Agricultural Fires and Student Performance: Evidence from Brazil

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Abstract

Sugarcane fires have significant environmental and health impacts, but their effect on academic performance remains underexplored. This study aims to fill this gap by examining the consequences of sugarcane fires on student performance using data from São Paulo's annual education assessment, which coincides with the end of the sugarcane harvesting season. São Paulo is an ideal setting for this study as it contributes over 60% of Brazil's total sugarcane output and accounts for approximately one-fifth of the global annual sugarcane tonnage. Leveraging wind direction data from air quality monitoring stations in sugar-growing regions and satellite data on fire locations occurring on exam days from 2009 to 2013, I construct an instrumental variable that exploits the exogeneity of wind direction to isolate the impact of fires on the cognitive performance of over 30,000 students. I find that a one-unit increase in the difference between upwind and non-upwind fires during the exam increases concentration levels of coarse particulate matter (PM10) by 0.11 standard deviations, which in turn reduces test scores by 0.016 standard deviations. The effect is observed on the day of the exam, similar for both language and mathematics exams and across boys and girls, but it is mainly concentrated among lower-performing students.

Key words: Air Pollution; Agricultural Fires; Education; Cognitive Performance
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1 Introduction

In many developing countries, agriculture remains the pillar of the economy. However, farmers still rely on traditional harvesting methods like controlled burns to clear land, manage weeds, rejuvenate nutrients, and dispose of crop residues (Andreae, 1991). The smoke originated from the biomass burning contains large amounts of pollutants, which cause increase in air pollution during harvesting seasons and are known to be harmful to human health, both at early stages of life (Rangel and Vogl, 2019) and among young and elderly (He et al., 2020).

This begs the question: what are the effects of the air pollution produced by agrilcultural fires during harvesting seasons on students' performance? To answer this question, I explore the setting of the sugar-growing regions of the Brazilian state of São Paulo to examine the impacts of agricultural fires on test performance. São Paulo is responsible for about 60% of Brazil's sugarcane, ethanol and sugar production and approximately 20% of the tonnage produced annually in the world (Rudorff et al., 2010). Traditional sugarcane harvesting begins with pre-harvest field burning, which is used to clean the field from straws and other debris and prepares it for the cane cutters.[1] After the burning, manual workers proceed to cut the remaining sugarcane stocks.[2] Sugarcane production in São Paulo has been linked with concerning environmental outcomes, particularly since sugarcane straw burning during the harvest period emits a large amount of polluting gases, causing respiratory problems in the local population (Arbex et al., 2007; Cançado et al., 2006). In addition to the large scope of sugarcane production in São Paulo's economy, the state of São Paulo has data on an annual low-stake educational assessment (known as SARESP by its Portuguese acronym) covering public state schools across all the state.[3] The timing of the SARESP coincides with the end of the harvesting season of sugarcane, which allows me to investigate the effect of sugarcane fires on cognitive performance during the exams.

Since agricultural fires are used to improve labor productivity, there could be other

[1]Cane cutters are agricultural workers equipped with machetes in order to cut down the sugarcane plants over its roots and special clothing to handle the burnt stocks.

[2]The fires are essential part of the manual harvesting process because the higher labor productivity of workers as cutting burnt sugarcane stock requires significantly less strength than a natural sugarcane stock.

[3]I will explain the SARESP examination in more detail in Section 3.3.

channels through which the use of fires can be correlated with test performance. To unveil the causal effects of agricultural fires on the cognitive performance students' achievement, I exploit exogenous variations in local wind direction during the exam period, in the spirit of Rangel and Vogl (2019) to assess the impact of different levels of exposure to air pollution on students' cognitive performance.[4] The intuition for this instrument is simple: although the location of agricultural fires is not random, wind direction as-good-as randomly assigns air pollution from fires to schools during exam days. From a methodological perspective, I am able to aggregate wind and pollutant data from air quality stations to identify pollution source locations that frequently change within an area. This allows me to identify pollution effects from economic confounders. Furthermore, because wind directions are random, the use of wind direction mitigates the problem of omitted variable bias, giving a causal impact of straw burning on cognitive function on test takers.

In the first part of my analysis, I examine the relationship between fires, wind direction and the concentration levels of coarse particular matter (PM_{10}) and ozone (O^3) across 13 air monitoring stations in the sugar-cane growing regions in the state of Sao Paulo. Using data on air pollution, I first show that fires upwind from a pollution monitor raise pollution significantly more than fires at other angles to the wind. An additional fire in the upwind direction increases particulate matter (PM_{10}) concentrations by 0.15 standard deviations during the month of the SARESP, with no significant effect on Ozone (O^3). In contrast, an additional fire in a non-upwind direction only increases PM10 concentration by 0.03 standard deviations while the impact of an additional non-upwind on ozone is essentially zero.

In light of the previous results, I examine the impact of upwind fires on exam outcomes across a sample of over 30,000 test takers per year. The results suggest that fires in the upwind direction of municipalities negatively impact student's tests scores both in language and mathematics. In my preferred specification, a one-unit increase in upwind fires decrease test scores by 0.014 standard deviations while a one-unit increase in non-upwind fires does

[4] Rangel and Vogl (2019) examine the health impacts of in utero exposure to smoke from sugarcane fires in São Paulo, using data on fire location and wind direction. I explore a similar variation with essentially the same data but focusing on the contemporaneous effects of upwind fires on the same day of the exam.

not have an effect on test scores. Putting differently, a one-unit increase in the net difference between upwind and non-upwind fires during the exam days decreases the average exam scores by 0.014 standard deviations. Further analysis by subject shows that a one-unit increase in the difference between upwind and downwind fires reduces language test scores by 0.016 standard deviations and math test scores by 0.016 standard deviations. The effect of an additional upwind fire is approximately 12% larger for girls, although they have a higher average test scores irrespective of grade. The effects are also concentrated among students in the bottom quartile of the distribution of test scores. Reassuringly, I find that the effect is concentrated on the days of the exams, indicating that there are no confounding factors coinciding with the agricultural fires, further validating the exclusion restriction. Finally, by leveraging my results, I perform a back-of-the-envelope calculation which suggests that a 1 standard deviation increase in PM10 reduces test scores by 0.1 standard deviations.

The results are closely related to the literature that studies the contemporaneous exposure to air pollution on cognitive performance. Ebenstein et al. (2016) show the potential long-term effect of transitory disturbances to cognitive performance during high-stakes exit exams in Israeli high schools and find a reduction in student test scores. Similarly, Zivin et al. (2020) investigate adverse consequences of agricultural fires on students' academic performance on the Chinese university-entry exam. They find that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ reduces test scores by 0.046 standard deviations. I build on these previous findings by showing that even under the low-stakes nature of the educational assessment, increased air pollution reduces test scores. In addition, I am able to locate the geographical position of schools over time, which allows to control for all school invariant characteristics that are correlated with fire exposure, cohort composition and student performance, isolating the impact of agricultural fires on test scores.

More generally, this paper speaks to the literature on the effects of air pollution on educational outcomes, most of which documented the adverse effects of air pollution on students' school attendance, cognitive abilities and academic performance (Currie et al., 2009, 2014; Almond et al., 2018; Chen et al., 2018).[5] Several papers have explored multiple sources of exogenous pollution variation from wind patterns to achieve causal identification

[5] See also Heissel et al. (2022), Gilraine (2023) and Pham and Roach (2023)

(Schlenker and Walker, 2016; Zivin et al., 2020; Lai et al., 2022; Duque and Gilraine, 2022). In the United States, Persico and Venator (2021) study the pattern of openings and closings of Toxic Release Inventory (TRI) sites, which are known to release high levels of toxic waste and air pollution, to identify the effects of acute and cumulative exposure to air pollution on children cognitive and health outcomes. Also in the United States, Gilraine and Zheng (2022) make use of variation in the yearly coal-based energy production and a shift-share instrument of fuel shares (coal, oil, gas and renewables) used by power production interacted with US growth rates in each power source to isolate the main channel of pollution emission on students test scores.

The remaining of the paper is organized as follows. Section 2 provides background information. Section 3 describes the data. Section 4 presents the empirical strategy. Section 5 shows the results. Section 6 presents some robustness checks. Section 7 concludes.

2 Background

2.1 Sugarcane Harvesting in Brazil

The state of São Paulo in Brazil plays a pivotal role in the production of sugarcane, holding significant influence both within the nation and on a global scale. With a contribution exceeding 60% of Brazil's total sugarcane output, São Paulo stands as a major driving force in the country's agricultural landscape. Furthermore, on a global stage, São Paulo's contribution accounts for approximately one fifth of the total annual sugarcane tonnage produced worldwide.

In the state of São Paulo, the harvest season on sugarcane takes place primarily between the months of April to November, peaking around June-September. Figure A1 shows the seasonal pattern in the tonnage of cane processed monthly by São Paulo mills from the National Union of Sugarcane Producers (UNICA) during 2009 to 2013. Sugarcane can be harvested using two different technologies: the traditional harvesting, by hand with pre-harvest field burning; and the mechanical harvesting, with no need for burning. The process entails intentionally setting fire to the sugarcane fields prior to manual harvesting.

The primary aim of this practice is to remove extraneous plant materials, such as leaves and tops, from the sugarcane stalks, making them easier to handle during subsequent manual cutting.

Pre-harvest sugarcane field burning has drawn significant attention due to its environmental and health implications (Cançado et al., 2006; Arbex et al., 2007). The burning releases a substantial amount of smoke, as well as particulate matter and gases, into the atmosphere. These emissions contribute to air pollution and can have adverse effects on air quality, both locally and beyond. In particular, the emission of pollutants such as carbon monoxide and fine particulate matter can pose risks to respiratory health (Jayachandran, 2009; Chagas et al., 2016; He et al., 2020).

Concerns over the environmental and health impacts of sugarcane field burning have led to discussions about potential alternatives. In 2002, São Paulo State introduced a plan (State Law n° 11,241) to gradually stop burning sugarcane fields before harvest on big farms by 2021. These alternatives aim to reduce the negative consequences of burning while still ensuring efficient sugarcane harvesting. Innovations such as mechanical harvesting techniques and strategies to manage crop residues are being explored to mitigate the environmental and health challenges associated with pre-harvest field burning.

