Agricultural Fires and Cognitive Function: Evidence from Crop Production Cycles

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Abstract

The use of controlled burning to clear agricultural land is a common practice in many parts of the world. This practice constitutes an important source of air pollution from agriculture. By exploring crop production cycles in China, this paper examines the impact of air pollution from agricultural fires on human cognitive health by linking household health survey data with fire points from remote sensing. The analysis shows a significant negative impact of fire points on cognitive health: respondents (aged 55 and above) in counties with high frequencies of fire points have scores 5.1% lower in a general cognition test, and recall 11.8% fewer objects in the delayed memory test. This impact is detected among respondents living in downwind counties but not the upwind counties. The cognitive impact from agricultural fires implies additional health costs from climate change that increases wildfire risks.

Keyword: agricultural fires, air pollution, climate change, cognitive function

JEL classification: I18, Q15, Q53

1. Introduction

In many developing countries, controlled burning continues to be a popular choice among farmers to rapidly eliminate agricultural waste from the previous harvest and to clear the land for the next planting season. Because agricultural burning usually occurs across a large area during the harvest season, it can generate substantial greenhouse gas emissions and contribute to severe seasonal air pollution (Zhang, Liu and Hao 2016). Pollutants emitted from agricultural burning, such as very small particulates and polycyclic aromatic hydrocarbons can lead to severe respiratory illnesses and are carcinogenic (Chen et al. 2017). Understanding the impact of air pollution from agricultural fires on public health is vital for designing environmental and agricultural policy to enhance sustainable agricultural practices and to improve public health.[1]

There exists a rich literature that documents a negative impact of air pollution on health outcomes such as increased risks of heart disease and lung cancer in both developed and developing countries (Arceo, Hanna and Oliva 2016; Chay and Greenstone 2003; Chen et al. 2013; Ebenstein et al. 2016). However, few studies focus on the impact of air pollution on cognitive function, especially in developing countries (Ebenstein, Lavy and Roth 2016). This study aims to quantify the effect of seasonal air pollution from agricultural fires on the cognitive function of nearby residents. The analysis links cognitive measurements from the China Health and Nutrition Survey (CHNS) with local agricultural fire points with detailed temporal and special resolution from remote sensing. China burns 112 million tons of crop straw per year: the burned proportion of straw is about four times more than the world average (Cai et al. 2011).

To address the concern that straw fire points are in general not randomly allocated across space, our identification strategy follows a Difference-in-Differences

[1] While much of the literature focuses on causes and consequences of air pollution from vehicle and industrial emissions (Almond et al. 2009; Chen et al. 2013; Davis 2008), few studies have causally measured the health impact of air pollution from agricultural production (Rangel and Vogl 2016; Sneeringer 2009).

(DID) approach by comparing cognition test scores of survey respondents in counties with high versus low frequencies of fire points during the autumn harvest period versus other periods.[2] The identification rests on the assumption that respondents in counties with high and low frequencies of fire points have the same trends of cognitive performance in non-harvest periods. This assumption holds in both graphical and regression analysis. The analysis also includes individual-respondent fixed effects and time fixed effects by taking advantage of the panel health data where the same respondents were sampled in different weeks of interview in follow-up surveys.

The results indicate that respondents (aged 55 and above) in counties with high frequencies of fire points have scores 0.044 points lower (-5.1%) in a general cognition test, and recall 0.474 fewer objects (-11.8%) in the delayed memory test. The results are largely driven by age cohorts 65 and above. This negative effect is consistent with existing epidemiological literature that aging populations are especially vulnerable to hazards in their immediate environment, suggesting that improvements to air quality may be an important mechanism for reducing age-related cognitive decline (Ailshire and Clarke 2015; Wilker et al 2015). Our analysis also reveals heterogeneous impacts of straw burning between rural and urban residents. This is consistent with the existing literature on socioeconomic gradient in health (Neidell 2004; Smith 1999) that the health burden of environmental problems is borne more heavily by rural residents because they earn lower income, have more limited options for avoiding the pollution, or have less access to medical care.

There are additional concerns underlying the causal interpretation. First, the lower cognitive test performance could be driven by factors such as fatigue or absent-mindedness since farmers are busily engaged in farm work during harvest season. We examine this possibility by testing the differences in impacts between households with any member working on a farm and households that are not engaged

[2] The treatment dummy, instead of the treatment intensity, is adopted to reduce measurement error. Details are explained in the *Empirical Framework*. In Table A4, as a robustness test, we provide the results from the specification where the treatment intensity is used as the key regressor.

in farm work. The results show that the impacts of fire points on cognition are not statistically different between these two groups, suggesting that other farm relevant activities are not confounding factors. Moreover, our focus on the cohort aged 55 and above also helps reduce this possibility because the older adults are less likely to participate in farm work. Second, there might be concerns that the adverse effects of fire points are caused by central heating because many main agricultural producing areas are located in northern China where central heating is provided in winter. However, this concern is not necessary because both the autumn harvest season and the cognitive impairment start before the central heating season starts. Moreover, the central heating is mainly provided in urban areas but our results are mainly driven by rural samples, suggesting that urban central heating is unlikely to be a confounding factor.

To further address the concerns of unobserved factors that could be correlated with both fire points and health outcomes, we leverage the spatial variation in wind direction and examine the heterogeneous cognitive impacts of straw burning on residents in upwind and downwind counties. We find negative impacts of fire points on respondents living in downwind counties but not in upwind counties. Respondents in counties with higher frequencies of upwind fire points within 50 miles have scores that are 0.032 points (-3.7%) lower in the general cognition test. We also find that the impacts of agricultural fires are smaller when the upwind fire points are farther away. This is consistent with the fact that pollutants decay as they travel and thus have a smaller impact on downwind residents. Because wind direction is largely random and exogenous, the findings reaffirm that our results are not driven by seasonal unobserved factors such as weather and economic conditions.

This study makes three contributions. First, it adds to the rich literature demonstrating the negative impact of air pollution on human health, labor productivity and labor supply (Chay and Greenstone 2003; Chang et al. 2016; Chen et al. 2013; Ebenstein, Lavy and Roth 2016; Zhang et al. 2017). Specifically, it provides new evidence on the seasonal impact of short-term air pollution exposure on cognition due to straw burning as part of the crop production cycle. It adds to a growing body of literature highlighting the difference between developed and developing countries due to possible costs of avoidance behavior and a nonlinear relationship between pollution and health (Arceo, Hanna, and Oliva 2016). It is also different from the literature within the context of developing countries because this paper focuses on the effects of short-term exposure on cognitive health rather than long-term exposure and mortality (Chen et al. 2013). Our study also adds to a growing literature that exploits pollution variations from wind direction (Barwick et al. 2017; Deryugina et al. 2016; Schlenker and Walker 2016), allowing us to disentangle pollution impacts from economic impacts.

Second, this study contributes to the limited but growing literature that highlights pollution from agricultural production (Brainerd and Menon 2014; Camacho and Mejia 2017; Lai 2017). The work most closely related to this paper is Rangel and Vogl (2016), which assesses the impact of smoke from sugarcane harvest fires on infant health across Brazilian states. They find that late-pregnancy exposure to upwind fires decreases birth weight, gestational length, and in utero survival. The current paper complements their study on infant health by highlighting the adverse effect of agricultural fires on aging populations that are also vulnerable to hazardous environment. This has significant policy implications in emerging counties like China, Brazil and Argentina where a large aging population imposes a substantial burden on the healthcare system and the economy. This paper also complements the existing literature by focusing on agriculture in China, which accounts for 10% of the country's GDP and whose productivity has significant global trade impacts. The estimates are relevant to China's policy efforts to find sustainable agricultural practices aimed at improving public health as well as reducing greenhouse gas emissions associated with food production.

Third, this paper informs the literature on the impact of climate change on health outcomes by providing a new pathway of impact. Changes in temperature and precipitation patterns from global climate change are predicted to increase wildfire activities in many parts of the world (Reid et al. 2016). The information on the potential health impact from increased wildfires is very limited.[3] Existing studies on wildfire and health usually lack adequate statistical power because wildfires tend to be episodic and short in duration, and exposed populations from individual events are often small. This study takes advantage of the fact that straw burning produces similar pollutants to wildfire, and should have similar health impacts. In addition, straw fires occur across large areas during the harvest seasons and smoke from straw burning is released in areas that are generally populated. The findings from this study suggest that increasing wildfire occurrences may be a new pathway by which climate change affects health. This result complements existing research that has shown that climate change affects human health through various channels such as the spread of vector borne diseases, increased mortality due to extreme weather conditions as well as reduction in regional crop yields leading to malnutrition (Deschenes and Moretti 2009; Deschênes and Greenstone 2011; McMichael, Woodruff and Hales 2006).

The remainder of this paper is organized as follows. The next two sections describe institutional background, the data and some graphical motivation. The following section examines the impact of straw burning on cognitive function. This section includes model specification, regression results, robustness checks and discussion. The final section concludes.

2. Institutional Background

2.1 Straw Burning in China

China has been expanding its food supply dramatically since it started the economic reform in its agriculture sector in late 1970s. The grain production in 2016 was nearly twice as much as the 1978 level, with an annual average growth rate of 1.9% (National Bureau of Statistics, 2016). Meanwhile, agricultural crop production generates tremendous amounts of agricultural crop residues. It was estimated that 748 million tons of crop straws were produced in 2009 (Cai et al. 2011). In particular, rice, wheat and corn straws are the top three crop residues in China, which make up 75%

[3] There are examples that estimate the direct economic losses from forest diebacks due to wild fire (Sohngen and Tian 2016).

of total domestic straw productions and 17.3% of global crop residues, ranking the first in the world (Bi et al. 2010; Chen et al. 2017).

A large amount of the crop straws has been abandoned or burned without being recycled or processed. In particular, China now burns 112 million tons of crop straws per year, accounting for 21.6% of the country's total (Cai et al. 2011). The burned proportion of straws is about 4 times more than the world average. Several factors contribute to the high burning rate in China. First, less crop residues are collected for household use nowadays. Traditionally, Chinese rural families used to collect and store crop residues as an essential fuel for cooking and heating, or to feed livestock. However, the energy source for cooking and heating has been largely replaced by fossil fuels, such as coal and natural gas. Moreover, with rapid urbanization and the development of large scale breeding in China, fewer farmers choose to raise livestock at home.

