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The Effects of Air Pollution on Students' Cognitive Performance: Evidence from Brazilian University Entrance Tests

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Abstract: We examine the contemporaneous causal relationship between outdoor air pollution levels and student cognitive performance in Brazil's nationwide university entrance examinations. Our analysis relies upon a unique and previously unexplored student-level data set allowing us to examine the effect of particulate matter (PM_{10}) on students' scores. In our main specification we construct individual-level panel data for the 2 days of exams across 3 years and apply student fixed effects to address potential endogeneity concerns. In addition, we take advantage of plausibly exogenous spatial and temporal variation in PM_{10} across municipalities in the states of Rio de Janeiro and São Paulo and utilize an instrumental variable approach based on wind direction. Our results suggest that air pollution negatively impacts the cognitive performance of students. We find suggestive evidence that boys may be more affected than girls, and less well-off exam takers at the bottom of the score distribution are more affected than their more privileged counterparts.

JEL Codes: I10, I20, J24, Q53

Keywords: Brazil, air pollution, cognitive performance, wind direction, particulate matter

THE WORLD HEALTH ORGANIZATION (WHO) estimates that globally as many as 4.2 million premature deaths each year are linked to exposure to ambient air pollution.[1] The WHO also points out that the health impacts associated with pollution

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1. See http://www9.who.int/airpollution/ambient/health-impacts/en/.

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exposure are not equitably distributed, with the poorest individuals in the poorest countries being disproportionately affected. The manner in which many common local air pollutants adversely affect health, particularly via the respiratory and cardiovascular systems, is now well known (Dockery et al. 1993; Hansen and Selte 2000; Weinhold 2008; Currie et al. 2009; Ling and van Eeden 2009; Neidell 2009; US EPA 2016). However, a more recent literature has examined the possibility that exposure to air pollution may also affect cognitive performance and, in turn, potentially human capital formation, productivity, and ultimately economic growth (Zweig et al. 2009; Currie et al. 2014; Ebenstein et al. 2016). If true, this raises the prospect of a "cycle of disadvantage" in which exposure to pollution constrains the development prospects of those who need it most.

The literature examining the impact of pollution exposure on human capital formation has found compelling evidence that air pollution, through its impact on health, increases school absenteeism (Currie et al. 2009; Ransom and Pope 2013; Chen et al. 2018; Liu and Salvo 2018), negatively affects school pupils' scores (Almond et al. 2009; Nilsson 2009; Zweig et al. 2009; Reyes 2011; Sanders 2012; Bharadwaj et al. 2017), and decreases low- and high-skilled workers' productivity (Chang et al. 2016; Heyes et al. 2016; Archsmith et al. 2018; Chang et al. 2019; Kahn and Li 2019). Other studies examine the accumulated impact of air pollution within a period of time on pupils' scores at school (Zweig et al. 2009). Overall, these studies look at the long-run impact of fetal (Almond et al. 2009; Sanders 2012; Bharadwaj et al. 2017) or around birth (Nilsson 2009; Reyes 2011) exposure to air pollution on students' scores and do so typically in developed country settings.

While many studies focus on the cumulative or long-run impacts of air pollution on pupils' academic performance, few pay heed to the contemporaneous effect of pollution exposure on student performance. One exception is Ebenstein et al. (2016), who find negative effects of air pollution exposure on the day of high-stakes examinations in Israel, with negative long-run effects on individuals' earnings. Another relevant study is Graff Zivin et al. (2020), who examine the impact of agricultural fires on Chinese students' exam scores. They differentiate between upwind and downwind fires and find the difference between the two to have a statistically significant effect on exam performance. With regard to Brazil, Bedi et al. (2021) conduct an experiment at the University of São Paulo and suggest that exposure to high levels of $PM_{2.5}$ reduces students' performance in a reasoning test. Here we add to this literature by investigating the impacts of particulate matter on students' scores in high-stakes exams by using a unique geographic and demographically representative data set. Despite the findings of Graff Zivin et al. (2020) and Bedi et al. (2021), there remains very limited evidence on the impacts of urban air pollution on students' cognitive performance in the most highly polluted cities and regions of the developing world.

This paper examines the causal relationship between outdoor air pollution levels on the day of the nationwide university entry examinations and students' cognitive performance in Brazil, and specifically in Rio de Janeiro and São Paulo, its most industrialized states. More precisely, we use Brazilian data on concentrations of ozone (O_3) and particulate matter (PM_{10}) and a rich administrative data set on students' scores to examine the impact of air pollution on academic performance in national examinations (Exame Nacional do Ensino Médio; ENEM).[2] This educational data set is combined with air pollution and weather monitoring station data to build a unique panel of data for the period 2015–17. We also test the effects of air pollution on the exam performance of male and female students separately since the previous literature has indicated that fetal exposure to pollution can have different long-term impacts on males and females (Jayachandran 2009; Sanders 2012). Similarly Ebenstein et al. (2016) found boys' exam performance to be more affected by air pollution than that of girls. In addition, we utilize students' socioeconomic characteristics to investigate the heterogeneous effects of air pollution on students' scores per different economic strata.

Our analysis contrasts with Ebenstein et al. (2016), who consider the impact of an overall air quality index on the Israeli national examination composite score, and with Graff Zivin et al. (2020). The latter work could neither establish the direct link between fires and air pollution nor assess the direct effect of air pollutants on students' scores due to lack of data on air pollution for the period of study. Unlike the previous literature, besides using student fixed effects, we also implement an instrumental variable (IV) approach to mitigate endogeneity concerns related to air pollution. Following Deryugina et al. (2019) and Bondy et al. (2020), we use wind direction as an exogenous shock capable of producing variation in air pollution levels on a particular day and locality. Our assumption relies on the fact that municipalities' daily wind direction is not directly related to students' scores in the national examinations except through its influence on air pollution. We take advantage of the geographic and temporal variation in wind direction in our data set to explore the exogeneity of our instrumental variable, that is, the variation in daily wind direction in the municipality in which the examination took place.

Our focus on Brazil is motivated by the fact that, by global standards, it experiences relatively high levels of air pollution and relatively low levels of academic performance. In terms of pollution, for instance, in 2015 the Environmental Company of São Paulo (Companhia Ambiental do Estado de São Paulo; CETESB) reported 972 occurrences of ozone levels being above WHO safe limits in the metropolitan area of that state.[3] Regarding academic achievements, in the OECD's Program for International Student Assessment (PISA) Brazil was ranked 39th out of 40 countries in 2019, revealing the relative underperformance of Brazilian students in comparison with their international counterparts, including most of Brazil's Latin American neighbors. Furthermore, OECD

2. PM_{10} represents particulate matter with a diameter of 10 micrometers or less.

3. The information can be found in the CETESB website: https://cetesb.sp.gov.br/.

research by Zapata et al. (2015) shows that only approximately 15% of 25–34-year-olds in Brazil completed tertiary education in 2014, compared to the OECD average of 41%.