2.2 Potential Mechanisms of Agricultural Fires on Test Scores

The burning of cane sugar releases a substantial amount of smoke, as well as particulate matter. These emissions contribute to air pollution (Andreae and Merlet, 2001). This source of air pollution can impact test scores through several mechanisms. First, exposure to air pollutants, such as fine particulate matter ($PM_{2.5}$), coarse particulate matter (PM_{10}) and nitrogen dioxide (NO_2), can lead to adverse respiratory health effects, especially asthma, which can result in learning disability (Neidell, 2004; Currie et al., 2014; Ward, 2015; Pham and Roach, 2023).

Second, exposure to pollutants may lead to long-term educational impairments that can negatively affect academic performance. Currie et al. (2009) find that high carbon monoxide (CO) levels below US federal air quality standards induce students to miss school days, although they can not differentiate between health effects or avoidance behavior, although studies have been able to link absenteeism to health-related factors (Chen et al., 2018).

Finally, air pollution can also impact the ability to concentrate and decision-making (Chang et al., 2016; Heyes et al., 2016; Archsmith et al., 2018). Studies have found that air pollution has been linked to increased levels of stress and fatigue (Shier et al., 2019), which can further impair cognitive functions. In exam settings, the adverse impact of increased air pollution on cognitive abilities can hinder students' performance and produce lower test scores as a result (Ebenstein et al., 2016; Zivin et al., 2020).

3 Data

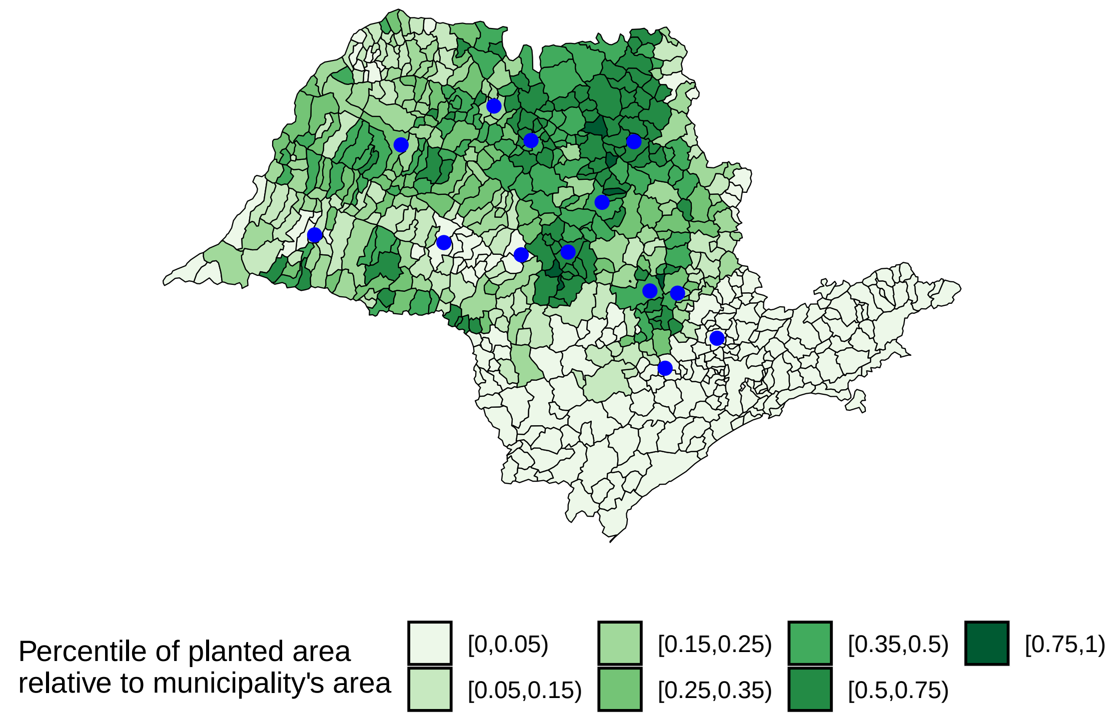
I combine data from three sources which are key for my analysis: satellite-based data to track fires; pollution and weather data from state-run air quality monitoring stations; and administrative data from the São Paulo State Secretariat of Education containing school and student-level information.

3.1 Air Monitoring Station and Weather Data

I collect data on pollution concentrations and atmospheric conditions from São Paulo's environmental agency CETESB (Companhia Ambiental do Estado de São Paulo). By levering essentially the same variation as in Rangel and Vogl (2019), I gather data from thirteen stations in sugar-growing areas from 2009 though 2013. Figure 1 in Appendix A plots the location of the air-quality stations and the sugar cane intensity over the map of the state of São Paulo.

Each station collects hourly information on temperature, relative humidity, wind direction, coarse particular matter (PM_{10}) and ozone (O^3). Both pollutants are measures in micrograms per cubic meter ($\mu g/m^3$). Table A1 presents summary statistics of the variables from each station. Given that SARESP takes place in two days, I collect information on temperature, humidity and the pollutants concentration levels for the hours corresponding to the exam hours and I convert these observations into two-days averages.

Figure 1: Sugarcane Plantation Intensity and Location of Air-Quality Stations - 2009/2013



Notes: The figure plots the sugarcane plantation intensity, measured as the percentile of planted area relative to municipality's area and location of air-quality stations. I use data on planted area from *Produção Agrícola Municipal* (PAM) by collected *Instituto Brasileiro de Geografia e Estatística* (IBGE) and municipalitie's areas, also from IBGE.

To build the wind variables, I follow Rangel and Vogl (2019) and divide wind directions into eight sectors. Each octant covers a 45º angle, with 0º representing the north direction. For every exam day, I count the number of occurrences of each wind octant and identify the prevailing wind for that day based on the octant with the highest count. In instances where there is a tie among octants, I select the one with the lowest angle to determine the prevailing wind direction.[6]

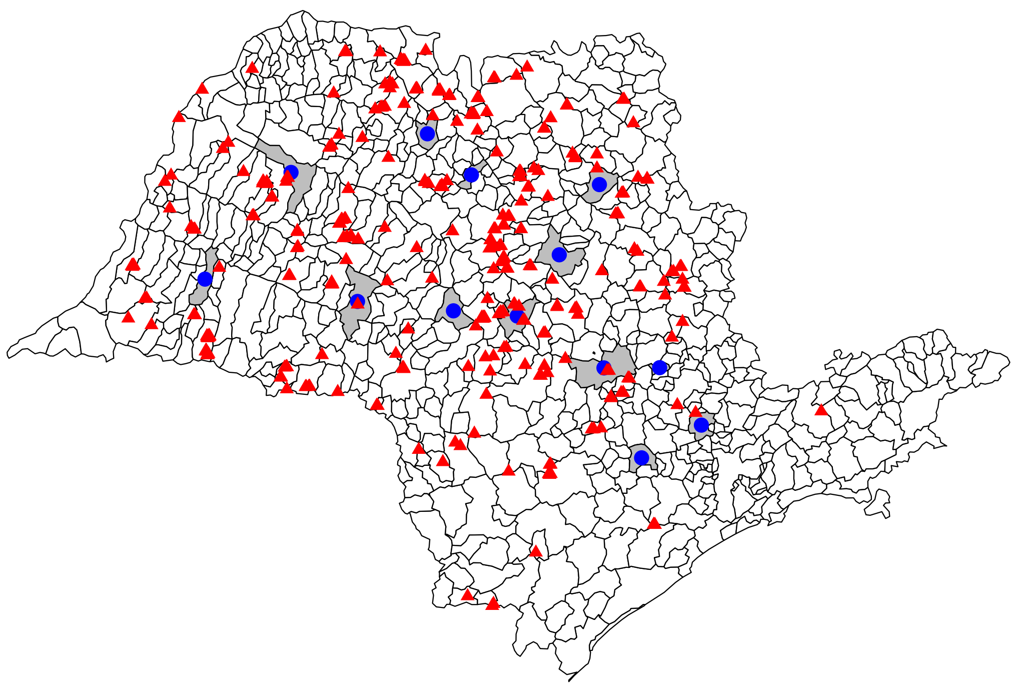
3.2 Satellite Remote-Sensing Data

I collect daily remote-sensing data on agricultural fires from the Brazilian space agency (Instituto Nacional the Pesquisas Espaciais - INPE). The data are captured by three satellites:

[6]The results are not sensitive to this choice.

NOAA-15, TERRA, and AQUA. Each satellite overpasses Brazil twice per day and report all fire points as small as 30m x 1m, but data output is at the pixel-day level, representing a 1km x 1km area for each day (Rangel and Vogl, 2019). The fire detection does not identify the precise size nor duration of each fire but since pre-harvest burns take place at all times of day, I sum the three data series into daily counts. Figure 2 shows the location of fires on the exam days from 2009-2013. From all detected fires during SARESP, I select and assign fires to a municipality if it occurred within 50km radius from the municipality's centroid and count the daily number of these fires. Alternative distances are also presented in the robustness checks section.

Figure 2: Fires during SAPESP in São Paulo - 2009/2013



Notes: Grey areas indicate the municipalities with air-quality stations. The blue dots represent the municipalities centroids. The red triangles indicate agricultural fires detected by satellites during the test days in 2009-2013.

To build our fire variables, I follow Rangel and Vogl (2019) and Zivin et al. (2020). Once fires are detected, I find the octant in which the fire is relative to the municipality centroid. As such, I define an upwind fire if the fire is in the same octant as the prevailing wind octant on the exam day. For each exam day, I count the number of upwind fires. Downwind fires are the fires located in the opposite octant of the prevailing wind octant. The remaining fires are defined as vertical fires.

3.3 Educational Data

For the educational outcomes, I utilise data from São Paulo State Achievement Test (SARESP). SARESP is a low-stake educational assessment from the state of São Paulo. The exam is used to help monitor public schools and plan continuing education programs for the state education network. The exam is carried out in two days every year in the month of November since 1996 and evaluates the performance of students in Portuguese and Math in the 3th, 5th, 7th, and 9th grades of primary school and the last grade of high school.[7]

I focus on test scores for the 5th and 9th grades of primary school. Similar to Koppensteiner and Menezes (2021), I normalise test scores to a mean of 250 and a standard deviation of 50 to allow to compare the effects across the different grades. State public schools are obligated to be part of the SARESP while municipal and private schools can opt to participate. I focus on state school students to avoid dealing with selection bias. Furthermore, I select schools located within 10 kilometers from the municipality centroid, similar to Currie et al. (2009) and Duque and Gilraine (2022). In my sample, I observe a total of 474 state schools across thirteen municipalities. Among these schools, 331 are situated within a distance of 10 kilometers from the centroid of their respective municipalities. In summary, the data consist of a pooled cross-section of students across all schools from the municipalities in the sample, containing information on their gender, age, grade, and test scores.