Second, small farming scale increases the unit costs to collect, store and transport crop straws, which makes recycling the straws unprofitable. Meanwhile, professional services to collect and transport crop straws have not been well developed in China. As a result, open burning is usually the most convenient and cost effective way to eliminate agricultural straw in order to prepare for the next season's farming. Burning also releases nutrients for the following growing season and helps limit mosquitoes and other pests in the fields (Commission for Environmental Cooperation 2014). Usually, straw burning is concentrated in two harvest periods. In the first harvest season (late May to the end of June) wheat and first season rice straw are burned in different areas of China. In the second harvest season (October), corn residue is largely burnt in northern China and second season rice straw is mostly burned in the south.

To address the environmental concerns about straw burning, the central government announced the goal to recycle 85% of crop straw by 2020 (China National Development and Reform Commission 2016). In order to accomplish this goal, the government uses a top-down strategy to regulate straw burning activities. The Ministry of Agriculture (MOA) and Ministry of Environmental Protection (MEP) have implemented burning bans by launching a series of central government files since 1997. In 2004, the MEP started to monitor crop fires via remote sensing data. The crop fire occurrences are taken by the central government as an important indicator to evaluate the efforts of local government in environmental regulation.

To meet the requirements of the central government, local governments usually offer a combination of punishments for straw burning and rewards for straw recycling. For example, before the harvest season, local government will ask farmers to sign on commitment letters and to promise not to burn the straws. In some provinces, a farmer who sets fire will generally face a fine from 200 RMB to 2000 RMB, or even a maximum of 15-day detainment if the burning leads to a severe fire. In term of rewards, some provinces provide monetary incentives to reuse the straws, including subsidies to farmers for shredding straw and using straw-based fertilizers as well as special funds established for pilot recycling projects. So far, the existing policies are still at local level and varies across regions. Despite the efforts have been made by central and local government, there is still great uncertainty whether the authorities will succeed in controlling straw burning due to inadequate regulation of burning behaviors and a lack of market demand for crop straws.

2.2 Straw Burning and Public Health

Straw burning is a public health concern. This type of burning generally takes place over very large areas during specific times of the year, which may lead to very high concentrations of pollutants such as polycyclic aromatic hydrocarbons (PAHs), dioxins and very small particulate matter ($PM_{2.5}$ and PM_{10}). Smoke from agricultural burning is released at or near ground level in areas that are generally populated, producing direct and intense exposure to pollutants for nearby populations.

The open burning of biomass emits PAHs, which are a group of more than 100 different chemicals (Jenkins et al. 1996). PAHs are usually formed during the incomplete burning of the biomass and contribute to production of particulate matter. The common sources of PAHs include cigarette smoke, road asphalt, vehicle engine exhaust, agricultural burning and hazardous waste management (Mumtaz and George

1995; Finlayson-Pitts and Pitts 1997). PAHs mainly attach to dust particles in the air, and particle-bound PAHs have a significant impact on health, especially via respiratory system impacts and via cancer incidence (WHO 2010).

The burning process is also a significant source of dioxins. Dioxins are highly toxic and carcinogenic pollutants. They remain in the environment for long periods of time before degrading into other chemical forms. Shih et al. (2008) show that the concentration of dioxins in the atmosphere is up to 17 times higher during the week of the most intense agricultural burning. Zhang, Huang and Yu (2008) find that larger amounts of dioxins are emitted in the provinces with more agricultural production. In particular, if the straw is treated with pesticides, the amount of dioxins released after burning increases sharply. It has been demonstrated, for example, that dioxin emissions increase by 150 times when biomass treated with the pesticide 2-4-D is burned (Muñoz et al. 2012).

A primary driver of negative impact of straw burning on cognitive function is the concentration of particulate matter. Previous research has identified a significant impact of particulate matter on various illnesses including heart disease, stroke, and lung cancer (Pope, Bates and Raizenne 1995; Chay and Greenstone 2003; Arceo, Hanna, and Oliva 2016). Recently, particulate matter and cognitive performance have received growing attention. Epidemiological studies show small particles penetrate deep into the lungs affecting blood flow and oxygen circulation (Pope and Dockery 2006). Small particles may also cause an inflammatory response in the lungs, which deteriorates the oxygen quality (Mills et al. 2009). These affect cognitive performance because the brain consumes a large fraction of the body’s available oxygen (Calderón-Garcidueñas et al. 2008). Supported by these medical research, more literature has been able to identify significant negative effects of air pollution on cognitive function in a variety of contexts such as high-stakes academic examinations and labor productivity (Chang et al. 2016; Ebenstein, Lavy and Roth 2016).

3. Data and Graphical Analysis

3.1 Data

To conduct the analysis, we combine several datasets including fire points from remote sensing, air quality, agricultural production, meteorological data and health data. In Table 1, we report the summary statistics for variables used in the analysis.

The remote sensing fire points come from the MODIS active fire product in the Fire Information for Resource Management System at NASA. The MODIS active fire product detects fires in 1km pixels that are burning at the time of satellite overpass under relatively cloud-free conditions using a contextual algorithm, where thresholds are first applied to the observed middle–infrared and thermal infrared brightness temperature; false detections are rejected by examining the brightness temperature relative to neighboring pixels (Giglio et al. 2003). Each MODIS active fire point represents the center of a 1km pixel. These data were collected from 2000 to 2016. We aggregate the original hourly data into weekly data. Burning agricultural waste creates non-specific sources of pollutants for the atmosphere and takes place over very large areas. It is therefore difficult to measure, but this remote sensing data from NASA makes this investigation possible.

Air quality data come from the Ministry of Environmental Protection (MEP) in China. The data include several air quality measures such as $PM_{2.5}$ and PM_{10}. It covers 1497 monitor stations in urban China and was collected from January 2015 to December 2016 with hourly measures aggregated to a weekly level. The MEP only makes available monitoring station level $PM_{2.5}$ data from 2013, initially for a small set of monitoring stations. This prevents us from directly exploring the impact of particulate matte concentration on cognitive health since the most recent health survey data was for 2006 as we discuss below. We linked the fire points with air quality data by calculating the number of fire points within a 50 mile buffer of air quality monitoring stations. Agricultural production data come from the Ministry of Agriculture. The data include annual production data for each crop at the county level from 2000 to 2009.

The weather variables are from the Integrated Surface Database (ISD), hosted by the National Oceanic and Atmospheric Administration (NOAA). The dataset has 407 monitoring stations in China that are in operation during the time period of our study. To match counties with weather stations, a distance matrix is constructed and weather data from the closest station is taken as that of the county. Measurements of wind directions are coded as angles in degrees, such that 0 corresponds to due North and 180 corresponds to due South. Wind direction of the day is calculated by adding up 24 hourly vectors of wind, with hourly wind speed as the length of each vector. Following Rangel and Vogl (2016), upwind direction is defined as the octant (45 degrees) sector between two counties and downwind direction is defined as the opposite octant sector between two counties. We aggregate daily fire points from upwind (downwind) counties at the weekly level.

The individual health data come from the China Health and Nutrition Survey (CHNS). CHNS has been frequently used in health related studies (Gørgens et al. 2012; Zhang 2012; Zhang and Xu 2016). CHNS is chosen for this research not only because of its rich health and demographic information but also because it lists the date of the interview. This interview date allows us to link health, weather and agricultural fire data. The survey is conducted using a multistage, random cluster process to draw a sample of about 7,200 households containing more than 30,000 individuals in 15 provinces that vary substantially in geography, economic development, public resources, and health indicators. It has nine waves to date (1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009 and 2011) and surveys all the age cohorts. We only use data from 1997 to 2006 because only these waves have comprehensive physical measurements including cognitive function. We further restrict the samples to cohorts aged 55 and above because the questions ascertaining cognitive function are only designed for the cohort aged 55 and above.

Cognitive function is measured through a set of questions including immediate and delayed recall of a 10-word list, counting backward from 20, serial seven subtraction, and orientation. These are popular measurements of cognitive functions widely used in epidemiological literature (Power et al. 2011; Suglia et al. 2007). First, interviewers slowly read ten words representing objects, such as house, wood and cat, and then asked respondents to repeat these objects within two minutes. Second, questions on backward counting, subtraction and orientation were asked. For example, orientation was assessed by asking the respondent the current date. Subtraction was evaluated by asking questions such as "How much does 100 minus 7 equal?" An average score was computed with the range from 0 to 1 (we call this score a general test score). Finally, respondents were required to recall again the objects mentioned previously within two minutes. Scores for both immediate and delayed recall ranged from 0 to 10 with higher scores indicating more accurate recall.

If the respondents die or migrate, they will be counted in the attrition and the samples are not used for analysis. If the respondents did not respond to some parts of the cognition test, the answers will be coded as missing and the samples are not in the analysis sample either. A potential concern arises if attrition and missing responses are correlated with the variable of interest. Sample selectivity could then lead to biased estimates. As it turns out, however, there is no evidence that attrition and missing answers are correlated with the variables of interest (Table A1). We run analogous DID regressions where the dependent variable is whether the answers of cognition tests are missing. In no regressions are the coefficients on the two-way interaction term significantly different from zero, which suggests that the respondents lost due to attrition or missing responses are random with respect to the research design.

Variable	Description	Obs.	Mean	Std. Dev.
Explanatory Variables				
Fire	Fire dummy(=1 if fire points larger than the average; =0 otherwise)	10619	0.26	0.44
UpFire	Fire dummy(=1 if upwind fire points larger than the average; =0 otherwise)	10330	0.22	0.41
DownFire	Fire dummy(=1 if downwind fire points larger than the average; =0 otherwise)	10330	0.30	0.46
Harvest	Autumn harvest week (=1 if the week belongs to harvest season; =0 otherwise)	10619	0.34	0.47
Age	Age (years)	10612	65.83	7.87

Variable	Description	Obs.	Mean	Std. Dev.
Explanatory Variables				
Income	Annual household income (10,000 yuan)	10482	1.52	1.70
Smoke	Currently smoke (yes=1; no=0)	10619	0.27	0.47
Drink	Currently drink (yes=1; no=0)	10619	0.29	0.45
Temperature	Temperature (degrees Fahrenheit)	10590	62.88	11.12
Precipitation	Precipitation (inches)	10590	1.00	4.99
Pressure	Air Pressure (bars)	10619	1.36	0.70
Explained Variables				
Cognition	Average score of 12 cognitive questions	10619	0.85	0.23
Memory1	Immediate recall test	9946	4.98	2.29
Memory2	Delayed recall test	9865	4.01	2.48

Table 1: Variable Description and Summary Statistics

Notes: This table reports the summary statistics for the main health outcomes. The variable *Fire* equals one if the number of fire points are larger than the sample average and equals zero otherwise. *UpFire* and *DownFire* are two analogous variables from counties at upwind and downwind directions, respectively.