Our findings suggest that an increase of 10 micrograms per cubic meter ($\mu g/m^3$) of PM_{10} on the day of the examination decreases students' scores by 6.1 points (8% SD). We find evidence that the students most affected by pollution are male, those with weaker school performance, and those from poorer households, although the differences that we find across these subsamples are not statistically significant. Finally, we run placebo tests using levels of pollution 1 day after the exams, with results reinforcing our main findings that it is indeed the poor air quality on the day of the exams that reduces exam scores. That is, pollution levels on the day after the tests have no significant impact on students' cognitive performance. We therefore believe that our study provides policy makers with important evidence of a contemporaneous link between air pollution and exam performance.

The remainder of this paper is organized as follows. In section 1, we describe our data. We present our empirical strategy in section 2. In section 3, we present our results and conduct sensitivity analysis. In section 4, we present our conclusions.

1. DATA AND SUMMARY STATISTICS

Our data set on daily air quality, weather conditions, and students' ENEM scores in São Paulo and Rio de Janeiro between 2015 and 2017 are collected from three main sources as detailed below. As our study comprises 3 years of examinations with students taking exams in 2 days (Saturdays and Sundays), we build a panel data at the student level and control for the day of examinations. We describe our data set and present summary statistics below.

1.1. Air Pollution Data

Air pollution data from São Paulo and Rio de Janeiro are collected from their respective environmental state agencies: the Environmental Company of São Paulo (Companhia Ambiental do Estado de São Paulo; CETESB) and the State Institute for the Environment (Intituto Estadual do Meio Ambiente; Inea). Both agencies are responsible for monitoring the air quality of the two states, using ground-level automatic and nonautomatic monitoring stations.[4] São Paulo has 63 automatic monitoring stations and 26 nonautomatic stations, while Rio de Janeiro has 58 automatic and 116 nonautomatic stations (see fig. A3; figs. A1–A4 are available online). Inea's and CETESB's websites provide the addresses, latitude, and longitude of their monitoring stations, which

4. The automatic stations are directly linked to a central computer that registers the pollution concentrations. In the nonautomatic stations, the samples are manually collected at the site to be analyzed in the laboratories of CETESB and Inea.

we used to merge this data set with the national examination scores, by municipality centroid location.

Unfortunately, for confidentiality reasons, the Ministry of Education in Brazil does not provide the exact address where each student took their examinations, only the municipality. Hence, we are not able to identify the closest monitoring station to the exact exam location. Nevertheless, following Graff Zivin et al. (2020), we proxy each exam venue's location using the centroid of the municipality in which the test took place. We then identify up to three pollution monitoring stations within 10 kilometers (km) of the municipality centroid and average hourly readings across those to form an average daily measure of pollution (table 1 reports summary statistics of PM_{10} and O_3).[5] We then calculate the inverted weighted distance (IWD) for PM_{10} and O_3 (in $\mu g/m^3$) following Currie and Neidell (2005), Sager (2019), and Bondy et al. (2020).[6]

1.2. Weather Data

To control for atmospheric climate we collected data on weather conditions from CETESB and Inea monitoring stations. This provides us with measures of temperature (in degrees Celsius, °C), relative humidity (in percentage, %), wind speed (in meters per second, m/s), and wind direction (in degrees).[7] The latter is used as an instrumental variable for PM_{10}. CETESB provides wind direction in cardinal mode; thus, to use it as a numerical variable, we transform it into degree direction. Moreover, as wind direction is an angle (360° circle) and covaries with wind speed (i.e., there are two components that need to be averaged together) to calculate its daily average we need to split out the east/west vector and the north/south vector, and then recombine them to find the speed and direction (Itron 2019; Webmet 2019).[8] The remaining climate measures are also registered on an hourly basis, with the daily means calculated and assigned to the examinations' municipalities using the IWD in a similar manner to which the pollution measure is built (Currie and Neidell 2005; Sager 2019; Bondy et al. 2020). Table 1 presents the summary statistics for weather conditions.

1.3. University Entrance Examination Scores and Other ENEM Data

The subject-specific ENEM scores are collected from the National Institute for Educational Research Instituto Nacional de Estudos e Pesquisas Educacionais Anísio

5. To be clear, if there are three monitors within 10 km we average across those, if there are two we average across those, and if there is only one then we use the daily average of that one monitor. If a municipality has no monitoring stations within 10 km of its centroid, then data for that municipality are dropped from our analysis. In our sensitivity analysis we increase the 10 km limit to 50 km.

6. Figures A1 and A2 show the daily average of both pollutants.

7. Unfortunately, we do not include rainfall as most stations do not present complete data for this variable for the period analyzed in this research.

8. As in Deryugina et al. (2019), wind direction refers to the direction the wind is blowing from.

Table 1. Summary Statistics: Air Pollution, Weather, and Exam Scores

Variable: Exam-Level Data	All	Girls	Boys
Total score (0–1,000 points)	526	516	537
	(76.2)	(71.3)	(78)
Sciences (0–1,000 points)	502	493	515
	(78.9)	(76.4)	(80.2)
Humanities (0–1,000 points)	558	550	569
	(77.3)	(76.2)	(77.5)
Languages (0–1,000 points)	532	532	534
	(68.4)	(67.1)	(70)
Mathematics (0–1,000 points)	512	494	535
	(116)	(106)	(125)
PM_{10} ($\mu g/m^3$)	17.5	17.5	17.5
	(6.11)	(6.13)	(6.08)
O_3 ($\mu g/m^3$)	41.5	41.5	41.6
	(12.3)	(12.3)	(12.1)
Temperature (°C)	20.6	20.6	20.6
	(3.2)	(3.25)	(3.24)
Humidity (%)	81.4	81.4	81.5
	(13.6)	(13.6)	(13.6)
Wind speed (m/s)	2.25	2.25	2.25
	(1.25)	(1.24)	(1.25)
Observations	2,931,368	1,671,910	1,259,458
N municipalities	47	47	47

Note. Table reports statistics for the estimation sample. Standard deviations between parentheses. *N* municipalities attends for the total number of municipalities where the exams took place with weather and air pollution measures available for the 3 years in our main sample.

Teixeira (INEP), an agency from the Brazilian Ministry of Education (INEP 2017). This is a rich administrative data set with detailed information on the students' scores per exam subject at the student and school level, and demographic information, such as household income, parental level of education, age, race, gender, and special needs (tables 1 and 2 summarize this information).