[7] The available data for SARESP starts in 2007 but due to data constrains in the air quality data, I use SARESP data from 2009 to 2013.

4 Empirical Strategy

4.1 Mechanism: Effect of Fires on Air Pollution

In this section, I examine the impact of agricultural fires on particulate matter concentration, focusing on wind direction as the key factor influencing air pollution exposure for test takers. To verify the hypothesis of the research design, which suggests that upwind fires contribute more to pollution compared to downwind fires, I use data from air monitoring stations regarding pollutant levels. I focus on the exposure to coarse particulate matter PM_{10}, a harmful byproduct of sugarcane burning with established health implications, but I also provide results from the same exercise using other pollutants such as ozone. To analyze the situation at the air monitoring station in municipality m on exam-year t, I apply the following model similar to Rangel and Vogl (2019):

$$y_{mt} = \beta^U upwind_{mt} + \beta^N nonupwind_{mt} + \boldsymbol{X}'_{mt}\gamma + \mu_m + \tau_t + \lambda_{mt} + \epsilon_{mt} \tag{1}$$

Where y_{mt} is the average pollution concentration from station m in exam-year t, $upwind_{mt}$ denotes the number of agricultural fires located in the upwind direction of municipality m during the days of the exam in year t, $nonupwind_{mt}$ represent the number of agricultural fires not located in the upwind direction of municipality m in year t. The parameters of interest are β^U and β^N, which tell us the effect of an additional upwind and non-upwind fire on aggregate local ambient pollution levels, respectively. The identification assumption for the model is that upwind and downwind fires randomly assign pollution to municipalities. But, since upwind fires are angled towards municipalities, I expect $\beta^U - \beta^N$ to be positive. The control variables $\boldsymbol{X}_{mt}$ include two-day averages of weather variables during exam days. In particular, I include dummies for each decile of humidity and temperature. I use station, date and station-year fixed effects to control for any unobserved municipality-specific characteristics in a flexible way. Standard errors are clustered at the municipality-level.

Equation (1) bears resemblance to the empirical model employed by Rangel and Vogl (2019), which finds a strong positive relationship between upwind fires and PM_{10} concentration levels. However, my research design focuses on the contemporaneous exposure of air pollution during exam days, raising concern regarding the sample size. To avoid the issue of lack of statistical power, I follow Zivin et al. (2020) and construct a panel of two-day moving averages of pollutant concentrations for the month of November in each year[8] and link them with proximate agricultural fires during the same period. Weather variables are now measured as two-day averages corresponding to each moving two-day period in the 30-day period.

4.2 Reduced-Form: Effect of Fires on Test Scores

In this section, I examine the reduced form relationship between agricultural fires during the SARESP exams and student's test scores. As previously discussed, the identification strategy relies on the random behavior of wind direction concerning fires, which generates contemporaneous variation in air pollution exposure across municipalities such that there are no factors other than differences in pollution levels that affect students cognitive performance during the exam. In other words, the variation in exposure is unlikely to be correlated with students' potential test scores.

One potential cause of concern when linking wind patterns in relation to fires with student outcomes is the possibility that upwind fires may disproportionately affect schools that differ across various characteristics. This variation in the impact on schools with differing attributes introduces potential confounding factors linked to the exposure of increased ambient air pollution. Although the identification strategy does not rely on baseline characteristics being balanced across schools in upwind and non-upwind municipalities, given the exogeneity of wind patterns, I can test for this. For this purpose, I denote schools as upwind schools if they are located in an upwind municipality and all others as no-upwind schools. Table B1 from Appendix B shows that schools in the municipalities that face upwind fires are similar across several characteristics to no-upwind schools. The selection of schools close to the municipality centroid further reduce the issue of alternative channels since schools away from the centroid may be close to agricultural fields where wind direction given a fire might have a limited impact.

[8] SARESP is taken in the month of November for all the years in my sample.

Using the occurrence of upwind and non-upwind fires near municipalities, I estimate the effect of exposure to these fires on test scores using the following equation:

$$y_{igs(m)t} = \beta^U upwind_{mt} + \beta^N nonupwind_{mt} + \boldsymbol{X}'_{mt}\gamma + \mu_t + \lambda_s + \theta_{sg} + \epsilon_{igs(m)t} \qquad (2)$$

Where $y_{is(m)t}$ is the normalized test score of student i in grade g of school s in municipality m in exam-year t, $upwind_{mt}$ denotes the number of agricultural fires located in the upwind direction of municipality m in year t, $nonupwind_{mt}$ represent the number of agricultural fires not located in the upwind direction of municipality m in year t. The weather variables controls $\boldsymbol{X}_{mt}$ are similar from equation (1). μ_t, λ_s and θ_{sg} are time, school and school-grade fixed effects, respectively, and $\epsilon_{igs(m)t}$ is an error term.

For identification, I assume that, conditional on year, school and school-grade fixed effects, the number of upwind and non-upwind fires faced by schools within municipalities in these sugar-cane growing regions during the exam is random. I include year fixed effects to control for common shocks to schools in a given year. School fixed-effects control for any unobserved time-invariant school characteristics and the composition of students in schools based on the school catchment area. For example, if a disadvantaged school has higher exposure to fires and lower test scores due to reasons unrelated to air pollution, school fixed effects will help control for this time-invariant unobserved heterogeneity. I also include school-grade fixed effects to control for differences in exam difficulty by grade in a year across schools. Finally, I cluster standard errors at the municipality-level.

5 Results

This section presents the empirical results. I begin by exploring the summary statistics of the data and the spatial and temporal pattern of the agricultural fires. In sequence, I explore the first-stage relationship of agricultural fires and wind direction on air pollution levels. Next, I describe the results of the upwind and non-upwind fires on SARESP exam scores.

5.1 Summary Statistics

The summary statistics for my sample of 170k students from 13 municipalities are presented in Table 1. The average test scores both in language and math are bellow 250 points. During the two-day test period, municipalities had an average of 0.88 fires. This is expected given that the tests are administered in November, near the end of the harvesting season. Fires are equally likely to be upwind or downwind on average, whereas vertical fires are much more frequent. In some instances, there is no wind even in the prevalence of a positive fire count. Non-upwind fires (the sum of downwind and vertical fires) are ten times more frequent as upwind fires. The last panel shows the summary statistics for the weather variables.

Table 1: Summary Statistics

	Obs.	Mean	Std. Dev.	Min	Max
	(1)	(2)	(3)	(4)	(5)
Score					
Portuguese	173,807	225.8	48.7	70	377.1
Math	173,807	240.9	47.3	78.9	410.8
(Portuguese + Math)/2	173,807	233.4	43.7	81.6	387.0
Agricultural Fires (45°)					
No. of Fires	65	0.88	1.88	0	11
Upwind	65	0.15	0.88	0	7
Downwind	65	0.21	0.62	0	3
Vertical	65	1.36	2.59	0	14
Non-Upwind	65	1.61	2.82	0	15
No Wind	65	0.03	0.24	0	2
Meteorological Conditions					
Temperature (C°)	65	20.5	25.2	17.5	28.7
Humidity (%)	65	53.9	68.7	7.82	86.2
Wind Speed (m/s)	65	2.12	2.17	0.33	2.87

5.2 First-Stage Mechanism: Effect of Fires on Air pollution

Table 2 shows the results from Equation (1). Column (1) shows that a one-unit increase in fires increases PM_{10} concentration level by 0.318 $\mu g/m^3$ or 3.0% of a standard deviation. Columns (2)-(4) present the impact of each type of wind direction in relation to the fire location. As expected, upwind fires account for a 15 % of a standard deviation in PM_{10} emission. Downwind fires also provide a small increase and the inclusion of vertical fires in column (4) does not change the estimate significantly.

Table 2: Effects of Fires on Two-Day (Moving) Average Air Pollution

	PM10						O3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
No. of Fires	0.318						-0.017		
	(0.071)						(0.069)		
Upwind		1.557			1.577	1.543		-0.384	-0.389
		(0.349)			(0.350)	(0.347)		(0.415)	(0.417)
Downwind			0.319		0.398			-0.209	
			(0.334)		(0.323)			(0.408)	
Non-upwind				0.346		0.340			0.145
				(0.161)		(0.153)			(0.145)
Upwind vs. Downwind					1.179			-0.175	
					(0.456)			(0.55)	
Upwind vs. Non-Upwind						1.202			-0.534
						(0.41)			(0.476)
Num.Obs.	1848	1848	1848	1848	1848	1848	1890	1890	1890
Dep.Var. Mean	26.23	26.23	26.23	26.23	26.23	26.23	50.45	50.45	50.45
Dep.Var. SD	10.43	10.43	10.43	10.43	10.43	10.43	12.54	12.54	12.54
R2	0.820	0.820	0.817	0.822	0.820	0.821	0.824	0.824	0.825
Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Station-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of the Equation (1). Fires are in the sample if they are within 50km of the municipality centroid. In addition, the angle used to define upwind fires is 45°. Standard errors are clustered at the municipality-level.

Including both upwind and downwind fires in the regression does not substantially impact the size of the estimates. The last row of column (5) suggest that an one-unit increase in the difference between upwind and downwind fires increase PM_{10} concentration by by 1.179 $\mu g/m^3$. The introduction of vertical fires onto non-upwind fires in column (6) has a twofold effect: it diminishes the coefficient associated with upwind fires while concurrently decrease the coefficient linked to non-upwind fires. This phenomenon is unsurprising, as vertical fires transport pollutants, but to a lesser extent than their upwind counterparts. Notably, the result in the last row of column (6) show that an additional point in the difference between upwind and nonupwind fires leads to an increase of 1.202 $\mu g/m^3$ in PM_{10} concentration levels. This increase constitutes roughly 4.5% of the mean and 11.5% of a standard deviation. Table B2 from Appendix B reports similar results without relaying on the two-day moving average procedure.[9]

Columns (7)-(9) repeat the same exercise but with ozone concentration levels. Ozone as a secondary byproduct of biomass does not appear to have a consistent pattern of dispersion when taking into account wind direction. These estimates are similar to Rangel and Vogl (2019) and Zivin et al. (2020).

