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Simone Ferro, Elena Meschi, Caterina Pavese

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UNIVERSITÀ DEGLI STUDI DI MILANO BICOCCA

Clouded minds: air pollution and student cognitive performance*

Simone Ferro† Elena Meschi‡ Caterina Pavese§

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Abstract

We estimate the causal effect of air pollution on primary school students' cognitive performance in Italy, exploiting daily within-municipality variation in pollution across exam dates. Using INVALSI administrative data on the universe of students over ten cohorts and a specification with individual fixed effects, we find that a 10 μg/m^3 increase in $PM_{2.5}$ reduces test scores by 4.4% of a standard deviation. Effects are concentrated in reasoning-intensive items, with no significant effect on knowledge-based items, are stronger for lower-achieving and emotionally vulnerable students, and are substantially mitigated by school mechanical ventilation and air-conditioning systems. These results highlight the cognitive costs of short-term pollution exposure and the potential of targeted infrastructure investments to reduce environmental inequality in education.

JEL Codes J01, I1, I2, Q53
Keywords: Air pollution, $PM_{2.5}$, test scores, memory and reasoning

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†University of Milan. Email: simone.ferro@unimi.it
‡University of Milan-Bicocca. Email: elena.meschi@unimib.it
§University of Bologna and CESifo. Email: caterina.pavese@unibo.it

1 Introduction

Air pollution ranks among the most pressing global challenges, with severe consequences for both the environment and public health. The World Health Organization (WHO)[1] estimates that ambient air pollution is responsible for approximately 4.2 million premature deaths each year, including around 300,000 within the European Union. Its adverse effects on human health, ranging from cardiovascular and respiratory diseases to cancer, are well documented and extensively reviewed in the economic literature (Currie and Walker, 2019). Beyond its well-known health impacts, recent economic research has increasingly examined the broader consequences of pollution, including effects on labor productivity, decision-making, and cognitive functioning (Aguilar-Gomez et al., 2022).

An emerging strand of literature focuses on the impact of air pollution on students' outcomes. While existing studies consistently document negative effects of pollution on test scores, there is limited evidence on the cognitive mechanisms underlying these effects, on the distribution of impacts across students, and on the extent to which they can be mitigated by policy interventions. Understanding both *how* air pollution affects cognitive performance and *who* is most affected is crucial for policymakers deciding which interventions to prioritize — whether investments in school infrastructure, the siting of new schools, or other targeted measures.

This paper contributes to this debate by providing new evidence on the short-term effects of air pollution on students' cognitive performance using administrative data from Italy, a country where pollution frequently exceeds WHO-recommended thresholds.

We address three main research questions. First, how does short-term exposure to air pollution on test days affect cognitive performance in a high-income country with moderate pollution levels?

Second, which cognitive processes are most affected? Rather than treating academic achievement as a single outcome, we distinguish between knowledge-based tasks and questions requiring reasoning and problem-solving, allowing us to assess whether pollution primarily disrupts higher-order cognitive functions—such as attention and log-

[1] World Health Organization (WHO), *Ambient (Outdoor) Air Quality and Health*, https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health.

ical reasoning—rather than the retrieval of previously acquired knowledge. Third, we examine whether vulnerability to pollution varies systematically across students and contexts, focusing on age, baseline achievement, emotional states during testing, and school infrastructure.

Our analysis combines universal-coverage data from standardized assessments administered by INVALSI over a ten-year period (2012/13–2022/23) with high-frequency reanalysis estimates of local air pollution at the municipality level.[2] To identify the causal effect of pollution on student achievement, we exploit variation in pollution across test days within municipalities and, crucially, within students across multiple exams taken on different days and in different grades. The structure of the testing calendar, which schedules different subjects on separate days within the same grade and tests students at multiple points in their schooling, allows us to compare the same student's performance under different pollution conditions. This enables the inclusion of individual fixed effects, alongside a rich set of controls for time, location, and testing conditions, thereby isolating plausibly exogenous within-student variation in pollution exposure across tests.

We find that short-term exposure to particulate matter ($PM_{2.5}$) significantly reduces student performance. A 10 $\mu g/m^3$ increase in $PM_{2.5}$ lowers standardized test scores by approximately 4.4% of a standard deviation. While this magnitude is broadly consistent with existing estimates, our setting allows us to move beyond average effects and examine the cognitive processes and student groups most affected.