The data for 2015 indicate that exams took place in 261 municipalities: 208 municipalities in the state of São Paulo and 53 in Rio de Janeiro state. In 2016, the data set indicates 209 municipalities in the state of São Paulo and 51 in Rio de Janeiro state, making a total of 260 municipalities where the ENEM took place. In 2017, the state of São Paulo held examinations in 209 municipalities, and the state of Rio de Janeiro in 52. Note that since we use monitoring stations as far as 10 km from the municipality centroid to construct our air pollution and meteorological measures, we end up with

Table 2. Summary Statistics: Demographic Information, Female and Male Samples

Variable: Demographic Information: Student-Level Data	Girls (%)	Boys (%)	All
Race:			
White	56.5	43.5	676,034
Black	56.4	43.6	209,759
Mixed race	58.1	41.9	512,356
Asian	60.2	39.8	31,787
Indigenous	51.5	48.5	6,285
Nondeclared	52.4	47.6	29,463
Type of school:			
Federal	51.3	48.7	9,096
State	58.9	41.1	390,906
Municipal	57.8	42.2	10,234
Private	54.4	45.5	175,079
Nondeclared	43.2	56.8	880,369
Mother's education:			
Never studied	63.8	36.3	40,175
Incomplete first elementary	61.9	38.1	192,868
Incomplete second elementary	59.3	40.7	192,269
Elementary	57.5	42.5	217,829
High school	56.2	43.8	519,969
Undergraduate	46.8	53.2	175,996
Postgraduate	47.4	52.6	87,369
Nondeclared	51.4	48.6	43,209
Father's education:			
Never studied	62.7	37.3	47,118
Incomplete first elementary	61.4	38.6	235,784
Incomplete second elementary	59	41	197,293
Elementary	56.7	43.3	197,121
High school	55.4	44.6	441,797
Undergraduate	52.7	47.4	146,295
Postgraduate	51.4	48.6	73,888
Nondeclared	58.3	41.7	126,388
Household income:			
No salary	59.7	40.3	25,797
1–7 min. wages	58.9	41.1	1,113,334
>7 min. wages	50.4	49.6	326,553
Number of students	835,955	629,729	1,465,684

Note. The percentages refer to the proportion of boys and girls in relation to the last column named "All," in which we display the absolute amount of students per category (in the first column). For example, in the type of school, we see that there are 9,096 students from federal schools, among them 51.3% are girls and 48.7% boys. The household income was built in 17 ranges following the Ministry of Education's categories. In this table, we condense the bins into three due to space.

47 municipalities within our final sample.[9] This reduction in the number of municipalities and hence number of spatial observations of pollution measures in our final sample consists of a trade-off decision that we must make. Had we opted for using stations located, for instance, 50 km from the municipality centroid, we would have experienced attenuation bias in our estimates.[10] As, in a given year, every student takes the test on the same day, the variation in air pollution comes from the fact that they take exams in different locations. Nonetheless, the reduction in the number of observations in our final panel does not affect the power of our study since we still end up with a very large sample size.

As for demographic information, the INEP data provide the highest level of education achieved by each student's parents. As such, we build categorical variables indicating each of the seven educational levels as follows: (i) never studied, (ii) incomplete first elementary if the parent attended school for a while but did not complete the first elementary, (iii) incomplete second elementary if the parent attended school for a while but did not complete the second elementary, (iv) elementary if the parent only completed elementary school, (v) high school if the parent completed high school, (vi) undergraduate if the parent completed undergraduate school, (vii) postgraduate if the parent completeda postgraduate level, and (viii) nondeclared if the students declared that they were unaware of their parents' level of education (Zweig et al. 2009).

Students' socioeconomic background is also likely to be an important predictor of their academic performance, particularly in developing countries where the degree of inequality is much higher than in developed nations. In Brazil it has been found that students' socioeconomic characteristics can determine up to 85% of the variation in exam scores (Estadao 2019). In light of this, in our models that use municipality fixed effects, we control for socioeconomic background using parental household income. The original data do not display the income in figures, preventing us from using that data as a continuous variable. As a result, we created dummies for each level of parental household income. According to the INEP's microdata information, there are 17 income ranges—monthly earnings from zero minimum wage until more than 20 times the minimum wage. As table 2 shows, 76% of students have a household income between one and seven times the minimum wage, 1.8% belong to families who do not receive a salary, and around 22.2% of students' parents received more than seven times the minimum wage.

1.3.1. The ENEM

The ENEM is a nonmandatory and standardized national exam used to evaluate high school students in Brazil and is the second largest in the world after the National

9. Figure A4 shows the maps of Rio and São Paulo with the total amount of municipalities from the raw data that hosted examinations and the municipalities within our final sample

10. Table A3 presents the number of observations and municipalities for the five samples using the different distances, as well as the ratio of municipalities used in the final sample and the raw data set.

Higher Education Entrance Examination in China. Since 2009, the exam has been used by federal and state universities as their admission test. The exam is also used to rank deprived students to receive points in the federal scholarship Universidade para Todos Program (or ProUni), as well as for certification for a high school degree.

The ENEM comprises four groups of multiple choice exams that take place on two days: humanities, sciences, languages, and mathematics, each of them with scores ranging from 0 to 1,000. The humanities exam includes history, geography, philosophy, and sociology; the science tests encompass chemistry, physics, and biology; and the language tests include Portuguese language, literature, foreign language (English or Spanish), arts, physical education, and information and communication technologies (INEP 2017). In 2015, the examinations occurred on October 24 and 25; in 2016, on November 5 and 6; and in 2017, on November 5 and 12. In each year the exams start at 13:30 and finish at 18:30 on the first day, and start at 13:30 and finish at 19:00 on the second day. In 2015 and 2016 on the first day, students took exams in humanities and sciences and on the second day languages and mathematics. In 2017 the order was slightly different, with students taking tests on languages and humanities on the first day and sciences and mathematics on the second day.

Although we have hourly data for both air pollution and weather variables, which would enable us to assign the measures of air pollution and weather condition at the exact moment of the exams, we follow the literature on the impact of air pollution on human capital and use the daily average of O_3, PM_{10}, humidity, temperature, wind speed, and wind direction (Ebenstein et al. 2016; Sager 2019; Bondy et al. 2020).

2. EMPIRICAL STRATEGY

We examine the partial correlation between PM_{10} exposure and test scores at the individual level for the years 2015–17. Nonetheless, there are a few identification challenges to overcome in order to establish the causal relation between air pollution and students' performance due to the possible presence of omitted correlated elements. For instance, one concern is that students' exam scores may be correlated with air pollution due to the fact that students from higher socioeconomic strata could live in municipalities with lower levels of air pollution (the parents could choose to live in less polluted areas, which are usually more expensive) (Banzhaf and Walsh 2008; Currie et al. 2014). Hence, although the candidates do not choose the exam venue, it is determined according to the student's household postcode (INEP tries to assign the examination venue as close as possible [up to 30 km] to each student's address). Hence, students who live in less polluted municipalities would end up taking exams in cities with cleaner air than other candidates who live in more deprived areas, which may be more polluted (Currie et al. 2014). This possibility of address selection is also highlighted by Neidell (2004, 2009), who characterizes it as an avoidance behavior by parents.

A final concern relates to the fact that the level of pollution and weather conditions in the days and venues where the exams are marked may influence the final marks, as the examiners could also have their productivity affected by these circumstances. However, all the tests are multiple choice, and the grades are given by a machine, which clearly is not affected by air pollution or weather determinants. Thus, to tackle those econometric concerns we apply two specification strategies as detailed below.