3.2 Graphical Motivation

To motivate the research design, we provide some descriptive analysis showing the relationship between agricultural production, fire points and air quality. In Figure 1, panel A presents the weekly counts of fire points from 2000 to 2016. The occurrences of fires exhibit a seasonal pattern. Panel B shows the average weekly counts of fire points, from which we can see clearly the seasonal pattern: China's spring festival (around week 10), summer harvest season and autumn harvest season. The fire points in the two harvest seasons are about 4 times more than the non-harvest and non-spring-festival seasons.

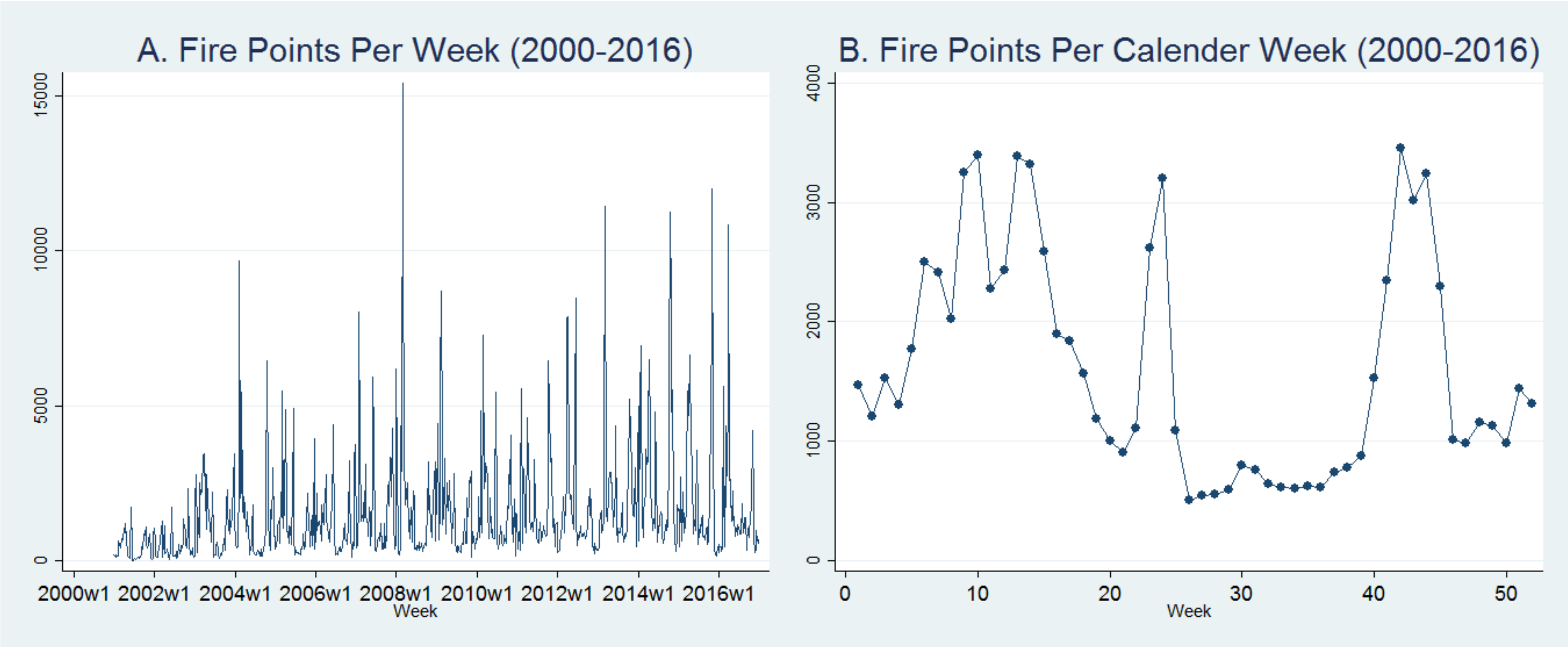
Figure 2 depicts the weekly number of fire points around 50 miles of air monitor stations in urban China in 2015 and 2016. The blue line and red line depict the evolution of the average number of fire points in cities with high and low agricultural production. “high agri” and “low agri” are defined as areas where crop production is higher and lower than the national average (2000-2009). In 2015 fire points jumped up in harvest seasons, especially the autumn harvest season. In 2016, because of the stronger government regulation forbidding farmers to burn the crop straw, the fire points did not jump as high as those in 2015.

Figure 3 depicts weakly average $PM_{2.5}$ concentration (in $\mu g/m^3$) in 2015 and 2016. The blue line and red line depict the evolution of average $PM_{2.5}$ in cities with high and low agricultural production nearby. The overall trend shows a quadratic pattern with worse air quality in the winter. Consistent with Figure 2, we observe a pike of $PM_{2.5}$ during the autumn harvest season (the left circle in each graph) in 2015 and we don’t find higher $PM_{2.5}$ in autumn harvest season in 2016 because of fewer fire points.

In Figure 4, we zoom into the autumn harvest season in 2015 *before* central heating starts. It is easier to see that the blue line jumps up during autumn harvest season and drops back after the harvest season. A difference-in-differences model shows stations with a high frequency of fire points have a higher level of $PM_{2.5}$ concentration by 10.21 $\mu g/m^3$ during the autumn harvest season.[4] This is consistent with the local press accounts that smoke from millions of acres of burning farmland billow toward the cities. This is also consistent with Chen et al. (2017) that biomass burning contributes to 12%, 15.8%, and 11% of $PM_{2.5}$ mass in Beijing, Dongying, and Chengdu. This also suggests that, because most Chinese air monitoring stations are located in urban areas, the air pollution is worse in rural areas where straw is burned.

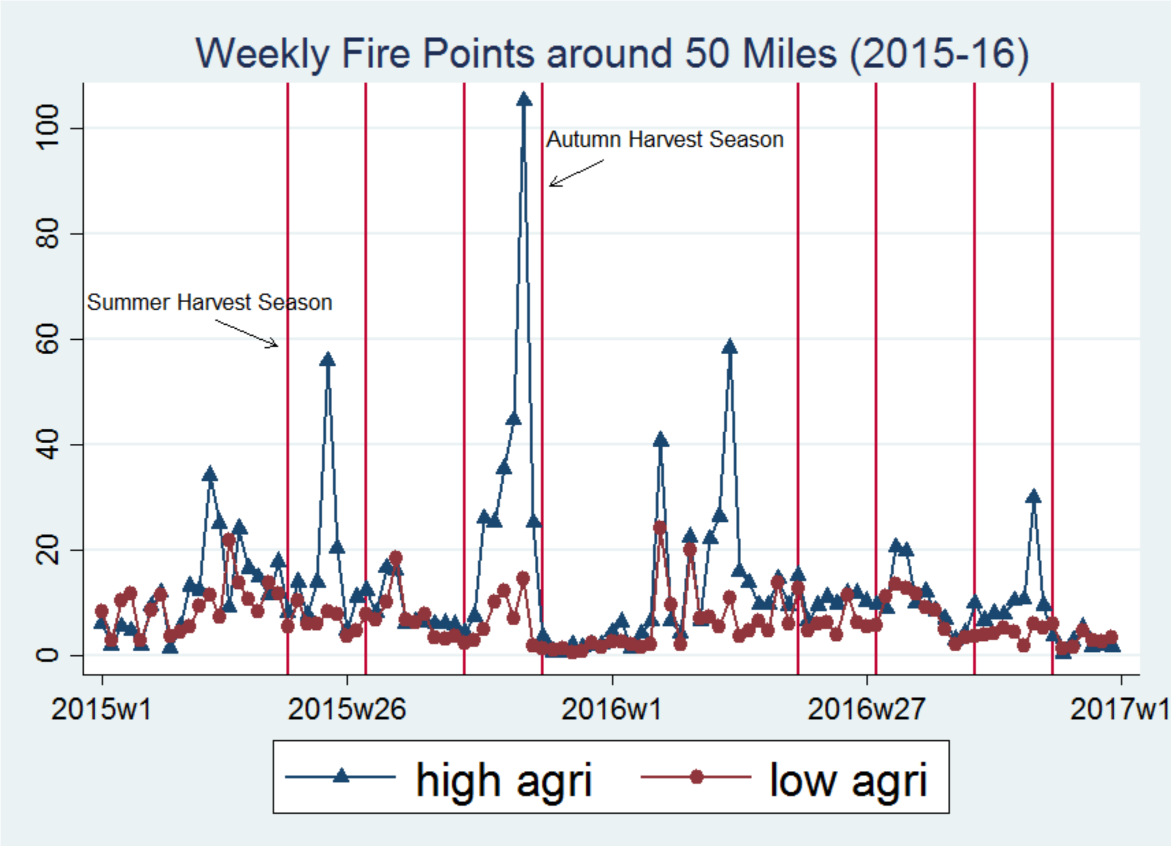
[4] Details are available upon request.

Figure 1: Weekly Fire Points from 2000 to 2016



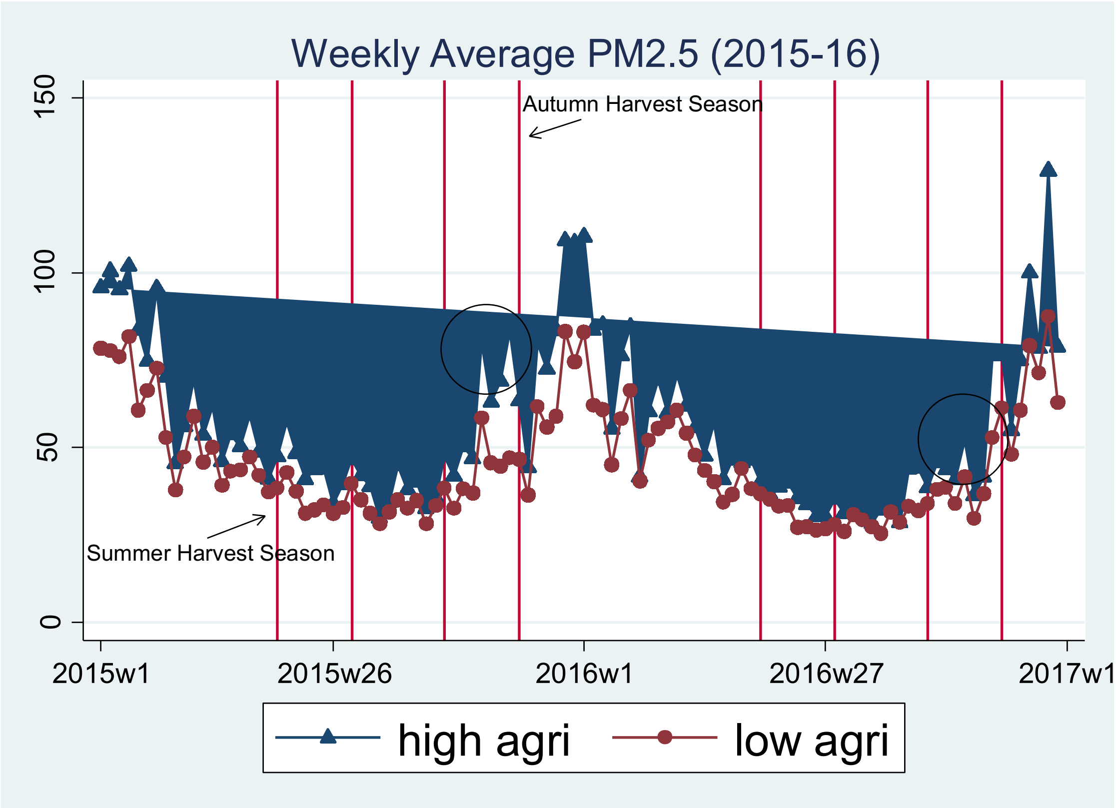
Note: This figure depicts the number of weekly fire points from 2000 to 2016