Our results reveal substantial heterogeneity in the effects of pollution. The negative impact of $PM_{2.5}$ is concentrated in reasoning-intensive tasks, while the effect on knowledge-based questions is small and not statistically significant, suggesting that pollution primarily disrupts executive functioning rather than memory retrieval. In addition, the effects are significantly larger for lower-performing and more emotionally vulnerable students, indicating that pollution disproportionately affects individuals who rely more heavily on sustained cognitive effort. Finally, we show that the negative effects of pollution are substantially attenuated in schools equipped with mechanical ventilation and air conditioning systems, highlighting the potential of targeted infrastructure investments to mitigate environmental inequalities in education.

[2] Our sample covers 10 out of the 11 school cohorts between 2012/13 and 2022/23, as INVALSI testing was suspended during the 2019/20 school year due to the COVID-19 pandemic.

This paper relates to two main strands of literature. The first examines the consequences of air pollution for human capital formation. While early studies focused primarily on the long-term effects of pollution exposure during gestation or early childhood (e.g., Bharadwaj et al. 2017; Sanders 2012; Currie et al. 2014), more recent work has analyzed the short-term impacts of daily pollution fluctuations on cognitive performance and academic achievement. For example, Ebenstein et al. (2016) show that high pollution on test days reduces high-school exam performance in Israel, while Marcotte (2017) and Andersen et al. (2025) document similar short-run impacts in the U.S. and Denmark, respectively. However, evidence for younger students remains limited, and most existing studies focus on either very high- or very low-pollution environments, raising questions about external validity in moderately polluted contexts such as Southern Europe. The second strand of literature examines how testing conditions—including temperature, noise, stress, and air quality—affect student outcomes (e.g., Graff Zivin and Neidell 2018; Park 2020; Heissel and Norris 2020; Ballatore et al. 2025). We contribute to this literature by leveraging within-student variation in exposure induced by the repeated testing structure across subjects and grades to identify the short-run cognitive effects of air pollution during test-taking.

Our analysis yields four main contributions. First, we provide new evidence on the short-term impact of air pollution on the cognitive performance of primary school students, a population that has received limited attention despite being particularly vulnerable to environmental stressors (WHO, 2018; Bateson and Schwartz, 2008). Second, we go beyond aggregate test scores to identify the cognitive domains most affected by pollution, distinguishing between memory-based and reasoning-intensive tasks, as well as between open- and closed-ended questions. Third, using detailed student questionnaires, we document substantial heterogeneity across non-cognitive traits, showing that emotional vulnerability amplifies the impact of pollution. Fourth, we examine the role of school infrastructure and environmental conditions, providing evidence that mechanical ventilation and air conditioning systems mitigate the negative effects of pollution on performance. Finally, our analysis is conducted in a setting characterized by low-stakes examinations. In contrast to high-stakes contexts (Ebenstein et al., 2016) and low-pollution environments (Andersen et al., 2025), this setting allows us to isolate the cognitive effects of pollution from strategic behavioral responses.

Our findings point to environmental conditions as key determinants of cognitive performance and educational inequality. The results suggest that even temporary exposure to pollution can interfere with higher-order cognitive processes, particularly among more vulnerable students, while also indicating that school infrastructure may play an important protective role. These patterns highlight the value of integrating environmental considerations into education policy and school design.

The remainder of the paper is organized as follows. Section 2 discusses the mechanisms linking air pollution to cognitive performance. Section 3 describes the institutional context, the data, and presents descriptive statistics. Section 4 outlines the empirical strategy and identification. Section 5 presents the main results and examines mechanisms, cognitive channels, and heterogeneity. Section 6 investigates coping strategies, focusing on mechanical ventilation and air conditioning systems and school location. Section 7 presents additional outcomes, including cheating and test-day absences. Section 8 reports robustness checks. Section 9 concludes.

2 Air pollution and cognitive performance: physiological and behavioral pathways

In this paper, we proxy air quality using $PM_{2.5}$, particulate matter with an aerodynamic diameter below 2.5 micrometers. $PM_{2.5}$ is the finest particle category routinely monitored by regulatory authorities and consists of a complex, heterogeneous mixture of solid granules and liquid droplets that vary by chemical composition and origin.[3] Their small size allows these particles to remain suspended in the air for extended periods and penetrate deeply into the human body. The impact of $PM_{2.5}$ on student outcomes operates through two primary and complementary channels: (i) physiological effects that alter physical functioning and brain processes, and (ii) behavioral and psychological effects that influence effort, attention allocation, and test-taking behavior.

