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The Unintended Impacts of Agricultural Fires: Human Capital in China

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ABSTRACT

The practice of burning agricultural waste is ubiquitous around the world, yet the external human capital costs from those fires have been underexplored. Using data from the National College Entrance Examination (NCEE) and agricultural fires detected by high-resolution satellites in China during 2005 to 2011, this paper investigates the impacts of fires on cognitive performance. To address the endogeneity of agricultural fires, we differentiate upwind fires from downwind fires. We find that a one-standard-deviation increase in the difference between upwind and downwind fires during the exam decreases the total exam score by 1.42 percent of a standard deviation (or 0.6 point), and further decreases the probability of getting into first-tier universities by 0.51 percent of a standard deviation.

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1. Introduction

The deliberate setting of fires as a tool for agricultural management has a long history that remains ubiquitous around the world today (Andreae and Merlet, 2001). In modern agriculture, the principal benefit from these fires takes the form of avoided labor costs otherwise required to clear brush, remove crop residues, and manage invasive plant species (Levine, 1991). At the same time, these fires generate considerable smoke comprised of a number of pollutants that are known to be harmful to human health (e.g., Chay and Greenstone, 2003; Currie and Neidell, 2005; Schlenker and Walker, 2015). Yet, the direct study of the causal relationship between agricultural fires on human health has been greatly hampered by concerns of endogeneity and the competing benefits and costs from local fires. One notable exception is the recent study by Rangel and Vogl (2018), which examines the impacts of sugarcane harvest fires in Brazil on infant health by exploiting wind direction for empirical identification. Given the emergent literature showing that pollution can also harm a range of other human capital outcomes (e.g., Graff Zivin and Neidell, 2012; Sanders, 2012; Hanna and Oliva, 2015; Stafford 2015; Chang et al., 2016, 2019; Ebenstein et al., 2016; Bharadwaj et al., 2017), the goal of this paper is to examine the impacts of agricultural fires on one important component of human capital – cognitive performance. Our analysis of impacts on young and healthy adults in a high-stakes environment, generalizes and extends evidence from a recent working paper that examines the impact of fires on survey-based measures of cognitive decline amongst the elderly in China (Lai et al., 2018).

More specifically, we exploit high-resolution satellite data on agricultural fires in the granary regions of China and a unique geocoded dataset on test performance on the Chinese National College Entrance Examination (NCEE) to investigate the impacts of fires on cognitive performance. This setting is attractive for a number of reasons. First, the majority of agricultural fires take place in the developing world where environmental controls are less stringent and the returns to human capital are generally substantial. China, in particular, is the largest grain producer in the world, with approximately one-third of all grain cropland managed through burning practices.[1]

Second, the NCEE is one of the most important institutions in China. It is taken by all seniors in high school (around 9 million students each year) and the exam score is almost the sole determinant of admission to institutions of higher learning in China. As such, the NCEE serves as a critical channel for social mobility with important implications for earnings over the lifecycle (Jia and Li, 2017). Test takers face high-powered incentives to do as well as possible on the test and thus any impact from agricultural fires is likely to represent an impact on cognitive performance rather than effort.

Finally, several features of the NCEE make it particularly well suited to causal inference. The exam date is fixed, and thus self-selection on test dates are impossible. Fortuitously for our research design, the exam takes place during the height of the agricultural burning season. Moreover, students must take the exam in the county of their household registration (*hukou*), rendering self-selection on exam locations virtually impossible. Our NCEE data includes test scores for the universe of students who were admitted into colleges and universities between 2005–2011 from the granary regions which form the basis of our study.

Despite the many virtues of our empirical setting, identifying the causal effect of agricultural fires on cognitive performance is challenging for reasons alluded to

[1] China Ministry of Agriculture: http://www moa.gov.cn/zwllm/zwdt/201605/t20160526_5151375.htm.

earlier. Agricultural fires are designed to reduce labor demands and improve farm profitability, both of which could also impact test performance. For example, if some agricultural labor is typically supplied by students, agricultural fires could improve test performance by providing them with more time to prepare for their exams. To address concerns of this type, we follow the approach recently pioneered by Rangel and Vogl (2018), and leverage exogenous variation in local wind direction during the exam period. Specifically, we compare the effect of upwind and downwind fires on students' test scores, and interpret that difference as the causal effect of pollution exposure on students' cognitive performance net of economic impacts. The implicit assumption under this approach is that, ceteris parabus, students upwind and downwind of the fire are differentially exposed to its pollution but share equally in its economic influences.

Our results suggest that a one-standard-deviation increase in the difference between upwind and downwind fires during the NCEE decreases the total exam score by 1.42 percent of a standard deviation (or 0.6 point), and further decreases the probability of getting into first-tier universities by 0.51 percent of a standard deviation. These impacts are entirely contemporaneous. Fires one to four weeks before the exam have no impact on performance. Reassuringly, neither do fires one to four weeks after the exam. The results are robust to alternative approaches for assigning pollution to test takers as well as a number of other specification checks. While a lack of pollution data from our study period does not allow us to utilize fires as an instrumental variable, data from a more recent period suggests that, consistent with evidence from Israel (Ebenstein et al., 2016) these cognitive impairments are likely the result of exposure to fine and coarse particulate matter.

Together, these results suggest that agricultural fires impose non-trivial external costs on the citizens living near them. They also contribute to ongoing debates about the appropriate role of standardized testing in determining access to higher education and employment opportunities (Ceci, 2000). While our analysis is based on NCEE test performance, the impacts are likely much broader, touching all aspects of life that rely on sharp thinking and careful calculations. Indeed, the impacts in lower-stakes environs may well be larger as the incentives to succumb to the fatigue and lack of focus that also typically accompanies exposure to pollution are greater, and thus more likely to exacerbate any impacts on cognitive decision making. Given the importance of human capital for economic growth (Romer, 1986), these impacts should play an important role in the calculus of developing country policy makers when designing rules to manage the use of agricultural fires.

The rest of the paper is organized as follows. In Section 2, we provide more background on the institutional setting. In Section 3 we describe each of the elements in our merged dataset. Section 4 describes our empirical strategy followed by our results in Section 5. Section 6 offers some concluding remarks.

2. Background

2.1 Agricultural Fire and Pollution

The practice of burning crop residues after an agricultural harvest in order to cheaply prepare the land for the next planting is commonplace across the developing world (e.g., Dhammapala et al., 2006; Viana et al., 2008; Gadde et al., 2009). While such burning can greatly reduce labor costs to farmers and potentially help with pest management, it also generates considerable particulate matter pollution (e.g., Li et al., 2007; Wang et al., 2009; Chen et al., 2017). Particulate matter (PM) consists of airborne solid and liquid particles that can remain suspended in the air for extended periods of time and travel lengthy distances. A large public health literature suggests that exposure to PM harms health (see EPA, 2004 for a comprehensive review). These risks arise primarily from changes in pulmonary and cardiovascular functioning (Seaton et al., 1995), which may, in turn, impair cognitive performance due to increased fatigue and decreased focus.

Particles at the finer end of the spectrum are particularly important in our empirical setting since they are small enough to be absorbed into the bloodstream and can even become embedded deep within the brain stem (Oberdörster et al., 2004). This can lead to inflammation of the central nervous system, cortical stress, and cerebrovascular damage (Peters et al., 2006). As such, greater exposure to fine particles is associated with lower intelligence and diminished performance over a range of cognitive domains (Suglia et al., 2008; Power et al., 2010; Weuve et al., 2012). Consistent with this epidemiological evidence, a recent study of Israeli teenagers found that students perform worse on high-stakes exams on days with higher PM levels (Ebenstein et al., 2016).

