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Juliana Carneiro, Matthew A. Cole and Eric Strobl

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Foetal Exposure to Air Pollution and Students' Cognitive Performance: Evidence from Agricultural Fires in Brazil

Juliana Carneiro, Matthew A. Cole and Eric Strobl*

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Abstract

This paper examines the impact of foetal exposure to air pollution from agricultural fires on Brazilian students' cognitive performance later in life. We rely on comparisons across children who were upwind and downwind of the fires while *in utero* to address concerns around sorting and temporary income shocks. Our findings show that agricultural fires increase $PM_{2.5}$, resulting in significant negative effects on pupils' scores in Portuguese and Maths in the 5^{th} grade through prenatal exposure. Back-of-the-envelope calculations suggest that a 1% reduction in $PM_{2.5}$ from agricultural burning has the potential to increase later life wages by 2.6%.

Keywords:Agricultural fires, air pollution, foetal exposure, cognitive performance

*Carneiro: University of Warwick, Department of Economics, The Social Sciences Building, Coventry, CV4 7AL, UK, (e-mail: juliana.cunhacarneiropinto@vwi.unibe.ch). Cole: University of Birmingham, Department of Economics, Birmingham Business School B15 2TT, United Kingdom, (Corresponding author.e-mail: m.a.cole@bham.ac.uk). Strobl: University of Bern, Department of Economics, Schanzeneckstrasse 1 A219, 3001 Bern, Switzerland, (e-mail: eric.strobl@vwi.unibe.ch). We are grateful to Matthew Neidell, Tatyana Deryugina and Sefi Roth for their helpful feedback. We also thank Nico Pestel and other participants of the conference EAERE June/2021 for their thoughtful comments. All errors and omissions are our own. This research has not been funded by any external organisation. The authors declare no known interests related to their submitted manuscript.

1 Introduction

Controlled agricultural burning is a traditional technique commonly used by farmers, particularly in parts of the developing world, to clear fields from previous harvests and to regenerate nutrients in the soil for the next seeding phase. There is growing evidence, however, that the smoke from agricultural fires contributes to increasing levels of fine particulates in the air, causing harmful health outcomes for nearby communities (Andreae & Merlet, 2001; L. Zhang et al., 2016; Chen et al., 2017; Lai et al., 2018; Rangel & Vogl, 2019; He et al., 2020). Since there is also compelling evidence that exposure to poor air quality can result in cognitive impairment (Currie, Neidell, & Schmieder, 2009; Sanders, 2012; Bharadwaj et al., 2017; Almond et al., 2018), the prevalence of agricultural burning in many countries suggests that cognitive impacts may be widespread in such rural communities. Focusing on Brazil, the purpose of this paper is to estimate the long-run causal effects of foetal exposure to air pollution from agricultural fires on students' academic performance in 5th grade (aged 10) national examinations.

A growing body of research has shown the *contemporaneous* effects of agricultural fires on cognitive outcomes of the elderly (Lai et al., 2018), on mortality rates (He et al., 2020), and on students' scores in university entrance examinations (Graff-Zivin et al., 2020), while Rangel & Vogl (2019) examine the effects of such fires on health at birth. However, to the best of our knowledge the effects of prenatal exposure to air pollution from agricultural burning on pupils' scores *later in life* have yet to be examined.[1] Filling this gap is challenging for several reasons. First, air pollution levels may be correlated with students' performance since parents may choose their residence according to the air quality of the region. Second, seasonal agricultural fires may raise farmers' productivity and incomes, and thus may affect students' cognitive performance by allowing parents to invest more in their children. Finally, sugarcane is harvested in Brazil in the winter, hence seasonality in weather conditions and winter-related diseases could potentially result in a spurious correlation between fires and foetal health. [2]

To address these challenges we follow Rangel & Vogl (2019) and interact fires with wind direction enabling us to predict spatial variation in the dispersion of smoke without being directly related to prenatal health or students' scores. As such, we are capable of causally evaluating the different cognitive outcomes of agricultural burning on pupils born upwind and downwind of the fires. Our study contributes to the literature in three ways.

[1] Other works have investigated the prenatal exposure to air pollution on students' performance but not in the context of agricultural fires. For an extensive literature review (Currie et al., 2014; Almond et al., 2018).

[2] Although a number of studies in the medical literature show a negative effect of biomass burning on health (Arbex et al., 2004; Cançado et al., 2006; Ribeiro, 2008; Uriarte et al., 2009), or its positive impact on asthma hospitalisations (Arbex et al., 2007) in Brazil, these studies still fall short of showing a causal relation by failing to disentangle the confounding effects of other health determinants that are also correlated with controlled fires.

First, while Rangel & Vogl (2019) examine the short-term effects of prenatal exposure to agricultural fires on babies' health, we provide the first analysis of the longer term effects (pupils' scores in the 5^{th} grade). Second, we focus on the effects of fire-induced *air pollution* on human health and hence show the mechanism through which fires affect health. To this end, we utilise an instrumental variable approach using counts of fires upwind from the population centroid of the municipality in which each student attended school, which arguably provides plausibly exogenous shocks to air pollution [3]. Finally, we examine fine particulate matter ($PM_{2.5}$)[4], which is the main by-product of agricultural burning and is recognised as having a stronger negative link with health and human capital than PM_{10} used in previous work (Zanobetti & Schwartz, 2009).

In a similar approach to ours, He et al. (2020) use the differences between upwind and downwind fires in China as instruments for air pollution to estimate the effects of straw burning on mortality. Our study is also related to Graff-Zivin et al. (2020) who investigate the effects of smoke from fires on the day of the Chinese university entrance examinations on candidates' performance, but their study is unable to establish the causal relation between air pollution and students' cognitive outcomes due to a lack of pollution data at the exact moment of the exams. Finally, we complement Bharadwaj et al. (2017) and Isen et al. (2014) by calculating the returns to cleaner air quality in terms of examination scores and, in turn, wages in Brazil.

More generally, this paper contributes to an extensive body of literature that relates the impact of air pollution to negative health outcomes (Seaton et al., 1995; Chay & Greenstone, 2003; Currie & Neidell, 2005; Ebenstein et al., 2017); to a decrease in the productivity of low and high-skilled workers' (Chang et al., 2016; Heyes et al., 2016; Archsmith et al., 2018; Chang et al., 2019; Kahn & Li, 2019); to an increase in school absenteeism (Currie, Hanushek, et al., 2009; Ransom & Pope, 2013; S. Chen et al., 2018; Liu & Salvo, 2018); and to a decrease in cognitive performance (Currie, Hanushek, et al., 2009; Zweig et al., 2009; Reyes, 2011; Ebenstein et al., 2016) due to its harmful effects on the respiratory and cardiovascular systems (Dockery et al., 1993; Seaton et al., 1995). Our work also adds to the foetal origins hypothesis (FOH) literature (Sanders, 2012; Currie, Neidell, & Schmieder, 2009; Currie et al., 2014; Bharadwaj et al., 2017; Almond et al., 2018) insofar as we aim to demonstrate the long-run damages caused by air pollution derived from agricultural fires during pregnancy in locations where concentrations of $PM_{2.5}$ would not traditionally have been considered to be high. Indeed, our data from the Brazilian Institute of Geography and Statistics (IBGE), indicates that around 61%

[3] Although we have secondary data on the place of birth, we cannot merge it with our main education data set. Therefore, we use each municipality's population centroid where the student attended school as a plausible proxy for municipality of birth since we calculate that 92% of students interviewed by the *Educational Census* in 2011 lived in the same municipality they were born. Section 4 presents more detailed explanation on this migration issue.

[4] $PM_{2.5}$ refers to fine aerosol particles with a diameter of less than or equal to 2.5 micrometers (μm) near the surface.

of fires take place on agricultural land. [5]

For our analysis we build an individual-level pooled cross-sectional data set with infants born between 2001 and 2008 in São Paulo state, Brazil which we merge by month, year of birth and municipality of residence with the location of the active fires. To control for atmospheric conditions that could also affect intrauterine health, we use satellite re-analysis data, with which we also construct our air pollution measures and main variables of interest. These consist of the counts of fires by upwind and downwind direction. In our setting and consistent with existing research, we find an impact of agricultural fires on students' performance, where an increase of 1SD of fires occurring during the prenatal phase decreases students' scores by 0.0339SD in Portuguese and 0.0317SD in Maths, with boys more negatively impacted than girls. We also find evidence that weaker pupils are significantly more sensitive to prenatal burning exposure in terms of both subjects. In addition, we show the impact of agricultural burning on higher levels of $PM_{2.5}$ and of this on reduced scores later in life. One can observe that an increase of 1 $\mu g/m^3$ of $PM_{2.5}$ during the first trimester of pregnancy causes a reduction in Portuguese and Maths scores by 0.021SD and 0.0167SD; the rise in the exposure to particulate matter during the third gestational period appears to decrease scores in Portuguese by 0.0266 and Maths by 0.0274SD. Back-of-the-envelope calculations indicate that a reduction of 10% of $PM_{2.5}$ during the whole gestational period would increase test scores by in Portuguese 1.3% and by 0.9% in Maths. Using previous estimates on returns to schooling this suggests a 2.6% fall in wages later in life. These findings are in line with the economics and medical literature on the harmful effects of foetal exposure to air pollution to the foetus' brain development, particularly during the first and third trimester (Rice & Barone Jr, 2000; Sunyer & Dadvand, 2019; McGuinn et al., 2020).

The remainder of this paper is organized as follows. In the next section we present a scientific background on foetal exposure to air pollution and agricultural fires in Brazil. In Section 3 we describe the data, while Section 4 details the empirical strategy. Results are presented in Section 5, and subjected to sensitivity analysis in Section 6. We provide heterogeneity and economic significance analysis in Sections 7 and 8. The final section concludes.

[5]The rest is spread across urban areas (3.2%), grazing (15%), forestry (15.3%), with the remaining fires being spotted in forests and other fields. To make these calculations, we overlay our fires data from NASA/FIRMS with land coverage data from the agricultural census from 2010 available at the IBGE website.

2 Background

2.1 Agricultural burning and air pollution in Brazil

In response to a national and international rise in demand for bio-fuel and sugar, São Paulo state more than doubled its share of area designated to sugarcane production from 10% to 23% during the past two decades, accounting for two thirds of all Brazilian production (McConnell et al., 2010; Rangel & Vogl, 2019). Figure 2 illustrates the rate of fire burning during the period of births that we consider in this paper (2001-2008). [6] The harvesting season for sugarcane starts in April until November, when the farmers set controlled fire to the fields to crop the cane (Fernandes, 1988; Kirchhoff et al., 1991; Rangel & Vogl, 2019). Usually the fires burn from a few hours to 24 hours during the peak (Lamsal et al., 2017).

We focus our attention on sugarcane since the bulk of the fires take place in areas dedicated to this crop. Nonetheless, there are others crops that also use the burning technique, such as maize, rice and wheat. Figure 3 provides sugarcane production as a share of total cultivated land in all municipalities in São Paulo while Figure 4 indicates that sugarcane plantation has increased since 2000, at the expense of the other three products. Furthermore, we can notice from Figure 1 that the areas with more fires coincide with the hot spot areas of sugarcane.