Physiological channel. The World Health Organization (WHO) identifies $PM_{2.5}$ as the air pollutant with the largest global health burden. Its microscopic particles—about 4% of the diameter of a human hair—can penetrate the respiratory system and enter the bloodstream, contributing to cardiovascular and respiratory diseases, systemic in-

[3]Figure A2 in the Appendix provides a graphical illustration of $PM_{2.5}$ to contextualize its scale.

flammation, and cancer (Rajagopalan et al., 2018; International Agency for Research on Cancer, 2013). Even short-term exposure can induce acute symptoms such as respiratory irritation, headaches, fatigue, and reduced oxygen saturation. These responses may directly lower students' ability to sustain mental effort and concentration during cognitively demanding tasks.

Beyond general physical symptoms, $PM_{2.5}$ exposure can affect the central nervous system. Air pollution is associated with neuroinflammation and oxidative stress, which can damage neural tissue and disrupt normal neurological functioning. Particulate matter may also impair cerebral blood flow and reduce oxygen delivery to the brain (Underwood, 2017). These biological mechanisms are linked to impairments in attention, executive functioning, and reasoning abilities (Forman and Finch, 2018; Delgado-Saborit et al., 2021), cognitive domains that are central to standardized test performance.

Behavioral and psychological channel. Air pollution may also affect performance through non-neurological pathways that operate via mental states and behavior. Short-term pollution exposure has been associated with changes in mood and increased irritability (Chung et al., 2025), as well as reduced motivation and effort (Graff Zivin and Neidell, 2012). Such responses can reduce on-task effort, persistence, and the efficient allocation of attention during tests, even if underlying cognitive capacity were unchanged. In school contexts, where performance depends critically on sustained engagement over a fixed time interval, these behavioral responses can translate into measurable declines in test scores. Pollution exposure may further influence outcomes indirectly through sleep disturbances (Liu et al., 2020) and increased absenteeism (Currie et al. (2009); Heissel et al. (2022)), both of which can affect preparedness and performance on test days.

Younger children are likely to be especially susceptible to these channels. Their organs and immune systems are still developing, and their brains exhibit high plasticity, making them more sensitive to inflammatory and neurotoxic insults. At the same time, children inhale more air per unit of body weight, breathe more frequently through the mouth, and spend more time close to ground-level pollution sources (WHO, 2018; Bateson and Schwartz, 2008). These features increase both exposure and biological vulnerability.

Consistent with these mechanisms, empirical studies document adverse effects of $PM_{2.5}$ on cognitive outcomes even at relatively low concentrations and over short exposure windows. Test-day pollution has been shown to reduce exam performance and cognitive functioning (Ebenstein et al., 2016; Carneiro et al., 2021; Andersen et al., 2025), while longer-term exposure has been linked to persistent deficits in human capital formation (Heissel et al., 2022; Persico and Venator, 2021). However, evidence for primary-school children remains limited, and little is known about which cognitive domains and behavioral channels drive the observed effects.

3 Background and Data

This section provides institutional background on the INVALSI testing framework and air quality in Italy, and describes the three main data sources used in our empirical analysis: (i) standardized test scores and student background information from INVALSI; (ii) data on air pollution and weather conditions; and (iii) administrative records from the Ministry of Education (MIUR) on school characteristics and infrastructure.

3.1 INVALSI Tests

3.1.1 Institutional Context

In Italy, compulsory education begins at age six and lasts for ten years. The education system is organized into two main cycles. The first is a comprehensive cycle comprising primary and lower secondary education, while the second consists of upper secondary education, where students choose between academic and vocational tracks. Our study focuses on primary education, which lasts five years and typically ends when students are around eleven years old. Throughout primary school, students generally remain in the same classroom and are taught by the same group of teachers assigned in first grade. The national curriculum is centrally defined and places strong emphasis on core subjects such as Mathematics, Literacy, and English. The vast majority of students attend public schools and are typically assigned to schools within their local catchment area based on their municipality of residence.

INVALSI (Istituto Nazionale per la Valutazione del Sistema Educativo di Istruzione e di Formazione) is the Italian national agency responsible for evaluating the education system through standardized assessments. The tests were introduced in the 2009/10 academic year, following a broader effort to establish a national framework for monitoring educational quality and to provide comparable, externally validated measures of student learning across Italian schools (INVALSI, 2023a).