2.2 Agricultural Fire in China

China is the largest grain producer in the world, accounting for 24% (0.62 billion tons) of global production.[2] Despite a legal ban on burning practices, approximately 31% of the stubble/stalks from maize, wheat, and rice plantings are burnt in situ, largely within China's granary regions. These fires generally take place annually each summer, potentially coinciding with the timing of the NCEE which takes place each year on June 7th and 8th.

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

Figure 1 illustrates the spatial distribution of agricultural fires during the NCEE from 2005 to 2011. Fire points are largely concentrated in four granary regions: Henan, Shandong, Anhui, and Jiangsu Provinces.[3] Due to missing NCEE data in Jiangsu in several years, our core analyses are focused on Henan, Shandong, and Anhui (referred to as baseline provinces hereafter). As can be seen in Figure 2, the peak of agricultural fires in these regions generally coincides with the time of the NCEE. In total, there are 401 counties in our baseline provinces.

2.3 NCEE

As the name suggests, the NCEE is a national exam used to determine admission into higher education institutions at the undergraduate level in China. It is held annually on June 7th and 8th, and is generally taken by students in their last year of high school. In contrast to college testing in the U.S., it is almost the sole determinant for higher education admission in China. Given the substantial returns to higher education in this setting (Jia and Li, 2017), this is a very high stakes exam. Every year, approximately 9 million students in China take the exam to compete for admission to approximately 2,300 colleges and universities.

The NCEE has two primary tracks: the arts track and the science track.[4] All students are tested on three compulsory subjects regardless of track: Chinese, mathematics, and English, with each worth 150 points. Students in the arts track take an additional combined test that includes history, politics, and geography worth 300 points, while students in the science track take an additional combined test that includes physics, chemistry, and biology worth 300 points. Thus, regardless of track, the maximum achievable score for each student is 750 points.

[3] A province is the largest administrative subdivision in China, followed by the prefecture, county and town.

[4] Students choose to study either in the arts track or in the science track at the end of their first year of high school.

In our focal provinces, the Chinese and math exams are scheduled for 9–11:30am and 3–5pm on June 7th, and the English and track test are scheduled for 9–11:30am and 3–5pm on June 8th.[5] Since provinces have some discretion in the design of their tests, exam difficulty can vary by track, province, and year. Our core analysis deploys province-by-year-by-track fixed effects to account for this possibility.

The NCEE tests are graded one to two weeks after the exams are completed by professionals (trained teachers) in hotels in each of the respective provincial capitals. Since this grading occurs in locations that differ from test takers in terms of both space and time, we are confident that the effect we estimate on NCEE scores is not the result of any potential impacts on graders.

3. Data

In order to measure the causal effect of agricultural fires on NCEE test performance in China, we require data from several broad categories. This section describes each of those pieces as well as details on how they are linked. As noted earlier, our core analysis is based on the test performance of students from Henan, Shandong, and Anhui Provinces who took the NCEE between 2005 and 2011.

3.1 Test Score Data

The NCEE data were obtained from the China Institute for Educational Finance Research at Peking University. This dataset provides a unique identifier and the total test score for the universe of students enrolled in a Chinese institution of higher education during our study period. The dataset also reports the subject specialization

[5] Shandong province extended the NCEE from two days to three days from June 7th to June 9th during 2007–2014. One exam on basic knowledge of technology, arts, sports, social practice, humanities and science was added on the morning of June 9th. This exam has 60 points. The total score for the NCEE is still 750 points because the combined test shrunk from 300 points to 240 points. To take this change into consideration, we include fires from June 7th to June 9th in 2007–2011 for Shandong, and find similar results, as shown in the robustness checks.

for each student, allowing us to explore heterogeneity across the science and art tracks.[6] Social and demographic characteristics for exam takers are not available.

Importantly, the student ID contains a six-digit code for county of residence, which allows us to match students to the county administrative centers. Testing facilities are located in local schools which are universally very close to county administrative center.[7] Therefore, we use the county administrative center to approximate the testing facilities. The information on which testing facility a student is assigned is unavailable. Our core analytic sample includes observations from approximately 1.3 million students. We supplement this dataset with data on the cut-off scores that determine admission eligibility to the elite universities in order to separately examine the impacts at the upper-end of the performance distribution. This data provides province-year-track specific thresholds, and is obtained from a website specialized for the exam: gaokao.com.

3.2. Agricultural Fire Data

Data on daily agricultural fires are collected from two satellites named TERRA and AQUA, which rely upon Moderate Resolution Imaging Spectroradiometer (MODIS) sensors to infer ground-level fire activity. The satellites overpass China four times a day (around 1:30 am, 10:30 am, 1:30 pm, and 10:30 pm in local time), and report all fire points detected with 1-km resolution (Justice et al., 2002; Kaufman et al., 1998). The fires are detected based on thermal anomalies, surface reflectance, and land use (Giglio et al., 2016). Since the size of a fire cannot reliably be inferred from satellite

[6] Unfortunately, the dataset does not report scores by specific subjects, thus precluding our ability to examine the impact of fires on specific subsets of the test.

[7] While we do not have data on the precise location of testing facilities during our study period, we can access this from more recent periods. In 2018, there were 494 testing facilities in our provinces of interest and 94% were within 5 km from the county administrative center. The furthest testing facility was less than 10 km from the center. Since testing occurs in high schools, and these locations are largely fixed, we are confident in our assertion that nearly all testing occurred near the county administrative center during our study period.

data (Giglio et al., 2009), we treat fires in adjacent pixels as distinct fires. We exploit data on fire radiative power, a measure of fire intensity, to at least partially probe the importance of this assumption.

A fire is linked to NCEE performance within a county if it occurs within a 50-km of the county administrative center during the two-day exam period in each year. Alternative distances are explored as part of our robustness analyses. Since proximity to a fire is likely correlated with the economic benefits as well as the environmental harms from fires, we eschew distance-weighting strategies on fires in our core analysis. These are, nonetheless, explored in our robustness checks.

3.3. Meteorological Data

Meteorological data is important for two reasons. First, as detailed in the next section, we exploit detailed data on wind direction to contrast impacts of those upwind and downwind of a given fire. Second, weather may also confound the interpretation of our results since the incidence of agricultural fires may be correlated with meteorological conditions. Our weather data are obtained from the National Oceanic and Atmospheric Administration of the United States.

We collect daily average weather data on temperature, precipitation, dew point, wind speed, wind direction and atmospheric pressure from 44 local weather stations during our sample period. Daily average wind direction is reported based on the hourly wind direction and wind speed through vector decomposition (Gilhousen, 1987; Grange 2014).[8] Given the sensitivity of wind direction to topography and other quite localized factors, we assign wind to test locations based on monitor data from the

[8] See http://www.webmet.com/met_monitoring/622.html and https://www ndbc noaa.gov/wndav.shtml.

source closest to the county administrative center, and drop counties with no wind stations within 50 km.[9]

We extract other weather data during the exam time and then convert from station to county using the inverse-distance weighting (IDW) method (Deschênes and Greenstone, 2007, 2011). The basic algorithm calculates weather for a given site based on a weighted average of all station observations within a 50-km radius of the county center, where the weights are the inverse distance between the weather station and the county administrative center.