Figure 2: Weekly Fire Points within 50 Miles of Air Quality Monitoring Stations (2015-2016)



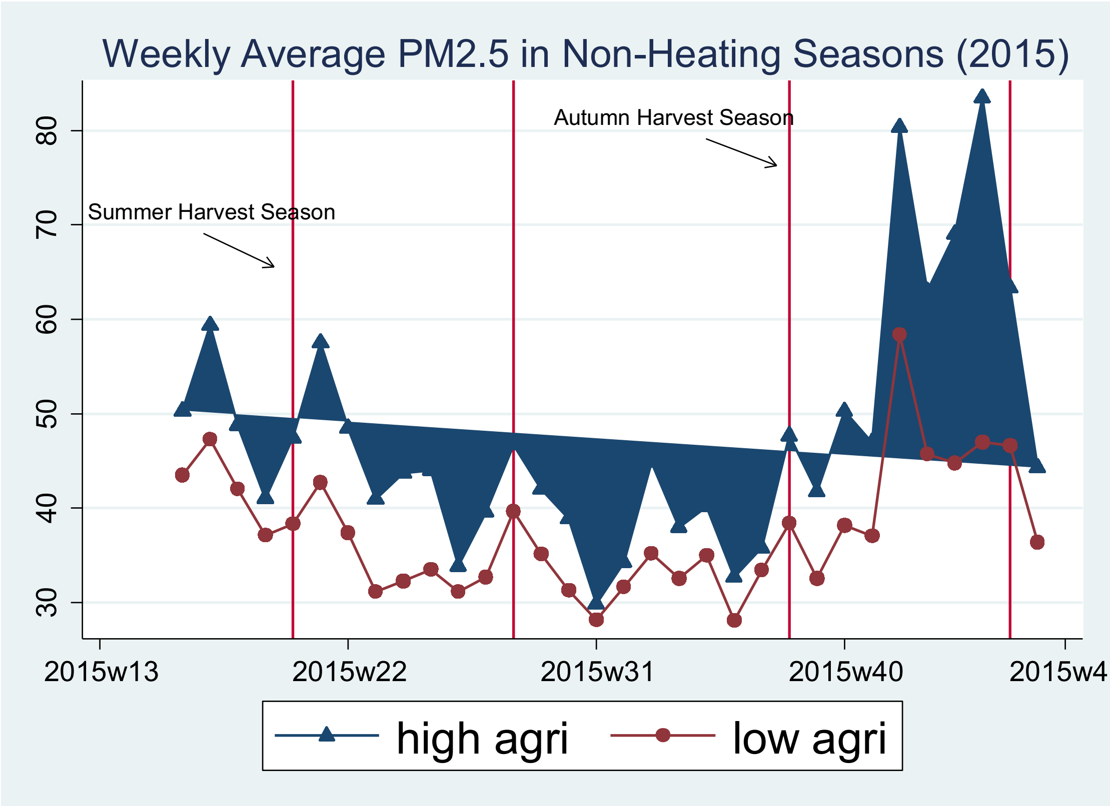
Note: This figure depicts the weekly number of fire points around 50 miles of air monitor stations in urban China in 2015 and 2016. The blue line and red line depict the evolution of the average number of fire points in cities with high and low agricultural production. "high agri" and "low agri" are defined as areas where crop production is higher and lower than the national average (2000-2009).

Figure 3: Weekly Average PM2.5 in 2015 and 2016



Note: This figure depicts the average air quality each week in urban China in 2015 and 2016. The blue line and red line depict the evolution of average air quality in cities with high and low agricultural production nearby. “high agri” and “low agri” are defined as areas where crop production is higher and lower than the national average (2000-2009).

Figure 4: Weekly Average PM2.5 in 2015 Autumn Harvest Season



Note: This figure depicts the average weekly air quality in urban China in 2015. The blue line and red line depict the evolution of average air quality in cities with high and low agricultural production nearby. "high agri" and "low agri" are defined as areas where crop production is higher and lower than the national average (2000-2009).

4. Empirical Framework and Results

4.1 Empirical Framework

In order to estimate the impact of straw burning on cognition, we specify the DID model as,

$$Cogn_{it} = \alpha + \beta_1 Fire_i + \beta_2 Harvest_t + \beta_3 Fire_i \times Harvest_t + \gamma' X_{it} + \mu_i + \lambda_t + \tau_w + \varepsilon_{it} \quad (1)$$

where $Cogn_{it}$ denotes cognitive test outcomes for individual i in week t. $Fire_i$ equals one if the households live in counties with higher frequencies of fire points than the sample average and zero otherwise.[5] $Harvest_t$ equals one during the one-month period after the autumn harvest season starts (weeks 43-47) and zero otherwise.[6] X_{it} is a vector of control variables including individual, household and weather characteristics. u_i is individual fixed effects and λ_t is time fixed effects common to all individuals in week t. τ_w is year effects unique to each survey wave. The model allows for an arbitrary covariance structure within communities over time by computing standard errors clustered at the community level (Bertrand, Duflo and Mullainathan 2004). Cluster bootstrap methods are also implemented at the community level to reaffirm the results.

The coefficient of interest is β_3, the impact of straw fires on cognitive function. A major identification concern is that fire points are not randomly allocated across space and time such that other unobserved factors, such as weather, socioeconomic status and changes in economic conditions, may generate a spurious relationship between

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[5] The treatment dummy is chosen here to reduce the measurement error. The health data are from 1997 to 2006 but the fire points are from late 2000 to 2016. Additional assumption is needed to assign treatment and control groups between 1997 and 2000. By using the treatment dummy as the key regressor, we assume the categorical division of treatment and control counties remain unchanged before and after 2000. This is reasonable because the dummy treatment and control groups are mainly driven by agriculture that is determined by natural resource endowment and not likely to switch, especially in the short term. By using the treatment intensity, i.e. number of fire points, the exact numbers of fire points need to be assigned to each county before 2000 but the fire data is not available for that time period. In Table A4, as a robustness test, we also provide the results of using the treatment intensity as the key regressor.

[6] The treatment period is chosen as one month after the harvest season starts because straw will not be burned at the beginning of the harvest season. As evidence, the fire points and $PM_{2.5}$ start to jump up one month after the harvest season starts in Figure 2 and Figure 4. As a robustness check, we allow the treatment window to vary across different provinces by choosing the weeks that have higher fire points than their medians as treatment weeks. We find similar results (Table A2).

fire points and cognitive function. Our strategy first employs individual fixed effects so that the estimates can be purged of the influence of unobserved time-invariant characteristics. We also include week fixed effects and survey year fixed effects to control for common seasonal and year changes. However, estimation strategies based solely on panel variation in fires are not enough to distinguish their effects from the effects of other time-variant unobserved health determinants.

We use the DID approach to compare the cognitive function of respondents in counties with high versus low frequency of fire points (i.e., treatment and control groups) during and out of the autumn harvest season.[7] The validity of the DID model requires that the time trends of cognitive health between the treatment and control groups are the same before autumn harvest periods. If the time trends are the same before the harvest seasons, then it is likely that they would have been the same in the harvest periods if the counties with more fire points had as many fire points as the group of counties with low frequencies of fire points. This parallel trend assumption is tested by both graphical and regression analysis.

Panel A in Figure 5 reports the average scores of the cognition test in each week of interview. The blue line and red line depict the evolution of the scores in counties with high and low frequencies of fire points. The cognition scores have some fluctuations between counties with high and low frequencies of fire points before the autumn harvest period. However, during the late autumn harvest season the scores in the counties with more straw burning drop faster than those with fewer straw fires. This timing is commensurate with Figure 4 when $PM_{2.5}$ increases. Panel B reports the average scores of the memory tests and have a similar pattern (though noisier) as panel A. These graphs serve as initial evidence that straw burning causally affects cognition through air pollution

[7] If $PM_{2.5}$ data were available during the survey period, we could directly examine the impact of $PM_{2.5}$ on cognitive health by leveraging fire points as the instrumental variable. But $PM_{2.5}$ data based on monitoring stations by the MEP is only available from 2013, preventing us from taking such an approach.