5.3 Effect of Fires on Test Scores

Table 3 presents the primary results on the impacts of agricultural fires on normalized exam scores. In column (1), I estimate the number of fires on the standardized test scores. The coefficient is relatively small (0.2% of standard deviation) and statistically insignificant. Column (2) shows the coefficient from the regression of upwind fires on test scores. In this specification, upwind fires reduce test scores by 1.5% of a standard deviation. Downwind fires also have a negative sign but it is not statistically significant. The results from column (4) suggest that non-upwind fires (downwind and vertical fires) increase test scores by 0.05 points. This estimate is not significant and it is 15 times smaller than the impact of upwind fires in absolute terms.

Columns (5) and (6) estimate Equation (2) with the respective variables in each row. In both cases, upwind fires significantly reduce test scores while downwind has a negative sign and non-upwind fires marginally increase it, however the results from column (6) are statistically significant. This difference in impact magnitude is consistent with the identifying assumption that testing locations facing upwind from the fire are exposed to higher fire-related air pollution than downwind and non-upwind locations. The last rows of

[9] Although Rangel and Vogl (2019) find larger estimates for the impact of upwind fires on PM_{10} concentration level using data for the same stations, my findings coincide with the end of the harvesting season in a very limited time-window - around the exam days - where the number of detected fires is smaller.

Table 3: Effects of Fires, Upwind Fires and Non-upwind fires on Overall Test Scores

	(1)	(2)	(3)	(4)	(5)	(6)
No. of Fires	-0.125					
	(0.109)					
Upwind		-0.766			-0.795	-0.767
		(0.221)			(0.252)	(0.216)
Downwind			-0.268		-0.404	
			(0.544)		(0.523)	
Non-upwind				0.050		0.052
				(0.276)		(0.269)
Upwind vs. Downwind					-0.391	
					(0.362)	
Upwind vs. Non-upwind						-0.819
						(0.383)
Num.Obs.	173807	173807	173807	173807	173807	173807
R2	0.199	0.199	0.199	0.199	0.199	0.199
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
School-Grade FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of the Equation (2). The dependent variable is average from languageand math test scores normalised to a (250,50) scale. Weather variables include quintile bins for average temperature, relative humidity and wind speed and also include the count of fires with non-measured wind direction. Standard errors clustered at the municipality level are in parentheses

column (5) and (6) show the difference between upwind, downwind and non-upwind fires. Both estimates suggest that an additional point in the difference leads to a drop in test score between 0.8-1.6% of standard deviation but only the latter is significant at 5% level.

In Table 4, I examine the results separately by subject, gender and student quality. In columns (1) and (2), I estimate the effect of agricultural fires on standardised language and math test scores, respectively. In both columns, the impact of upwind fires are negative and statistically significant. I find that an additional upwind fire activity during the exam decreases math test scores by about 0.796 points and language test scores by 0.598 points, an effect equal to roughly 1.6% and 1.2% of a standard deviation, respectively. The results from the third row suggest that an one-unit increase in the difference between upwind and non-upwind fires is associated with a reduction of 1.82% of a standard deviation in math test scores (0.910 points) and 1.16% of a standard deviation in language test scores (0.581 points).

Columns (3) and (4) highlight that girls are more negatively affected by agricultural fires than boys. The results indicate that effects among girls are between 6% larger than among boys. The results demonstrate effect sizes of about 1.6% of a standard deviation for boys and 1.8% for girls. I attribute this to higher asthma rates among girls in the age group of my sample, which is mostly comprised of children and early adolescents (Almqvist et al., 2008) as opposite to late adolescents in their study.

Table 4: Heterogeneity in Agricultural Fire's Impact on SARESP Scores

	Subject		Gender		Levels of Proficienty		
	Language	Math	Boys	Girls	Low	Medium	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Upwind	-0.598	-0.796	-0.781	-0.838	-0.385	-0.143	0.012
	(0.205)	(0.235)	(0.245)	(0.207)	(0.123)	(0.071)	(0.117)
Non-upwind	-0.017	0.114	0.034	0.064	-0.004	0.078	-0.092
	(0.229)	(0.274)	(0.322)	(0.222)	(0.115)	(0.054)	(0.065)
Upwind vs. Non-upwind	-0.581	-0.91	-0.815	-0.902	-0.381	-0.221	0.104
	(0.284)	(0.441)	(0.461)	(0.324)	(0.139)	(0.094)	(0.122)
Num.Obs.	173807	173807	88807	85000	43430	86934	43443
R2	0.162	0.171	0.189	0.217	0.235	0.026	0.050
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-Grade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of the Equation (2) for the sub-populations. Dependent variables in columns (1) and (2) are math and Portuguese standardised test scores normalised at a (250,50) scale. In columns (5) to (7), Low are students bellow the 25th percentile of the test score distribution; Medium are students between the 25th and 75th percentile; and High are students above the 75th percentile;

The results in columns (5) to (7) indicate that most of the effect is concentrated among lower-performing students. For students in the bottom quartile of the test score distribution, an additional fire in the upwind direction is associated with a 0.385 point decrease in test score (0.7% of a standard deviation) while an additional non-upwind fire has no impact on test scores. I associate this fact with suggestive evidence of a fatigue-inducing factor of air pollution. In my view, this association arises from the fact that SARESP is a low-stake examination, it is plausible that students exposed to higher levels of air pollution may exert less effort due to the onset of fatigue. Students between second and third quartile face a smaller reduction in test scores, in which an one-unit increase in upwind fires reduce test scores by 0.143. The results from the third row suggest that an one-unit increase in the difference between upwind and non-upwind fires is associated with a reduction of 0.221 points (0.4% of a standard deviation). Students at the top quartile of the distribution of test scores are unaffected by upwind or non-upwind fires as both estimates are statistically insignificant.

6 Robustness Checks

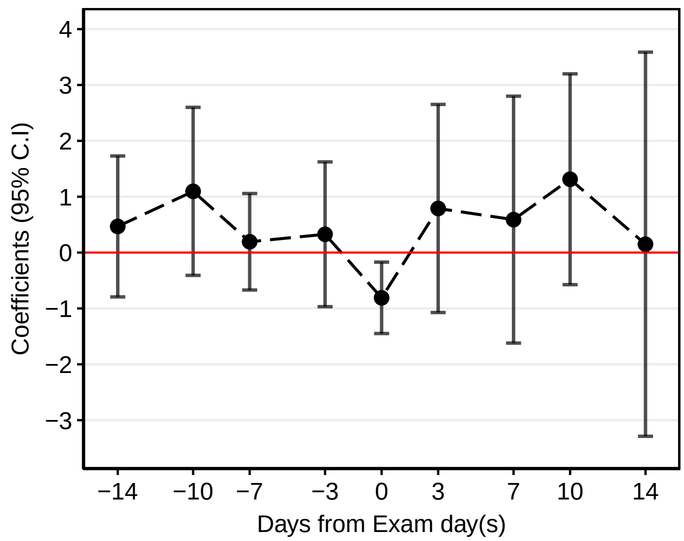
I now address robustness checks related to the benchmark specifications. I first test if fires not contemporaneous to the actual exam affect exam scores. In sequence, I utilise different dependent variables to validate the normalization procedure when using different grades. Additionally, I present the results using on alternative angles and distances.

A. Dynamic Effect of Agricultural Fires:

By looking at the response on cognitive performance to contemporaneous pollution shocks, I may neglected an important dynamic effect of pollution on test performance. In principle, if the effect is entirely contemporaneous, upwind and non-upwind fires prior to the exam should exhibit no impact on test scores. The same argument can be made for fires after the exam. To test this, I estimate equation (2) using the number of upwind and non-upwind fires within two weeks before and after the exam date.

Figure 3 plots the difference between the coefficients of upwind and nonupwind fires on test scores for each individual regression. As shown in the figure, upwind fires the day of a test has a negative impact on test takers while fires on one week prior or after the exam are unrelated to performance and fires within a time window of two weeks produce noisy estimates. This result lends support to the argument that the impact of upwind fires on test scores is a transitory effect of pollution, with the effect driven primarily by exposure on the day of the exam, similar to Ebenstein et al. (2016) and Zivin et al. (2020).

Figure 3: Dynamic effects of agricultural fires on SARESP test scores



Notes: The figure plots the difference in coefficients of upwind and non-upwind fires from Equation (2). Each coefficient and confidence interval are estimated in separate regression that consider fires happening in different day from the the exam day. Standard errors are clustered at the municipality-level.

B. Alternative Dependent Variables

In Table 5, I experiment with a number of alternative dependent variables. Similar effect sizes would reinforce the robustness of the main identification strategy. In column (1), I check whether upwind fires affect the probability of students attending both exams. One concern arises from the possibility that upwind fires may hinder the ability of certain students to take the test. This potential impact could result in a non-random selection of participants. To address this concern, I estimate equation (2) using a dummy dependent variable that indicates whether the students took both exams in a given year. Specifically, if a student took the language exam, which happens on the first day, but did not take the math exam in the second day, the variable will be zero. The estimates from column (1) indicate that both upwind and non-upwind fires do not produce a significant impact on the probability of a student taking both tests.

In columns (2) and (3), I use the logarithm and the standardized test scores, respectively. The results show comparable effects in both cases, with estimates approximately equal to 1.0% and 1.6% standard deviations for an one-unit increase in the difference between upwind and non-upwind fires. These results closely align with the estimates in Table 3.

In column (4), the dependent variable is a dummy that assigns 1 if the student have a adequate proficiency level in language and math. The level of proficiency required to be considered adequate in SARESP's terms differs from subject and grade. Students enrolled in the 5th grade must achieve a test score equal or greater than 200 points in language and 225 points in mathematics to be have a adequate proficiency level while students in the 9th must have a test score equal or greater than 275 points in language and 300 points in math. Using the test scores in my sample, students in the 5th grade must be at the 51 and 59 percentiles to be qualified as having adequate proficiency in language and math respectively, while students in the 9th grade must be at the 75 and 87 percentiles to be qualified as having adequate proficiency in language and math respectively. Merging both grades yields that only 34% students in my sample have an adequate proficiency level in language and math. Upwind fires continue to have a significant negative impact on test performance. An one-unit increase in the difference between upwind and non-upwind fires decreases the probability of a student achieving an adequate proficiency threshold in language and math by 0.004 percent, roughly 0.85% of standard deviation, although the difference is statistically insignificant.