3.4. Pollution Data

While the detrimental impacts of agricultural fires on air quality have been documented in the environmental science literature, data availability does not allow us to make this link explicitly in our setting. Ground monitoring pollution data at the station-day level in China is not available prior to 2011, and there are infamous stories of data manipulation of the Air Pollution Index and PM_{10} in China apply to the period prior to 2013 (Ghanem and Zhang, 2014).[10] In addition, satellite data is not well suited for ground-level measurement at fine temporal and spatial scales required for our analyses, especially during burning seasons with smoke plumes (You et al., 2015). Nonetheless, we provide a first-stage estimation, of sorts, by estimating the relationship between air pollution and agricultural fires using data from a more recent period: 2013–2016. Since NCEE data is not available for this period, we view this

[9] Given the relative sparsity of weather stations in our study areas, assigning wind direction to a given location by using inverse distance weighting strategies from multiple monitors is not feasible (Palomino and Martin, 1995). It is worth noting that dropping counties without a wind station within 50 km is tantamount to dropping the most rural counties in our sample. Consistent with this notion that they are more agrarian, we see that the average number of fires during the NCEE in the dropped counties was 14, as opposed to the 7 fires in the counties that retain for our analysis. While these differences will not bias our estimates, they do have potentially important implications for generalizability.

[10] Pollution measurement is unlikely to be manipulated after 2013-2014 due to automation and real-time reporting in the provision of data from monitoring stations in China.

analysis as one designed to shed light on the mechanisms through which agricultural fires might impact cognitive performance.

Daily pollution data are obtained from the China National Environmental Monitoring Center (CNEMC), which is affiliated with the Ministry of Environmental Protection of China. Monitoring stations report data for the six major air pollutants – particulate matter less than 10 microns in diameter (PM_{10}), particulate matter less than 2.5 microns in diameter ($PM_{2.5}$), sulfur dioxide, nitrogen dioxide, ozone, and carbon monoxide – that are used to construct the daily Air Quality Index (AQI) in China. For each pollutant, we construct a two-day average concentration level, corresponding to the length of the exam period. Fires that took place more than 50 km from a county center are excluded from this analysis. We select all pollution monitoring stations within 50 km from a county administrative center and calculate the pollution level at the center using the IDW method. Our analysis relies on data from 212 distinct pollution monitors, with an average distance of 24.5 km.

3.5 Summary Statistics

Table 1 reports summary statistics from our merged dataset. We have data on nearly 1.4 million test takers from 159 counties in our baseline provinces from 2005–2011. The average test performance over our study period was 553.3 out of 750, with slightly higher average scores in the science track (relative to the art track). Each county experiences an average of 7 fires during the two-day test period over the course of our study period, although variability across testing-site-years is considerable. These fires are nearly equally likely to take place upwind and downwind of testing centers, with an average of 1.5 upwind, 2.0 downwind, and the remainder vertical fires that are neither upwind or downwind based on the 45-degree measure of dominant wind direction (as detailed in the next section). Summary statistics on meteorological conditions, including temperature, dew point, precipitation, wind speed and atmospheric pressure, are also listed in the bottom panel of Table 1.

4. Empirical Strategy

Our goal is to estimate the effect of agricultural fires on NCEE test performance. We start by estimating the following equation:

$$Y_{icpt} = \alpha_0 + \beta fire_{cpt} + X_{cpt}\theta + \tau_c + \pi_{ptm} + \xi_{icpt} \tag{1}$$

where Y_{icpt} denotes the logarithm of the exam score of student *i* in county c in province p in year *t*. We use $fire_{cpt}$ to denote the total number of agricultural fires in county *c* on the two exam days in each year. X_{cpt} is a vector of the two-day averages of our meteorological variables during exam days. As is standard in the literature (Deschênes and Greenstone, 2007), we use a non-parametric binned approach to flexibly control for the potential nonlinear effects of these weather variables.[11] We use county fixed effects τ_c to control for any unobserved county-specific time invariant characteristics. We also include π_{ptm}, province-by-year-by-track fixed effects, to control for differences in exam difficulty by major track in a province and year. These fixed effects will also control for any other shock that is common across cohorts studying the same subjects within a province, such as variation in instructor quality at local high schools. The error terms ξ_{icpt} are clustered by county to allow for autocorrelation within each county.[12] Thus, the identifying variation we exploit to estimate Equation (1) is based on comparisons of student performance in the same

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[11] Specifically, we select 7 bins for temperature and dew point (5 °F for each bin), 8 bins for wind speed (2 miles per hour for each bin), 6 bins for precipitation (0.5 inch for each bin), and 5 bins for pressure (200 millibars for each bin).

[12] Our estimates are robust to alternative clustering by prefecture, as well as two-way clustering by county and by year. See the robustness checks for details.

major track of counties within the same province who varied in their exposure to agricultural fires within a given year.

One limitation of the approach described above is that proximity to agricultural fires is not randomly assigned, raising potential endogeneity concerns. In particular, agricultural fires are meant to reduce the labor demands of the farm. If children provide some of this labor, then the presence or absence of nearby fires may influence the time that students have to prepare for their exams. Similarly, agricultural fires may increase farm profitability and indirectly influence test performance through a variety of income channels. To address these concerns, we utilize data on wind direction.[13]

In particular, we differentiate between upwind fires and downwind fires, exploiting the fact that upwind fires will have a larger impact on air quality at a county center than downwind fires, but that wind direction is irrelevant for the labor and income channels that might threaten identification of the pollution-driven impacts of fires in this setting. As such, the primary model specification that we deploy for the majority of our analyses takes the following form:

$$Y_{icpt} = \alpha_0 + \beta_{cpt}^{u} upwind_{cpt} + \beta_{cpt}^{d} downwind_{cpt} + X_{cpt}\delta + \tau_c + \pi_{ptm} + \varepsilon_{icpt} \quad (2)$$

where $upwind_{cpt}$ denotes the number of agricultural fires located in the upwind direction of county c in province p in year t, and $downwind_{cpt}$ represents fires located in the opposite direction. The other variables are identical to those used in Equation (1).

Upwind fires are defined as those located within a 45-degree central angle from the dominant daily wind direction in each county following the procedure

[13] A nascent literature exploits variations in wind directions to causally estimate pollution's effect (e.g., Anderson, 2015; Schlenker and Walker, 2015; Deryugina et al., 2016).

detailed in Rangel and Vogl (2018).[14] Downwind fires are defined as those scattered in the opposite direction to upwind fires. The remaining fires are classified as vertical fires and should be viewed as areas that are exposed to more fire-driven pollution exposure than those exposed to downwind fires but less than those exposed to upwind fires. In some cases, we aggregate downwind and vertical fires into a larger category, which we refer to as non-upwind fires. See Figure 3 for an illustration of how these classifications are constructed.

In our analysis, daily upwind and downwind fires within a county are aggregated to correspond to the two-day period of the exam. The parameters of interest are β^u_{cpt} – the impact of upwind fires, β^d_{cpt} – the impact of downwind fires, and $\beta^u_{cpt} - \beta^d_{cpt}$, which captures the difference between upwind and downwind effects on test scores, and therefore can be interpreted as the causal effect of agricultural fires on test scores via air pollution.

5. Results

This section presents our empirical results. We begin by exploring the impacts of agricultural fires on NCEE test performance. Then we conduct additional analyses exploring the timing of those effects and several dimensions of heterogeneity. Next we present a series of robustness checks. This is followed by an exploration of mechanisms using available pollution data from a more recent period to examine the relationship between agricultural fires and criteria air pollutant concentrations upwind and downwind of the burn site.

[14] We also explore broader and narrower angles to determine upwind fires as part of our robustness analysis. The results remain qualitatively unchanged.