Sugarcane fires can cover large areas, emitting aerosols such as poly-cyclic aromatic hydrocarbons (PAHs), organic and black carbon, sulfur dioxide (SO_2), ozone (O_3), carbon monoxide (CO), nitrogen oxides (NOx) and particulate matters ($PM_{2.5}$ and PM_{10}) which are carried by wind often towards surrounding populations (Guoliang et al., 2008; Akagi et al., 2011; Wu et al., 2018). According to the United States Environmental Protection Agency (EPA), $PM_{2.5}$ is the main pollutant released from agricultural burning, whereas emissions of SO_2, NOx and CO are relatively minor (Y. Zhang et al., 2013). The formation of O_3 depends non-linearly upon temperature, solar radiation and other precursors and is a by-product not instantaneously found from biomass burning (Jaffe et al., 2013; Rangel & Vogl, 2019). This feature makes straw burning a rather suitable source of air pollution to analyse given that we know the exact location of the fires, but also the fact that agricultural fires are close to populated regions, raising much greater concerns about human capital impacts than is the case for wild fires which generally take place in more remote areas.

[6] From Figures A1 and A2, one can also observe the time series pattern. Since 2007, several agro-environmental protocols have been enacted aiming at regulating environmental degradation from agricultural activities. The Green Ethanol Protocol (SIMA, 2017), issued in 2017, restricts sugarcane straw burning.

2.2 Air pollution and intrauterine development

Several studies have investigated the harmful impacts of prenatal exposure to air pollution on infant health and cognitive performance (Almond & Edlund, 2009; Sanders, 2012; Bharadwaj et al., 2017; Almond et al., 2018). As the brain requires large amounts of oxygen to function well, studies have suggested that cognitive performance is likely damaged as a result of both short and long-term exposure to air pollutants (Calderón-Garcidueñas et al., 2008). Other works associate exposure to air pollution with a decrease in total gray and white matter volumes (Erickson et al., 2020). McGuinn et al. (2020) find links between foetal exposure to $PM_{2.5}$ and behavioral development in children from Mexico City. Dix-Cooper et al. (2012) show that a decrease of children's neurodevelopmental performance in rural Guatemala is associated with prenatal and postnatal exposure to carbon monoxide from woodsmoke. As prebirth represents critical periods of vulnerability for the developing nervous system, Rice & Barone Jr (2000) show that cognitive damage may last from utero to teens. Sunyer & Dadvand (2019) demonstrate the negative impacts of foetal exposure to pollution on brain development during the first trimester .

3 Data

We build a repeated individual-level cross-sectional data set of monthly air quality, weather conditions, agricultural fires and students' scores in the fifth grade in São Paulo state. As our data set come from the satellites Terra and Aqua, which started to operate between 1999 and 2002, we choose to examine cohorts of students born between 2001 and 2008. Furthermore, we opt for remote sensing data instead of ground-based monitoring stations since the agricultural fires are predominantly located within rural areas, in which pollution and meteorological stations were scarce during our time period of analysis.

3.1 Fires

We collect daily remote-sensing data on agricultural fires from the National Aeronautics and Space Administration (NASA)'s Fire Information for Resource Management (FIRMS). The data are captured by two satellites TERRA and AQUA which rely on Moderate Resolution Imaging Spectroradiometer (MODIS) sensors to detect ground-level fire activity. Each satellite overpasses Brazil twice per day (morning, afternoon, evening and night) (Kaufman et al., 1998; Justice et al., 2002). The fire detection algorithm developed by researchers at the University of Maryland is built upon thermal anomalies, surface reflectiveness, water, cloud masking and land use, and the publicly available data is provided at a resolution of 1km x 1km (Giglio et al., 2009, 2016). Notwithstanding, it is not possible to know the precise size of each fire from the data (Giglio et al., 2009).

Thus, we consider and count fires in neighbouring pixels individually (Graff-Zivin et al., 2020).

The dataset also provides the confidence of detection for each potential fire identified by the satellites. That is, each fire receives a probability of occurrence (from 0% to 100%) according to the meteorological conditions and vegetation at the exact time the fire was detected (Giglio et al., 2016). As a result, in our specifications we use the fire weighted by its confidence to minimise classical measurement error (Rangel & Vogl, 2019; Graff-Zivin et al., 2020).

A fire is attributed to a student if it occurred within a catchment area of 50km radius of her municipality's centroid. [7]. Unfortunately, we do not know the municipality of birth of each individual. Hence, we use the centroid of the municipality where the pupil lives when she takes the exams as a plausible proxy for the exact location of birth as the majority of students do not usually migrate. [8] Although we have secondary data on the place of birth, we cannot merge it with our main education data due to the lack of unique students' identifiers in both data sets. Alternative distances are also used and presented in the robustness checks section.

In Table 1, we report the summary statistics for agricultural fires by wind direction at the trimester level used for the whole period of the main estimation sample (2001-2008). Also, Figures 2 and A1 present the time series behaviour of monthly average fires for that period. From these figures we can observe a strong seasonal pattern of fires with peaks in the winter months, and a not very clear time trend. The seasonality of fires coincides with the agricultural phases, corroborating the link between the sugarcane harvesting period and the peak in identified burning sites.[9]

3.2 Weather Conditions

We use the Japanese 55-year Re-analysis (JRA-55) data on atmospheric conditions. The JRA-55 is the second Japanese global atmospheric re-analysis project conducted by the Japan Meteorological Agency (JMA), covering data back to 1958. Re-analysis uses past climatic observations from satellite and terrestrial monitoring stations, as well as meteorological models to systematically produce data sets for climate monitoring and research.[10]

We gather gridded daily data on temperature in Kelvins (which we transform to degrees Celsius (^0C)), precipitation (in millimeters, mm), relative humidity (in percentage,

[7]As in Rangel & Vogl (2019), we exclude fires within 5km from the municipality population centroid since they are unlikely to stem from agricultural sources

[8]Section 4 presents more detailed explanation of this migration issue.

[9]In Figure A2, we present the overall time series behaviour from 2001 until 2017, i.e., we add the period ranging from 2009 to 2017 since the students took exams from 2011 to 2017.

[10]Auffhammer et al. (2013) provide a thorough discussion on the consistency of re-analysis data for economics studies.

%), wind components and cloud coverage (in percentage, %). Apart from the latter, these weather conditions may influence the way air pollution geographically spreads. As such, we include them as control variables in our models. Regarding cloud coverage, it is important since the satellite imagery for fire detection is negatively related to the amount of cloud in the sky. That is, the detection of small fires may be hindered by thicker clouds [11] (He et al., 2020). The spatial resolution of each grid is 0.56° x 0.56°, and the data are 3-hourly that we average by day per grid and then aggregate to the average at the trimester level. To construct the variables for wind conditions we use the vector decomposition method and calculate the prevalent wind per trimester (Grange, 2014; Rangel & Vogl, 2019).

3.3 Air Pollution

The pollutants and other chemical elements, such as $PM_{2.5}$, Carbon Monoxide (CO), Sulfate (SO_4), Ozone (O_3), Black Carbon (BC) and Organic Carbon (OC), dust (DS) and sea salt (SS), utilised in this work come from the second Modern-Era Retrospective analysis for Research and Applications (MERRA-2), provided by NASA and built upon a plethora of data sources, such as remote sensing imagery and terrestrial stations. The gridded data available has a spatial resolution of 0.5° x 0.625° and comes in hourly intervals, which we aggregate to daily and trimester frequency. To this end we implement the same procedure as for the weather variables; i.e., we first average per day, then we calculate the quarterly average.

$PM_{2.5}$ is not directly available from the Merra-2's data set and so is calculated using the formula below (Buchard et al., 2016; Provençal et al., 2017).

$$PM_{2.5} = 1.375 * SO_4 + 1.8 * OC + BC + DS + SS \tag{1}$$

where SO_4, OC, BC, DS and SS are measured in kilogram per cubic meter (kg/m^3), which we finally transform to micro-gram per cubic meter (μ/m^3). Our calculated $PM_{2.5}$ concentrations are consistent with those observed by terrestrial monitoring stations.

Table 1 presents the descriptive statistics for our main estimation sample with 1,190,717 students. The average quarterly concentration of $PM_{2.5}$ in our sample is 14.3 $\mu g/m^3$, with a maximum concentration of 59.5 $\mu g/m^3$ and a standard deviation of 4.24. [12] Table 1 also shows the number of fires similarly distributed per wind direction, indicating the randomness of the latte during the burning periods.

[11] We include cloud coverage in our estimations and, as robustness checks, we show that the results remains similar when not accounting for cloud coverage.

[12] To put these figures in context, the World Health Organisation guidelines state that annual mean exposure to $PM_{2.5}$ should not exceed $5\mu g/m^3$ (reduced from 10 $\mu g/m^3$ in 2021) and 24 hour mean exposure should not exceed $15\mu g/m^3$.

Table 1: Descriptive Statistics

Variables	Mean	SD	Min	Max
Scores				
Portuguese	219	47.8	84.9	339
Maths	234	47.5	78.92	367
Pollutants (trimester avg.)				
$PM_{2.5}$ ($\mu g/m^3$)	14.3	4.24	4.64	59.5
CO ($\mu g/m^3$)	0.25	0.096	0.062	0.92
O_3 ($\mu g/m^3$)	57.87	9.44	38.46	95.3
Agricultural Fires (trimester avg.)				
Upwind	4.57	8.12	0	98
Downwind	6.23	9.55	0	109
Vertical	31.40	33.97	0	279
Meteorological Conditions (trimester avg.)				
Rain (mm)	2.73	2.66	0.00	92.4
Temperature (^0C)	22.2	2.69	13.4	35.6
Wind Speed (m/s)	2.05	0.77	0.13	8.52
Cloud coverage (%)	40.4	13.1	6.24	99.9
Humidity (%)	70.3	8.54	25	97.6
Students' Characteristics (%)				
Female	50.3			
Male	49.7			
White	37.7			
Mixed	30.5			
Black	17.7			
Asian	2			
Indigenous	2.2			
Non-declared	9.9			
Father's Education				
Low	44.2			
High	14.1			
Non-declared	42.8			
Observations	1,190,717			
Municipalities	645			

Notes: Summary statistics of some of the key variables: scores range from 0 to 350 points for Portuguese and 0 to 400 points for Maths, counts of agricultural fires and meteorological conditions during pregnancy (from 2000 to 2008) in the municipalities in the State of São Paulo. For father's level of education, we consider low if the below UG level and high with UG or above. The fires locations are defined within 45 degrees from the daily prevalent wind direction in a municipality.

3.4 Education

Our data on students' exam scores come from the National Institute for Educational Research *Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira* (INEP), an agency from the Brazilian Ministry of Education. Every two years the students in the fifth grade pass a nationwide examination to assess the quality of education in Brazil (*Prova Brasil)* via tests and socioeconomic questionnaires (INEP, 2017). This forms a rich administrative data set with detailed information on the students' scores in Portuguese and Mathematics, demographic information, such as their age, race and gender, as well as parental level of education. From this data we build a repeated pooled cross-section at the student level with cohorts taking examinations from 2011 to 2017 (Table 1 summarises this information). The Portuguese scores range from 0 to 350 points, and Maths from 0 to 400 points, and, in our regressions, we follow the literature and use these scores in standard deviation form as dependent variables (Garg et al., 2020). In addition, we include cohorts of students taking the fifth grade exams in 2011, 2013, 2015 and 2017. As for the year of birth, the children in our data set were born from 2001 to 2008.[13]

4 Empirical Strategy

First, we examine the long-term impacts of foetal exposure to agricultural fires on students' scores in the 5^{th} grade (reduced form). Second, to show that air pollution is the channel through which fires affect cognitive performance we estimate the partial correlation between agricultural fires and air pollution (first stage) and, finally, the impacts of being exposed *in utero* to air pollution from these fires on students' outcomes later in life (second stage).