2.1. Panel Fixed Effects Model

As students take exams on 2 days, we employ student fixed effects and control for the exact day of the examinations. The main model thus takes the following form:

$$\begin{aligned} S_{imt} = {} & \beta \mathrm{PM}_{mt} + \tau \mathrm{TEMP}_{mt} + \rho \mathrm{HUMID}_{mt} + \psi \mathrm{WINDSPEED}_{mt} \\ & + \phi_i + \theta_t + \varepsilon_{imt}, \end{aligned} \tag{1}$$

where S_{imt} is the test score of student i at municipality m at time t,[11] PM_{mt} is our measure of air pollution (PM_{10}) (in μ/m3) at municipality m at time t, TEMP_{mt} is the daily average temperature at municipality m at time t in degrees Celsius, HUMID_{mt} is the relative humidity measure at municipality m at time t in percentage,[12] $\mathrm{WINDSPEED}_{mt}$ is the mean of wind speed measured at municipality m at time t in m/s, and ϕ_i is student fixed effects. By including fixed effects and weather controls, we are able to compare students' performance in the exams on the different days with different levels of air pollution given each student's characteristics. Hence, confounding factors stemming from time-invariant differences between students can be eliminated from our list of identification concerns. For example, socioeconomic background and parents' level of education are subsumed by the student fixed effects. As we know the day of each examination, we are able to add θ_t as a control for exam fixed effects and rule out the concern that the tiredness of students in the second day of exams would confound the real effects of air pollution on their performance due to extra exhaustion in the second day of tests. In addition, we can eliminate another concern regarding differences in level of pollution from Saturdays and Sundays (when the exams take place) by including these time-varying controls. Finally, the standard errors are clustered by municipality centroid to control for spatial and serial correlation within each municipality in which examinations took place, and ϵ_{imt} is an idiosyncratic error term.

2.2. The Instrumental Variable Approach

After using student fixed effects and controlling for weather conditions, there may still remain concerns about the existence of classical measurement error. For example, the students' actual exposure to outdoor air pollution may differ from the monitoring

11. We use standardized test scores to account for the different subjects of the examination. Thus, standardized scores = (scores – $\overline{\text{scores}}$)/SD; where $\overline{\text{scores}}$ is the mean and SD is the standard deviation. That is, we normalize the official scale scores to a mean equal to zero and standard deviation equal to 1 (Rosa et al. 2019; Garg et al. 2020).

12. In our econometric models, we add linear and quadratic terms for both temperature and relative humidity, and their linear and quadratic interaction.

stations' readings, which may bias our estimates downward due to attenuation bias (Moretti and Neidell 2011; Schlenker and Walker 2015; Chen et al. 2018). Furthermore, as explained above, PM_{10} is not randomly assigned, leading to the potential presence of unobserved time-varying effects that we cannot account for. Therefore, we also experiment with an instrumental variable approach to estimate our models. In this regard we follow previous works, as, for example, Deryugina et al. (2019), Anderson (2020), and Bondy et al. (2020), and adopt wind direction as our instrument for air pollution, which can be considered a natural experiment that results in exogenous shocks to local air pollution in a specific area due to wind shocks (Currie et al. 2014).

Following Deryugina et al. (2019) and Bondy et al. (2020), we use *k*-means cluster to create three groups for all the pollution monitors in our sample. Clustering is largely used to assign pollution monitors into a predetermined number of groups according to the groups' latitude and longitude. Hence, each group represents a geographic area.[13] To choose the optimal number of regional clusters, we use the *k*-means cluster algorithm (Makles 2012). First, we follow the official Instituto Brasileiro de Geografia e Estatistica (IBGE) regional division of the São Paulo and Rio de Janeiro states to define as 11 the number of maximum possible clusters the municipalities in our final sample could belong to. The IBGE adopts several forms to classify the territory into smaller regions, for example, macro-regions, micro-regions, and meso-regions. We adopted the latter classification in line with CETESB's and Inea's monitoring stations' organization to define the municipalities from our sample into those regional groups. We found 11 regional levels, which we inputted in the *k*-means algorithm to find the optimal number of clusters per latitude and longitude. Figure 1 shows the within sum of squares (WSS), log(WSS), η^2, which is similar to the R^2, and the proportional reduction of error (PRE) coefficient (PRE) for all *k*-cluster solutions. Accordingly, clustering with $k = 3$ appears to be the optimal solution. More specifically, at $k = 3$ we see a kink in the WSS and log(WSS). The term η^2 points to a reduction of the WSS by 88% and PRE to a reduction of about 79% compared with the $k = 2$ solution. Yet, the reduction in WSS is negligible for $k > 3$.[14]

Note that the number of groups is somewhat (by latitude and longitude) arbitrarily chosen (Deryugina et al. 2019; Bondy et al. 2020). As a result, β_b^g varies across geographic groups (Deryugina et al. 2019). It follows that, in using the interaction between the geographic groups with the wind direction dummies, we aim to mitigate the concern that a municipality's pollution monitors may not properly measure the average

13. *K*-means clustering aims to split *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest mean. *K*-means algorithm minimizes within-cluster variances (squared Euclidean distances) and tends to find clusters of comparable spatial extent, i.e., by latitude and longitude in our case.

14. Our results do not leave doubt concerning the $k = 3$ choice. Nonetheless, the *k*-means response depends on the initial cluster centers chosen by the researchers. Thus, we repeated the process 50 times and found $k = 3$ to be the optimal answer 83% of the time. Furthermore, for more details on how to calculate the WSS, η^2, and PRE, consult Makles (2012).

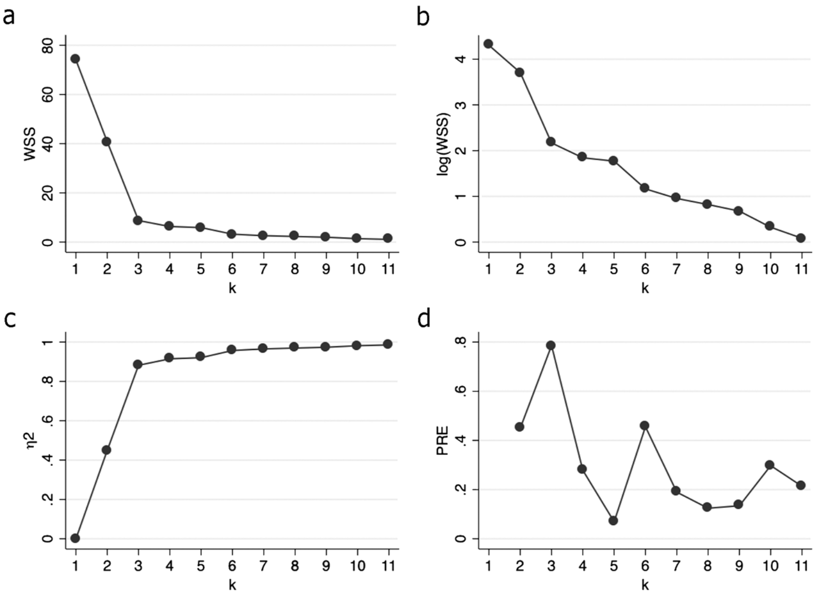

Figure 1. The within sum of squares (WSS) (*a*), log(WSS) (*b*), η^2 (*c*), and PRE (*d*) for all K cluster solutions (optimal number of clusters). The figure indicates clustering with $k = 3$ to be the optimal solution. At $k = 3$, there is a kink in the WSS and log(WSS), respectively; η^2 points to a reduction of the WSS by 88% and PRE to a reduction of about 79% compared with the $k = 2$ solution. However, the reduction in WSS is negligible for $k > 3$.

pollution each student within each municipality is affected by since the pollution station locations are sparse throughout the two states Rio de Janeiro and São Paulo. Furthermore, we also do not know the precise location of the exam venues within each municipality. As such, our identification strategy limits the effect of municipality wind direction on pollution to be the same for all stations within each of the three geographic groups, which comprise various municipalities. As explained by Deryugina et al. (2019) and by Bondy et al. (2020), this confinement shortens the impact of pollution variation from different sources, reducing measurement error in our models. The concern here is that the 47 municipalities in our sample engulf a large area, and wind may carry particulate matter from different sources.[15] That is, if the station is close to the point source, its measures are likely to be higher than another station located far from the point source, which may cause measurement error in our estimations. On the other hand, nonpoint sources tend to present more similar influence on the monitors in the same group and, hence, are more likely to be responsible for the variation on pollution

15. Note that we consider the direction the wind blows from, instead of the direction that the wind blows to, as in Anderson (2020).

that we expect to capture from the variables $1[G_c = g] \times \text{WindDir}_{mt}^{90b}$ (Deryugina et al. 2019).