Unlike high-stakes examinations in many other countries, INVALSI tests are explicitly designed as low-stakes assessments: results carry no direct consequences for students' academic progression or school funding, and are intended primarily as a diagnostic tool for teachers, school administrators, and policymakers (INVALSI, 2023a). This feature of our setting is particularly relevant for the interpretation of our estimates, as it limits the scope for strategic behavioral responses by students or teachers, allowing us to more cleanly isolate the cognitive effects of pollution exposure.[4]

Despite the institutional effort to monitor and improve educational quality, Italian students consistently perform below the OECD average in international assessments. In the 2022 PISA cycle, Italy ranked below the OECD mean in Mathematics, Literacy, and Science (OECD, 2023). Similar patterns emerge from the PIRLS and TIMSS assessments, which document below-average Literacy and mathematics proficiency among Italian primary school students relative to their European peers (IEA, 2022, 2020).

A distinctive and well-documented feature of the Italian education system is the pronounced geographical gradient in student achievement. Students in the northern regions — particularly in the provinces of Trento, Bolzano, and the Veneto — consistently outperform their peers in the South by margins that, in some subjects and grades, exceed half a standard deviation (INVALSI, 2023b; Bratti et al., 2007). This north-south divide reflects long-standing structural disparities in school quality, socioeconomic conditions, and local labor market returns to education (Bratti et al., 2007), and is a salient feature of the Italian context that motivates our focus on heterogeneity across students and schools.

[4] The low-stakes nature of INVALSI assessments contrasts with the high-stakes setting studied by (Ebenstein et al., 2016), who examine the Israeli matriculation exam, where performance has direct consequences for university admission and labor market outcomes.

3.1.2 INVALSI Data

Our analysis relies on administrative data from INVALSI tests to students in grades 2, 5, 8, 10, and 13 - corresponding approximately to ages 7, 10, 13, 15, and 18. These assessments are mandatory, anonymous, and externally evaluated, and have been conducted annually since the 2009/10 academic year. They measure proficiency in Mathematics and Literacy, with English (reading and listening) added from the 2017/18 academic year onward.

The tests in different subjects are conducted on separate days, but the same schedule applies across all schools nationwide. Test dates are typically scheduled within the first two to three weeks of May, with slight variations across academic years. The dataset has a panel structure, enabling us to track students' performance across the three subjects over time and across grades.

Our study focuses on ten cohorts of primary school students who attended grades 2 and 5 from 2012/13 to 2022/23. These grades are selected because our identification strategy depends on accurately linking test scores to daily air pollution data, which requires a precise test administration date. Such dates are consistently available only for primary school tests, which are paper-based and conducted on fixed dates. In contrast, tests for higher grades are computer-based and administered over flexible time windows with the actual test date not systematically recorded by INVALSI. As a result, our analysis is restricted to primary school students, for whom test timing is reliably documented for both grades.

The primary outcomes of our analysis are standardized test scores in Mathematics, Literacy, and English (reading and listening). These scores are reported on a scale standardized by INVALSI, with a mean of 200 and a standard deviation of 40 within each cohort, grade, and subject. This within-cohort standardization ensures comparability across school years, absorbing any changes in curriculum requirements or test difficulty over the sample period.

INVALSI also adjusts the scores using a "cheating factor," which accounts for the likelihood of cheating within a student's class (for further details, see Quintano et al. (2009)).[5]

We also defined a number of additional outcomes. First, following INVALSI guide-

[5] In our preferred specification, we focus on cheating-corrected standardized scores. In Section 7, we investigate the effect of air pollution on cheating and raw test scores.

lines, we classified test questions in Mathematics and Literacy into two cognitive domains. The first domain, *Knowledge*, evaluates the application of specific acquired knowledge, such as grammar in Literacy or formulas and operations in Mathematics. The second domain, *Reasoning and Problem Solving*, assesses students' ability to use reasoning and logic to apply knowledge in various contexts, such as reading comprehension for Literacy or solving logical and quantitative problems in Mathematics. To the best of our knowledge, this is the first study to manually extract this information directly from the test guidelines.

Second, we distinguish between question formats and, in particular, between open and multiple-choice questions. Open-ended questions require students to provide explanatory written responses, while multiple-choice questions involve selecting from a predefined set of options. See Table 9 in the Appendix for examples corresponding to each question type.