5.1 Baseline Findings

Table 2 presents our primary results on the impacts of agricultural fires on exam scores in logarithms. As shown in column (1), combining all fires together as in Equation (1) yields attenuated estimates that are close to zero and statistically insignificant. Column (2) shows that upwind fires significantly reduce test scores, whereas columns (3) and (4) reveal no significant effect for downwind and non-upwind fires, respectively.

Our main specification in column (5), where we put upwind and downwind fires together, shows that a one-point increase in the difference between upwind and downwind fires leads to a 0.0126 percent drop in scores. When we compare upwind and non-upwind fires as an alternative, the coefficient remains negative and significant, but is smaller in magnitude (see column 6). This diminished effect size is consistent with the notion that students at testing locations that lie in a vertical wind direction from the fire are exposed to more fire-related air pollution than downwind students but less than those that are upwind. While we spend more time putting these magnitudes in context later in the paper, it is worth noting that they are broadly consistent with the negative impacts of extreme heat on test performance found by others in China as well as other countries (Park, 2018; Graff Zivin et al., 2018a, 2018b).

5.2 Dynamic Effects

We next explore the temporal effects of exposure to agricultural fires. In particular, Figure 4 depicts results by moving exposure windows up to four weeks before and four weeks after the NCEE exam dates. The results confirm that the impacts are entirely contemporaneous. We find no statistically significant impact of agricultural fires in the one to four weeks prior to the NCEE. Our falsification test based on future fires is similarly insignificant. Whether exposure to fires has a long-run impact on cognitive attainment, above and beyond the effects that we are finding for cognitive performance is an open question that cannot be answered using our research design which exploits short-run 'shocks' to pollution exposure.

5.3 Heterogeneity

In this section, we explore the heterogeneity of our core results along two dimensions, as shown in Table 3. The first column simply reproduces the results from our preferred specification for our primary results (column 5 in Table 2). Columns (2) and (3) of Table 3 explore heterogeneity along another dimension: the subject track. It appears that the impacts are negative and highly statistically significant for those in the science track while only marginally significant for those in the arts track. This may reflect the differential sensitivity of the prefrontal cortex – the part of the brain responsible for more mathematical style reasoning, and is consistent with other evidence on the impacts of environmental stressors on cognitive performance (Graff Zivin et al., 2018a). This pattern of results might also, at least partly, be driven by the gender composition of students across tracks. While we do not have individual level gender data, the male ratio is typically much higher in science track than arts track and other work has found the cognitive performance of males to be more sensitive to PM pollution than females (Ebenstein et al., 2016).

The next four columns of Table 3 examine how the impacts of agricultural fires vary across the student ability distribution by estimating Equation (2) using a quantile regression approach. This regression is especially important for two reasons. First, since we only observe NCEE scores for students that were eventually admitted to an institution of higher learning, we might be worried about sample selection resulting from negative effects at the lower end of the ability distribution. Second, differences in impacts across the ability distribution could have profound long-run impacts on income inequality given the highly nonlinear returns to scores. Our results find no impacts among low ability students, thus minimizing concerns about selection bias. Moreover, the impacts appear to be concentrated near the very top of the performance distribution – above the 75th percentile. This can be seen most clearly in Figure 5, which further breaks down estimates by decile.

Column (8) offers another perspective on the higher end of the ability distribution by focusing on the impacts of agricultural fires on the likelihood of admission into an elite university in China based on the cutoff scores that govern that process. The cutoff score in each province is the lowest score of students admitted to the first-tier universities in China. It is determined by the admission quota of each university and the ranking of student scores in each province. Upwind fires continue to have a significant negative impact on test performance. A one percentage point (or one standard deviation) increase in the difference between upwind and downwind fires, decreases the probability of admission to an elite university by 0.027 percent (or 0.51 percent of a standard deviation). Given the sizable impacts of an elite education in China on lifetime earnings (Jia and Li, 2017), these impacts should be viewed as economically meaningful, even if they may be largely re-distributional by privileging the admission of students from less exposed counties over those from more exposed ones.

5.4 Robustness Checks

In this section, we provide a number of robustness checks. We begin by exploring alternative ways to assign the exposure of test takers to agricultural fires. The first column of Table 4 reproduces our main results, which limit our focus to fires within 50 km of a testing center. The next four columns vary that distance from 30-70 km in

10-km increments. As can be seen in Panel A, the impact of an additional fire is considerably larger when we focus on nearer fires, but this pattern of results no longer holds when we standardize our outcome measure based on the variability of test scores, as in Panel B. Unsurprisingly, the results become smaller as we include test takers further away from the fire. At a 70-km radius, as seen in column (5) of Table 4, the results are no longer significant. Together, these results highlight the relatively localized impacts of agricultural fires.

In columns (6) – (8) of Table 4, we explore the sensitivity of our results to alternative central angle measures to determine whether an individual is upwind or downwind of a fire. Recall that our baseline model specification uses the angle of 45 degrees to define upwind and downwind fires (see column 1). As we alter the angle to 30, 60, and 90 degrees, the estimates remain significant, but become smaller as the angles become larger. This pattern of results is consistent with standard models of pollution dispersion, as wider angles will expand the 'treated' upwind sample to include more individuals with peripheral levels of exposure. It also further validates that our upwind and downwind measures are doing a reasonable job of capturing the relevant transport of pollution from fires to test centers.

Table 5 experiments with alternative ways to define a fire. Column (1) reproduces our core results from Table 2, while column (2) takes a more aggressive approach to classifying fires as exogenous by limiting our attention to those fires within the 50-km radius of a county administrative center but that take place in a different county. While our use of wind direction is meant to capture the economic effects from agricultural fires, the enforcement of any policies designed to limit agricultural fires or protect air quality occurs primarily at the county level (He et al., 2018). Thus, our focus on non-local fires should help address any potential concerns about the endogeneity of local policies vis-à-vis testing outcomes. The results using this specification are largely unchanged.[15]

In column (3), we inverse-distance weight fires to better reflect the distance of the fire from the county administrative center. In column (4), we account for the intensity of the fire by weighting by the fire radiative power (FRP) in *Watts* of each event. The estimates remain statistically significant, but are slightly smaller in magnitude than those under our preferred specification. Finally, we use reliability measures from the fire dataset to adjust for the probability that a hotspot is genuinely a fire (see Rangel and Vogl, 2018 for more details). The results after this adjustment are statistically significant and slightly larger in magnitude.

In Table 6, we explore a final set of robustness checks. As before, the first column reproduces our core results for ease of comparability. We report the estimates using alternative ways of clustering standard errors either by prefecture in column (2), or by county and by year (two-way clustering) in column (3). The estimates are robust to these different clustering approaches, suggesting that spatial and temporal autocorrelation is not a big concern in our setting. In column (4), we add controls for visibility. These controls are important as impaired visibility may trigger avoidance behavior in the lead up to the exam.[16] In addition, gray skies can impair one's sense of psychological well-being, particularly if worried that diminished air quality might affect their test performance. In column (5), we expand our focus in Shandong to the third day, which only takes place in this province. In column (6), we add the data we have from Jiangsu Province, which only covers part of our study period. The

[15] On average, 6 of the 7 fires within 50 km of the county center occur in another county. That said, they are typically further from testing locations – 35.2 km versus 19.5 km away on average – which may explain their diminished significance.

[16] Since visibility is significantly correlated with PM (the Pearson coefficient between visibility and $PM_{2.5}$ is -0.24, and is -0.38 after controlling for temperature and dew point), we model it using 3 miles-of-visibility bins (a total of 5 bins).

coefficients barely budge across the first three checks. The results are slightly smaller and now only significant at the 10-percent level under the final one.