4.1 Prenatal exposure to fires and students' scores

To estimate the effects of prenatal exposure to agricultural fires on students' scores we start by using the following basic equation:

$$Scores_{jmi} = \beta fires_{mi} + \psi W_{mi} + \alpha X_j + \mu_m + \iota_i + \theta_t + \epsilon_{jmi} \tag{2}$$

where $Scores_{jmi}$ is the standardised 5^{th} grade test score in either Portuguese or Maths of child j born in municipality m, at time i. The term $fires_{mi}$ denotes the number of fires in a municipality at the trimester level in SD for ease of interpretation. We include W_{mi}, a vector of weather condition controls during pregnancy, such as temperature,

[13] Although the students also take tests in the ninth grade, we do not include these cohorts in our analysis. Firstly because the data for the ninth graders are less complete. Secondly, the dropout and repetition rates for older students are far higher than for younger ones, hence, there would be pupils born well before 2001, i.e., the first year of our satellite data.

relative humidity, wind speed, cloud coverage and rainfall per trimester. To allow for non-linearity in the effect of temperature on scores we create five temperature bins between less than 15 and more than 35 degrees (5 degree bins) in our main specification but also, for completeness, experiment with using temperature in the linear form, squared, and interacted with other weather variables (Deschênes et al., 2009). The term X_j is a vector of controls for observable individual characteristics that can be related to their exam scores, such as the father's highest level of education[14], students' race and gender. The term μ_m accounts for municipality fixed effects, while ι_i is a vector controlling for month and year of birth fixed effects. The latter accounts for unobserved time-invariant municipality and cohort characteristics, and θ_t controls for the year of the exam.

Standard errors in Equation 2 are clustered by municipality to control for spatial and serial correlation within each locality. Although we do not have the exact place of birth, we believe that using the municipality where the student attended school as a proxy for municipality of birth is reasonable enough since the *Educational Census* assesses that 92 percent of children did not move location between birth and the exam year.

A concern that arises with the above approach is that agricultural burning could be related to positive temporary income shocks for local families who have an increase in income during the harvesting season, which would also affect foetal health and students' scores as a result via the income channel. More precisely, as seasonal agricultural fires increase both farmers' productivity and revenues, it may affect students' academic performance since the overall household income increases, allowing parents to invest more in their children. Furthermore, sugarcane is harvested in São Paulo in the winter, hence seasonality in weather conditions and winter-related diseases could cause a spurious correlation between fires and foetal health.

Another challenge to the identification strategy above relates to the fact that students' exam scores may be correlated with air pollution from agricultural fires since wealthier parents could choose to live in less polluted areas (Banzhaf & Walsh, 2008; Currie et al., 2014). This location choice is a form of avoidance behaviour which may bias our estimations (Neidell, 2004, 2009; Bharadwaj et al., 2017; Carneiro et al., 2021). In addition, our meteorological data set, which is produced by re-analysis modelling, may bias our estimates if children's actual exposure to outdoor air pollution differs from the forecast readings in our data. Hence, our IV approach detailed below is also intended to address this classical measurement error problem (Moretti & Neidell, 2011; Schlenker & Walker, 2015; S. Chen et al., 2018). [15]

To address the aforementioned potential biases we follow Rangel & Vogl (2019) and

[14]We do not have the years of education of the student's parents. Rather, the original micro-data provides the highest level of education achieved by them. As such, we build dummies indicating each of these levels.

[15]Pollution levels and weather conditions on exam days are unlikely to influence the scores via examiners' productivity since all the tests are mechanically marked.

adopt the following model as our main specification:

$$\begin{aligned} Scores_{jmi} = \beta_0 upwindfires_{mi} + \beta_1 downwindfires_{mi} + \psi W_{mi} + \alpha X_j + \\ \mu_m + \iota_i + \theta_t + \epsilon_{jmi} \end{aligned} \tag{3}$$

In this reduced form, $\beta_0 upwindfires_{mi}$ is the count of agricultural fires in the upwind direction of a municipality centroid, and $\beta_1 downwindfires_{mi}$, fires located in the opposite direction. Our parameter of interest is the difference between β_0 and β_1, which we expect to be negative, and unveils the causal relation between fires and cognitive performance. That is, we take advantage of the fact that upwind fires have a stronger negative impact on air pollution than downwind fires, while wind direction is plausibly exogenous not affecting income and students' scores. Therefore, we expect β_0 minus β_1 to be negative, i.e., students' born upwind from the fires are more negatively affected than their counterparts born downwind.

To build our fire variables, we follow Rangel & Vogl (2019); He et al. (2020); Graff-Zivin et al. (2020) and count the daily number of fires within 50km of a municipality's centroid. Alternatively we also consider fires detected within the same wind octant in a day to be upwind, fires located in the opposite octant to be downwind, and all the remainder fires are defined as vertical, setting a 45^0 angle. As such, we define upwind fires as those located within a 45 central angle from the average daily wind direction within each municipality. In other words, upwind fires have the smoke blowing towards the municipality's centroid. Downwind fires are located in the opposite direction, while we call the ones situated in the other directions vertical fires. The rationale of this classification is that municipalities situated upwind from fires are exposed to more air pollution coming from the fires than downwind locations, whereas the air pollution in the municipalities located in the vertical direction is less influenced by smoke than the upwind villages, but more affected by fires than their downwind counterparts. [16]

4.2 Mechanisms: agricultural burning, air pollution and students' scores

We now turn our attention to the air pollution channel through which agricultural fires may impact cognitive performance. To do so we start by estimating the effect of sugarcane burning on air pollution (first stage) and then the impact of the foetal exposure to it on students' scores (second stage).

[16] In our sensitivity analysis section we aggregate vertical and downwind directions to form an alternative set of analysis since these directions present similar behaviour; and use other angles to define upwind fires. All results remain very close to the main specification.

4.2.1 The instrumental variable approach

We utilise our fire variables constructed via the analysis above as instruments for air pollution and estimate the effects of prenatal exposure to air pollution on students' scores by pooling our individual-level cross-sectional data for the exams occurring 2011-2017. The structural equation is as follows:

$$Scores_{jmi} = \phi pollutant_{mi} + \psi W_{mi} + \alpha X_j + \mu_m + \iota_i + \theta_t + \epsilon_{jmi} \tag{4}$$

where the terms in Equation 4 are defined as in Equation 2, except for *pollutant*, which is the average level of pollution at the trimester and municipality levels. Our study focuses on the effect of the pollutant $PM_{2.5}$ on cognitive performance, although in robustness exercises we include O_3 and CO as co-pollutants.

Our main assumption relies upon the exogeneity of the upwind/downwind fires since they do not directly affect the children's cognitive performance, except from their effect on air pollution. As such, our approach can be considered as a natural experiment that utilises exogenous shocks to local air pollution in a specific area (Schlenker & Walker, 2015; Anderson, 2015; Deryugina et al., 2019; Graff-Zivin et al., 2020; He et al., 2020; Carneiro et al., 2021). Our model can be formally described as:

$$\begin{aligned} Pollutant_{mi} = \gamma_0 upwindfires_{mi} + \gamma_1 downwindfires_{mi} + \psi W_{mi} + \alpha X_j + \\ \mu_m + \iota_i + \theta_t + \epsilon_{mi} \end{aligned} \tag{5}$$

$$Scores_{jmi} = \beta \widehat{Pollutant}_{mi} + \omega W_{mi} + \rho X_j + \nu_m + \lambda_i + \delta_t + \eta_{jmi} \tag{6}$$

where Equation 5 is identical to Equation 3, except for the outcome variable, which here is the pollutant measure (in $\mu g/m^3$) linked to students *j*, in municipality m and time of birth *i*. The main explanatory variable in Equation 6 is $\beta \widehat{Pollutant}_{mi}$, which is the predicted value from Eq. 5. The coefficient of interest in Equation 5 is γ, which provides the estimated effect of upwind fires on $PM_{2.5}$. The pollution level and weather controls correspond to the average during each of the three trimesters of pregnancy while the fire count is the amount of fires in each trimester. In Equation 6, we are interested in β as it reports the estimated causal effects of pollution on pupils' scores.

4.2.2 Identification concerns

A limitation of our analysis relates to the lack of information on the conception date, therefore, we cannot precisely establish the trimesters of pregnancy. For instance, if there are more preterm births in the second instead of the third trimester (Heft-Neal et al., 2021), then this would mean that we are classifying some students incorrectly, i.e., we are assuming that their first trimester is earlier than it really is. If so, this would then lead to some measurement error in all three trimesters. Nonetheless, our results can be interpreted in light of the overall harmful effects of foetal exposure to burning pollution.[17]

Another concern is that people may migrate to avoid air pollution, which could also bias our estimates. To demonstrate that our estimates are unlikely to be affected by migration, we used secondary data from the Education Census of the Ministry of Education in Brazil and from the Education Assessment on the Quality of Education in the State of São Paulo (SARESP). According to these secondary data sets, 92% of students who responded to the Census questionnaire were still living in the same municipality of birth. The remaining 8% lived around 8km from the school and were born in locations at maximum 44km away from the municipality where they attend school, with 90% living less than 23km away. Furthermore, from the SARESP data set, we calculate that roughly 82% of respondents who knew where the mother lived for the last 10 years were born in the same location where they attended school. That is, their mothers did not migrate during pregnancy.

Lastly, a limitation for studies on foetal shocks effects later in life is how to address the influence of time-varying investments in human capital parents may make to overcome prenatal exposure to pollution, which is not possible to control for in our sample (Bharadwaj et al., 2017; Almond et al., 2018). Nonetheless, other works have shown that the compensating parental responses present very small effects (Bharadwaj et al., 2013; Halla & Zweimüller, 2014; Bharadwaj et al., 2018). Any unobservable investments that parents make to compensate cognitive impairments stemming from *in utero* pollution exposure will be contained in our error term and represent another negative externality from air pollution.[18]

5 Results

5.1 The effects of agricultural fires on academic performance

Table 2 reports the results for our main model (Eq. 3) which estimates the impacts of foetal exposure to agricultural fires on students' performance. All models include flexible weather controls, and the equations include the number of fires (weighted by their probability of occurrence) by wind direction (in SD). We start by presenting our estimates for Eq. 2 in Columns 1 and 2, where we count the fires together irrespective of wind direction. We find the effect of fires on both Portuguese and Maths to be negative and statistically significant in the first and third trimesters. Columns 3 and 4 report the results from our main specification, in which we categorise fires according to wind

[17] Rangel & Vogl (2019) also face this caveat when estimating the impact of fires on birth outcomes in São Paulo and focus their attention on the third trimester of pregnancy.

[18] Almond et al. (2018) reports a thorough review of the literature on foetal shocks.

direction, per trimester of pregnancy. We show that an increase of one SD in the difference between the number of upwind and downwind fires in the first trimester leads to a decrease of 0.0159SD in Portuguese and 0.0196 in Maths scores; 0.0098SD decrease in Portuguese due to exposure during the third trimester and no significant effect found for Maths during the third trimester. The bottom part of the Table presents the sum of coefficients for the three gestational periods, from which we can see that an increase in 1SD in the fires occurred during the prenatal phase decreases students' scores by 0.0339SD in Portuguese and 0.0317SD in Maths. Thus, despite some measurement error from potential trimester misclassification (due to lack of data on pre-births and/or conception date), altogether, the whole pregnancy period effects (the sum of the three trimesters) are substantial and significant, revealing the negative impacts of foetal exposure to students' outcomes later in life.

