM_{2.5}$ on Death with Nonlinear Weather.

VARIABLES	(1) All-Cause	(2) Cardiorespiratory	(3) Non-Cardiorespiratory
Panel A: Reduced Form			
Straw Burning *(per 10 points)*	1.38*	1.69**	−0.81
	(0.79)	(0.83)	(0.99)

(*continued on next column*)

Table A8 (*continued*)

VARIABLES	(1) All-Cause	(2) Cardiorespiratory	(3) Non-Cardiorespiratory
Panel B: IV and OLS			
IV: $PM_{2.5}$ *(per* 10 $\mu g/m^3$*)*	2.89**	3.54**	−1.69
	(1.46)	(1.54)	(2.19)
OLS: $PM_{2.5}$ *(per* 10 $\mu g/m^3$*)*	0.29	0.45	−0.26
	(0.25)	(0.39)	(0.47)
Observations	1538	1538	1538
# Counties	209	209	209

Notes: Each cell represents a separate regression. Panel A reports the reduced-form estimates of straw burning's effects on the log number of deaths. Panel B presents the IV and OLS estimates of effects of $PM_{2.5}$ on logged number of deaths. County, month, year fixed effects, and weather conditions (wind speed, wind direction, temperature, precipitation, relative humidity) are controlled. Temperature is nonlinearly controlled in 5 bins: (,15), [15,20), [20,25), [25,30), and [30). Standard errors in parentheses are two-way clustered at county and month level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A9
Lagged Effects of Straw Burning and $PM_{2.5}$ on Log # of Death.

VARIABLES	(1) All-Cause	(2) Cardiorespiratory	(3) Non-Cardiorespiratory
Panel A: Reduced Form			
Straw Burning *(per 10 points)*	1.72*	1.96**	−0.65
	(0.93)	(0.96)	(1.00)
L1. Burning	0.77	0.68	−0.33
	(0.76)	(0.81)	(1.08)
Panel B: IV and OLS			
IV: $PM_{2.5}$ *(per* 10 $\mu g/m^3$*)*	2.90***	3.46***	−1.07
	(1.10)	(1.22)	(2.04)
OLS: $PM_{2.5}$ *(per* 10 $\mu g/m^3$*)*	0.32	0.47	−0.25
	(0.23)	(0.38)	(0.47)

Notes: Each cell represents a separate regression. Panel A reports the reduced-form estimates of concurrent and previous straw burning's effects on deaths. Panel B presents the IV and OLS estimates of effects of $PM_{2.5}$ on deaths. County, month, year fixed effects and weather conditions (wind speed, wind direction, temperature, precipitation, relative humidity) are controlled nonlinearly in quadratic terms. Standard errors in parentheses are two-way clustered at county and month level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A10
IV Estimates of Effects of $PM_{2.5}$ on Death with Varying Distance (%).

VARIABLES	(1) All-Cause	(2) Cardiorespiratory	(3) Non-Cardiorespiratory
(per 10 $\mu g/m^3$*)*			
35 km	2.78	4.10**	−3.11
	(2.00)	(1.70)	(3.13)
40 km	2.76	3.92**	−2.83
	(1.92)	(1.69)	(2.84)
45 km	3.11**	4.03***	−2.22
	(1.48)	(1.45)	(2.40)
50 km	3.25**	3.80**	−1.21
	(1.43)	(1.48)	(2.10)
60 km	3.22***	3.63***	−0.79
	(1.02)	(1.14)	(1.72)
70 km	3.32***	3.70***	−0.76
	(0.97)	(1.09)	(1.70)
80 km	3.23***	3.68***	−0.64
	(1.09)	(1.22)	(1.40)
90 km	3.25***	3.53***	−0.10
	(1.22)	(1.26)	(1.23)
100 km	3.26**	3.47***	0.29
	(1.27)	(1.28)	(1.26)
Observations	1538	1538	1538
# Counties	209	209	209

Notes: Each cell represents a separate regression. Straw fires and $PM_{2.5}$ within 35 km–100 km from a county center are explored in each row, respectively. Columns (1)–(3) report the effects on all-cause mortality, cardiorespiratory mortality and non-cardiorespiratory mortality, respectively. County, month, year fixed effects and weather conditions (wind speed, wind direction, temperature, precipitation, relative humidity) are controlled. Standard errors in parentheses are two-way clustered at county and month level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table A11
Effects of Straw Burning and $PM_{2.5}$ on Death with Administrative Center.

VARIABLES	(1)	(2)	(3)
	All-Cause	Cardiorespiratory	Non-Cardiorespiratory
Panel A: Reduced Form			
Straw Burning *(per 10 points)*	1.14**	1.37**	−1.00
	(0.53)	(0.56)	(0.88)
Panel B: IV and OLS			
IV: $PM_{2.5}$ *(per* 10 μg/m^3*)*	2.57***	3.09***	−2.24
	(0.94)	(1.00)	(2.16)
OLS: $PM_{2.5}$ *(per* 10 μg/m^3*)*	0.46**	0.69**	−0.22
	(0.19)	(0.32)	(0.42)
Observations	1868	1868	1868
# Counties	255	255	255

Notes: Each cell represents a separate regression. Panel A reports the reduced-form estimates of upwind burning's effects on the log number of deaths. Panel B presents the IV and OLS estimates of effects of $PM_{2.5}$ on deaths. County, month, year fixed effects and weather conditions (wind speed, temperature, precipitation, relative humidity) are controlled. Standard errors in parentheses are two-way clustered at county and month level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A12
Examining Pre-trends in Straw Burning and $PM_{2.5}$.

VARIABLES	Straw Burning (points)	$PM_{2.5}$ (μg/m^3)
	(1)	(2)
2017	−136.3**	−3.94***
	(49.3)	(1.07)
2016	−190.8**	−5.62***
	(60.4)	(1.07)
2014	−36.4	−0.51
	(119.2)	(1.50)
2013	86.8	2.51
	(164.5)	(2.21)
2012	66.0	–
	(187.6)	–
Observations	186	155
R-squared	0.71	0.93
# Provinces	31	31
Province FE	Y	Y
Year FE	Y	Y
Weather	Y	Y

Notes: Each column represents a separate regression using an event-study approach (Jacobson et al., 1993). 2015 before the straw recycling subsidy program is the base year. Standard errors in parentheses are clustered by province and year. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A13
Agricultural Production and Placebo Tests.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	$PM_{2.5}$ (μg/m^3)	PM_{10} (μg/m^3)	SO_2 (ppb)	NO_2 (ppb)	Yield (kg/ha)	Grain Output (10k tons)
Subsidy	−3.02	−3.05	0.03	1.07	−42.22	40.29
	(1.89)	(4.01)	(1.29)	(0.99)	(122.70)	(28.57)
Data	Non-Burning Season				Yearly	Yearly
Observations	155	186	186	186	186	186
R-squared	0.934	0.906	0.860	0.830	0.978	0.999
# Provinces	31	31	31	31	31	31
Province FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Weather	Y	Y	Y	Y	Y	Y

Notes: Each column represents a separate DiD regression. Columns (1)–(4) report the effects of the subsidy on air pollutants during non-burning seasons. Columns (5)–(6) list the effect of straw recycling subsidy on agricultural yield and total grain output. Province and year fixed effects and weather conditions (wind speed, wind direction, temperature, precipitation, relative humidity) are controlled. Standard errors in parentheses are clustered by province. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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