In the end, our results appear quite robust to alternative methods of measuring fires, assigning exposure, clustering standard errors, and defining our sample population. That the magnitudes of results change in expected directions as we tighten or liberalize the approach we use to assign fires to testing facilities is particularly reassuring.

5.5 Mechanisms: The Effect of Agricultural Fires on Air Pollution

In this section, we estimate the effect of agricultural fires on air pollution, to confirm that air pollution is the channel through which agricultural fires affect students' exam scores and to place our results in a broader context. As described earlier, we do so by using data from the 2013–2016 period for which daily air pollution measurements, even in more rural areas, are available. The ideal design for this analysis would focus exclusively on the two-day exam period, but this leaves us with limited statistical power. Instead, we construct a panel of two-day moving averages of pollutant concentrations in June and link them with proximate agricultural fires during the same period. The empirical model for this estimation is nearly identical to the one described in Equation (2), except that the dependent variable is now one of the six criteria air pollutants. Weather variables are now measured as two-day averages of the corresponding to each moving two-day period in June for which we have pollution measures.

The results are shown in Table 7. The first two rows list the two-day averages and standard deviations of each pollutant in June during 2013–2016. The PM_{10} concentration is approximately 78 μg/m^3 and the $PM_{2.5}$ concentration is approximately 46 μg/m^3, both of which greatly exceed World Health Organization guidelines. The other pollutant levels are more modest, although still higher than those typically found in developed countries. Turning to our estimates, we find a significant and substantial effect of upwind agricultural fires on PM_{10} and $PM_{2.5}$. A one-point increase in upwind agricultural fires increases PM_{10} and $PM_{2.5}$ concentrations by 0.476 μg/m^3 and 0.262 μg/m^3, respectively. We also detect a weak effect of downwind fires on PM_{10}, and the coefficient of upwind-downwind difference becomes insignificant compared with that of $PM_{2.5}$. This may be due to the fact that PM_{10} is heavier than $PM_{2.5}$ and thus less responsive to wind direction. The impacts on $PM_{2.5}$ are non-trivial: a one-standard-deviation change in the upwind-downwind difference is associated with a 5.6 percent standard-deviation change in $PM_{2.5}$.

In contrast, downwind fires have no impacts on air quality, providing further validation for our empirical strategy to uncover the pollution-driven impacts of agricultural fires on NCEE test performance. We find no effect of agricultural fires on other pollutants, including SO_2, NO_2, CO, and O_3. In general, these estimates are consistent with those found in the scientific literature (Li et al., 2007) and recent empirical analysis done by Rangel and Vogl (2018) in Brazil, both of which find that agricultural fires primarily emits PM.

Given that the samples are different for our estimates of the impacts of fires on pollution and the impacts of fires on test performance, we are unable to provide an instrumental variable estimate of the effect of PM on student scores. We provide a rough estimate akin to Wald estimator as an alternative. Using the ratio of the reduced-form estimates over the first-stage estimates based on the differences in upwind and downwind fires, we find that a one-standard-deviation elevation in $PM_{2.5}$ (29.6 μg/m^3) will lower average student scores by 13.6 percent of a standard deviation (5.8 points). While these magnitudes are quite modest, they are roughly three times as large as those found for the impact of PM on Israeli test takers (3.9 percent for $PM_{2.5}$, see Ebenstein et al., 2016). A simple transformation further shows that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ reduces test scores by 4.6 percent of a standard deviation, which is larger than the 1.7 percent estimated from Ebenstein et al. (2016). This likely reflects the higher levels of pollution in our setting, but may also be the result of our empirical strategy which relies on wind direction rather than an approach that assigns pollution equally to all of those within a certain distance of a pollution monitor. In addition, our estimates are also larger than those estimated for temperature (e.g., Graff Zivin et al., 2018a, 2018b; Goodman et al., forthcoming). That said, our estimates here should be treated with some caution, as our 'two-stage approach' relies on data from adjacent but distinct time periods.

6 Conclusions

In this paper, we analyze the relationship between agricultural fires and cognitive performance on high-stakes exams in China. We find that fires decrease the performance of students, with effects concentrated amongst the highest ability test takers. A one-standard-deviation increase in the difference between upwind and downwind fires during the NCEE decreases the total exam score by 1.42 percent of a standard deviation (or 0.6 point), and further decreases the probability of getting into first-tier universities by 0.51 percent of a standard deviation. The effects are entirely contemporaneous and generally quite localized. To our knowledge, this is the first evidence that the negative impacts of agricultural fires extend beyond health to include impacts on human cognition among otherwise unimpaired young adults.

Given the substantial returns to higher education in China, these results suggest that agricultural fires may exacerbate the challenges associate with ruralurban inequality that pervades the Chinese economy. At the same time, they help bolster the case for the enforcement of new regulations that limit agricultural fires in China and provide additional evidence on the need for interventions in much of the less developed world where these practices are largely ungoverned. Moreover, the impacts almost certainly extend beyond agricultural fires to include forest and other forms of wildfires, which are expected to intensify in the coming decades under climate change. Since these types of fires tend to be large and far more harmful to human health (e.g., Frankenberg et al. 2005; Jayachandran 2009; Borgschulte et al., 2018), it seems likely that their impacts on human capital endpoints like cognition are also likely to be substantial.

The implications beyond fires are also profound. Our analysis suggests that the principal driver of these cognitive impairments is particulate matter pollution. A simple back of the envelope calculation suggests that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ reduces test scores by 4.6 percent of a standard deviation. These results are larger than those found for performance on high school exit exam performance in Israel (Ebenstein et al., 2016). They may also help explain the emerging evidence on the detrimental effects of particulate matter on labor productivity in cognitively demanding occupations (Heyes et al., 2016; Chang et al., 2019; Archsmith et al., 2018).

While performance on high-stakes exams is clearly cognitively demanding, it remains an open question how these impacts translate to the cognitive tasks that are more typical of everyday living. Our results are also silent on how exposure to fires, or the pollution they emit, may impact learning and thus cognitive attainment. Should such impacts exist, they pose particular challenges for communities that experience repeated and prolonged exposure to fires of this sort. Together, they comprise a fruitful area for future research.

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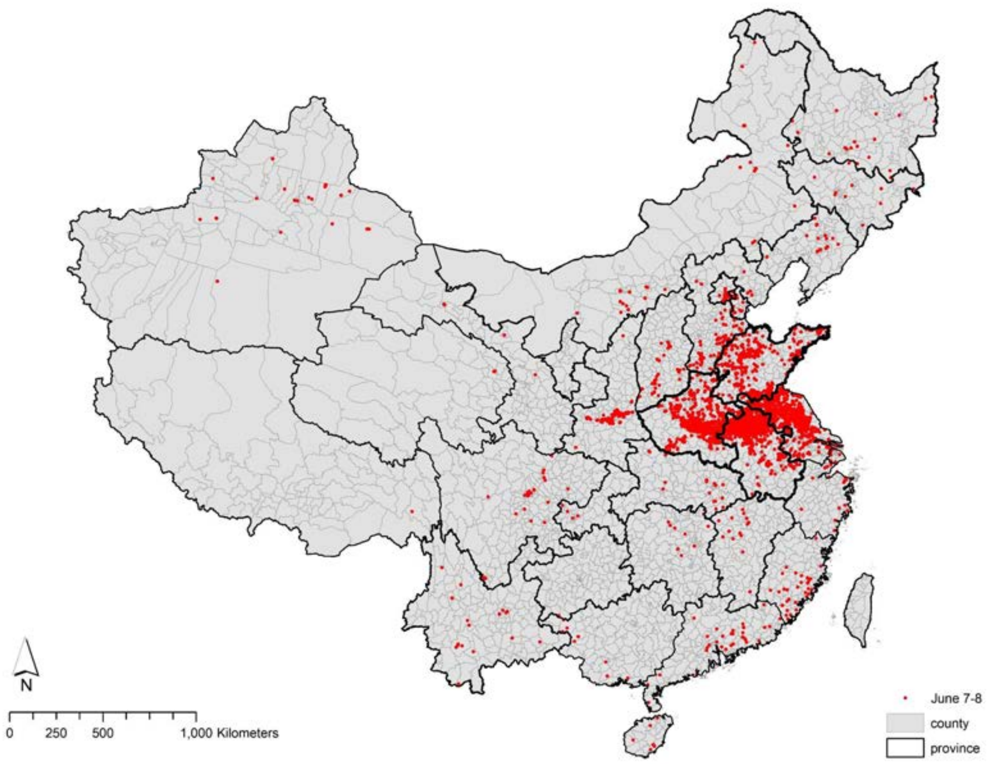