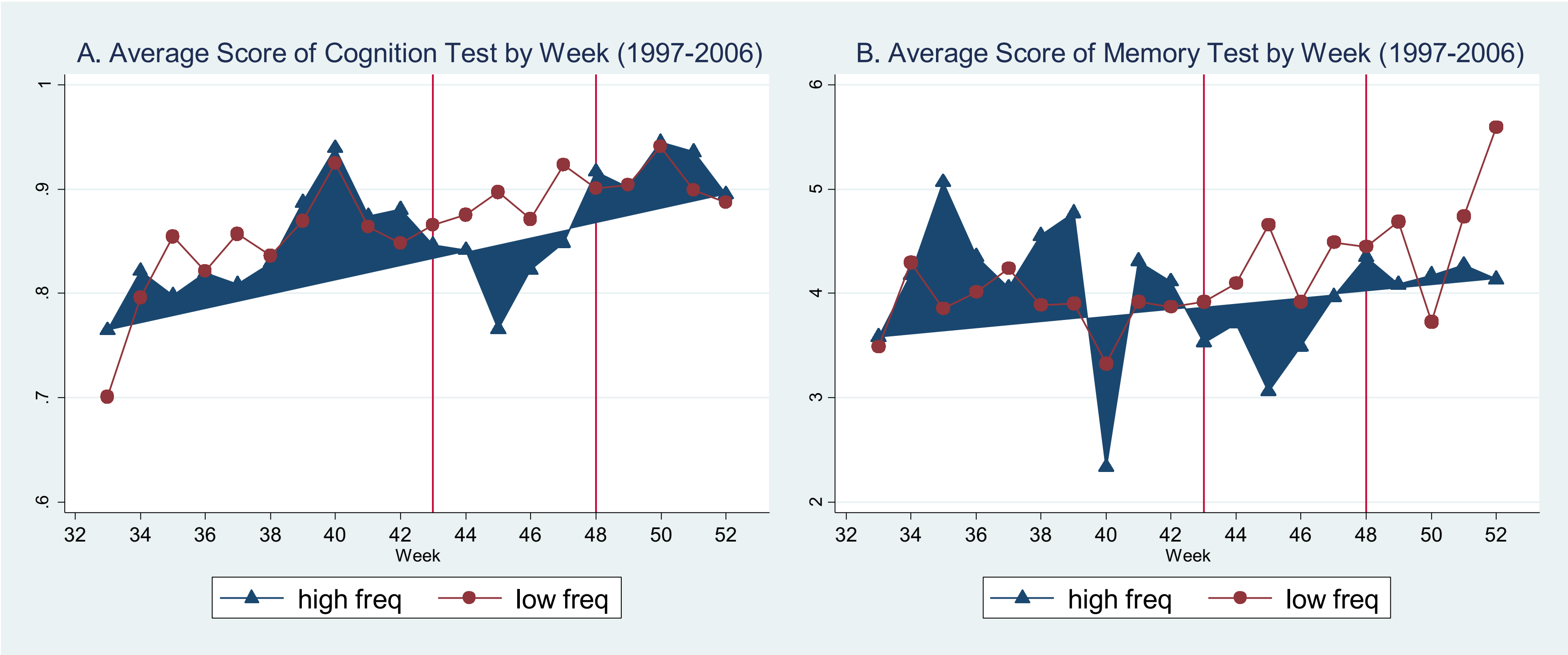

Figure 5: Average Scores of Cognition and Memory Tests by Week (1997-2006)

Note: Panel A (Panel B) reports the average scores of the cognition test (memory test) in each week of interview. The blue line and red line depict the evolution of the scores in counties with high and low frequencies of fire points. “high freq” and “low freq” are defined as areas where fire frequency is higher and lower than the sample average (2000-2016).

Formally, we test whether the pre-harvest trends of cognitive function are different for respondents in counties with high and low frequencies of fire points by estimating a slightly modified version of Equation (1). We use only the observations before the harvest season and modify Equation (1) by excluding the Harvest dummy variable and including separate week dummies (weeks 33-42). In this model, we cannot statistically reject the hypothesis that the pre-harvest week dummies are the same for counties with high and low frequencies of fire points at conventional levels of statistical significance (Table A3). The regression results confirm the parallel trend assumption and provide initial evidence that straw fire causally affects the cognitive function.

4.2 Main Results

Table 2 reports the impact of fire points on several cognitive measures. The first two columns report results from the general cognition test. Model (1) has no control variables and Model (2) includes control variables. The results are robust to inclusion of control variables. We find that respondents (aged 55 and above) in counties with higher frequencies of fire points have scores that are 0.044 points (-5.1%) lower in the general cognition test. The next four columns report results of the immediate and delayed memory tests.[8] In the immediate memory test, the impact of straw fire is not significant (but close to 10% significance). In the delayed recall memory test, we find that respondents recall 0.474 fewer objects (-11.8%) in counties with higher frequency of fire points. These results suggest that those affected populations have temporally lower cognitive ability and their memory decreases faster than those not affected.

We investigate differential impacts of agricultural fires. First, we divide the samples into the cohorts that are older and younger than 65. In Table 3, we find that previous results are largely driven by the cohort aged 65 and above. Respondents (aged 65 and above) in counties with higher frequencies of fire points have scores that

[8] Fewer observations are available for the immediate and delayed recall models because of missing responses.

are 0.055 units (-6.4%) lower in the general cognition test and recall 0.431 fewer objects (-10.7%) in the delayed recall memory test. These findings are consistent with existing epidemiological literature that aging populations are especially vulnerable to hazards in their immediate environment. The findings here highlight the negative impact of short-term exposure, which complements the existing medical findings that long-term exposure to ambient air pollution is associated with cognitive impairment and age-associated brain atrophy (Ailshire and Clarke 2015; Wilker et al. 2015).

Second, we divide the respondents into rural and urban samples. The results indicate that the negative impacts of straw burning are mainly driven by rural samples (Table 4). This is consistent with the fact that rural residents, compared with urban residents, live closer to the straw fire points and thus suffer severer impacts. This is also consistent with existing literature on the socioeconomic gradient in health (Neidell 2004; Smith 1999), which postulates that the health burden of environmental problems is more heavily borne by rural residents because they have lower income, more limited options for avoiding the pollution, or less access to medical care.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Cognition		Immediate Recall		Delayed Recall	
Fire × Harvest	-0.045**	-0.044**	-0.310	-0.281	-0.528***	-0.474**
	(0.010)	(0.024)	(0.105)	(0.147)	(0.007)	(0.021)
Observations	10,619	10,448	9,946	9,803	9,865	9,724
Control variables	No	Yes	No	Yes	Yes	Yes
Year and Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 2: The Impact of Straw Fire on Cognitive Function

Notes: This table shows the impact of straw fire on cognitive function (a general cognitive test, immediate recall and delayed recall) in a difference-in-differences model, accounting for individual fixed effects and time fixed effects. The model only includes respondents aged 55 and above. The control variables include socioeconomic characteristics and weather variables. The first, third and fifth models are without control variables and the second, fourth and sixth models include all the control variables. Robust p-values are reported in parentheses ***. p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Cognition		Immediate Recall		Delayed Recall	
(A) Age 65 and above						
Fire × Harvest	-0.060**	-0.055**	-0.276	-0.252	-0.501**	-0.431*
	(0.025)	(0.035)	(0.239)	(0.292)	(0.022)	(0.063)
Observations	5,332	5,219	5,008	4,910	4,958	4,864
(B) Age 55 to 65						
Fire × Harvest	-0.029*	-0.031*	-0.240	-0.186	-0.389	-0.329
	(0.080)	(0.082)	(0.332)	(0.463)	(0.210)	(0.303)
Observations	5,287	5,229	4,938	4,893	4,907	4,860
Control variables	No	Yes	No	Yes	No	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: The Impact of Straw Fire on Cognitive Functions by Age Cohort

Notes: This table shows the impact of straw fire on cognitive function by age cohort (above and below 65) in a difference-in-difference model, accounting for individual fixed effects and time fixed effects. The control variables include socioeconomic characteristics such as age and household income. Model (1), (3) and (5) are without control variables and fixed effects and Model (2), (4) and (6) include all the control variables and fixed effects. Robust p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Cognition	(2)	(3) Immediate Recall	(4)	(5) Delayed Recall	(6)
(A) Rural						
Fire × Harvest	-0.043**	-0.035*	-0.331	-0.217	-0.537**	-0.390*
	(0.030)	(0.084)	(0.129)	(0.317)	(0.019)	(0.096)
Observations	6,643	6,557	6,179	6,111	6,137	6,069
(B) Urban						
Fire × Harvest	-0.060*	-0.052*	-0.151	0.057	-0.744	-0.600
	(0.055)	(0.080)	(0.787)	(0.908)	(0.271)	(0.392)
Observations	3,976	3,891	3,767	3,692	3,728	3,655
Control variables	No	Yes	No	Yes	No	Yes
Year and Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: The Impact of Straw Fire on Cognitive Functions in Rural and Urban Areas

Notes: This table shows the impact of straw fire on cognitive function by urban and rural household in a difference-in-difference model, accounting for individual fixed effects and time fixed effects. The control variables include socioeconomic characteristics and weather variables. The first, third and fifth models are without control variables and the second, fourth and sixth models include all the control variables. Robust p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.3 Robustness Checks

There are additional concerns for the causal interpretation of our findings. First, because farmers are usually busily engaged in farm work during harvest season, the results could be driven by factors such as fatigue or absent-mindedness. For example, households that participate in farm harvest activities may be too busy to answer the questionnaire patiently such that they receive lower scores in the cognition tests. If it is busy farm work that causes lower scores in cognition tests, we should observe this at the beginning of the harvest season, instead of starting in late-harvest periods. We examine this possibility by testing the impact difference between households with any member working on a farm and households that are not engaged in farm work. If the results are driven by farm relevant activities, we should expect different impacts between farm and non-farm households. In Table 5, we find that the impacts of fire points on cognition are not different between these two groups, suggesting other farm relevant activities are not confounding factors. Additionally, our focus on the cohort aged 55 and above also helps reduce this possibility because the older adults are less likely to participate in farm work.

The second concern is with respect to winter heating. Because many main agricultural producing areas are located in northern China where central heating is provided in winter, the results may be driven by air pollution caused by central heating. However, this is not likely because both the autumn harvest season and the cognitive impairment start before the central heating season starts. Also, we divide the respondents into urban and rural samples in Table 4, if the results are confounded by central heating, we should expect more significant impact on urban samples because central heating is mainly provided in urban areas. We find the results are mainly driven by rural samples, suggesting central heating is not a confounding factor.

	(2)	(3)	(6)	(7)	(10)	(11)
VARIABLES	Cognition		Immediate Recall		Delayed Recall	
Fire × Harvest	0.007	-0.000	-0.121	-0.209	-0.062	-0.175
× Farm Household	(0.813)	(0.997)	(0.752)	(0.584)	(0.877)	(0.668)
Observations	10,619	10,448	9,946	9,803	9,865	9,724
R-squared	0.610	0.619	0.650	0.656	0.643	0.648
Control variables	No	Yes	No	Yes	No	Yes
Year and Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Impact Differences between Farm Households and Non-Farm Households

Notes: This table tests the impact difference of straw fire on cognitive function between farm and non-farm household in a difference-in-difference model, accounting for individual fixed effects and time fixed effects. The control variables include socioeconomic characteristics and weather variables. The first, third and fifth models are without control variables and the second, fourth and sixth models include all the control variables. Robust p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.4 Exploring Wind Direction

The validity of DID results might be called into question if there are seasonal unobserved factors that are co-varying with fire points and health. For example, the seasonal disease, temperature or rainfall during harvest periods may be different in areas with high and low frequency of fire points, generating spurious relationships between fires and health. Local economic conditions may also confound the estimation if they are tied closely with harvest activities and fire points.

To further address the concern of unobserved factors, we leverage the spatial pattern of wind direction in distributing air pollution from neighbor counties. We replicate the analysis in Equation (1) by replacing the *Fire* dummy variable with a new dummy variable that is constructed from fire points in counties within 50 miles at the upwind directions. Following Rangel and Vogl (2016), upwind direction is defined as the octant (45 degrees) sector between two counties. As a comparison, we also construct a fire dummy variable from counties at the downwind directions, defined as the opposite octant sector between two counties.