C. Alternating Distances and Angles

Table 6 reports the results regarding the effects of upwind fires on student's test scores when I vary the distance and angles of the location of fires. The pattern of results from columns (1)-(5) show a consistency with regards to the effect of upwind fires on test scores. The large portion of the difference in the estimates comes from the size of effect of non-upwind fires in columns (5) when accounting for fires up to 70km from the municipality

Table 5: Alternative Dependent Variables

	Tesk Taker	ln(Test Score)	Stand. Test Score	Adequate Level
	(1)	(2)	(3)	(4)
Upwind	0.000	-0.003	-0.015	-0.005
	(0.001)	(0.001)	(0.004)	(0.002)
Non-upwind	0.000	0.000	0.001	-0.001
	(0.001)	(0.001)	(0.005)	(0.002)
Upwind vs. Non-upwind	0.000	-0.004	-0.016	-0.004
	(0.001)	(0.002)	(0.008)	(0.003)
Num.Obs.	201312	173807	173807	173807
Mean Dep.Var	0.88	5.43	0	0.34
Sd.Dep.Var	0.33	0.2	1	0.47
R2	0.032	0.216	0.199	0.142
Year FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
School-Grade FE	Yes	Yes	Yes	Yes

Notes: This table reports estimates of the Equation (2) for the different dependent variables. In column (1), the dependent variable is a dummy variable indicating whether a student took both tests. Column (2) uses the natural logarithm of test scores. Column (3) reports results using normalized test scores at a (0,1) scale. In column (4), I utilise a dummy that indicates if a student from grade g has a test score in language and math that is equal or greater than the threshold test score for SARESP that is considered to be an adequate level of proficiency. Standard errors are clustered at the municipality-level.

centroid. The similarity between coefficients results from the trade-off between the number of observed fires and the influence of wind direction. When examining the 30km distance, the occurrence of fires is lower, but due to the proximity, the wind can transport pollution to schools without significant dispersion. On the other hand, at 70km, more fires can be observed, but the pollution has to travel greater distances to reach the schools.

In columns (6)–(8), I explore the sensitivity of my results to alternative central angle measures. All estimates remain with the predicted sign for the upwind fires but with sizes differing substantially. Column (5) reports the reduced-form results when setting the angles at 30 degrees. The effect size is similar to the 45º angle presented in Table 3, but standard errors are noticeably larger, resulting in imprecise estimates. I attribute this to the narrower angle being associated with more precision in wind direction (Rangel and Vogl, 2019) and capturing less upwind fires which produces additional noise. In column (6), the impact of upwind fires becomes larger, approximately 43% as large as the effect in column (6) from

Table 6: Robustness Check on Different Distances and Angles

	Distance					Angle		
	30km	40km	50km	60km	70km	30°	60°	90°
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Upwind	-0.571	-0.664	-0.767	-0.694	-0.471	-0.622	-1.104	-0.156
	(0.237)	(0.265)	(0.216)	(0.240)	(0.204)	(0.325)	(0.255)	(0.220)
Non-upwind	0.222	0.473	0.052	-0.024	-0.054	-0.115	0.169	-0.131
	(0.717)	(0.345)	(0.269)	(0.178)	(0.154)	(0.185)	(0.238)	(0.267)
Upwind vs. Non-upwind	-0.793	-1.137	-0.819	-0.67	-0.417	-0.507	-1.273	-0.025
	(0.804)	(0.481)	(0.383)	(0.293)	(0.273)	(0.314)	(0.309)	(0.319)
Num.Obs.	173807	173807	173807	173807	173807	173807	173807	173807
R-Squared	0.199	0.199	0.199	0.199	0.199	0.199	0.199	0.199
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School-Grade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of the Equation (2) using alternative distances and angles. In the main estimations, fires are in the sample if they are within 50km of the municipality centroid. In addition, the angle used to define upwind fires is 45°. Standard errors are clustered at the municipality-level.

Table 3). The estimates are very precise and show the predicted sign. Using a wider angles in column (7) yields result close to Zivin et al. (2020), which match the typical pollution spread models, i.e, when the angles are wider, more municipalities with varying levels of exposure are included in the "treated" upwind group.

7 Conclusion

Pre-harvest fires remains a cheap option to increase labor productivity in the process of harvesting sugarcane. However, it produces several negative externalities with regards to health (Rangel and Vogl, 2019; He et al., 2020; Lai et al., 2022) and education (Zivin et al., 2020; Carneiro et al., 2021).

This paper explores the relationship between agricultural fires and test scores among public state school students from a major sugar-producing area in Brazil. The identification strategy leverages on the exogeneity of wind direction in relation to the location of agricultural fires to isolate the main mechanism that contemporaneously impact student performance on SARESP, the increased level of air pollution.

The results indicate that an additional fire in the upwind direction increases PM_{10} emissions by 0.15 standard deviations with no significant increase in ozone emissions. The impact from upwind fires on test scores is smaller, with an one-unit increase in upwind fires decreasing the total exam score by 0.015 standard deviations. Using the ratio of the reduced-form estimates over the first-stage estimates based on upwind fires[10], I find that a 1 standard deviation increase in the PM_{10} reduces test scores by 0.1 standard deviation. These results compare with evidence from high-stakes exams in other countries, with magnitude being roughly three times as large as those found for Israeli test takers (Ebenstein et al., 2016) and 30% smaller relative to Chinese test takers (Zivin et al., 2020).

The effect is transitory and caused by contemporaneous fires on the day of testing. The impact from upwind fires on test scores is larger in the math portion of the exam and it is about 8% larger for girls. The effects are also concentrated among students in the bottom quartile of the distribution of test scores. Additionally, when the upwind fire is further away, the impacts on test scores are smaller but the effects behave linearly with respect to distance. Overall, these findings are consistent with the other papers that have explored the relationship between air pollution and students performance (Ham et al., 2014; Bharadwaj et al., 2017; Persico and Venator, 2021; Duque and Gilraine, 2022; Pham and Roach, 2023).

[10]The preferred estimations are the column (6) of Table 2 and column (6) of Table 3. In both, I used a Wald-type estimator on the reduced form results of the coefficient of upwind fires, similar to Rangel and Vogl (2019).

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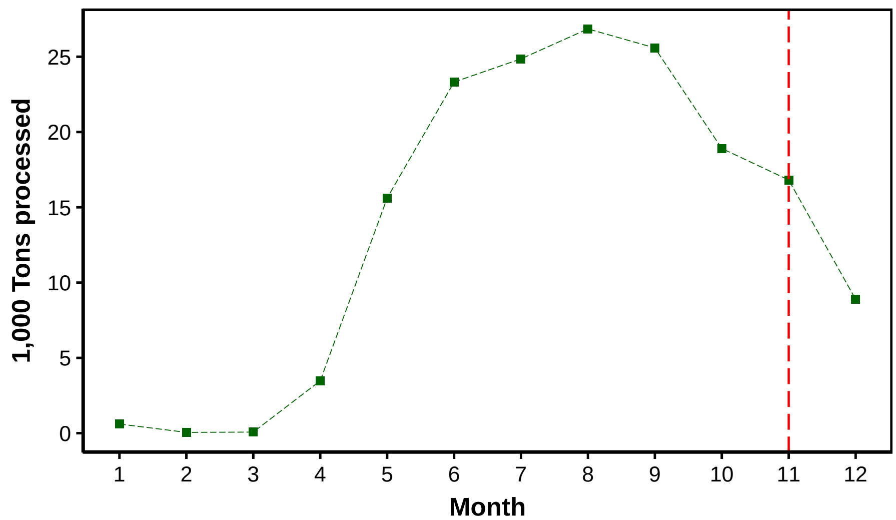
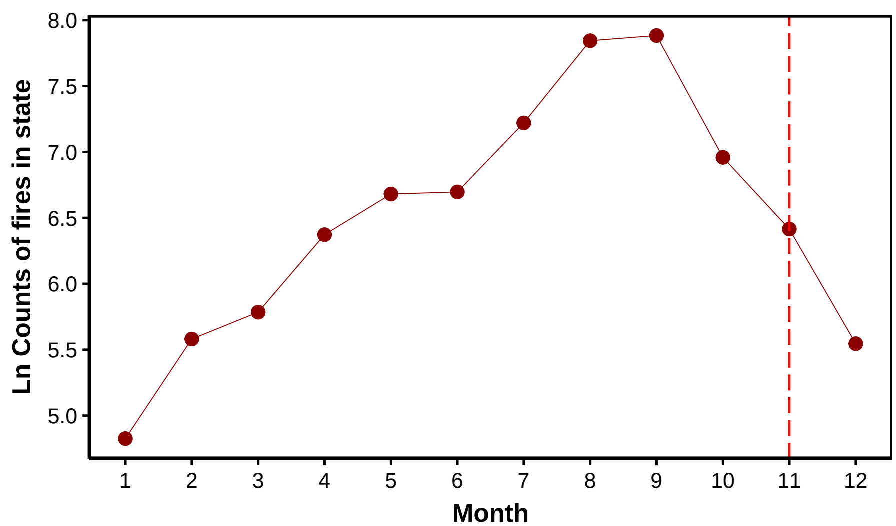
Appendix A

Figure A1: Sugar Cane Monthly Tonnage and Monthly Count of Fires in Sao Paulo State

(a)



(b)



Notes: Panel (a) shows the monthly milled sugarcane tonnage within the state of Sao Paulo (2009-2013). The data comes from the National Union of Sugarcane Producers (UNICA). Panel (b) shows the logarithm of satellite-based fire count using daily remote-sensing data on agricultural fires from the Brazilian space agency (Instituto Nacional the Pesquisas Espaciais - INPE).