To identify the causal relationship between pollution and the students' scores we follow the strategy employed by Deryugina et al. (2019) and Bondy et al. (2020) to build our instrumental variable. To this end we rely on the assumption that municipalities' daily wind direction is not directly related to the students' scores in the national examinations, except through its influence on air pollution. Therefore, as argued by Deryugina et al. (2019), we do not need to know the exact source of pollution since the use of wind direction—which can be considered random to the pollution-exam relationship—to predict air quality eliminates the concern of potential correlation between what generates pollution and other factors affecting student performance. We take advantage of the geographic and temporal variation in wind direction in our data set as the source of exogeneity of our instrumental variable. That is, we use the variation in daily wind direction in the municipality where the examination took place as an instrument for pollution. Our model can be formally described as:

$$\begin{aligned}\text{Pollutant}_{mt} = {} & \sum_{g \in G} \sum_{b=0}^{2} \beta_b^g 1[G_c = g] \times \text{WindDir}_{mt}^{90b} + \theta_1 \text{temp}_{mt} + \theta_2 \text{humidity}_{mt} \\ & + \theta_3 \text{windspeed}_{mt} + \nu_i + \phi_t + \varepsilon_{imt},\end{aligned} \tag{2}$$

$$\begin{aligned}\text{Score}_{imt} = {} & \alpha \widehat{\text{Pollutant}_{mt}} + \psi_1 \text{temp}_{mt} + \psi_2 \text{humidity}_{mt} + \psi_3 \text{windspeed}_{mt} \\ & + \mu_i + \omega_t + \upsilon_{imt},\end{aligned} \tag{3}$$

where Score_{imt} is the test score of student i at municipality m at time t. The variable $1[G_c = g]$ indicates the monitor group g each municipality was classified into out of the total three G. The set of variables in $1[G_c = g] \times \text{WindDir}_{mt}^{90b}$ account for our excluded instruments, where each of the g clusters is interacted with $\text{WindDir}_{mt}^{90b}$ and equals 1 if the daily average wind direction in the municipality m is in the 90-degree interval [90b, 90b+90] and 0 otherwise, with the interval [270, 360] omitted and used as the reference wind direction (Deryugina et al. 2019). Equation (2) is the first stage in which we expect $\hat{\beta}$ to be significant as an indication that wind direction at municipality m and time t affects the level of pollution at municipality m and time t (relevance assumption).

Figure 2 shows the structure of our instruments by depicting the daily average PM_{10} across the 47 municipalities where the exams took place in our final sample by wind direction measured by its daily mean. It illustrates the relationship from our first stage, suggesting that days with wind blowing from the north, northeast, and east have on average higher levels of PM_{10}.[16]

Our instrumental variable approach confirms our fixed effects results. Primarily, our valid set of instruments helps us to address potential unobserved factors that could

16. Table A1 reports the first-stage estimations and the *F*-test statistics for the strength of our instruments.

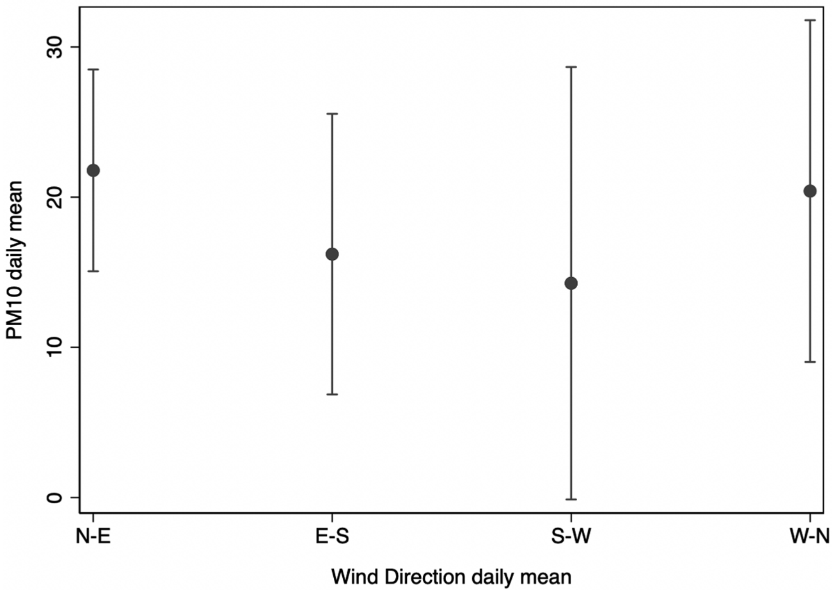

Figure 2. The effect of wind direction on air pollution. Daily average of PM_{10} concentrations for the 47 municipalities in the final sample per direction from where the wind blew during the exams days. 95% confidence intervals. Details on the data described in the text.

remain in our baseline findings. Suffice it to say that our estimates are roughly the same in both empirical strategies. In addition, by using interactions between wind direction and geographical clusters, we are capable of demonstrating plausibly exogenous variation in air pollution measures across different regions constituting our sample.

As for the validity of our instrument, wind direction fulfills the relevance requirement since it varies along with the concentration of PM_{10} as demonstrated by the *F*-test statistics in tables A1 and 4 (tables A1–A3 are available online). Moreover, with regard to the exogeneity requirement, the main assumption is that wind direction only affects students' scores via air pollution.

Although the previous literature has shown that O_3 and PM_{10} are not highly correlated, we use the daily average of pollution measures of PM_{10} as our main pollutant measure (Zweig et al. 2009; Ebenstein et al. 2016; Sager 2019). This separate equations approach, that is, the focus on one particular pollutant, has been used by, for example, Currie (2009) and Arceo et al. (2016). Other work prefers to use a composite measure of air pollution.[17] Nonetheless, we estimate equations with both pollutants jointly as a

17. For instance, Ebenstein et al. (2016), Chen et al. (2018), and Bondy et al. (2020) use the air quality index (AQI).

robustness check, and, as table 7 shows, the estimate signs and magnitudes of PM_{10} remain stable as when estimated separately.

For the temperature variables we build six bins of the size 3°C, with the first bin comprising temperatures between 16°C and 19°C, and the last bin for temperatures between 28°C and 31°C. This approach allows temperature to have a nonlinear impact. In all specifications, we use linear and quadratic terms for temperature (or bins) and humidity and their interactions (Ebenstein et al. 2016).