Table 6 reports the cognitive impact of fire points from surrounding counties in upwind and downwind directions. We find that respondents in counties with higher frequencies of upwind fire points have scores that are 0.032 units (-3.7%) lower in the general cognition test but we did not find significant impacts of downwind fire points. This is consistent with our expectation that air pollution caused by fire points at the upwind counties will affect the population health in the downwind counties. In Figure 6, instead of using fire points in upwind counties within 50 miles, we report the cognitive impacts of fire points in upwind counties within different distances. We find the overall impacts decrease when the fire points from upwind counties with longer distances are included.[9] This suggests that the amount of pollutants decays as they travel. We also find a similar pattern for cognitive impacts using fire points in downwind counties but the magnitudes are smaller (Figure 7).

[9] The cognitive impacts of fire points in neighbor counties within 30 miles are smaller due to less samples are included in the analysis. For some counties, the centroids between nearest neighbor counties are larger than 30 miles so counties without neighbors within 30 miles will be dropped.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Cognition		Immediate Recall		Delayed Recall	
(A) Upwind						
UpFire × Harvest	-0.026	-0.032*	-0.053	-0.074	-0.153	-0.175
	(0.134)	(0.059)	(0.830)	(0.751)	(0.526)	(0.477)
Observations	10,330	10,168	9,669	9,536	9,596	9,464
(B) Downwind						
DownFire × Harvest	0.008	0.003	0.270	0.186	0.224	0.113
	(0.690)	(0.868)	(0.180)	(0.336)	(0.298)	(0.608)
Observations	10,330	10,168	9,669	9,536	9,596	9,464
Control variables	No	Yes	No	Yes	No	Yes
Year and Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: The Cognitive Impact of Straw Fire from Upwind and Downwind Counties

Notes: This table shows the cognitive impact of straw fire in counties at upwind and downwind directions in a difference-in-difference model, accounting for individual fixed effects and time fixed effects. The control variables include socioeconomic characteristics and weather variables. The first, third and fifth models are without control variables and the second, fourth and sixth models include all the control variables. Robust p-values are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Our estimation using wind direction can serve as a robustness test to rule out the seasonal omitted variables. If it is the unobserved local weather and economic conditions, instead of agricultural fires, that drive our results, we should not see significant cognitive impact from fire points in upwind counties because wind direction is random. If the weather and economy in surrounding counties (both upwind and downwind counties) are all correlated, which drives the correlation between fire points from upwind counties and local unobserved factors that affect local health, then we should expect similar significant impact of fire points from downwind counties on cognition, but we did not.

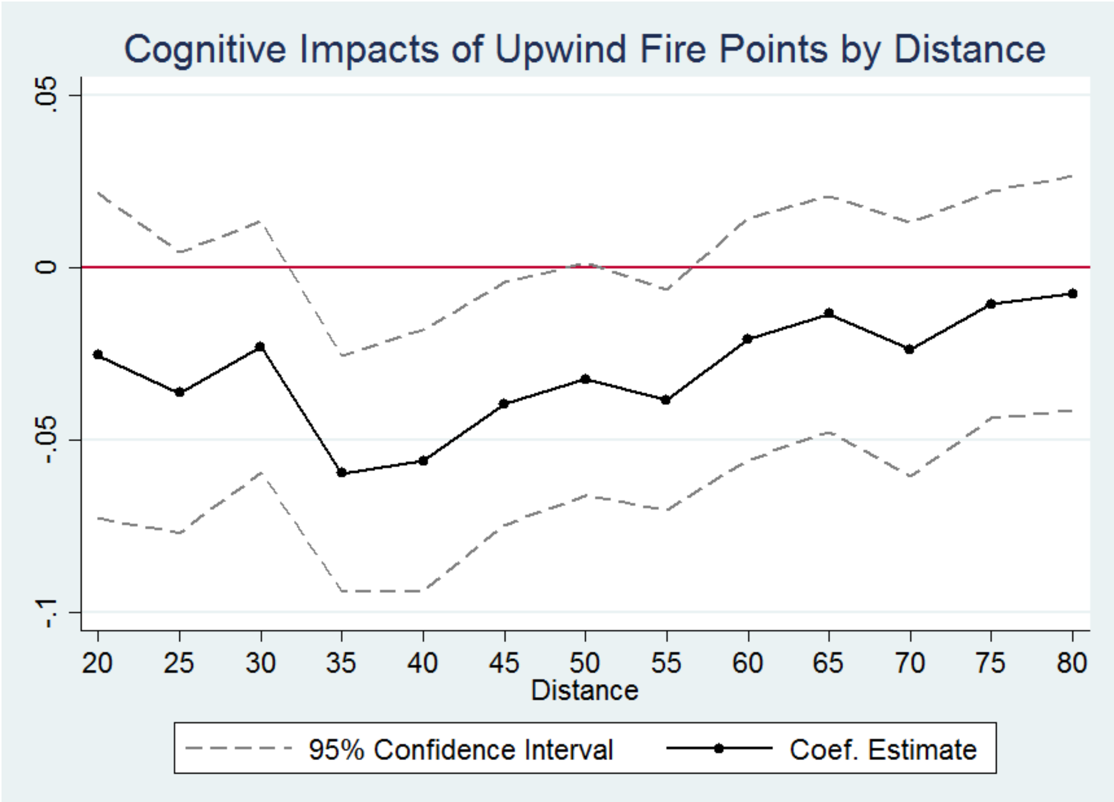

Figure 6: Cognitive Impacts of Upwind Fire Points by Distance
Note: This figure reports the cognitive impact of agricultural fire from surrounding counties in upwind directions within different distances.

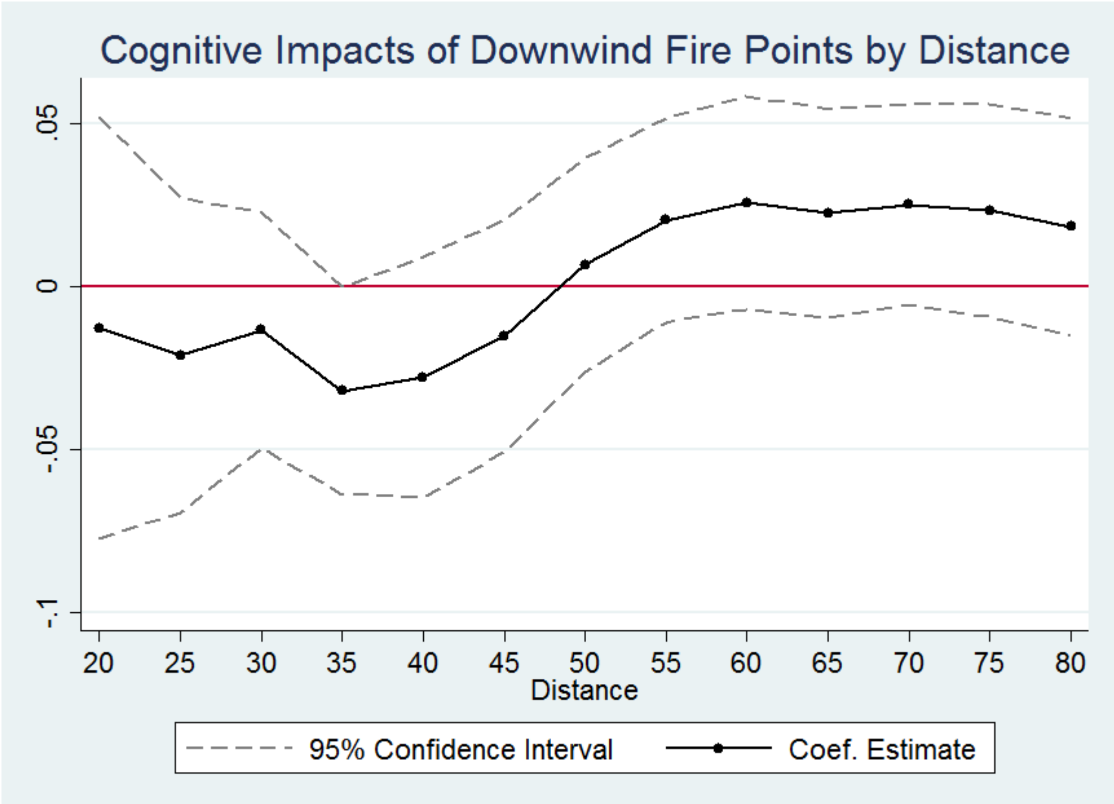

Figure 7: Cognitive Impacts of Downwind Fire Points by Distance

Note: This figure reports the cognitive impact of agricultural fire from surrounding counties in downwind directions within different distances.

4.5 Discussion

The findings in this paper reveal a causal impact of agricultural fires on cognitive health, contributing to our understanding on the health impact of wildfires. Epidemiological studies have demonstrated the association between wildfire smoke exposure and general respiratory morbidity, exacerbations of asthma and Chronic Obstructive Pulmonary Disease (Linares et al. 2014; Reid et al. 2016), but very few have investigated the cognitive impact of wildfire and the findings are inconclusive in those studies. For example, Ho et al. (2014) find that the widespread haze due to forest fires in Indonesia in June 2013 is associated with mild psychological stress, but Moore et al. (2006) find no increase in physician visits for mental illness associated with PM during the 2003 wildfire season in British Columbia and Duclos et al. (1990) find no increase in mental health hospitalizations during the 1987 California fires. Our study complements existing literature by providing one of the few estimates of the cognitive impact of air pollution due to biomass burning by leveraging spatially and temporally rich data on agricultural fire points and panel data on health surveys.

Our analysis focuses on the health impact of short-term air pollution exposure, in contrast to that of long-term exposure from policies that promote the use of central heating or living close to streets with heavy traffic (Chen et al. 2013; Sunyer et al. 2014). Several recent studies also find significant cognitive impacts of short-term air pollution. Ebenstein, Lavy and Roth (2016) show that transitory $PM_{2.5}$ exposure is associated with a significant decline in student performance as well as future educational attainment and earnings in Israel. Bensnes (2016) finds that an increase in the ambient pollen level by one standard deviation at the mean leads to a 2.5% standard deviation decrease in test scores, with potentially larger effects for allergic students. In addition to cognitive function, Daniels et al. (2014) and Hansen (1990) show that urban firefighters who are occupationally exposed to short-term smoke are at increased risk of developing lung cancer.