Table A1: Air-Quality Stations - Descriptives

	Wind Speed (m/s)	Temperature (C°)	Humidity (%)	PM10 ($\mu g/m^3$)	Ozone ($\mu g/m^3$)
Station 1	2.19 (0.28)	24.61 (1.27)	69.82 (4.12)	28.54 (6.48)	39.71 (6.83)
Station 2	1.95 (0.18)	27.07 (1.1)	67.09 (9.08)	21.12 (4.72)	56.21 (10.08)
Station 3	2.19 (0.18)	24.72 (1.25)	69.02 (6.28)	23.67 (4.54)	51.54 (7.37)
Station 4	2.32 (0.12)	25.86 (0.84)	64.56 (6.95)	23.34 (4.31)	49.6 (1.72)
Station 5	2.24 (0.47)	25.12 (1.2)	64.61 (7.81)	26.61 (6.01)	48.84 (12.82)
Station 6	2.29 (0.28)	25.25 (0.96)	73.53 (6.17)	23.86 (2.87)	49.99 (2.47)
Station 7	2.34 (0.16)	22.18 (1.9)	78.48 (6.08)	21.4 (3.36)	42.26 (7.8)
Station 8	2.65 (0.21)	24.99 (1.2)	64.87 (6.7)	16.67 (2.78)	57.24 (7.21)
Station 9	2.24 (0.24)	24.23 (1.22)	77.18 (6.43)	28.71 (2.89)	47.93 (9.41)
Station 10	1.93 (0.15)	26.74 (1.6)	62.31 (8.88)	16.19 (3.6)	51.94 (10.03)
Station 11	1.96 (0.22)	26.63 (2.26)	64.8 (4.29)	21.59 (7.22)	43.4 (12.33)
Station 12	2.22 (0.26)	26.65 (1.17)	63.78 (8.2)	23.32 (5.93)	49.88 (11.74)
Station 13	1.58 (0.07)	23.98 (1.14)	75.01 (1.83)	23.69 (3.66)	45.63 (8.77)

Notes: Weather conditions' values were imputed using station-specific two-day averages. Standard deviation are in parentheses.

Appendix B

Table B1: Balance test of school and family characteristics from (Non-)Upwind municipalities

	Upwind	Non-upwind	Difference
	(1)	(2)	(3)
A. School Infrastructure			
Internet Access	0.968	0.989	-0.021
	(0.176)	(0.105)	[0.197]
Piped Water	1.00	0.998	0.002
	(0.00)	(0.04)	[0.083]
Public Sewage	0.968	0.983	-0.015
	(0.176)	(0.129)	[0.359]
Library	0.024	0.041	-0.017
	(0.153)	(0.199)	[0.234]
No. of Classrooms	13.49	13.03	0.459
	(7.32)	(4.96)	[0.490]
Distance from Municipality Centroid	6.30	4.87	1.43
	(2.53)	(2.37)	[<0.001]
Distance from Air Quality Station	3.59	4.01	-0.418
	(2.85)	(2.90)	[0.117]
B. School Characteristics			
No. of Employees	59.59	63.23	-3.62
	(24.7)	(26.7)	[0.117]
No. of Teachers	22.45	21.84	0.611
	(13.7)	(14.5)	[0.634]
Share of White Students	0.687	0.697	-0.010
	(0.08)	(0.09)	[0.232]

Continued on next page

Table B1 – continued from previous page

	Upwind	Non-upwind	Difference
	(1)	(2)	(3)
Share of Non-White Students	0.304	0.294	0.010
	(0.08)	(0.09)	[0.218]
No. of School Days	227.5	226.1	1.34
	(3.82)	(4.75)	[0.001]
C. Family Characteristics			
< 30 min. from school	0.866	0.827	0.039
	(0.341)	(0.378)	[<0.001]
Employed Father	0.540	0.527	0.013
	(0.498)	(0.499)	[0.007]
Employed Mother	0.687	0.697	-0.010
	(0.08)	(0.09)	[0.232]
High School Father	0.223	0.240	-0.017
	(0.416)	(0.427)	[<0.001]
High School Mother	0.249	0.259	-0.010
	(0.432)	(0.438)	[0.019]
College Father	0.033	0.048	-0.013
	(0.175)	(0.207)	[<0.001]
College Mother	0.032	0.045	-0.013
	(0.178)	(0.213)	[<0.001]

Note: This table presents a difference in test between schools in municipalities that faced a positive number of upwind fires and schools in non-upwind municipalities. Data on schools infrastructure and characteristics comes from the *Censo Escolar*, a comprehensive survey data conducted annually by the Brazilian Ministry of Education (Ministério da Educação - MEC) through the National Institute of Educational Studies and Research Anísio Teixeira (Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira - INEP).

Table B2: Effect of wind direction on pollutant concentration in November without two-day moving averages

	PM10						O3		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
No. of Fires	0.222						0.016		
	(0.121)						(0.086)		
Upwind		1.060			1.077	1.057		-0.172	-0.165
		(0.305)			(0.308)	(0.308)		(0.214)	(0.219)
Downwind			0.205		0.274			-0.181	
			(0.271)		(0.267)			(0.237)	
Non-upwind				0.137		0.135			0.035
				(0.145)		(0.142)			(0.102)
Upwind vs. Downwind					0.804			0.009	
					(0.392)			(0.302)	
Upwind vs. Non-Upwind						0.922			-0.2
						(0.399)			(0.277)
Num.Obs.	1861	1861	1861	1861	1861	1861	1903	1903	1903
Mean Dep.Var	26.26	26.26	26.26	26.26	26.26	26.26	50.45	50.45	50.45
Sd. Dep.Var	11.61	11.61	11.61	11.61	11.61	11.61	13.97	13.97	13.97
R2	0.763	0.764	0.762	0.762	0.764	0.764	0.784	0.784	0.784

Notes: This table reports estimates of the Equation (1). Columns (1)-(6) report the results where the dependent variable is the concentration level of PM10 in $\mu g/m^3$. Columns (7)-(9) report the results where the dependent variable is the concentration level of O3 in $\mu g/m^3$. Standard errors clustered at the municipality level are in parentheses.

Table B3: Different Distance from Schools from Municipality Centroids

	2.5km	5km	7.5km	10km	12.5km	15km
	(1)	(2)	(3)	(4)	(5)	(6)
Upwind	-0.832	-0.431	-0.523	-0.699	-0.718	-0.044
	(0.540)	(0.476)	(0.195)	(0.231)	(0.293)	(0.313)
Non-upwind	0.278	-0.265	0.030	0.044	-0.073	-0.235
	(0.410)	(0.236)	(0.210)	(0.259)	(0.189)	(0.179)
Upwind vs. Downwind	-1.109	-0.166	-0.552	-0.743	-0.645	0.191
	(0.591)	(0.509)	(0.289)	(0.364)	(0.399)	(0.414)
Num.Obs.	32462	85693	141495	173807	197975	216571
R2	0.171	0.172	0.192	0.199	0.197	0.196
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
School-Grade FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: his table reports estimates of the Equation (2). The dependent variable is average from language and math test scores normalised to a (250,50) scale. Weather variables include quintile bins for average temperature, relative humidity and wind speed and also include the count of fires with non-measured wind direction. Standard errors clustered at the municipality level are in parentheses.

Table B4: Effects of Any Upwind Fires and Non-upwind fires on Overall Test Scores

	(1)	(2)	(3)	(4)	(5)	(6)
Any Fire	0.884					
	(1.114)					
Any Upwind		-2.547			-2.992	-3.295
		(1.154)			(1.300)	(1.469)
Any Downwind			-1.641		-1.990	
			(1.242)		(1.153)	
Any Non-upwind				-0.312		-0.974
				(0.770)		(0.762)
Upwind vs. Downwind					-1.002	
					(1.372)	
Upwind vs. Downwind						-2.321
						(1.218)
Num.Obs.	173807	173807	173807	173807	173807	173807
R2	0.199	0.199	0.199	0.199	0.199	0.199
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
School-Grade FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of the Equation (2). The dependent variable is average from language and math test scores normalised to a (250,50) scale. The variables Any fires represent an indicator variable that assigns value 1 for any positive number of detected fires within 50km from the municipality centroid. The remaining variable follow the same logic. Weather variables include quintile bins for average temperature, relative humidity and wind speed and also include the count of fires with non-measured wind direction. Standard errors clustered at the municipality level are in parentheses.

Appendix C

School Location and Increased Exposure of Pollution

In the previous estimations, the underlining assumption was that an upwind fire equally impacted all schools within 10km from the municipality centroid. The reduced-form results from Table 3 provide evidence of this assumption. One of the features in the school data is that I am able to locate the geographic position of schools relative to the municipalities centroids, air quality stations and the location of fires that occurred around exam days. In this section, I find the octant sector in which the school is relative to the upwind and downwind fires and allow for heterogeneity within municipalities by differentiating schools into groups based on their geographical positions relative to the upwind and downwind fires.

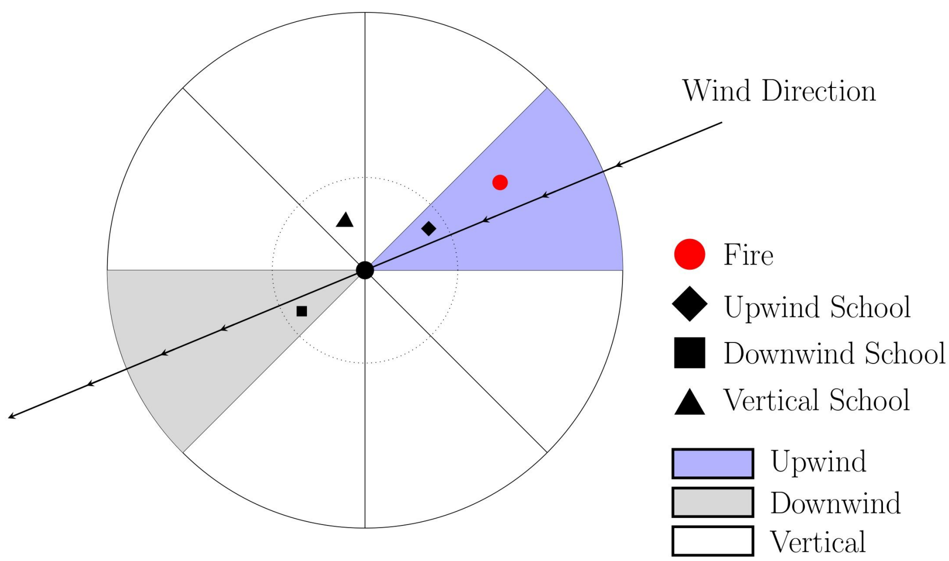
First, I use the same procedure described in Section 3 to find upwind and downwind fires. Second, I find the octant in which a school is relative to the municipality centroid. Since I know in which octant the fire and prevailing wind direction are, by including the location of the school, it is possible to find which school from a given municipality are in the same octant as the fire and prevailing wind direction. As such, I can define an upwind school if the school is in the same octant as an upwind fire. Similar to prior definitions, a downwind school is a school in the opposite octant of an upwind fire.