Figure 1. Agricultural Fires During NCEE in China in 2005–2011

Notes: Red dots indicate agricultural fires detected by satellites during June 7th–8th (NCEE) in 2005–2011 in China.

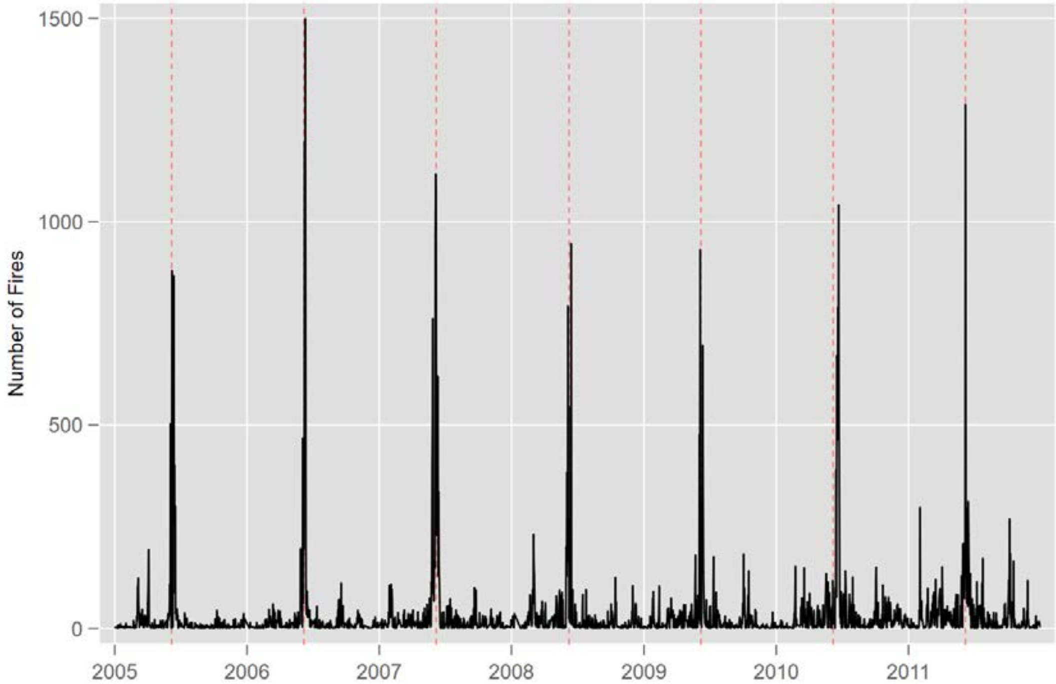

Figure 2. Daily Agricultural Fires in Anhui, Henan and Shandong in 2005–2011

Notes: This figure plots daily number of agricultural fires in Henan, Shandong and Anhui Provinces during 2005–2011. Red dash lines indicate the NCEE period each year.

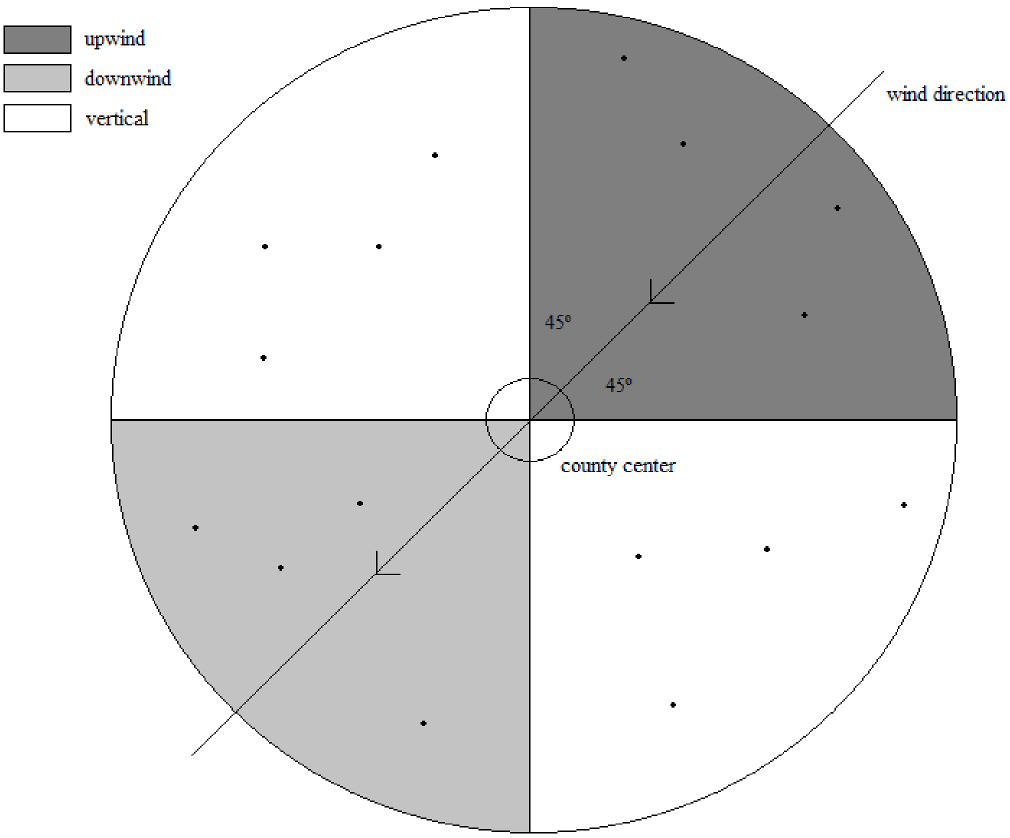

Figure 3. Definition of Upwind and Non-Upwind Agricultural Fires

Notes: Definitions of upwind, downwind and vertical agricultural fires within 50 km from the center of a county is illustrated using northwest wind as an example. Non-upwind fires include fires in the downwind and vertical directions.