3. EMPIRICAL RESULTS

3.1. Main Results

Table 3 provides our estimations' results. For completeness we start by using municipality fixed effects. From column 1 we can observe that an additional 10 $\mu g/m^3$ of PM_{10} corresponds to a reduction in students' scores by 1%, though not significant. On the other hand, when it comes to utilizing student fixed effects and controlling for day fixed effects, the results in column 3—our preferred specification—suggest that an increase of 10 $\mu g/m^3$ of PM_{10} on the day of examinations leads to a highly significant reduction of 8% of a standard deviation in students' scores.

To explore possible nonlinearity between air pollution and students' cognitive performance, we present results from a complementary specification using a dummy variable for air pollution that equals 1 if the level of PM_{10} is above 20 $\mu g/m^3$—WHO's acceptable threshold for this pollutant. After controlling for student and day fixed effects, our results reported in column 4 suggest that students face a significant reduction of 11% SD in their scores.

While our main specification using student fixed effects illustrates the relationship between bad air quality and students' cognitive performance, there might remain potential unobserved time-varying circumstances which that strategy may not be capturing. As such, we turn to our instrumental variable findings. First, our IV first-stage *F*-test statistic informs us that wind direction is indeed a strong predictor of air pollution and hence a strong instrument.[18] Second, our findings in table 4 suggest that an additional 10 $\mu g/m^3$ of PM_{10} on exam days caused the students' marks to drop by 8% SD (col. 3). If we compare this with the baseline fixed effects results presented in column 1, we notice that the results remain broadly the same even though there is a slight reduction in the sample size.

When it comes to nonlinear PM_{10} for the instrumental variable specification, column 4 in table 4 displays the same pattern of results as the one using linear pollution measure (col. 2). That is, students taking exams in venues and days above the WHO's threshold have their scores reduced by 13% SD compared to their counterparts exposed

18. Figure 2 and table A1 provide the first-stage estimations.

Table 3. The Effects of PM_{10} on Students' Scores (Main Specification with Flexible Weather Controls)

	Municipality Fixed Effects		Student Fixed Effects	
Variables	(1)	(2)	(3)	(4)
PM_{10} (10 $\mu g/m^3$)	−.01		−.08***	
	(.05)		(.03)	
1 if $PM_{10} > 20$		−.04		−.11***
		(.03)		(.04)
Student FE	N	N	Y	Y
Student controls	Y	Y	N	N
Day FE	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y
Observations	2,944,911	2,944,911	2,931,368	2,931,368
N municipalities	47	47	47	47
R-squared	.17	.17	.07	.07

Note. The dependent variable in all regressions is the students' test scores (in SD). Robust standard errors in parentheses clustered by municipality centroid. Estimates for controls not shown: student controls include gender, race, and mother's level of education (cols. 1 and 2), municipalities FE (cols. 1 and 2) student FE, day FE, temperature in bins, relative humidity and its square, interactions of these weather variables, and wind speed. PM_{10} accounts for its linear form measured in $\mu g/m^3$; $PM_{10} > 20$ corresponds to a dummy that equals 1 if $PM_{10} > 20$ and zero otherwise. FE = fixed effects.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

to air pollution levels equal to or below to 20 $\mu g/m^3$. Also, regarding the first stage for the nonlinear approach, the *F*-test statistic still reveals that wind direction is a strong predictor of air pollution.

3.2. Heterogeneity across Subpopulations

In this section we analyze the heterogeneous effect of the treatment (air pollution) for our preferred specification reported in columns 3 and 4 from table 3: (i) by gender, (ii) across the distribution of scores per municipality, and (iii) in terms of different levels of income. Through this heterogeneity inspection, we aim to unveil how different subpopulations have their cognitive performance affected by the exposure to air pollution during high-stakes examinations.

With regard to gender differentials, our findings in table 5 suggest that boys are more negatively affected by poor air quality during exams than girls. To put this into perspective, an increase of 10 $\mu g/m^3$ of PM_{10} causes males' scores to drop by 11% SD, while girls suffer a reduction of 6% SD. This heterogeneity is also observed when using

Table 4. Particulate Matter's Impact on Scores: Models with Instrumental Variable Wind Direction

	Baseline		With Instruments	
Variables	(1)	(2)	(3)	(4)
PM_{10} (10 μg/m^3)	−.08***		−.08***	
	(.03)		(.01)	
1 if PM_{10} > 20		−.11***		−.13***
		(.04)		(.01)
F first stage			55.4	71
Observations	2,931,368	2,931,368	2,405,938	2,405,938
N municipalities	47	47	47	47

Note. The dependent variable in all regressions is the standardized students' tests scores (in SD). See table 3 for full specification. Columns 1 and 2 identical to cols. 3 and 4 from table 3. Flexible weather controls; student and day fixed effects (FE). Standard errors clustered by municipality and bootstrapped with 500 repetitions.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

Table 5. Heterogeneity in Particulate Matter's Impact on Students' Scores per Gender

	All	Girls	Boys	All	Girls	Boys
Variables	(1)	(2)	(3)	(4)	(5)	(6)
PM_{10} (10 μg/m^3)	−.08***	−.06***	−.11***			
	(.03)	(.03)	(.03)			
1 if PM_{10} > 20				−.11***	−.08**	−.15***
				(.04)	(.03)	(.05)
P-value *Z*-test (girls − boys)		p = .88			p = .88	
Observations	2,931,368	1,671,910	1,259,458	2,931,368	1,671,910	1,259,458
N municipalities	47	47	47	47	47	47
R-squared	.07	.09	.08	.07	.09	.08

Note. The dependent variable in all regressions is the standardized students' test scores (in SD). Robust standard errors in parentheses clustered by municipality centroid. *Z*-tests of the difference in the gender-specific coefficients (i.e., cols. 2–3 and 5–6) present p-values > .1. Estimates for controls not shown: student fixed effects (FE), day FE, temperature in bins, relative humidity and its square, interactions of these weather variables, and wind speed. PM_{10} accounts for its linear form measured in μg/m^3; PM_{10} > 20 corresponds to a dummy that equals 1 if PM_{10} > 20 and zero otherwise.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

a nonlinear pollution variable; the results persist, with boys' scores being reduced by 15% SD and girls' by 8% SD, meaning that boys who sat the examinations in days with air pollution levels above the WHO's acceptable threshold faced a reduction in scores 7 percentage points greater than girls (cols. 5 and 6). However, as table 5 indicates, Z-tests of the difference in the estimated coefficients for boys and girls present p-values > .1.

Nevertheless, these suggestive findings are consistent with previous studies, including Jayachandran (2009), Sanders (2012), and Ebenstein et al. (2016). Even though the role of gender in the effects of air pollution on respiratory health remains unclear, some epidemiology studies point out that males are more affected than females. For example, Abbey et al. (1998) link PM_{10} exposure to reduced lung functioning among males but not females, Galizia and Kinney (1999) find similar results regarding the exposure to O_3, and Chen et al. (2017) identify that contemporaneous and cumulative exposure to air pollution has a stronger negative effect for men than for women. Similarly, Ebenstein et al. (2016) find the effect of pollution on exam performance to differ by gender and cite the increased incidence of asthma among boys as a possible cause.