Our findings are in line with the literature on the impacts of prenatal exposure to air pollution on cognitive impairment. Several studies have shown a negative association between poor air quality during pregnancy and brain cell formation mainly during the first and third trimesters of pregnancy (Woody & Brewster, 1990; Ikonomidou et al., 1999; Sunyer & Dadvand, 2019), effects that may last from utero to chilhood and teens (Rice & Barone Jr, 2000; Dix-Cooper et al., 2012). The economics research also sheds light on the negative impacts of foetal exposure to pollution and later life academic performance (Currie, Neidell, & Schmieder, 2009; Bharadwaj et al., 2017).

5.2 Mechanisms

5.2.1 Relevance of upwind and downwind fires as instruments

Since we have three endogenous variables - the average $PM_{2.5}$ by trimester - we need three first stage equations. But, since we interact each wind direction with fires also per trimester there are enough instruments to identify the causal effect of the three endogenous variables. In Table 3 we show results for separate equations per trimester of pregnancy (Columns 1 to 3), and for equations with the three trimesters together (Columns 4 to 6). We are interested in the difference between upwind and downwind fires, which is shown to be positive and significant for all trimesters. Hence, as expected, fires located upwind increase air pollution more than downwind fires. Column 1 shows that a 1SD increase in upwind fires increases $PM_{2.5}$ by 0.439 $\mu g/m^3$ or 10% SD, 0.4775 $\mu g/m^3$ or 11% SD, and 0.2824 $\mu g/m^3$ or 7% SD during the first, second and third trimesters, respectively. The last three columns account for the three trimesters together and show similar conclusions, i.e., upwind fires are strongly causally related to the level of air pollution per trimester of pregnancy.

These first stage results confirm that upwind fires persistently affect pollution more than the other directions across the different forms for which we build the instrument set.

Table 2: Effects of agricultural fires on students' scores (SD)

VARIABLES (SD)	(1) Portuguese	(2) Maths	(3) Portuguese	(4) Maths
All fires(1tr)	-0.029***	-0.0235***		
	(0.0063)	(0.0062)		
All fires(2tr)	0.0131	0.0176**		
	(0.008)	(0.0078)		
All fires(3tr)	-0.0147***	-0.0092*		
	(0.0045)	(0.0048)		
Upwind(1tr)			-0.0146***	-0.0149***
			(0.0028)	(0.0039)
Downwind(1tr)			0.0013	0.0047
			(0.0052)	(0.006)
Upwind(2tr)			0.0011	0.006*
			(0.0033)	(0.0032)
Downwind(2tr)			0.0092	0.0082
			(0.0073)	(0.0073)
Upwind(3tr)			-0.0076***	-0.0068**
			(0.0029)	(0.0032)
Downwind(3tr)			0.0023	0.0031
			(0.0047)	(0.0048)
Upwind-downwind(1tr)			-0.0159**	-0.0196**
			(0.0067)	(0.009)
Upwind-downwind(2tr)			-0.0081	-0.0022
			(0.0077)	(0.0081)
Upwind-downwind(3tr)			-0.0098*	-0.0099
			(0.0061)	(0.0065)
Upwind-downwind			-0.0339***	-0.0317**
(Whole pregnancy)			(0.0119)	(0.0137)
Observations	1,187,660	1,187,660	1,187,660	1,187,660
R-squared	0.143	0.122	0.143	0.122
Municipality FE	Y	Y	Y	Y
Month and year birth FE	Y	Y	Y	Y
Year exam FE	Y	Y	Y	Y
Weather	Y	Y	Y	Y

Notes: Robust standard errors in parentheses clustered by municipality centroid. All models control for municipality FE, year of exam, month and year of birth, and students' controls. Estimates for controls not shown: temperature bins, rainfall and its square, relative humidity and its square, wind speed and cloud coverage. Upwind and downwind direction account for the sum of fires (weighted by confidence) upwind and downwind from the municipality centroid (in SD). Upwind-Downwind stands for the difference between the coefficients of the respective directions. *** p<0.01, ** p<0.05, * p<0.1.

This reinforces the main assumption that we rely on that local air quality is more affected by fires located upwind from the municipality's population centroid. In addition, and in line with previous research, these findings suggest that poor air quality is the channel through which agricultural fires affect humans' cognitive health (Lai et al., 2018; He et al., 2020; Graff-Zivin et al., 2020).

5.2.2 Impact of air pollution on students' scores (Second Stage)

Table 4 reports the results regarding the effects of $PM_{2.5}$ on students' scores for each trimester of pregnancy. We start by presenting our OLS estimates of Portuguese and Maths scores (Columns 1 and 2). These results show that $PM_{2.5}$ in the first and second trimesters seem to have a positive impact on Portuguese and on Maths, and no effects on the third gestational period. However, for the reasons explained above, OLS estimates are likely biased.

We therefore turn to our specifications using the counts of upwind and downwind fires as instrumental variables (Columns 3 and 4). One can observe that an increase of 1 $\mu g/m^3$ of $PM_{2.5}$ during the first trimester of pregnancy causes a reduction in Portuguese and Maths scores by 0.0205SD and 0.0167SD; the rise in the exposure to particulate matter during the third gestational period appears to decrease scores in Portuguese by 0.0266 and Maths by 0.0274SD. The increase in the exposure to poor air quality during the second trimester, although positive, does not seem to significantly affect students' performance. These results relating to earlier gestational periods are not as surprising as one might think since the literature points to the existence of selection bias when it comes to backwards dating of exposure to air pollution and the exact date of birth. Thus, this is a recurrent issue in several works on *in utero* shocks. For example, Rangel & Vogl (2019)'s findings also suffer from the same limitation. These results are in line with the medical and economics literature on foetal exposure to air pollution and cognitive performance (Rice & Barone Jr, 2000; Dix-Cooper et al., 2012; Currie et al., 2014; Almond et al., 2018; Sunyer & Dadvand, 2019; McGuinn et al., 2020).

When we look at the bottom part of the table, altogether, an increase of 1 $\mu g/m^3$ of $PM_{2.5}$ during the whole gestational period, leads to a significant and sizeable drop in students' scores by 0.04SD in Language and by 0.031SD in Maths. With regard to this, the literature shows evidence that different parts of the brain perform different functions with white matter being linked to language and verbal reasoning skills and gray matter associated with mathematical skills (Popescu et al., 2019; Houston et al., 2019). In addition, pollution affects the white and gray matter differently, corroborating our findings suggesting that air pollution generates slightly different effects on exam performance by subject (Clougherty, 2010; Calderón-Garcidueñas et al., 2011; Erickson et al., 2020; Graff-Zivin et al., 2020; Carneiro et al., 2021).

Table 3: Impact of fires on particulate matter (First Stage)

Dep. Var. ($\mu g/m^3$)	(1) $PM_{2.5}$_1tr	(2) $PM_{2.5}$_2tr	(3) $PM_{2.5}$_3tr	(4) $PM_{2.5}$_1tr	(5) $PM_{2.5}$_2tr	(6) $PM_{2.5}$_3tr
Upwind_1tr	0.563***			0.527***	-0.220***	-0.000534
	(0.0487)			(0.0599)	(0.0432)	(0.0439)
Downwind_1tr	0.124			0.167***	-0.176***	-0.0907**
	(0.0664)			(0.0439)	(0.0430)	(0.0398)
Upwind_2tr		0.500***		0.117***	0.479***	-0.112***
		(0.0773)		-0.0297	(0.0696)	(0.0415)
Downwind_2tr		0.0225		0.138***	0.0977**	-0.0959***
		(0.0537)		(0.0296)	(0.0420)	(0.0340)
Upwind_3tr			0.404***	-0.0451	0.0879***	0.382***
			(0.0331)	(0.0441)	(0.0255)	(0.0295)
Downwind_3tr			0.121**	-0.166***	0.249***	0.137***
			(0.0573)	(0.0506)	(0.0506)	(0.0496)
Upwind-downwind (1tr)	0.439***			0.36***	-0.044	0.091
	(0.1017)			(0.08)	(0.064)	(0.0738)
Upwind-downwind (2tr)		0.4775***		-0.0205	0.3818***	-0.0166
		(0.1199)		(0.0466)	(0.0931)	(0.0565)
Upwind-downwind (3tr)			0.2824***	0.1208	-0.1607**	0.2457***
			(0.0746)	(0.0816)	(0.0703)	(0.0627)
Observations	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660
R-squared	0.793	0.797	0.810	0.814	0.814	0.818

Notes: Robust standard errors in parentheses clustered by municipality centroid. All models control for municipality FE, year of exam, month and year of birth, and students' controls. Estimates for controls not shown: temperature bins, rainfall and its square, relative humidity and its square, wind speed and cloud coverage. Upwind and downwind direction account for the sum of fires (weighted by confidence) upwind and downwind from the municipality centroid (in SD). Upwind-Downwind stands for the difference between the coefficients of the respective directions. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Effects of particulate matter on students' scores (SD) - OLS and IV

VARIABLES	(1) Portuguese	(2) Maths	(3) Portuguese	(4) Maths
	OLS		IV	
$PM_{2.5}$(1tr)	0.0022**	0.0014	-0.0205**	-0.0167**
($\mu g/m^3$)	(0.0011)	(0.0013)	(0.0093)	(0.0074)
$PM_{2.5}$(2tr)	0.0123***	0.0123***	0.00690	0.013
($\mu g/m^3$)	(0.0022)	(0.002)	(0.0079)	(0.0067)
$PM_{2.5}$(3tr)	-0.0019	-0.0021	-0.0266***	-0.0274***
($\mu g/m^3$)	(0.0038)	(0.0034)	(0.0068)	(0.0076)
$PM_{2.5}$ ($\mu g/m^3$)			-0.04***	-0.031***
(Whole pregnancy)			(0.014)	(0.0126)
First stage F-test			10	10
Observations	1,187,660	1,187,660	1,187,660	1,187,660
R-squared	0.143	0.122	0.052	0.038
Municipality FE	Y	Y	Y	Y
Month and year birth FE	Y	Y	Y	Y
Year exam FE	Y	Y	Y	Y
Weather	Y	Y	Y	Y

Notes: Robust standard errors in parentheses clustered by municipality centroid. All models control for municipality FE, year of exam, month and year of birth, and students' controls. Estimates for controls not shown: temperature bins, rainfall and its square, relative humidity and its square, wind speed and cloud coverage. Instruments are the sum of fires (weighted by confidence) upwind and downwind from the municipality centroid (in SD). First stage Kleibergen-Paap rk Wald F statistic. PM_{25}_1tr, PM_{25}_2tr and PM_{25}_3tr account for their linear form for trimester 1, 2 and 3 of pregnancy measured in $\mu g/m^3$. *** p<0.01, ** p<0.05, * p<0.1.

6 Sensitivity Analysis

To assess the internal validity of our research design and results we carry out a set of robustness tests. In the first exercise, we vary the distance between the location of fires and the population centroid of each municipality, using 20 to 100 km (50km was used in the main equations). The results remain overall similar as can be seen in Tables A1 and A2. [19]

We also vary the angles used to classify students living upwind or downwind of the fires (originally, 45^0). Since wider angles capture more observations from vertical directions that are not exactly upwind, and hence more students with lower levels of exposure, our results in Table A3 show that larger angles yield coefficients with smaller magnitude than the baseline (Column 2).[20]

In Table 5, we use placebo trimesters to show that the exposure to agricultural fires in trimesters before conception and after birth do not compete with the actual gestational periods in determining test scores, confirming that our controls for time of birth and year of exam are capturing serial correlation in smoke exposure. Panels A and B report results with trimesters prior to and after birth with overall non-significant effects of fires on students' scores in both subjects. In Panel C, our estimates for four years after birth suggest that poor air quality is not overall significant.