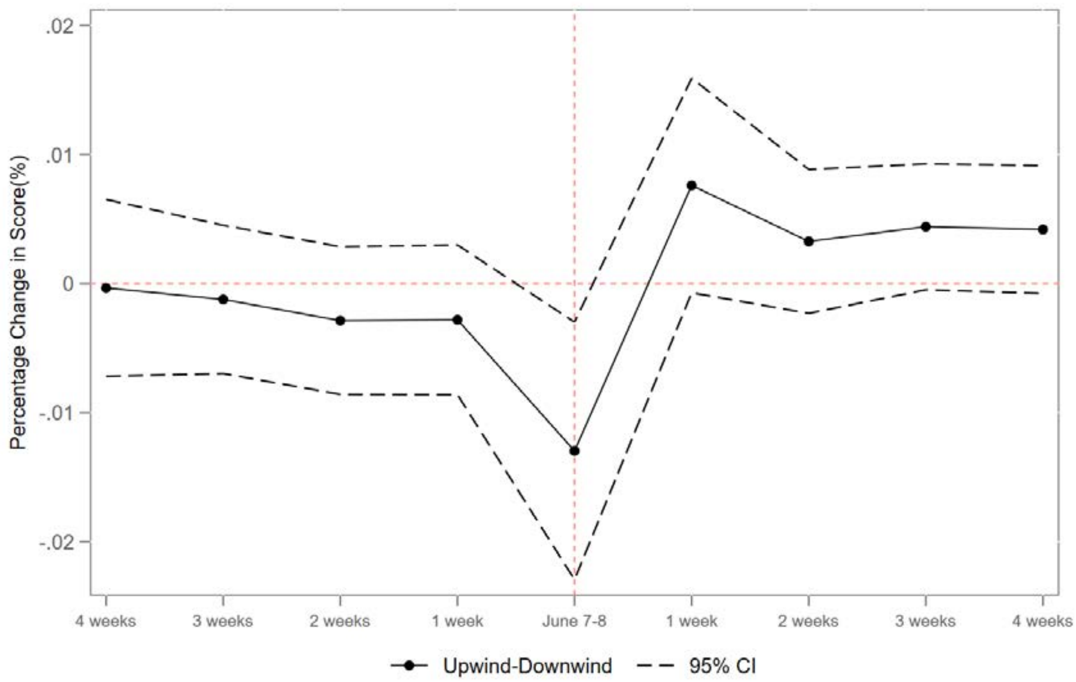

Figure 4. Dynamic Effects of Agricultural Fires on Score (%)

Notes: This figure plots the dynamic effects of agricultural fires on NCEE scores in percentage. Dashed lines indicate the 95% confidence intervals.

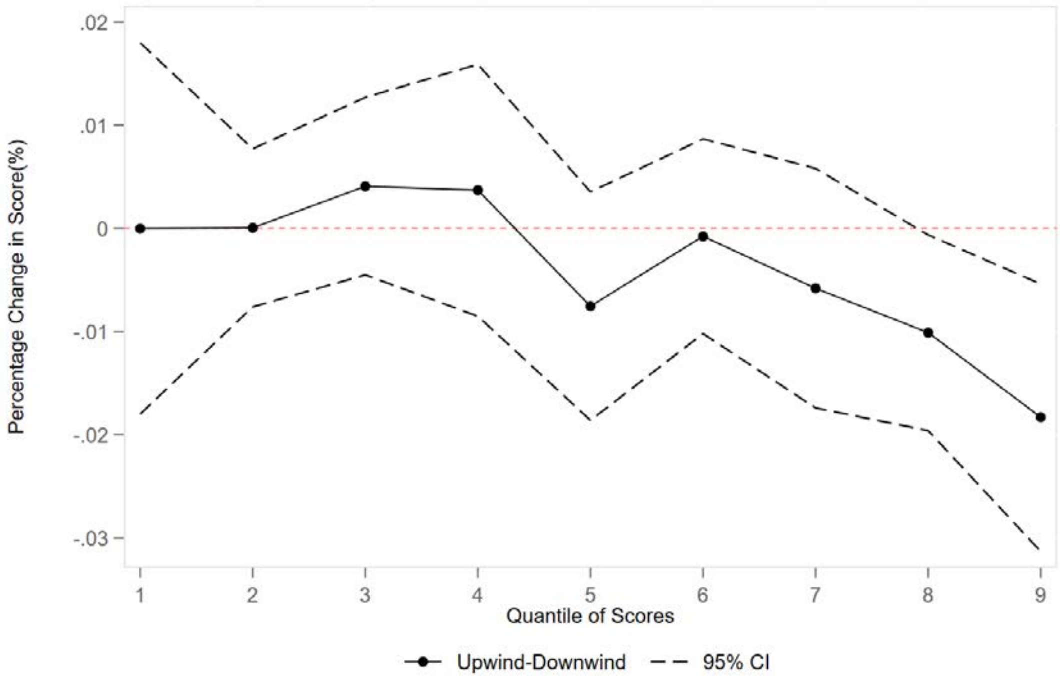

Figure 5. Effects of Agricultural Fires on Scores by Decile

Note: The estimates of upwind-downwind differences in agricultural fires' impact on percentage point changes in NCEE scores are plotted in the solid connected line. The dashed lines represent the 95% confidence intervals.

Table 1. Summary Statistics

Variable	Obs. (1)	Mean (2)	SD (3)	Min (4)	Max (5)
Score (0-750)	1,387,974	553.3	42.4	102	708
Science	873,851	555.9	43.4	129	708
Arts	311,744	545.7	39.4	102	684
Agricultural Fires	1,087	7.0	26.3	0	345
Upwind: 45º	1,087	1.5	8.8	0	177
Downwind: 45º	1,087	2.0	8.6	0	155
Vertical: 45º	1,087	3.4	14.2	0	257
Non-Upwind: 45º	1,087	5.4	20.2	0	298
Meteorological Conditions					
Temperature (ºF)	1,087	75.8	5.7	57	90
Dew Point (ºF)	1,087	60.6	5.7	40	73
Precipitation (inch)	1,087	0.1	0.3	0	2
Wind Speed (mile/hour)	1,087	5.4	2.0	1	15
Atmospheric Pressure (millibar)	1,087	599.0	356.9	0	1010

Note: Summary statistics of key variables, including scores, agricultural fires and meteorological conditions, during NCEE in Anhui, Henan and Shandong in 2005-2011 are listed. Upwind fires are defined fires within 45 degrees from the daily dominant wind direction in a county.

Table 2. Effects of Agricultural Fires on Score in Baseline Provinces (%)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
(per 1 fire)						
All	-0.0005					
	(0.0012)					
Upwind		-0.0054***			-0.0070***	-0.0072***
		(0.0018)			(0.0021)	(0.0019)
Downwind			0.0038		0.0056	
			(0.0035)		(0.0036)	
Nonupwind				0.0000		0.0015
				(0.0014)		(0.0015)
Upwind-Downwind					-0.0126**	
					(0.0051)	
Upwind-Nonupwind						-0.0087***
						(0.0031)
Observations	1,188,933	1,188,933	1,188,933	1,188,933	1,188,933	1,188,933
R-squared	0.317	0.317	0.317	0.317	0.317	0.317
County FE	Y	Y	Y	Y	Y	Y
Prov-Year-Track FE	Y	Y	Y	Y	Y	Y
Weather	Y	Y	Y	Y	Y	Y