Figure C1 illustrates an example. The outer circle represents the 50km perimeter around the municipality centroid for which I use to count the number of fires, while the inner circle represents the 10km perimeter for which I use to select the school in my sample. In the figure, a fire is detected on the second octant (between 45°and 90°) and the prevailing wind direction is coming from the northeast (NE). The combination of prevailing wind direction and fire in the same octant defines an upwind. Since there is only one fire in this example, the count of upwind fire is 1.[11] The black diamond, triangle and square represent three different schools. Similarly to the definition of upwind fire, I define a school as an upwind school if it is located in the same octant as an upwind fire. Notice that it is possible to have multiple fires in the upwind direction, so an upwind school can be subjected to more than

[11] If, for example, the fire was detected in the opposite octant and the direction of the wind was still NE, then this would define a downwind.

one upwind fire. A downwind school is defined as a school that is located in the opposite direction of an upwind fire, which is represented by the black square school in the example.

Figure C1: School Location and Upwind Fires



Notes: The figure illustrates the difference between upwind schools to downwind and vertical schools. Upwind schools, denoted by the black diamond, are in the same octant as the fire and wind direction. Downwind schools are in the opposite octant of the wind and the fire. Vertical schools cover the remaining octants. The black circle in the center denotes the municipality centroid.

In this heterogeneity analysis, I assume that schools positioned in the same octant as an upwind fire encounter increased exposure to air pollution from agricultural fires, in contrast to downwind and vertical schools. As a result of this differential exposure, I expect that schools in the same octant will demonstrate lower test scores. Given the absence of data at the school level, I rely on the first stage mechanism to validate the assumption of our heterogeneity analysis. By leveraging the empirical relationship between wind patterns and air pollution levels from agricultural fires, I estimate the following model:

$$y_{igs(m)t} = \sum_{k \in \{\text{U,D,V}\}} \beta^k School^k_{s(m)t} + \boldsymbol{X}'_{mt}\gamma + \mu_t + \lambda_s + \theta_{sg} + \epsilon_{is(m)t} \tag{3}$$

Where $y_{is(m)t}$ is the normalized test score of student i of school s in municipality m in exam-year t. The subscripts $\{U, D, V\}$ denote upwind, downwind and vertical schools, respectively. Thus, $School^k_{s(m)t}$ denotes the number of fires a school s of type k faces in year t. In the example above, the school represented by the black diamond is in the same direction of one upwind fire, hence it is an upwind school with count one.[12] Similar to Equation (2), I include dummies for each decile of humidity, temperature and wind speed as controls for weather variables and I use year, school and school-grade fixed effects. Finally, I cluster standard errors at the municipality-level.

Table C1: Effects of Fires, Upwind Fires and Non-upwind fires on Overall Test Scores

	(1)	(2)	(3)	(4)	(5)	(6)
Upwind School	-0.469			-0.471	-0.531	-0.533
	(0.223)			(0.223)	(0.231)	(0.230)
Downwind School		-0.089		-0.141		-0.199
		(0.359)		(0.369)		(0.368)
Vertical School			-0.071		-0.113	-0.114
			(0.195)		(0.194)	(0.194)
Num.Obs.	173807	173807	173807	173807	173807	173807
R2	0.199	0.199	0.199	0.199	0.199	0.199
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
School-Grade FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of the Equation (2). In all columns, the dependent variable is the test scores standardized at a (250,50) scale. Upwind schools is the number of fires a school in the same octant as the fires and the prevailing wind direction face. Downwind schools is the number of fires a school in the opposite octant as the fires and prevailing wind direction face. Vertical schools is the number of fires a school in the adjacent octants of upwind fire. Standard errors are clustered at the municipality-level.

Table C1 reports the results regarding the effects of upwind fires on student's test scores when I take in consideration the position of school relative to fires and wind direction. In

[12] If, for example, there were two upwind fires in Figure C1, the school would be type U and have count two.

columns (1)-(3), I estimate the basic model from equation (3) for each unique variable separately. In column (1), I find that an additional upwind fire during the exam decreases test scores by about 0.469 points (0.9% of a standard deviation) for schools located in the same wind octant as the agricultural fires. Columns (2) and (3) report that downwind and vertical schools also show a reduction in test scores, but the estimates are not statistically significant. Comparing the effect sizes individually, it is clear that the upwind schools are much more affected that non-upwind school, with estimates being 6 times larger than the other ones. Columns (4) and (5) present the estimates by jointly regressing equation (3). The results, to a large extent, remain similar. The coefficients associated with upwind schools remains negative and statistically significant. Notably, the estimates of downwind and vertical schools exhibit larger coefficients, but the estimate lacks precision.

The full equation results are shown in column (6). For upwind schools, an additional fire in the upwind direction is associated with a 0.53 point decrease in test score (1.06% of a standard deviation). Comparing this estimate with the upwind coefficient in column (6) from Table 3, it provides a relevant source of within-municipality heterogeneity. The previous results suggested that an additional upwind fire reduces test score by 0.69 points in all schools within 10km from the municipality centroid. Here, the schools from the same original sample are subjected to a 0.55 point decrease in schools are located in the same octant as the upwind fire. While the effects are not additive, the estimations from column (6) and column (6) from Table 3 suggest that upwind schools account for approximately of 76% of the reduction in test scores within an upwind municipality. Downwind and vertical schools do not show a similar pattern of results, with both estimates being statistically insignificant.

Appendix D

Is Long-Term Exposure a Confounding Factor?

Although the results have suggested a strong causal relationship between agricultural fires, air pollution and short-term cognitive disruptions during the exam day, there is strand of the literature that reports similar results from pollution shocks during the school year. These cumulative pollution shocks could impede human capital formation through several channels. First, health effects may reduce attendance. Currie et al. (2009) found that high levels of carbon monoxide were associated with reduced school attendance for students in Texas. Second, physiological response can be triggered by higher levels of ambient air pollution. Heissel et al. (2022) found that traffic pollution increase behavioral incidents on schools located downwind of major highways in Florida. Third, cumulative and year-round exposure to air pollution can be associated with increased levels of stress and fatigue that can result in learning disability (Pham and Roach, 2023). Taken together, these findings suggest that sustained exposure to pollution sources throughout the school year may have broader effects on test scores, extending beyond the immediate impact of air pollution exposure.

As shown in Figure A1, agricultural fires are at their highest during the months of August and September, which closely coincides with the peak of the harvesting. Given that harvesting activity is relatively high in other months outside of the month of the SARESP, one concern is that fire activity prior to the exam can potentially contribute to a lingering impact on air quality during the school year. Using yearly data on agricultural fires and air pollution for the same air quality monitoring stations used in this paper, Rangel and Vogl (2019) found a substantial PM_{10} increase of 9.87 $\mu g/m^3$ for each z-score increase in upwind fires, which is about 50% of standard deviation and approximately 6 times larger than the first stage results in Table 2. This sustained exposure to agricultural fires throughout the harvesting season, including the months leading up to the exam, raises the question of whether the observed cognitive disruptions are not only a result of immediate exposure but also influenced by cumulative and prolonged effects.

To test if the exposure to upwind fires during the school-year up to date of exam impacts test scores, I use equation (2) but instead I utilise the number of agricultural fires located in the upwind and non-upwind directions of municipality m until the days of the exam in year t. The weather variables X_{mt} include dummies for each decile of humidity and temperature of their yearly averages. The identification strategy still relies on the assumption that the exposure to air pollution from agricultural fires is conditionally random given wind patterns. However, a potential concern arises from the limitations in capturing avoidance behaviors, such as students switching schools or parents implementing other behavioral responses during the school year due to air pollution concerns. Although the model and the data are not perfectly equipped to causally estimate the impact of year-to-year variation in pollution exposure on cognitive performance, correlational evidence of the medium-term exposure to air pollution through the relationship of wind patterns and agricultural fires may further reinforce my prior findings.

Table D1 reports the results from equation (2) using total number of agricultural fires located in the upwind and non-upwind directions of municipality m until the days of the exam in year t and yearly weather controls. Because of the concerns that I have expressed, the degree of how much the exclusion restriction is valid is uncertain. Therefore, I interpret the results as correlations. With this in mind, the results from columns (1)-(3) suggest that the number of upwind and non-upwind fires are negatively correlated with test scores. However, the estimates are not statistically significant and the size of estimate is close to zero. The inclusion of both variables in the regression does not impact the estimates substantially, which remain negative, statistically insignificant and close to zero. The results suggest that the overall impact from being exposed to upwind fires over time might not significantly affect test performance. On the other hand, these results also back up previous findings that upwind fires affecting test scores contemporaneously. This consistency supports the idea that the effects of upwind fires on test scores on the day of the test are still significant.

Table D1: Long-Term Exposure to Agricultural Fires on SARESP Scores

	(1)	(2)	(3)
Upwind days	-0.019		
	(0.083)		
Non-upwind days	0.028		
	(0.063)		
Upwind days/No. of days		-0.050	
		(0.266)	
Non-Upwind days/No. of days		0.081	
		(0.208)	
No. of upwinds/No. of days			1.853
			(9.558)
No. of non-upwinds/No. of days			-0.422
			(2.448)
Upwind vs. Non-upwind	-0.046	-0.13	2.274
	(0.121)	(0.397)	(11.298)
Num.Obs.	173807	173807	173807
R2	0.199	0.199	0.199
Year FE	Yes	Yes	Yes
School FE	Yes	Yes	Yes
School-Grade FE	Yes	Yes	Yes

Note: This table reports estimates of Equation (2). The dependent variable is the average of language and math test scores normalized to a (250,50) scale. Weather variables include quintile bins for average temperature, relative humidity, and wind speed, and also include the count of fires with non-measured wind direction. Standard errors clustered at the municipality level are in parentheses.