As biomass burning contains not only $PM_{2.5}$ but also CO and O_3 in smaller proportions [21], Table 6 presents results of our estimations with the three in separate equations and as co-pollutants. One can notice that the First stage Kleibergen-Paap rk Wald F statistics for both pollutants drops below the threshold of 10. Hence, first, we use the LIML estimator for those equations. When we compare the results with co-pollutants, we notice that the main results with $PM_{2.5}$ remain overall qualitatively the same (Columns 1 and 6). Besides this, in Table 7, we report the relation between fires and the three pollutants at the municipality level, suggesting that all of them are affected by fires and wind. However, the R-squared for the equations of CO and O_3 are smaller, suggesting that these pollutants are less affected by the upwind burning than $PM_{2.5}$.

In our fifth set of robustness checks (Table A4), we present results for specifications with linear weather variables (Columns 1 and 2) to demonstrate that our baseline estimates with binned weather controls are not sensitive to different forms of meteorological controls. The results remain generally the same, indicating that our main estimates are not driven by unobserved weather conditions correlated with wind and students' performance. In addition, we show specifications using fire counts non-weighted by probability of occurrence (Columns 3 and 4) and without controlling for cloud coverage (Columns 5 and 6). From Table A4 Panels A and B, one can observe that the results remain broadly

[19] Similarly in Rangel & Vogl (2019) and He et al. (2020).

[20] Graff-Zivin et al. (2020) find similar exercise and results.

[21] $PM_{2.5}$, CO and O_3 present a pairwise correlation of 51% and 54% significant at the 5% level.

Table 5: Agricultural Fires and Students' Scores - Pre and post birth

Variables	(1) Portuguese	(2) Maths
Panel A: Trimesters prior to birth		
Upwind-downwind (-3)	-0.0028	0.0003
	(0.0077)	(0.0092)
Upwind-downwind (-2)	0.017***	0.018***
	(0.0048)	(0.0051)
Upwind-downwind (-1)	-0.0028	0.0012
	(0.0082)	(0.0087)
Observations	1,187,622	1,187,622
Upwind-downwind (Three trimesters)	0.0114	0.0206
	(0.0122)	(0.0137)
Panel B: Trimesters after birth		
Upwind-downwind (+1)	0.007	0.0002
	(0.0077)	(0.0078)
Upwind-downwind (+2)	0.0053	0.0085
	(0.0085)	(0.0085)
Upwind-downwind (+3)	0.008	0.0069
	(0.011)	(0.0098)
Observations	1,187,660	1,187,660
Upwind-downwind (Three trimesters)	0.0203	0.0156
	(0.014)	(0.0151)
Panel C: Year after birth		
Upwind-downwind (+1yr)	0.0142***	0.0183***
	(0.046)	(0.0052)
Upwind-downwind (+2yr)	-0.008	-0.0063
	(0.0044)	(0.0044)
Upwind-downwind (+3yr)	0.0105	0.01
	(0.064)	(0.007)
Upwind-downwind (+4yr)	- 0.0117	-0.0138
	(0.076)	(0.0071)
Observations	1,187,467	1,187,467
Upwind-downwind (Four years ahead)	0.005	0.0082
	(0.0118)	(0.0121)

Notes: All equations follow specification from Table 2. Panel A displays coefficients for trimesters prior to birth (Column 1 refers to Portuguese, and Column 2 to Maths as outcome variables. Panels B and C show two equations each using trimesters and 4 years after birth.

Table 6: Impacts of Carbon Monoxide and Ozone on students' scores

VARIABLES	(1) Portuguese	(2) Portuguese	(3) Portuguese	(4) Portuguese	(5) Portuguese	(6) Maths	(7) Maths	(8) Maths	(9) Maths	(10) Maths
PM25_1tr	-0.0205***			0.00515	-0.00390	-0.0167**			0.0172	-0.00947
	(0.0093)			(0.0332)	(0.0428)	(0.0074)			(0.0341)	(0.0410)
PM25_2tr	0.0069			0.0226	-0.00	0.013*			0.0323	-0.00
	(0.0079)			(0.0226)	(0.0253)	(0.0067)			(0.0241)	(0.0225)
PM25_3tr	-0.0266***			-0.0314***	-0.0379***	-0.0274***			-0.0273***	-0.0393***
	(0.0068)			(0.0081)	(0.00979)	(0.0076)			(0.00857)	(0.0120)
CO_1tr		-0.673		-0.619			-0.968**		-1.220	
		(0.450)		(0.810)			(0.443)		(0.880)	
CO_2tr		-0.993***		-2.091			-0.748*		-2.311	
		(0.378)		(1.507)			(0.432)		(1.694)	
CO_3tr		-0.493		-1.817			-0.203		-2.231	
		(0.473)		(1.846)			(0.389)		(2.010)	
O3_1tr			-0.0186*		-0.0454			-0.0258**		-0.0461
			(0.0102)		(0.0384)			(0.0119)		(0.0441)
O3_2tr			-0.0172***		-0.0311			-0.0107		-0.0197
			(0.00620)		(0.0359)			(0.00734)		(0.0396)
O3_3tr			-0.000945		-0.0144			0.000648		-0.00878
			(0.00681)		(0.0334)			(0.00615)		(0.0345)
F	10	6	11	0.6	1.3	10	6	11	0.6	1.3
Observations	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660

Notes: All equations follow specification from Table 4. First stage Kleibergen-Paap rk Wald F statistic. We estimate the equations using LIML due to the F statistics below 10. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Effects of fires on co-pollutants

Variables	(1) $PM_{2.5}$ (1tr)	(2) $PM_{2.5}$ (2tr)	(3) $PM_{2.5}$ (3tr)	(4) CO (1tr)	(5) CO (2tr)	(6) CO (3tr)	(7) O_3 (1tr)	(8) O_3 (2tr)	(9) O_3 (3tr)
Upwind-downwind (1tr)	0.252***			0.003***			0.039		
	(0.038)			(0.0004)			(0.036)		
Upwind-downwind (2tr)		0.245***			0.003***			0.106***	
		(0.040)			(0.0004)			(0.034)	
Upwind-downwind (3tr)			0.259***			0.003***			0.087***
			(0.038)			(0.0004)			(0.03)
Observations	58,050	58,050	58,050	58,050	58,050	58,050	58,050	58,050	58,050
Municipalities	645	645	645	645	645	645	645	645	645
R-squared	0.191	0.159	0.150	0.072	0.077	0.082	0.184	0.167	0.217

Notes: Robust standard errors in parentheses clustered by municipality centroid. All models control for municipality FE, month and year. Estimates for controls not shown: temperature bins, rainfall, relative humidity, wind speed and cloud coverage. *** p¡0.01, ** p¡0.05, *** p<0.01, ** p<0.05, * p<0.1.

similar.

7 Heterogeneity

In this section we explore the heterogeneity of the treatment effects (air pollution) for our preferred specifications (Table 4): (i) by gender (Table 8); (ii) across the distribution of scores (Table 9); and (iii) income per municipality (Table 9).

With regards to gender differentials, overall our findings reported in Table 8 suggest that boys are more negatively affected by pollution from agricultural burning than girls. Columns 1 and 4 repeat the results of our baseline models for ease of comparison with girls' and boys' performances in Portuguese (Columns 2 and 3) and Maths (Columns 5 and 6) exams. Firstly, one can note that the pattern of signs and significance concerning the gestational periods remains the same, with exposure to fires during the first and third trimesters showing significant effects on cognitive performance at school. From Column 3, we notice that boys are more affected in the third trimesters, though the effects are not statistically significant. However, we do not find any significant difference between genders when looking at the effects during the whole pregnancy period.

Epidemiology studies are still coming to terms on the part played by gender when it comes to the impacts of bad air quality on health. However, there are a few works suggesting that boys are more affected than girls. Abbey et al. (1998) find association between being exposed to PM_{10} and impaired lung function for males but not for females, and Galizia & Kinney (1999) show the equivalent aftermath regarding O_3. In a similar vein, Ebenstein et al. (2016) suggest that boys present lower academic performance than girls once exposed to contemporaneous air pollution, and X. Chen et al. (2017) find that males are more sensitive to both contemporaneous and cumulative exposure to bad air quality than females.

We also split our final sample into subsets according to low and high scores within each municipality. From Panel A Table 9, one can note that weaker students (below median) are more sensitive to exposure during the third trimester of pregnancy than the others (above median) in the scores distributions for both subjects, though not significant. These findings are in accordance with Ebenstein et al. (2016) who also show evidence of weaker students' poorer performance as a result of poor air quality during examinations.

Finally, we use parents' level of education as a proxy for socioeconomic status and display the results by low or high level of income. The bottom part of Panel B Table 9 suggests there is no significant overall difference between students below and above the median. However, these results have to be interpreted with caution as this particular question contains a lot of missing values from students who did not know their parents' education level. [22]

[22] In the Online Appendix, we include Tables A5 and A6 with the heterogeneity analysis for the reduced

Table 8: Heterogeneity per gender - Second stage

Pollution and Scores (Second stage)	(1)	(2) Portuguese (SD)	(3)	(4)	(5) Maths (SD)	(6)
	All	Girls	Boys	All	Girls	Boys
$PM_{2.5}$ (1tr)	-0.0205**	-0.0278***	-0.0157	-0.0167**	-0.0200**	-0.0144
$(\mu g/m^3)$	(0.00931)	(0.0103)	(0.00978)	(0.00744)	(0.00830)	(0.00822)
$PM_{2.5}$ (2tr)	0.00690	-0.000648	0.0127	0.0130	0.00452	0.0198***
$(\mu g/m^3)$	(0.00787)	(0.00925)	(0.00749)	(0.00674)	(0.00722)	(0.00703)
$PM_{2.5}$ (3tr)	-0.0266***	-0.0202***	-0.0292***	-0.0274***	-0.0171**	-0.0310***
$(\mu g/m^3)$	(0.00683)	(0.00694)	(0.00899)	(0.00755)	(0.00778)	(0.00935)
First Stage F-test	10	11	10	10	11	10
Observations	1,187,660	543,030	644,630	1,187,660	543,030	644,630
$PM_{2.5}$ $(\mu g/m^3)$	-0.04***	-.0486***	-0.0322**	-0.031**	-0.0326***	-0.0256*
(Whole pregnancy)	(0.014)	(0.0155)	(0.0153)	(0.0126)	(0.0135)	(0.0143)
Low-High (p-value)		> 0.1			> 0.1	

Notes: Equations follow specification from Table 4. First stage Kleibergen-Paap rk Wald F statistic. We estimate the equations using LIML due to the F statistics below 10. Girls-Boys show the p-value from the difference between the respective coefficients for the whole pregnancy period. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Heterogeneity per scores and income distributions - Second Stage