Note: Each column represents a separate regression with different fixed effects and controls. Weather conditions, include temperature, dew point, wind speed, precipitation and atmospheric pressure, are controlled nonlinearly using bins. Standard errors in parentheses are clustered by county. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Heterogeneity (%)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Track		Score				Admission
	Baseline	Arts	Science	25%	50%	75%	95%	First-Tier
(per 1 fire)								
Upwind	-0.0070***	-0.0104*	-0.0058***	-0.0013	-0.0022	-0.0064*	-0.0109***	-0.0198**
	(0.0021)	(0.0053)	(0.0017)	(0.0018)	(0.0022)	(0.0034)	(0.0026)	(0.0089)
Downwind	0.0056	0.0142	0.0024	-0.0039	-0.0046	0.0011	0.0204***	0.0070
	(0.0036)	(0.0105)	(0.0023)	(0.0032)	(0.0036)	(0.0034)	(0.0071)	(0.0111)
Upwind-Downwind	-0.0126**	-0.0246	-0.0083***	0.0026	0.0024	-0.0075	-0.0313**	-0.0269*
	(0.0051)	(0.0153)	(0.0030)	(0.0038)	(0.0058)	(0.0057)	(0.0048)	(0.0159)
Observations	1,188,933	311,744	873,851	1,188,933	1,188,933	1,188,933	1,188,933	1,185,595
R-squared	0.3171	0.3987	0.2426	0.0001	0.0001	0.0000	0.0000	0.0464

Note: Each column represents a separate regression. Column (2) – (3) differentiate the effects of agricultural fires on scores by track. Column (4) – (7) list the estimates by student score quantile. Column (8) reports the effects on admission likelihood to first-tier universities. Weather conditions, include temperature, dew point, wind speed, precipitation and atmospheric pressure, are controlled nonlinearly using bins. County and province-by-year-by-track fixed effects are always controlled. Standard errors in parentheses are clustered by county. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Robustness Checks with Alternative Distances and Angles

	Distances					Angles		
	50km	40km	30km	60km	70km	30º	60º	90º
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: per 1 fire								
Score (%)								
Upwind - Downwind	-0.0126**	-0.0201**	-0.0219**	-0.0070*	-0.0024	-0.0140**	-0.0101***	-0.0079***
	(0.0051)	(0.0086)	(0.0107)	(0.0040)	(0.0033)	(0.0064)	(0.0037)	(0.0023)
Panel B: per 1 S.D.								
Score (% S.D.)								
Upwind - Downwind	-1.42	-1.43	-0.97	-1.13	-0.49	-1.18	-1.47	-1.51
Observations	1,188,933	1,188,933	1,188,933	1,188,933	1,188,933	1,188,933	1,188,933	1,188,933

Note: Columns (1) – (5) report the effects of agricultural fires on NCEE score in provinces of Anhui, Shandong and Henan using different distances from a county center with 45 degrees for wind directions. Columns (6) – (8) list the estimates using different definitions of upwind and non-upwind direction, namely 30, 60 and 90 degrees. Panel A lists the percentage change in scores in response to an increase of one agricultural fire. Panel B lists the percentage changes in standard deviation (S.D.) of scores when agricultural fires increase by one S.D. Weather conditions, including temperature, dew point, wind, precipitation and atmospheric pressure, are controlled nonlinearly using bins. County and province-by-year-by-track fixed effects are always controlled. Standard errors in parentheses are clustered by county. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Alternative Measures of Fires

VARIABLES	Baseline (1)	Non-Local (2)	Distance-Weighted (3)	FRP-Weighted (4)	Probability-Weighted (5)
Panel A: per 1 fire					
Score (%)					
Upwind-Downwind	-0.0126**	-0.0139*	-0.0086**	-0.0081**	-0.0193**
	(0.0051)	(0.0079)	(0.0040)	(0.0039)	(0.0077)
Panel B: per 1 S.D.					
Score (% S.D.)					
Upwind-Downwind	-1.42	-1.25	-1.17	-1.46	-1.55
Observations	1,188,933	1,188,933	1,188,933	1,188,933	1,188,933

Note: Column (1) repeats the baseline estimates on the effects of upwind-downwind difference in agricultural fires on score. Column (2) reports the effects of non-local upwind-downwind difference on score. Column (3) lists the estimate from distance-weighted fires. Column (4) weights the fires by intensity measured by fire radiative power (FRP). Column (5) lists the estimates using probability-weighted agricultural fires. Panel A lists the percentage change in scores in response to an increase of 1 fire point. Panel B lists the percentage changes in standard deviation (S.D.) of scores when agricultural fires increase by 1 S.D. Weather conditions, including temperature, dew point, wind, precipitation and atmospheric pressure, are controlled nonlinearly using bins. County and province-by-year-by-track fixed effects are always controlled. Standard errors in parentheses are clustered by county. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Robustness Checks

VARIABLES	Baseline (1)	Cluster by Prefecture (2)	Cluster by County and by Year (3)	Controlling for Visibility (4)	Shandong-3 Days (5)	Four Provinces (6)
Panel A: per 1 fire						
Score (%)						
Upwind-Downwind	-0.0126**	-0.0126**	-0.0126*	-0.0130**	-0.0138**	-0.0088*
	(0.0051)	(0.0054)	(0.0057)	(0.0051)	(0.0054)	(0.0045)
Panel B: per 1 S.D.						
Score (% S.D.)						
Upwind-Downwind	-1.42	-1.42	-1.42	-1.47	-1.56	-0.99
Observations	1,188,933	1,188,933	1,188,933	1,188,933	1,188,933	1,372,466

Note: Column (1) repeats the baseline estimates on the effects of upwind-downwind difference in agricultural fires on score. Column (2) clusters the standard errors by prefecture. Column (3) two-way clusters the standard errors by county and by year. Column (4) controls for visibility using 3-miles-of-visibility bins. Column (5) considers the changes in NCEE dates in Shandong since 2007. Column (6) shows estimates using 4 provinces (Jiangsu added). Panel A lists the percentage change in scores in response to an increase of 1 fire point. Panel B lists the percentage changes in standard deviation (S.D.) of scores when agricultural fires increases by 1 S.D. Weather conditions, including temperature, dew point, wind, precipitation and atmospheric pressure, are controlled nonlinearly using bins. County and province-by-year-by-track fixed effects are always controlled. Standard errors in parentheses are clustered by county. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7. Two-Day Moving Averages of Agricultural Fires and Air Pollution in June During 2013-2016

	(1)	(2)	(3)	(4)	(5)	(6)
	PM_{10}	$PM_{2.5}$	SO_2	NO_2	CO	O_3
(per 1 fire)	(μg/m^3)	(μg/m^3)	(ppb)	(ppm)	(ppb)	(ppb)
Mean	78.1	45.5	9.1	13.3	0.7	39.3
	(50.7)	(29.6)	(7.6)	(8.0)	(0.4)	(19.2)
Upwind	0.476***	0.262**	-0.005	0.012	0.000	0.012
	(0.179)	(0.108)	(0.019)	(0.022)	(0.001)	(0.037)
Downwind	0.221*	-0.052	0.008	-0.009	-0.001**	-0.011
	(0.122)	(0.045)	(0.008)	(0.009)	(0.000)	(0.022)
Upwind-Downwind	0.254	0.314**	-0.013	0.022	0.001	0.022
	(0.261)	(0.134)	(0.024)	(0.027)	(0.002)	(0.051)
Observations	18,408	18,450	18,676	18,678	18,442	18,434
R-squared	0.498	0.426	0.493	0.459	0.557	0.533
County FE	Y	Y	Y	Y	Y	Y
Prov-Year FE	Y	Y	Y	Y	Y	Y
Weather	Y	Y	Y	Y	Y	Y

Note: Each column represents a separate regression at the county level. Columns (1) – (6) regress the two-day moving average concentrations of each pollutant on the number of upwind and downwind agricultural fires within 50km from a county during June in Anhui, Henan and Shandong. County and province-by-year fixed effects, weather (temperature, dew point, precipitation, atmospheric pressure, wind speed) are always controlled. Standard errors in parentheses are clustered by county. *** p<0.01, ** p<0.05, * p<0.1