Our findings have important implications on potential healthcare costs. A growing body of medical research suggests that cognition impairment, even in a small range, is a predictor of serious health consequences including dementia, Alzheimer's disease, cardiovascular events and life satisfaction (O'donnell et al. 2012; Ritchie and Touchon 2000). Moreover, there exist evidence that cognition decline increases the mortality risk across the entire spectrum of cognitive impairment (Brayne and Calloway 1988; St. John et al. 2015). Neale et al. (2001) find that the risk of mortality for population who suffer mild cognition impairment is 23% higher than those without cognition impairment. Agricultural fires can affect the cognitive health of a large rural population in developing countries, which could in turn increase late life disability and risk of deaths, and healthcare costs in the long run.

5. Conclusion

Understanding the health effect of air pollution from agricultural production is essential for designing efficient environmental and agricultural policies. By linking remote sensing fire points with the China Health and Nutrition Survey (1997-2006), we compare cognition test scores of the survey respondents in counties with high versus low frequencies of fire points during the autumn harvest periods versus other periods. Individual respondent fixed effects are also included by taking advantage of the panel health data where the same sample respondents are interviewed in different weeks in follow-up surveys.

We find that respondents (aged 55 and above) in counties with high frequencies of fire points have scores that are 0.044 lower (-5.1%) in a general cognition test, and recall 0.474 fewer objects (-11.8%) in the delayed memory test. The results are largely driven by the cohort aged 65. This is consistent with existing epidemiological literature that documents how aging populations are especially vulnerable to hazards in their immediate environment, suggesting that improvements to air quality may be an important mechanism for reducing age-related cognitive decline (Ailshire and Clarke 2015; Wilker et al 2015). The results are also largely driven by the rural residents that are closer to the fire points and thus suffer severer impacts. This is consistent with existing literature on socioeconomic gradient in health (Neidell 2004; Smith 1999) that health burden of environmental problems might more likely to be borne by rural residents because they have lower income, more limited options for avoiding the pollution, or less access to medical care.

In addition, we leverage the spatial variation of wind direction and find significantly negative impacts of fire points on respondents living in downwind counties but not upwind counties. We also find that the impacts of agricultural fires are smaller when the fire points are from upwind counties that are farther away. This is consistent with the fact that pollutants decay as they travel and thus have less impacts on downstream populations. The findings relying on exogenous wind direction reaffirm that our results are not driven by seasonal unobserved factors such as weather and economic conditions.

Agricultural fires have been used for thousands of years, but their health impacts are not fully understood. Straw burning may lead to high concentrations of pollutants such as polycyclic aromatic hydrocarbons (PAHs), dioxins and very small particulate matter (PM2.5 and PM10), all of which are carcinogenic pollutants. Although the current study provides evidence that straw burning affects cognitive function, other health outcomes deserve future research. These studies will not only strengthen our understandings of health impact of agricultural air pollution in developing countries but also inform the potential health impacts of climate change which is believed to increase the frequency and duration of wildfires.

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References

Ailshire, J.A., Clarke, P., 2015. Fine particulate matter air pollution and cognitive function among US older adults. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences* 70, 322-328

Almond, D., Chen, Y., Greenstone, M., Li, H., 2009. Winter heating or clean air? Unintended impacts of China's Huai river policy. *American Economic Review*, 99(2): 184-90.

Arceo, E., Rema H., and Oliva, P. 2016. Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico City. *Economic Journal* 126 (591): 257–80.

Barwick, J. P., Li, S., Rao, D. and Zahur, N., 2017. Air pollution, health spending and consumer willingness to pay for clean air in China, working paper.

Bensnes, S.S. 2016. You sneeze, you lose:: The impact of pollen exposure on cognitive performance during high-stakes high school exams, *Journal of Health Economics* 49, 1-13.

Bertrand, M., Duflo, E., Mullainathan, S., 2004. How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics* 119, 249-275

Bi, Y., Wang, Y., Gao, C.Y., 2010. Straw resource quantity and its regional distribution in China. *Journal of Agricultural Mechanization Research* 3, 1-7

Brainerd, E., Menon, N., 2014. Seasonal effects of water quality: The hidden costs of the Green Revolution to infant and child health in India. *Journal of Development Economics* 107, 49-64

Brayne, C. and Calloway, P. 1988. Normal ageing, impaired cognitive function, and senile dementia of the Alzheimer's type: a continuum? *The Lancet* 331, 1265-1267.

Cai, Y. Q., Qiu, H. G., and Xu, Z. G. ,2011. Evaluation on potentials of energy utilization of crop residual resources in different regions of China. *Journal of Natural Resources*, 26(10), 1637-1645.

Calderón-Garcidueñas, L., Mora-Tiscareño, A., Ontiveros, E., Gómez-Garza, G., Barragán-Mejía, G., Broadway, J., Chapman, S., Valencia-Salazar, G., Jewells, V., Maronpot, R.R., 2008. Air pollution, cognitive deficits and brain abnormalities: a pilot study with children and dogs. *Brain and Cognition* 68, 117-127

Camacho, A. and Mejia, D. 2017. The health consequences of aerial spraying illicit crops: The case of Colombia, *Journal of Health Economics* 54, 147-160.

Chang, T., Zivin, J.S.G., Gross, T., Neidell, M.J., 2016. Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy*, 8(3): 141-69.

Chay, K., Greenstone, M., 2005. Does air quality matter? Evidence from the housing market. *Journal of Political Economy* 113, 376-424

Chay, K., Greenstone, M., 2003. The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession. *Quarterly Journal of Economics* 118, 1121-1167

China Statitical Yearbook, 1976-2016, National Bureau of Statistics of the People's Republic of China, China Statistics Press

Chen, J., Li, C., Ristovski, Z., Milic, A., Gu, Y., Islam, M.S., Wang, S., Hao, J., Zhang, H., He, C., 2016. A review of biomass burning: Emissions and impacts on air quality, health and climate in China. *Science of The Total Environment*.

Chen, Y., Ebenstein, A., Greenstone, M., Li, H., 2013. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proceedings of the National Academy of Sciences* 110, 12936-12941

China National Development and Reform Commission. 2016. Guidelines on straw utilization plans for the 13th Five-Year. Retrieved on line Mar. 26, 2017 from http://www.ndrc.gov.cn/zcfb/zcfbtz/201612/t20161207_829417.html

Commission for Environmental Cooperation. 2014. Burning Agricultural Waste: A Source of Dioxins. Montreal, Canada: Commission for Environmental Cooperation.

Daniels, R.D., Kubale, T.L., Yiin, J.H., Dahm, M.M., Hales, T.R., Baris, D., Zahm, S.H., Beaumont, J.J., Waters, K.M. and Pinkerton, L.E. 2014. Mortality and cancer incidence in a pooled cohort of US firefighters from San Francisco, Chicago and Philadelphia (1950–2009), *Occup Environ Med* 71, 388-397.

Davis, L. W. 2008. The effect of driving restrictions on air quality in Mexico City, *Journal of Political Economy*, 116, 38-81.

Deschenes, O. and Moretti, E. 2009. Extreme weather events, mortality, and migration, *Review of Economics and Statistics* 91, 659-681.

Deschênes, O. and Greenstone, M. 2011. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US, *American Economic Journal: Applied Economics* 3, 152-185.

Duclos, P., Sanderson, L.M. and Lipsett, M. 1990. The 1987 forest fire disaster in California: assessment of emergency room visits, *Archives of Environmental Health: An International Journal* 45, 53-58.

Ebenstein, A., Lavy, V. and Roth, S. 2016. The long run economic consequences of high-stakes examinations: evidence from transitory variation in pollution. *American Economic Journal: Applied Economics*, 8 (4). pp. 36-65. ISSN 1945-7782

Finlayson-Pitts, B.J., Pitts, J.N., 1997. Tropospheric air pollution: ozone, airborne toxics, polycyclic aromatic hydrocarbons, and particles. *Science* 276, 1045-1051

Giglio, L., Descloitres, J., Justice, C.O., Kaufman, Y.J., 2003. An enhanced contextual fire detection algorithm for MODIS. *Remote Sensing of Environment* 87, 273-282

Gørgens, T., Meng, X., Vaithianathan, R., 2012. Stunting and selection effects of famine: A case study of the Great Chinese Famine. *Journal of Development Economics* 97, 99-111

Ho, R.C., Zhang, M.W., Ho, C.S., Pan, F., Lu, Y. and Sharma, V.K. 2014. Impact of 2013 south Asian haze crisis: study of physical and psychological symptoms and perceived dangerousness of pollution level, *BMC psychiatry* 14, 81.

Jenkins, B.M., Jones, A.D., Turn, S.Q., Williams, R.B., 1996. Particle concentrations, gas-particle partitioning, and species intercorrelations for polycyclic aromatic hydrocarbons (PAH) emitted during biomass burning. *Atmospheric Environment* 30, 3825-3835

Lai, W., 2017. Pesticide use and health outcomes: Evidence from agricultural water pollution in China. *Journal of Environmental Economics and Management*. Forthcoming.

Linares, C., Carmona, R., Tobías, A., Mirón, I. and Díaz, J. 2015. Influence of advections of particulate matter from biomass combustion on specific-cause mortality in Madrid in the period 2004–2009, *Environmental Science and Pollution Research* 22, 7012-7019.

McMichael, A.J., Woodruff, R.E. and Hales, S., 2006. Climate change and human health: present and future risks, *The Lancet* 367, 859-869.

Mills, N.L., Donaldson, K., Hadoke, P.W., Boon, N.A., MacNee, W., Cassee, F.R., Sandström, T., Blomberg, A., Newby, D.E., 2009. Adverse cardiovascular effects of air pollution. *Nature Clinical Practice Cardiovascular Medicine* 6, 36-44

Moore, D., Copes, R., Fisk, R., Joy, R., Chan, K. and Brauer, M. 2006. Population health effects of air quality changes due to forest fires in British Columbia in 2003: estimates from physician-visit billing data, *Canadian Journal of Public Health* 105-108.

Muñoz, M., Gullett, B.K., Touati, A., Font, R., 2012. Effect of 2, 4-dichlorophenoxyacetic acid (2, 4-D) on PCDD/F emissions from open burning of biomass. *Environmental Science & Technology* 46, 9308-9314

Neale R, Brayne C, Johnson A L., 2001. Cognition and survival: an exploration in a large multicentre study of the population aged 65 years and over. *International Journal of Epidemiology*, 30(6), pp.1383-1388.

Neidell, M.J. 2004. Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma, *Journal of Health Economics* 23, 1209-1236.