Appendix E

Heterogeneity Analysis Across Income Groups

Papers in the literature of the impact of air pollution have found substantial heterogeneity across income groups. Jayachandran (2009) found that the impact of smoke from massive wildfires on fetal, infant, and child mortality is much larger in poorer areas of Indonesia. Ito and Zhang (2020) found that higher income households have a larger willingness to pay for air purifiers compared to lower-income households in China. Despite these findings, only few papers have explored socioeconomic differences concerning the effects of air pollution on education outcomes. One noteworthy study addressing this gap is Persico and Venator (2021). Examining the impact of a Toxic Release Inventory (TRI) openings in Florida, they found consistently diminished test scores for all students, irrespective of their socioeconomic backgrounds. However, their study addresses the role of medium-term pollution exposure on test scores rather than directly exploring the immediate short-term effects of exposure on the day of the test. In considering the contemporaneous effect, I expect that there shouldn't be variation in the impact of upwind fires on test scores across income groups, as they are subjected to the same pollution shock. However, this assumption may not hold true if one of the groups can alleviate the consequences of cumulative air pollution exposure or possesses underlying factors that differentiate their response to such exposure. Avoidance behavior also can be different across income groups, as higher income individuals can migrate to less polluted areas (Chen et al., 2022) or engage in defensive investment against pollution (Zivin and Neidell, 2009; Neidell, 2009).

To evaluate if there are differences on the response of upwind and non-upwind fires on test scores across income groups, I utilise the SARESP parents questionnaire. Parents from public state school students are required to answer a questionnaire covering questions regarding evaluation of school, evaluation of child's activities within and outside of the school, work situation, level of education, and socioeconomic information. Data on family household income comes from the SARESP parents questionnaire. Parents are asked what is the family income of the household, that is, the sum of the salaries of those who work and live in your house. This item originally had six categories: lower than R$851.00, from R$851.00 to R$1,275.00, from R$1,276.00 to R$2,125.00, from R$2,126.00 to R$4,250.00, more than R$4,250.00 and don't know/don't want to answer. Figure E1 shows the distribution of family income reported by the parents of the students for upwind and non-upwind municipalities. The figure presents two striking features: first, 70% parents of students enrolled in public state schools that took SARESP reported having a household income bellow R$2125,00 (438 U$ in 2023), which in 2013 would be equivalent to 3.1 minimum wages at the federal level. Second, municipalities exhibit similar distributions of family income irrespective of upwind status. In fact, the figure shows that a municipality (or school) being subjected to a upwind fire is not particularly correlated with lower income, that could cause a form of selection bias in the results. Moreover, wind patterns assign pollution to high and low income students in a similar fashion, which strengthens the exclusion restriction of the instrument.

Figure E1: Share of Students By Income Groups

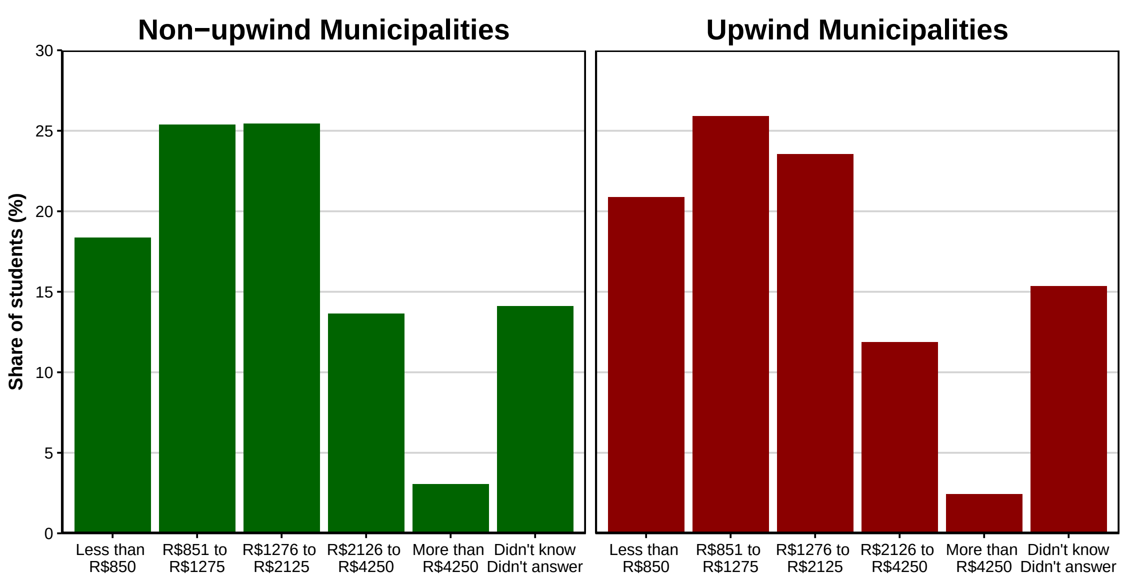


Table E1 shows the difference in means across income groups and upwind and non-upwind municipalities. In columns (1) and (2) from Panel A, I calculate the average and standard deviation test scores for each income group of upwind and non-upwind municipalities.

Unsurprisingly, the results show that income is positively correlated with test scores for both upwind and non-upwind municipalities, even among a homogeneous set of public school students. This is not unexpected since higher income is associated with a multitude of socioeconomic characteristics that are themselves correlated with higher test scores. A second feature of Panel A is that students in upwind municipalities have lower test scores than students in non-upwind municipalities for every income groups. Column (3) provides the results from a difference in means test, which shows that all groups except group 3 (R$1276 to R$2125) have economically significant differences in test scores.

Table E1: Heterogeneity in Agricultural Fire's Impact on SARESP Scores

	Upwind	Non-Upwind	Difference
	(1)	(2)	(2) - (1)
A. Income Groups			
Less than R$850	229.90	234.71	4.81
	(52.3)	(49.8)	[0.001]
R$851 to R$1275	243.16	247.86	4.70
	(50.2)	(49.1)	[0.001]
R$ 1276 to R$ 2125	258.09	259.07	0.66
	(49.4)	(49.0)	[0.520]
R$ 2126 to R$4250	265.04	269.34	4.33
	(49.3)	(48.4)	[0.002]
More than R$ 4250	261.2	264.4	2.97
	(52.1)	(50.8)	[0.381]
B. Income Dummy			
Low Income (A)	237.4	242.4	5.04
	(51.5)	(49.8)	[0.001]
High Income (B)	260.6	262.7	2.11
	(49.6)	(49.2)	[0.010]
(A) - (B)	-23.27	-20.34	-
	[0.001]	[0.001]	

Note: This table reports the effects of upwind and non-upwind fires on SARESP scores, broken down by income groups. "Low Income" refers to the income groups "no income or lower than R$1275.00". Standard deviations are in parentheses. The differences are calculated as the scores for non-upwind fires minus the scores for upwind fires. The p-values for the differences are reported in brackets.

In Panel B, I utilise the two categories of income to perform the same exercise. The differences remain statistically significant across upwind and non-uwpind municipalities, being larger among the low income group. Conditional on being on a upwind, the difference across income groups is also significant and larger than the difference among income groups in non-upwind municipalities.

Table B1 showed that schools in upwind and non-upwind municipalities exhibit similar characteristics in terms of infrastructure and number of employees and teachers. Therefore, the remaining variation in test scores is likely attributable to differences in contemporaneous exposure to pollution on exam days, irrespective of which income group students are. This result suggest that cumulative air pollution exposure is not likely a channel through which agricultural fires can impact test scores, based on the results of papers that establish that higher income groups engage in defensive investment against pollution and avoidance behavior.

To further examine whether income plays a role in diminishing the impacts of contemporaneous exposure to air pollution on test performance, I collapsed the data into two categories: "no income or lower than R\$1275.00", and "more than R\$1275.00." From the original sample, 85% of the parents answered the item with one of the designed answers. I use equation (2) to estimate the exposure of upwind and non-upwind fires on test scores in the days of exam for each of the samples separately. Table E2 shows the results.

In column (1), the coefficient of upwind fires is negative but statistically insignificant. Comparing the estimates in column (6) to the results shown in Table 3, the size of coefficient of upwind fires is about half. A one-point increase in the difference between upwind and non-uwpind fires reduce test scores by 1.24% of a standard deviation (0.620 points), however the estimate is imprecisely estimated and insignificant.

Columns (2) and (3) show the results which for the two income groups. Column (2) reveals that among low-income students, upwind fires are associated with a decrease in test scores by 1.9% of a standard deviation (0.950 points). This effect size is notably larger compared to the estimate for the full sample in column (1), suggesting that low-income students are more vulnerable to the adverse effects of air pollution from fires on cognitive

Table E2: Regression Results by Income Group

	Full Sample	Low Income	High Income
	(1)	(2)	(3)
Upwind	-0.456	-0.950	0.112
	(0.548)	(0.612)	(0.576)
Non-upwind	0.164	0.189	0.078
	(0.231)	(0.248)	(0.251)
Upwind vs. Non-Upwind	-0.620	-1.139	0.035
	(0.572)	(0.7)	(0.519)
Num.Obs.	123440	53598	51595
R2	0.218	0.231	0.181
Year FE	Yes	Yes	Yes
School FE	Yes	Yes	Yes
School-Grade FE	Yes	Yes	Yes

Notes: This table reports estimates of Equation (2). Full Sample includes all observations, while Low Income and High Income groups are defined based on income thresholds. Standard errors clustered at the municipality level are in parentheses.

performance. This disparity may stem from several socioeconomic factors that exacerbate susceptibility, such as limited access to healthcare, heightened exposure to environmental pollutants, and potentially inadequate living conditions. Conversely, column (3) reports positive coefficients for high-income students, though statistically insignificant.

Overall, these results reveal that low-income students are more affected by upwind fires that high-income students. Nevertheless, to find if the upwind fire coefficients from the two regressions are equal, I employ a simple t-test difference. I find no statistical difference between the two estimates. While this indicates that low and high-income students do not have statistically significant differences in test scores (conditional on upwind and weather variables), the direction and magnitude of the coefficients suggest that low-income students might be more vulnerable to the detrimental effects of air pollution from upwind fires.[13]

[13]This implies that even if my results do not conclusively show a disparity, the patterns highlight a future area of research that explores income heterogeneity on contemporaneous shocks of air pollution on students outcomes.