PANEL A: Scores Dep. Var. (SD)	(1) Baseline	(2) Low Portuguese	(3) High	(4) Baseline	(5) Low Maths	(6) High
$PM_{2.5}$ (1tr)	-0.0205**	-0.0112	-0.0089	-0.0167**	-0.0096	-0.0074
	(0.0093)	(0.0078)	(0.0063)	(0.0074)	(0.0066)	(0.0062)
$PM_{2.5}$ (2tr)	0.0069	0.00103	0.00235	0.013*	0.0078	0.0056
	(0.0079)	(0.0067)	(0.0046)	(0.0067)	(0.0053)	(0.0043)
$PM_{2.5}$ (3tr)	-0.0266***	-0.0176**	-0.001	-0.0274***	-0.0146**	-0.0118*
	(0.0068)	(0.0072)	(0.0061)	(0.0076)	(0.0067)	(0.0071)
F	10	10	10	10	10	10
Observations	1,187,660	593,099	594,560	1,187,660	593,214	594,446
$PM_{2.5}$	-0.04***	-.0278**	-0.0076	-0.031***	-0.0164	-0.0136
(Whole pregnancy)	(0.014)	(0.0126)	(0.0099)	(0.0126)	(0.0108)	(0.0104)
Low-High (p-value)		> 0.1			> 0.1	

PANEL B: Income Dep. Var. (SD)	Baseline	Low Portuguese	High	Baseline	Low Maths	High
$PM_{2.5}$ (1tr)	-0.0205**	-0.0234**	-0.0236*	-0.0167**	-0.0242***	-0.0134
	(0.0093)	(0.0095)	(0.0135)	(0.0074)	(0.0082)	(0.0104)
$PM_{2.5}$ (2tr)	0.0069	0.0053	0.0095	0.013*	0.0105	0.0255***
	(0.0079)	(0.0078)	(0.0099)	(0.0067)	(0.007)	(0.0083)
$PM_{2.5}$ (3tr)	-0.0266***	-0.0277***	-0.032**	-0.0274***	-0.0276***	-0.0288**
	(0.0068)	(0.0089)	(0.014)	(0.0076)	(0.0093)	(0.0131)
F	10	9	9	10	9	9
Observations	1,187,660	275,712	148,899	1,187,660	275,712	148,899
$PM_{2.5}$	-0.04***	-0.0458***	-0.0461**	-0.031***	-0.0413***	-0.0167
(Whole pregnancy)	(0.014)	(0.0152)	(0.0218)	(0.0126)	(0.0142)	(0.0187)
Low-High (p-value)		> 0.1			> 0.1	

Notes: Panels A and B follow specification from Table 4. First stage Kleibergen-Paap rk Wald F statistic. We estimate the equations using LIML due to the F statistics below 10. Low-High shows the p-value from the difference between the respective coefficients for the whole pregnancy period. *** p<0.01, ** p<0.05, * p<0.1..

form equations, with overall qualitatively similar results to those of the second stage regressions in this section.

8 Economic Significance

The literature on the returns of education has shown that better cognitive test scores at school are positively related to individual higher earnings in the future (Murnane et al., 1995; Murphy & Peltzman, 2004; Blau & Kahn, 2005; Chetty et al., 2011; Currie et al., 2012; Curi & Menezes-Filho, 2015; Bharadwaj et al., 2017), to lower probability of drop-outs (Rivkin, 1995; Hanushek, 1996); and to higher economic growth (Hanushek & Kimko, 2000). Curi & Menezes-Filho (2015) shows evidence of a 5% reduction of salary per 10% reduction of scores. Therefore, using our estimated cognitive performance effects for the whole pregnancy period (Table 4) and estimates of the returns to exams scores from Brazil (Curi & Menezes-Filho, 2015), we present a back-of-the-envelope calculation suggesting that, *ceteris paribus*, a drop of $PM_{2.5}$ by 10% (0.1*14.3 = $1.43\mu g/m^3$ (Table 1)) during the gestational period would raise students' scores in languages by 1.3% (1.43*0.04*47.8/219 (Table 4) and in Maths by 0.9% (1.43*0.031*47.5/234); and consequently elevate future individuals' earnings by 2.6% and 1.8% respectively.

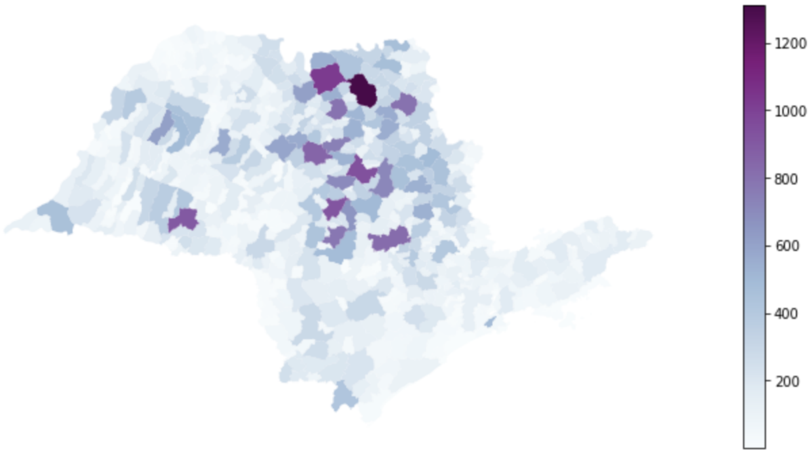
9 Conclusion

In this paper we examined the relationship between foetal exposure to air pollution from agricultural fires and cognitive performance in fifth grade exams in Brazil. To this end we merge data from the Brazilian Ministry of Education, NASA's satellite remote sensing data with active fire detection, and air pollution data and atmospheric conditions data from the Japanese Reanalysis archive, JRA-55. Our empirical strategy, which relies upon wind direction and fires' location as predictors of air pollution, provides evidence that exposure to agricultural burning, and as a result poor air quality, during the gestational period causes a reduction in the cognitive ability of students. More precisely, we show that students living in municipalities located upwind from the fires present lower academic performance than their downwind counterparts. To put our findings into perspective, we demonstrate that students exposed to an additional 1SD of fires during their gestational period suffer a reduction of 0.0339SD in Portuguese and 0.0317SD in Maths scores in the fifth grade. We also find evidence that weaker pupils are significantly more sensitive to prenatal burning exposure in terms of both subjects' scores. In addition, we demonstrate the impact of agricultural burning on higher levels of $PM_{2.5}$ and of this on reduced scores later in life. More specifically, we find that a 1 $\mu g/m^3$ of $PM_{2.5}$ during the first trimester of pregnancy causes a reduction in Portuguese and Maths scores by 0.021SD and 0.0167SD. In contrast, an increase in exposure to particulate matter during the third gestational period appears to decrease scores in Portuguese by 0.0266 and Maths by 0.0274SD.

Back-of-the-envelope calculations indicate that a reduction of 10% of $PM_{2.5}$ during the whole gestational period, i.e., $1.43\mu/\text{m3}$, would increase scores by 1.3% in Portuguese and by 0.9% in Maths and ultimately increase wages by 2.6%. These findings are in line with the economics and medical literature on the harmful effects of foetal exposure to air pollution to the foetus' brain development, particularly during the first and third trimester (Rice & Barone Jr, 2000; Sunyer & Dadvand, 2019; McGuinn et al., 2020).

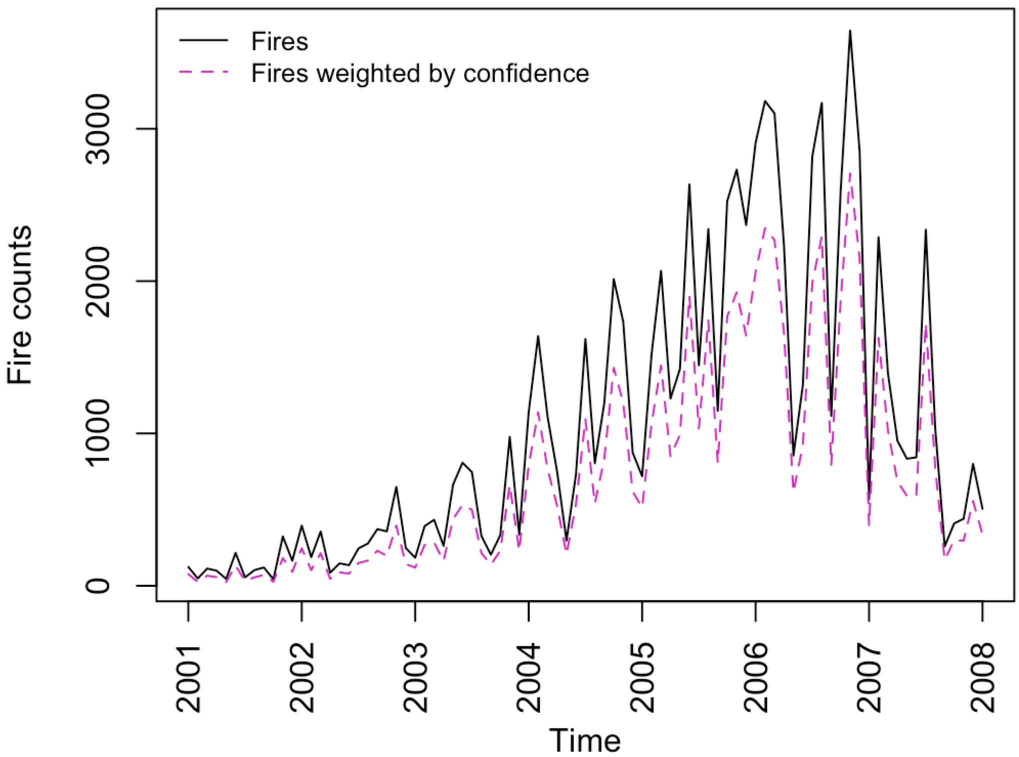
In sum, our results provide evidence suggesting that cognitive performance may be hindered by *in utero* exposure to agricultural fires. This finding has implications for the many parts of the world where agricultural fires are commonplace. The signing of the Green Ethanol Protocol in 2017, which aims to boost the mechanisation of harvesting, should reduce the extent of the burning in São Paulo state to the benefit of air quality and human capital accumulation. If successful, this policy perhaps provides a model for other countries to follow.

Figure 1: Total of agricultural fires per municipality from 2000 to 2008



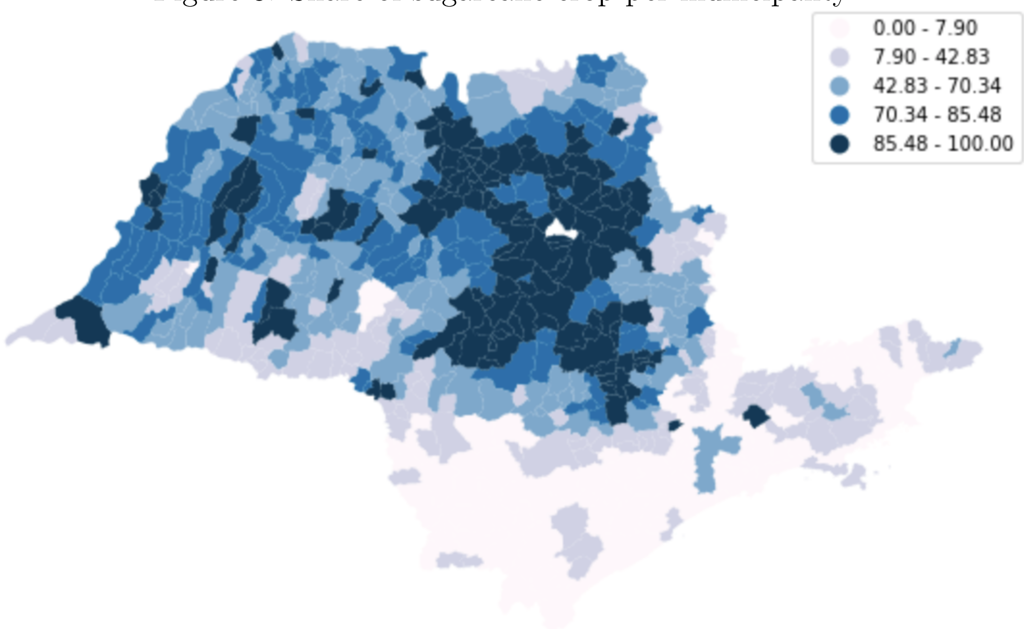
Note: Total amount of fires per municipality in the state of São Paulo during the birth years of our sample cohorts.