O'donnell, M., Teo, K., Gao, P., Anderson, C., Sleight, P., Dans, A., Marzona, I., Bosch, J., Probstfield, J. and Yusuf, S. 2012. Cognitive impairment and risk of cardiovascular events and mortality, *European Heart Journal* 33, 1777-1786.

Organization, W.H., 2010. WHO guidelines for indoor air quality: selected pollutants. WHO.

Pope, C., Bates, D.V., Raizenne, M.E., 1995. Health effects of particulate air pollution: time for reassessment? *Environmental Health Perspectives* 103, 472

Pope, C.A., Dockery, D.W., 2006. Health effects of fine particulate air pollution: lines that connect. *Journal of the Air & Waste Management Association* 56, 709-742

Power, M.C., Weisskopf, M.G., Alexeeff, S.E., Coull, B.A., Spiro III, A. and Schwartz, J. 2011. Traffic-related air pollution and cognitive function in a cohort of older men, *Environmental Health Perspectives* 119, 682.

Rangel, M.A., Vogl, T., 2016. Agricultural fires and infant health. National Bureau of Economic Research working paper.

Reid, C.E., Brauer, M., Johnston, F.H., Jerrett, M., Balmes, J.R. and Elliott, C.T., 2016. Critical review of health impacts of wildfire smoke exposure, *Environmental Health Perspective* 124, 1334-1343.

Ritchie, K. and Touchon, J. 2000. Mild cognitive impairment: conceptual basis and current nosological status, *The Lancet* 355, 225-228.

Shih, S.-I., Lee, W.-J., Lin, L.-F., Huang, J.-Y., Su, J.-W., Chang-Chien, G.-P., 2008. Significance of biomass open burning on the levels of polychlorinated dibenzo-p-dioxins and dibenzofurans in the ambient air. *Journal of Hazardous Materials* 153, 276-284

Smith, J., 1999. Healthy bodies and thick wallets: the dual relationship between health and economic status. *Journal of Economic Perspectives* 13(2):145–66.

Sneeringer, S., 2009. Does animal feeding operation pollution hurt public health? A national longitudinal study of health externalities identified by geographic shifts in livestock production. *American Journal of Agricultural Economics*, 91(1), pp.124-137.

Sohngen, B. and Tian X., 2016. Global climate change impacts on forests and markets. *Forest Policy and Economics*, 72, pp.18-26.

St John, P.D., Tyas, S.L. and Montgomery, P.R. 2015. Cognition, even in the normal range, predicts disability: cross-sectional and prospective analyses of a population-based sample, *International Journal of Geriatric Psychiatry* 30, 1008-1016.

Suglia, S.F., Gryparis, A., Wright, R.O., Schwartz, J. and Wright, R.J. 2007. Association of black carbon with cognition among children in a prospective birth cohort study, *American journal of epidemiology* 167, 280-286.

Sunyer, J., Esnaola, M., Alvarez-Pedrerol, M., Forns, J., Rivas, I., López-Vicente, M., Suades-González, E., Foraster, M., Garcia-Esteban, R. and Basagaña, X. 2015. Association between traffic-related air pollution in schools and cognitive development in primary school children: a prospective cohort study, *PLoS medicine* 12, e1001792.

Wilker, E.H., Preis, S.R., Beiser, A.S., Wolf, P.A., Au, R., Kloog, I., Li, W., Schwartz, J., Koutrakis, P., DeCarli, C., 2015. Long-term exposure to fine particulate matter, residential proximity to major roads and measures of brain structure. *Stroke* 46, 1161-1166

Zhang, J., 2012. The impact of water quality on health: Evidence from the drinking water infrastructure program in rural China. *Journal of Health Economics* 31, 122-134

Zhang, J. and Xu, L.C. 2016. The long-run effects of treated water on education: The rural drinking water program in China, *Journal of Development Economics* 122, 1-15.

Zhang, L., Liu, Y. and Hao, L. 2016. Contributions of open crop straw burning emissions to PM2. 5 concentrations in China, *Environmental Research Letters* 11, 014014.

Zhang, Q., Huang, J., Yu, G., 2008. Polychlorinated dibenzo-p-dioxins and dibenzofurans emissions from open burning of crop residues in China between 1997 and 2004. *Environmental Pollution* 151, 39-46

Zhang, X., Zhang, X. and Chen, X., 2017. Happiness in the air: How does a dirty sky affect mental health and subjective well-being?. *Journal of Environmental Economics and Management* 85, 81-94.

Appendix:

Table A1: Test of Attrition Bias

	(1)	(2)
VARIABLES	Missing Responses	
Harvest	0.022	0.020
	(0.540)	(0.700)
Fire × Harvest	-0.010	-0.018
	(0.642)	(0.347)
Age		0.223***
		(0.000)
Age square		-0.002***
		(0.000)
Smoke		0.087***
		(0.000)
Drink		0.077***
		(0.000)
Income		-0.004
		(0.117)
Temperature		-0.001
		(0.611)
Precipitation		0.001
		(0.132)
Pressure		0.011*
		(0.094)
Constant	0.362***	-6.429***
	(0.000)	(0.000)
Observations	23,017	22,539
R-squared	0.668	0.715
Control variables	No	Yes
Year and Week FE	Yes	Yes
Individual FE	Yes	Yes

Notes: This table tests the attrition bias in a difference-in-differences model, accounting for individual fixed effects and time fixed effects. The dependent variable equals one if the answers for cognitive tests are non-missing and zero otherwise. The control variables include socioeconomic characteristics and weather variables. The first model is without control variables and the second model includes all the control variables. Robust p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Robustness Check by Using Province Specific Treatment Window

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Cognition		Immediate Recall		Delayed Recall	
Harvest	0.002	0.005	0.338*	0.338*	0.442**	0.433**
	(0.925)	(0.813)	(0.088)	(0.075)	(0.034)	(0.031)
Fire × Harvest	-0.037*	-0.035	-0.374*	-0.428**	-0.478*	-0.503*
	(0.090)	(0.112)	(0.073)	(0.042)	(0.071)	(0.060)
Age		0.065***		0.155		0.297*
		(0.001)		(0.393)		(0.086)
Age square		-0.000***		-0.001*		-0.001
		(0.000)		(0.077)		(0.135)
Smoke		-0.006		0.163*		0.077
		(0.609)		(0.064)		(0.453)
Drink		0.004		-0.011		-0.056
		(0.565)		(0.904)		(0.576)
Income		0.004		0.028		0.005
		(0.133)		(0.206)		(0.852)
Temperature		-0.000		-0.012		-0.022**
		(0.769)		(0.165)		(0.042)
Precipitation		-0.000		-0.013		-0.012
		(0.823)		(0.112)		(0.210)
Pressure		0.000		0.078		0.124
		(0.931)		(0.276)		(0.109)
Constant	0.919***	-1.198	5.745***	1.836	4.636***	-7.770
	(0.000)	(0.269)	(0.000)	(0.851)	(0.000)	(0.416)
Observations	10,741	10,568	10,055	9,911	9,974	9,831
R-squared	0.606	0.615	0.648	0.654	0.641	0.647
Control variables	No	Yes	No	Yes	No	Yes
Year and Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table tests the robustness of the impact of straw fire on cognitive function by allowing the treatment window to vary in each province in a difference-in-differences model, accounting for individual fixed effects and time fixed effects. The control variables include socioeconomic characteristics and weather variables. The first, third and fifth models are without control variables and the second, fourth and sixth models include all the control variables. Robust p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Parallel Trend Tests

VARIABLES	(1) Cognition	(2) Immediate Recall	(3) Delayed Recall
Week34 × Fire	0.035	0.323	0.597
	(0.814)	(0.852)	(0.768)
Week35 × Fire	-0.099	0.066	0.608
	(0.439)	(0.970)	(0.751)
Week36 × Fire	0.029	0.555	1.177
	(0.831)	(0.741)	(0.528)
Week37 × Fire	-0.027	0.565	0.700
	(0.859)	(0.753)	(0.728)
Week38 × Fire	0.052	0.490	0.966
	(0.696)	(0.775)	(0.628)
Week39 × Fire	0.023	0.826	0.444
	(0.860)	(0.636)	(0.820)
Week40 × Fire	0.080	0.404	0.653
	(0.789)	(0.888)	(0.807)
Week41× Fire	-0.000	0.564	0.443
	(1.000)	(0.736)	(0.826)
Week42 ×Fire	0.019	0.578	0.580
	(0.875)	(0.724)	(0.753)
Observations	6,152	5,880	5,827
R-squared	0.727	0.753	0.740
Control variables	Yes	Yes	Yes
Year and Week FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes

Notes: This table tests the parallel trend assumption in a difference-in-differences model, accounting for individual fixed effects and time fixed effects. The control variables include socioeconomic characteristics and weather variables. All three models include all the control variables. Robust p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4: The Impact of Straw Fire (Treatment Intensity) on Cognitive Function

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Cognition		Immediate Recall		Delayed Recall	
Harvest	0.042	0.030	-0.448	-0.750	-0.215	-0.943
	(0.287)	(0.596)	(0.280)	(0.138)	(0.656)	(0.119)
Fire × Harvest/1000	-0.021*	-0.020*	-0.005	-0.004	-0.072	-0.083
	(0.067)	(0.073)	(0.951)	(0.964)	(0.472)	(0.391)
Age		0.063***		0.136		0.341**
		(0.000)		(0.453)		(0.044)
Age square		-0.000***		-0.001		-0.001
		(0.000)		(0.147)		(0.131)
Smoke		-0.005		0.165*		0.076
		(0.654)		(0.063)		(0.441)
Drink		0.004		-0.037		-0.070
		(0.610)		(0.683)		(0.467)
Income		0.003		0.023		0.002
		(0.142)		(0.270)		(0.956)
Temperature		-0.000		-0.013		-0.025**
		(0.686)		(0.118)		(0.030)
Precipitation		-0.000		-0.011		-0.010
		(0.805)		(0.214)		(0.356)
Pressure		0.000		0.076		0.125
		(0.941)		(0.290)		(0.113)
Constant	0.915***	-1.065	6.067***	2.425	4.899***	-9.712
	(0.000)	(0.286)	(0.000)	(0.804)	(0.000)	(0.303)
Observations	10,619	10,448	9,946	9,803	9,865	9,724
R-squared	0.610	0.619	0.649	0.655	0.642	0.647
Control variables	No	Yes	No	Yes	No	Yes
Year and Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the impact of continuous fire points on cognitive function (a general cognitive test, immediate recall and delayed recall) in a difference-in-differences model, accounting for individual fixed effects and time fixed effects. The model only includes respondents aged 55 and above. The control variables include socioeconomic characteristics and weather variables. The first, third and fifth models are without control variables and the second, fourth and sixth models include all the control variables. Robust p-values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.