Next we assess whether students at different points of the performance distribution are differently affected by poor air quality. To this end we split our final sample into subsets of low and high scores within each municipality. One can note from panel A of table 6 that students below the average have their scores 1 percentage point more impacted than pupils that rank above the average. Stated differently, stronger students exposed to an additional 10 $\mu g/m^3$ of PM_{10} during the exams have their performance reduced by 6% SD (col. 3), while weaker students are more negatively affected, presenting a drop of 7% SD (col. 2). When we compare this to the baseline estimation (col. 1) using the whole sample, the average reduction is 8% SD. Another comparison is made between the top 5% scores and bottom 5%. Column 4 shows that students who rank very low in the exam suffer a reduction of 5% on their marks, while students on the top of the distribution seem not to be significantly affected by an increase of pollution levels during examinations (col. 5). Finally, columns 6–10 depict results from the same exercises utilizing the nonlinear pollution variable. These findings suggest that students above the median and who took the exams in days with PM_{10} above the WHO'S threshold are more negatively impacted, with scores dropping by 12% SD, while students in the top 5% of the ranking are again not significantly affected by taking exams in days with pollution levels higher than 20 $\mu g/m^3$. Again, we note that the differences in our results across the performance distribution are not statistically significant.

In panel B of table 6 we slice our sample to look into how students from different socioeconomic strata may be disproportionately affected by air pollution during the tests (Hsiang et al. 2019). For example, Neidell (2004) finds that less well-off households are more impacted by air pollution given their reduced capability of compensating behavior. Students from poorer backgrounds seem to be more affected by poor air quality. It may also be due to the fact that weaker students and low income are correlated

Table 6. Heterogeneity in Particulate Matter's Impact on Students' Scores across Subpopulations

Variables	Baseline (1)	Below Median (2)	Above Median (3)	Bottom 5 Percentile (4)	Top 5 Percentile (5)	Baseline (6)	Below Median (7)	Above Median (8)	Bottom 5 Percentile (9)	Top 5 Percentile (10)
	A. The Distribution of Examination Scores									
PM_{10} (10 $\mu g/m^3$)	−.08***	−.07***	−.06**	−.05***	−.03					
	(.03)	(.02)	(.03)	(.01)	(.03)					
1 if $PM_{10} > 20$						−.11***	−.07*	−.09***	−.05**	−.04
						(.04)	(.04)	(.03)	(.02)	(.03)
P-value *Z*-test (diff. ability)		$p = .41$		$p = .26$			$p = .66$		$p = .39$	
	B. Low and High Socioeconomic Status									
PM_{10} (10 $\mu g/m^3$)	−.08***	−.09***	−.08**	−.09***	−.07					
	(.03)	(.02)	(.04)	(.02)	(.06)					
1 if $PM_{10} > 20$						−.11***	−.10*	−.12***	−.09**	−.10**
						(.04)	(.05)	(.04)	(.04)	(.05)
P-value *Z*-test (diff. income)		$p = .41$		$p = .37$			$p = .62$		$p = .56$	

Note. The dependent variable in all regressions is the standardized students' test scores (in SD). Robust standard errors in parentheses clustered by municipality centroid. *Z*-tests of the difference in the income- and ability-specific coefficients present p-values > .1. Estimates for controls not shown: student fixed effects (FE), day FE, temperature in bins, relative humidity and its square, interactions of these weather variables, and wind speed. PM_{10} accounts for its linear form measured in $\mu g/m^3$; $PM_{10} > 20$ corresponds to a dummy that equals 1 if $PM_{10} > 20$ and zero otherwise.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

(Ebenstein et al. 2016). We therefore subsampled the individuals according to their household incomes and compared them using the mean of the municipality average income. While the differences are again not statistically significant, from panel B of table 6 one can notice that students below the median or below the bottom 5% face a reduction of 9% SD in their scores for every extra 10 $\mu g/m^3$ in the day of the tests (cols. 2 and 4), whereas wealthier students are not significantly impacted by a deterioration in air quality.

3.3. Sensitivity Analysis

To assess the robustness of our results, we experiment with a number of alternative specifications. So far we have reported results in which we include only one pollutant at a time in our estimations. Given the generally high correlation between many common local air pollutants, there continues to be debate around whether or not different pollutants have independent health effects (see, e.g., Lipfert et al. 2009; Cao et al. 2011; Gan et al. 2011; Katanoda et al. 2011; Chen et al. 2012). In our sample, O_3 and PM_{10} have a pairwise correlation of 0.10, significant at 5%. Nevertheless, table 7 provides the results from estimations in which both pollutants are included together. For ease of comparison, we report the baseline models with student fixed effects in columns 1 and 2 and with instrumental variables approach in columns 3 and 4. Columns 5–8 show the results of equations with both pollutants.

First, the estimation using student fixed effects presents the same coefficient for the linear form of PM_{10} with O_3, negative but not significant. That is, the effect of an increase of 10% of particulate matter on the day of the exams reduces students' scores by 8% SD as seen in the baseline model (col. 1). For our instrumental variable specification with copollutant, similarly to our finding using only particulate matter to capture air quality (col. 4), column 8 demonstrates that students passing exams in venues and days with levels of PM_{10} higher than the WHO's threshold suffer a reduction of 14% SD in their scores compared to others who are subjected to lower levels of that pollutant. Furthermore, the O_3 coefficient seems to continue to suggest no effect on students' grades. Therefore, in line with Bedi et al.'s (2021) work on cognitive performance and air pollution in São Paulo, we see that PM_{10} continues to have overall the same impact on test takers, while O_3 does not present a significant effect on the latter. These are expected results since PM_{10} penetrates indoors more easily than O_3; hence one would indeed expect a smaller impact, or no impact at all, of the latter pollutant in a copollutant estimation.

In a second exercise we include a 1-day lead in our main specification with the linear form of PM_{10} to capture common situations, for example, political events and weather shocks. To do so we use data on air pollution from 1 day ahead of the actual date. Table 8 shows that air pollution levels in the day after the exams do not significantly affect students' performance. Accordingly, an additional 10 $\mu g/m^3$ on the day of the examinations is still responsible to a decrease of 5% SD in students' scores, while PM_{10} measures from

Table 7. The Effects of PM_{10} on Students' Scores (with Copollutant O_3)

	Baseline Model				With Copollutant			
	FE	FE	IV	IV	FE	FE	IV	IV
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM_{10} (10 $\mu g/m^3$)	–.08***		–.08***		–.08***		–.15*	
	(.03)		(.01)		(.03)		(.09)	
1 if $PM_{10} > 20$		–.11***		–.13***		–.05		–.14**
		(.04)		(.01)		(.04)		(.06)
O_3 (10 $\mu g/m^3$)					.01	.01	–.08	–.07
					(.02)	(.02)	(.06)	(.06)
F first stage			55.4	71			106	118
Observations	2,931,368	2,931,368	2,405,938	2,405,938	2,931,368	2,931,368	2,388,034	2,388,034
N municipalities	47	47	47	47	47	47	47	47
R-squared	.07	.07	.08	.08	.07	.07	.08	.08