Figure 2: Monthly average of counts of fires from 2001-2008



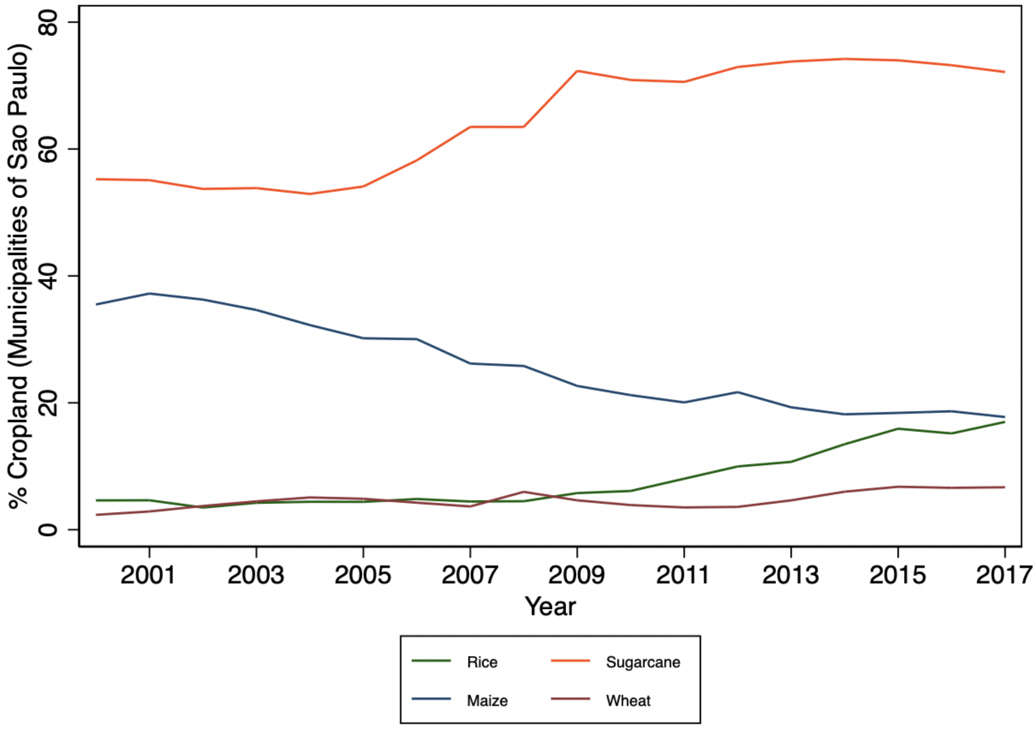
Note: The graph shows the monthly average of counts of fires and fires confidence-weighted from 2001-2008 in São Paulo state. We can see a that the peak of fires occur during the winter months.

Figure 3: Share of sugarcane crop per municipality



Note:This figure shows the share of sugarcane crop per municipality from 2000 to 2017. One can notice that the areas with higher concentration of this crop coincide with the areas with largest number of fire counts (Fig. 1).

Figure 4: Share of rice, sugarcane, maize and wheat planted per municipality from 2000 to 2017



Note:This figure depicts the proportion of land destined to the plantation of four crops that potentially utilise agricultural burning. One can note that sugarcane is the crop that uses this technique the most in the State of São Paulo throughout the period.

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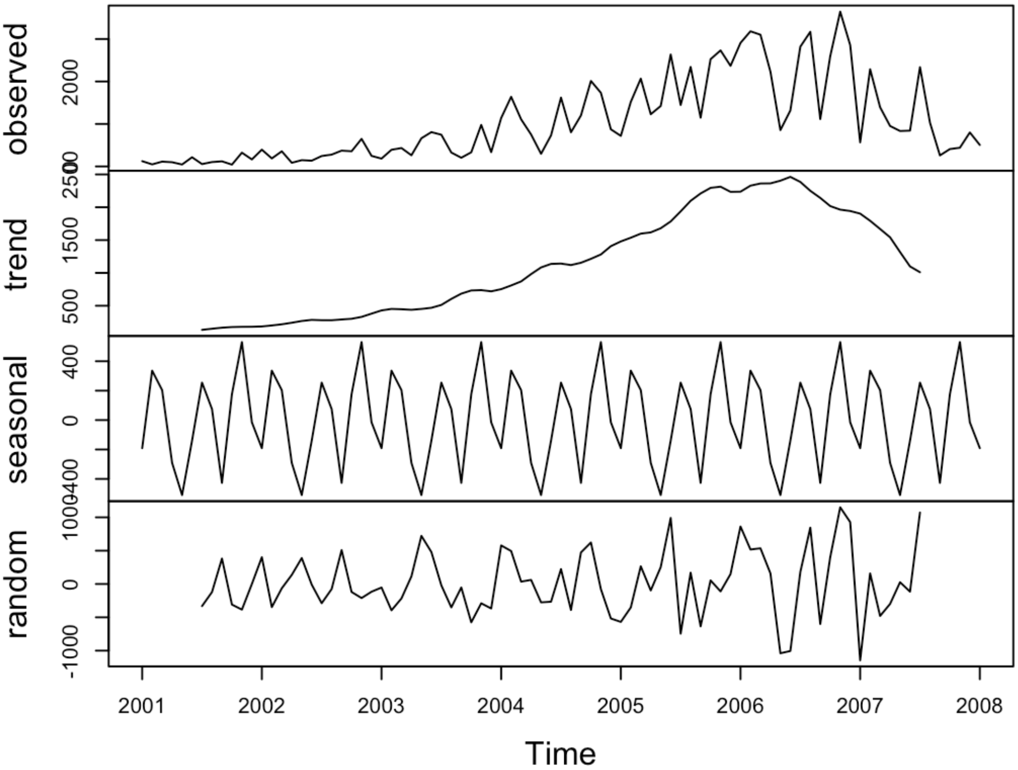
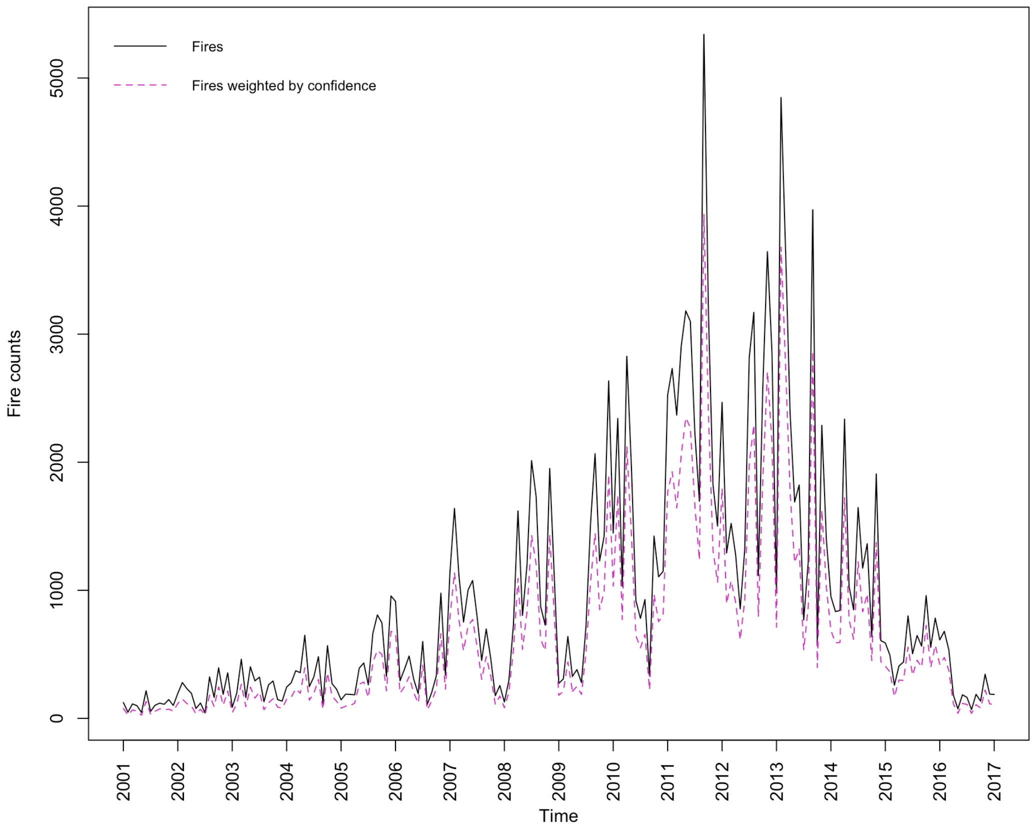
A Online Appendix

Figure A1: Decomposition Additive Time Series of monthly average counts of fires from 2001-2008



Note: The graphs shows Decomposition Additive Time Series of monthly average counts of fires from 2001-2008 in São Paulo state. We can see a strong seasonality with the peak of fires occur during the winter months and a not clear time trend.

Figure A2: Monthly average of counts of fires from 2001-2017



Note: The graph shows the monthly average of counts of fires and fires confidence-weighted from 2001-2017 in São Paulo state. We can see a that the peak of fires occur during the winter months.

Table A1: Robustness checks altering catchment distances for the reduced form (fires on scores)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance (km)	50	20	30	40	60	70	80	90	100
Panel A: Dep. Portuguese									
upwind-downwind_1tr	-0.0159**	0.0014	-0.0022	-0.0042	-0.0183**	-0.0199**	-0.0231***	-0.024***	-0.0253***
	(0.0067)	(0.0051)	(0.0059)	(0.0047)	(0.0074)	(0.0086)	(0.0088)	(0.0078)	(0.0074)
upwind-downwind_2tr	-0.0081	-0.0023	-0.0051	-0.0049	-0.0147**	-0.0136*	-0.0138*	-0.0114	-0.0099
	(0.0077)	(0.0049)	(0.0057)	(0.0068)	(0.0073)	(0.0076)	(0.0084)	(0.0089)	(0.0087)
upwind-downwind_3tr	-0.0098	0.0021	0.0019	-0.0033	-0.0155**	-0.0142**	-0.0177**	-0.0204**	-0.022***
	(0.0061)	(0.0046)	(0.0056)	(0.005)	(0.0072)	(0.007)	(0.0077)	(0.0085)	(0.008)
Observations	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance (km)	50	20	30	40	60	70	80	90	100
Panel B: Dep. Maths									
upwind-downwind_1tr	0.0196**	0.004	-0.0005	-0.0037	-0.023**	-0.026**	-0.029***	-0.029***	-0.0297***
	(0.009)	(0.0045)	(0.0068)	(0.0062)	(0.0097)	(0.011)	(0.0111)	(0.0098)	(0.0091)
upwind-downwind_2tr	-0.0022	0.0028	-0.0009	-0.00008	-0.0095	-0.0099	-0.0103	-0.0092	-0.0088
	(0.0081)	(0.0055)	(0.006)	(0.0071)	(0.0078)	(0.0079)	(0.0083)	(0.0089)	(0.0085)
upwind-downwind_3tr	-0.0099	0.0035	0.0023	-0.0015	-0.0163**	-0.016**	-0.019**	-0.022**	-0.024***
	(0.0065)	(0.0048)	(0.0058)	(0.0052)	(0.0087)	(0.0079)	(0.0084)	(0.0094)	(0.0087)
Observations	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660

Notes: All equations follow specification from Table 2. Column 1 shows the main specification with the baseline distance of 50km. *** p<0.01, ** p<0.05, * p<0.1.