Note. The dependent variable in all regressions is the standardized students' test scores (in SD). Robust standard errors in parentheses clustered by municipality centroid. Estimates for controls not shown: student fixed effects (FE), day FE, temperature in bins, relative humidity and its square, interactions of these weather variables, and wind speed. PM_{10} and O_3 account for their linear form measured in $\mu g/m^3$; $PM_{10} > 20$ corresponds to a dummy that equals 1 if $PM_{10} > 20$ and zero otherwise.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

Table 8. The Effects of PM_{10} on Students' Scores (Baseline Model + 1 Day Lead)

Variables	Baseline (1)	Baseline + Lead (2)	Lead (3)
PM_{10}	−.08***	−.05**	
	(.03)	(.02)	
PM_{10} (lead)		−.00	.02
		(.02)	(.02)
Observations	2,931,368	2,172,680	2,172,680
N municipalities	47	47	47
R-squared	.07	.08	.08

Note. The dependent variable in all regressions is the standardized students' test scores (in SD). Robust standard errors in parentheses clustered by municipality centroid. Included student fixed effects (FE), day FE, flexible weather controls. PM_{10} is linear in 10 $\mu g/m^3$.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

the following day have no impact on pupils' marks. These results suggest that our main findings on students' cognitive performance are driven not by other factors that started before the test day and correlated with pollution but solely by exposure to poor air quality on the day of the test, hence, a contemporaneous effect.[19]

We next conduct a third exercise to check the robustness of our results. As we do not know the precise location where the students took their exams, we have so far used the municipality centroid as a proxy for the exam venues and measured pollution using the average of up to three pollution monitoring stations within 10 km of that centroid. However, if a school is located toward the periphery of a municipality, then the monitoring stations within 10 km of the centroid may not be the best measure of pollution levels at that school's location and, if there are fewer than three monitors within 10 km, we are omitting monitoring stations from our analysis that may be closer to the school's location. To see whether this is affecting our results we here extend the 10 km limit to 50 km and plot the results in figure 3. We can see that PM_{10} continues to negatively affect scores, but the impacts fade and the standard errors inflate as the distance rises, with the coefficients corresponding to the 50 km estimation not being statistically significant. This would seem to suggest that the 10 km cut-off more accurately captures pollution concentrations at exam venues and that the pollutants' levels decay insofar as they travel.[20]

Finally, to demonstrate the sensitiveness of our main specifications with binned weather controls, table A2 shows that the pollutant's coefficient becomes positive

19. Similar results can be found, e.g., in Bedi et al. (2021).
20. Similar results can be found, e.g., in Lai et al. (2018).

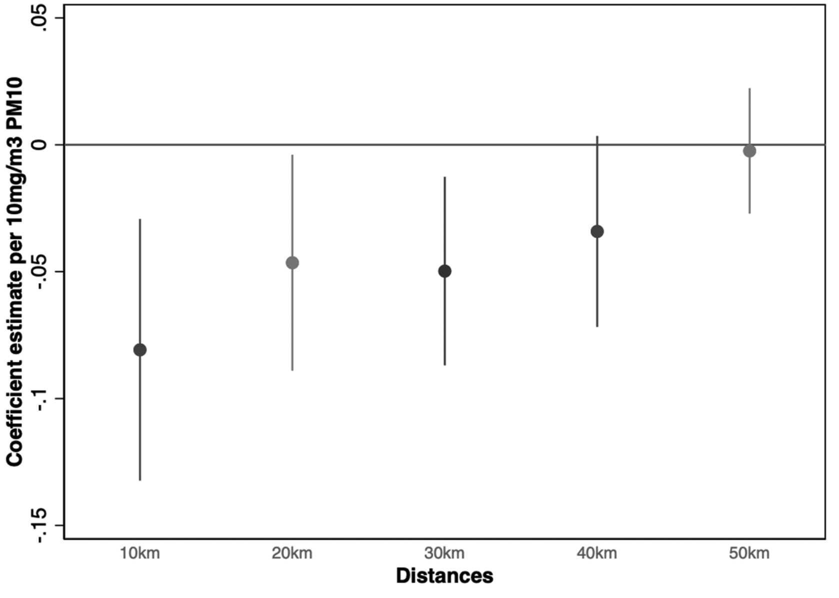

Figure 3. Cognitive impact of PM_{10} per distance from the station to the municipality centroid. This figure reports the cognitive impact of air pollution within different distances; 10 km is the baseline model. All the specifications follow the main model with student fixed effects, day controls, and flexible weather condition as in column 3 of table 3. We note an increase of standard errors, suggesting that the further away the stations, the less precise and significant the estimates.

and significant when we do not include those variables (cols. 1 and 2), corroborating the largely known fact that controlling for meteorological conditions is important. Furthermore, columns 3 and 4 present our specifications using linear weather controls and columns 5 and 6 with their squares and interactions. These results suggest that our main estimates are being driven not by unobserved meteorological conditions correlated with wind and students' performance but solely by the effects of air pollution.

4. CONCLUSION

In this paper we take advantage of the individual-level panel data structure of a Brazilian student exam data set to estimate the causal effect of contemporaneous exposure to air pollution on students' performance in university entrance exams from 2015 to 2017. To identify this relationship we use student fixed effects as our main specification strategy but, as robustness checks, we also experiment with a wide range of control variables such as individual characteristics, parents' level of education, household income, weather controls (temperature, humidity, and wind speed), and day and municipality fixed effects. To address possible biases in our estimations stemming from classical measurement error and omitted variables, we also perform an instrumental variable approach where we rely on the temporal and geographical variation in wind direction to build our instrument. Our main assumption is that this variation is exogenous since it does not directly affect the students' scores except through its effect on air pollution.

Our results consistently suggest a harmful effect of air pollution on exam performance. Indeed, we find that an increase of 10 $\mu g/m^3$ of PM_{10} on the day of the examination decreases students' scores by around 6 points (8% SD). Even when including a more flexible measure of our treatment that is utilizing a dummy variable to account for the days in which PM_{10} exceeded the WHO's acceptable threshold, our findings still point to negative effects of air pollution on cognitive performance during examinations. We run several sensitivity checks and falsification tests which suggest that our results are not driven by spurious correlations.

We also find suggestive evidence that the effect of air pollution on exam performance appears to differ for males and females, with the performance of the former more adversely affected. This finding is consistent with previous studies, including Jayachandran (2009), Sanders (2012), and Ebenstein et al. (2016). Although the role of gender in the effects of air pollution on respiratory health remains unclear, some epidemiology studies point out that males are more affected than females. For example, Abbey et al. (1998) link PM_{10} exposure to reduced lung function among males but not females, and Galizia and Kinney (1999) find similar results regarding the exposure to O_3. Similarly, Ebenstein et al. (2016) find the effect of pollution on exam performance to differ by gender and cite the increased incidence of asthma among boys as a possible cause. Finally, our results also suggest that poorer students may be more susceptible to air pollution than wealthier exam takers. These findings are also in accordance with previous studies (see, e.g., Neidell 2004; Ebenstein et al. 2016). All in all, our findings provide plausible evidence to suggest that cognitive performance may be hindered by poor air quality, but unequally so.

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