Table A2: Robustness checks altering catchment distances for the second stage (pollution on scores)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance (km)	50	20	30	40	60	70	80	90	100
Panel A: Dep. Portuguese									
pm25_1tr	-0.021**	-0.048**	-0.0304***	-0.0188	-0.023***	-0.021****	-0.021***	-0.0226***	-0.0252***
	(0.008)	(0.02)	(0.0109)	(0.0092)	(0.0089)	(0.007)	(0.0064)	(0.0067)	(0.0066)
pm25_2tr	0.0069	0.0034	0.0111	0.0092	0.0045	0.0046	0.0064	0.0077	0.0075
	(0.0079)	(0.0102)	(0.0084)	(0.0082)	(0.008)	(0.0068)	(0.0062)	(0.0063)	(0.0058)
pm25_3tr	-0.0266***	-0.0613***	-0.044***	-0.0302***	-0.0295***	-0.0291***	-0.0319***	-0.0336***	-0.0376***
	(0.068)	(0.024)	(0.0127)	(0.0079)	(0.0072)	(0.007)	(0.0077)	(0.0074)	(0.0074)
F	10	2	3	9	12	13	17	19	23
Observations	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance (km)	50	20	30	40	60	70	80	90	100
Panel B: Dep. Maths									
pm25_1tr	-0.0167**	-0.0421**	-0.0247**	-0.0152	-0.02203***	-0.0209***	-0.0207***	-0.0226***	-0.0248***
	(0.0074)	(0.018)	(0.0099)	(0.0094)	(0.0081)	(0.0068)	(0.0062)	(0.0062)	(0.0061)
pm25_2tr	0.013*	0.0097	0.0163**	0.0144**	0.0083	0.0073	0.0087	0.01*	0.009*
	(0.0067)	(0.0095)	(0.0071)	(0.0068)	(0.0073)	(0.0062)	(0.0056)	(0.0058)	(0.0054)
pm25_3tr	-0.0274***	-0.0603***	-0.042***	-0.0306***	-0.0319***	-0.032***	-0.034***	-0.0363***	-0.0401***
	(0.0076)	(0.0227)	(0.0129)	(0.0081)	(0.0087)	(0.0086)	(0.0093)	(0.009)	(0.0088)
F	10	2	3	9	12	13	17	19	23
Observations	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660

Notes: Notes: Panels A and B follow specification from Table 4. First stage Kleibergen-Paap rk Wald F statistic. We estimate the equations using LIML due to the F statistics below 10. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Robustness checks altering angles defining upwind fires

	(1)	(2)	(3)	(4)	(5)	(6)
Angles(in degrees)	30	45	90	30	45	90
		OLS			IV	
Panel A:						
Dep. Var. Portuguese						
upwind-downwind	-0.029**	-0.0159**	-0.014**			
	(0.0139)	(0.0067)	(0.0063)			
upwind-downwind	-0.009	-0.0081	-0.0111			
	(0.0086)	(0.0077)	(0.0091)			
upwind-downwind	-0.0152*	-0.0098	-0.00			
	(0.0092)	(0.0061)	(0.0051)			
pm25_1tr				-0.036***	-0.021**	-0.0203*
				(0.0125)	(0.008)	(0.0117)
pm25_2tr				0.0113	0.0069	0.009
				(0.013)	(0.0079)	(0.0112)
pm25_3tr				-0.042***	-0.0266***	-0.024**
				(0.0111)	(0.068)	(0.0113)
F				10	10	20
Observations	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660
Panel B:	30	45	90	30	45	90
Dep. Var. Maths		OLS			IV	
upwind-downwind	-0.029**	-0.0196**	-0.0116*			
	(0.0139)	(0.009)	(0.0069)			
upwind-downwind	-0.0074	-0.0022	-0.0048			
	(0.009)	(0.0081)	(0.0091)			
upwind-downwind	-0.0159*	-0.0099	0.0016			
	(0.0091)	(0.0065)	(0.0058)			
pm25_1tr				-0.0194	-0.0167**	-0.008
				(0.0149)	(0.0074)	(0.0118)
pm25_2tr				0.0199	0.013*	0.019
				(0.0149)	(0.0067)	(0.0118)
pm25_3tr				-0.028**	-0.0274***	-0.0151
				(0.013)	(0.0076)	(0.0112)
F				10	10	20
Observations	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660

Notes: Panels A and B follow specification from Tables 2 and 4. First stage Kleibergen-Paap rk Wald F statistic. We estimate the equations using LIML due to the F statistics below 10. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Robustness checks

Variables	(1) Portuguese	(2) Maths	(3) Portuguese	(4) Maths	(5) Portuguese	(6) Maths
Panel A: Fires and Scores	Linear Weather		Non-weighted		Non-cloud	
(Reduced form)						
Upwind-downwind (1tr)	-0.015**	-0.019**	-0.013**	-0.016**	-0.018**	-0.021**
	(0.007)	(0.01)	(0.006)	(0.008)	(0.007)	(0.01)
Upwind-downwind (2tr)	-0.005	0.0006	-0.006	0.0002	-0.01	-0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)
Upwind-downwind (3tr)	-0.007	-0.007	-0.005	-0.004	-0.011	-0.011
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Observations	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660
Upwind-downwind	-0.027***	-0.0254*	-0.024**	-0.02	-0.039***	-0.036**
(Whole pregnancy)	(0.011)	(0.014)	(0.011)	(0.012)	(0.013)	(0.015)
Panel B: PM2.5 and Scores	Linear Weather		Non-weighted		Non-cloud	
(IV)						
PM25 (1tr)	-0.021**	-0.018***	-0.016	-0.009	-0.022**	-0.019**
	(0.009)	(0.007)	(0.011)	(0.008)	(0.009)	(0.007)
PM25 (2tr)	0.002	0.007	0.01	0.018***	0.005	0.011
	(0.006)	(0.006)	(0.008)	(0.006)	(0.007)	(0.006)
PM25 (3tr)	-0.024***	-0.024***	-0.023***	-0.023***	-0.029***	-0.03***
	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.008)
Observations	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660	1,187,660
F	13	13	11	11	13	13
PM25	-0.043***	-0.035***	-0.029**	-0.014	-0.046***	-0.038***
(Whole pregnancy)	(0.013)	(0.012)	(0.015)	(0.012)	(0.014)	(0.012)

Notes: Panels A and B follow specification from Tables 2 and 4, except for in Columns 1 and 2 we use linear weather variables; Columns 3 and 4, the fires count are non-weighted by their probability of occurrence; and Columns 5 and 6, we do not include cloud coverage in the equations. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Heterogeneity per gender - Reduced form

Fires and Scores (Reduced form)	(1)	(2)	(3)	(4)	(5)	(6)
	Portuguese (SD)			Maths(SD)		
	All	Girls	Boys	All	Girls	Boys
Upwind-downwind (1tr)	-0.0159**	-0.0086	-0.0207***	-0.02**	-0.012	-0.0245**
	(0.0067)	(0.0066)	(0.0072)	(0.009)	(0.0075)	(0.0102)
Upwind-downwind (2tr)	-0.0081	-0.005	-0.009	-0.0022	0.0028	-0.0042
	(0.0077)	(0.0078)	(0.0078)	(0.0081)	(0.0074)	(0.0087)
Upwind-downwind (3tr)	-0.0098*	-0.0061	-0.013**	-0.0099	-0.0065	-0.0116
	(0.0061)	-0.0064	(0.0059)	(0.0065)	(0.0063)	(0.0067)
Observations	1,187,660	543,030	644,630	1,187,660	543,030	644,630
R-squared	0.1426	0.1163	0.1314	0.1221	0.1122	0.1321
Upwind-downwind	-0.0339***	-0.0197	-0.0428***	-0.0317**	-0.0157	-0.0403***
(Whole pregnancy)	(0.0119)	(0.0121)	(0.0121)	(0.0137)	(0.0123)	(0.015)
Girls-Boys (p-value)		> 0.1			> 0.1	

Notes: Equations follow specification from Table 2. First stage Kleibergen-Paap rk Wald F statistic. We estimate the equations using LIML due to the F statistics below 10. Girls-Boys shows the p-value from the difference between the respective coefficients for the whole pregnancy period. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Heterogeneity per scores and income distributions - Reduced form

	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Scores	Baseline	Low	High	Baseline	Low	High
Dep. Var. (SD)		Portuguese			Maths	
Upwind-downwind (1tr)	-0.0159**	-0.0128*	-0.0033	-0.0196**	-0.0203***	-0.007
	(0.0067)	(0.0072)	(0.0035)	(0.009)	(0.0074)	(0.0056)
Upwind-downwind (2tr)	-0.0081	-0.0125*	-0.0015	-0.0022	-0.0103*	0.0028
	(0.0077)	(0.0069)	(0.0043)	(0.0081)	(0.0062)	(0.0051)
Upwind-downwind (3tr)	-0.0098*	-0.0084*	-0.003	-0.0099	-0.0109**	-0.0048
	(0.0061)	(0.0048)	(0.0038)	(0.0065)	(0.0046)	(0.0045)
Upwind-downwind (Whole pregnancy)	-0.0339***	-0.0337***	-0.0078	-0.0317**	-0.0415***	-0.009
	(0.0119)	(0.011)	(0.0067)	(0.0137)	(0.011)	(0.0088)
Low-High		-0.0259**			-0.0325**	
		(0.0129)			(0.0141)	
PANEL B: Income	Baseline	Low	High	Baseline	Low	High
Dep. Var. (SD)		Portuguese			Maths	
Upwind-downwind (1tr)	-0.0159**	-0.0148*	-0.021***	-0.0196**	-0.0121	-0.0231**
	(0.0067)	(0.0082)	(0.0081)	(0.009)	(0.0087)	(0.0092)
Upwind-downwind (2tr)	-0.0081	-0.0073	-0.0098	-0.0022	0.0058	-0.0048
	(0.0077)	(0.0102)	(0.0092)	(0.0081)	(0.0093)	(0.0109)
Upwind-downwind (3tr)	-0.0098*	-0.0116*	-0.013*	-0.0099	-0.0091	-0.0141**
	(0.0061)	(0.0064)	(0.0069)	(0.0065)	(0.0078)	(0.0066)
Upwind-downwind (Whole pregnancy)	-0.0339***	-0.0204	-0.0438***	-0.0317**	-0.0154	-0.042***
	(0.0119)	(0.0146)	(0.0141)	(0.0137)	(0.0149)	(0.0157)
Low-High		0.0234			0.0266	
		(0.0203)			(0.0216)	

Notes: Panels A and B follow specification from Table 2. In Panels A and B, Low-High shows the p-value from the difference between the respective coefficients for the whole pregnancy period. *** p<0.01, ** p<0.05, * p<0.1.