The test score data are complemented by a student questionnaire administered on the day of the Math test. This survey captures, among other things, non-cognitive aspects, particularly students' emotional states during the testing process. Students respond to four statements using a 4-point Likert scale (Strongly Disagree, Disagree, Agree, Strongly Agree), indicating whether: (i) they were worried before the test, (ii) they felt nervous during the test, (iii) they believed they were performing poorly while taking the test, and (iv) they felt calm during the test. Table A2 in the Appendix reports the exact survey items.

In addition, the INVALSI dataset includes detailed background and demographic information on students, including gender, month of birth, citizenship and parental education.

3.2 Air Pollution

3.2.1 Air Pollution in Italy

Italy is characterized by marked regional variation in air pollution exposure, with the Po Valley ranking among the most polluted areas in Europe. $PM_{2.5}$ concentrations have consistently exceeded EU annual limits over the past decade, with exceedances concentrated in urban and industrial areas.[6] Figure A1 in the Appendix displays $PM_{2.5}$

[6]EU Air Quality Standards, European Environment Agency.

concentrations across European countries in 2023, benchmarked against both the EU annual limit and the more stringent WHO guideline. The figure confirms that northern Italy — and the Po Valley in particular — ranks among the most polluted regions in Europe. This reflects a combination of high population density, intensive industrial and agricultural activity, and unfavorable orographic and meteorological conditions — including low wind speeds and thermal inversions — that inhibit pollutant dispersion.

3.2.2 Air Pollution and Weather Data

To characterize air quality, we obtain $PM_{2.5}$ concentration estimates from the Copernicus Atmosphere Monitoring Service (CAMS) reanalysis data, available at the hourly level with a resolution of 0.1×0.1 degrees. We complement this information with weather information (temperature, wind speed, and precipitation) from the Copernicus-ERA5 reanalysis data, available at the hourly level with a resolution of 0.25×0.25 degrees.

We aggregate these data by taking the inverse-distance weighted average values of the four closest grid points to the centroid of the municipality. Weather variables are measured as daily averages, whereas $PM_{2.5}$ exposure is defined as the mean of hourly concentrations in the 24 hours preceding the start of the school-day test (i.e., from 9 a.m. on the test day back to 10 a.m. on the prior day). We then merge pollution and weather data at the municipal and test-day level.[7]

3.3 School Infrastructures: MIUR Data

The third data source is open data from the Ministry of Education (MIUR), which has published annual information on school facilities, equipment, and neighborhood characteristics since 2017. Although direct school-level identifiers are not provided, we are able to match approximately 70% of our sample to this dataset thanks to information on school characteristics available from both sources.

The data include detailed indicators on (i) the presence of mechanical ventilation and air conditioning systems at the school-building level and (ii) contextual character-

[7]Notice that, given the spatial resolution of the CAMS reanalysis data, municipalities in close proximity may share some of the same grid points, inducing mechanical correlation in their pollution estimates. However, our clustering aggregates municipalities over much wider areas, allowing for both temporal and spatial correlation within these clusters. Furthermore, results are stable across alternative clustering specifications, as shown in Section 8.

istics of the surrounding area, which we exploit in Section 6 and Section 8 to explore potential heterogeneities and test the robustness of our findings. Specifically, schools report whether their buildings are equipped with mechanical ventilation and air conditioning systems and whether the school is located near closed industrial sites, waste disposal areas, degraded urban areas, polluting firms, sources of noise pollution, or areas with heavy traffic.[8]

We merge ventilation and air conditioning systems data with INVALSI records at the level of school year and individual school building. Since this information is not regularly updated, we assume that the absence of air ventilation systems at the beginning of a building's timeline reflects its status in prior years. In contrast, we merge neighborhood characteristics at the school-building level only, as these features are time-invariant over the observation window.

3.4 Descriptive statistics

Table 1 presents summary statistics for test scores, pollution and weather variables, and students' demographic characteristics in our sample.

Our sample includes the full population of students enrolled in second and fifth grade in Italy between the 2012/13 and 2022/23 school years,[9] who were present on the test days. Due to the panel structure of the data, students contribute multiple observations corresponding to the different subjects in which they are tested.[10] Students observed in both grades after the introduction of English tests can contribute up to six observations (two in second grade and four in fifth grade), while students observed in only one grade contribute a minimum of two observations.

Overall, the pooled sample comprises approximately 22 million observations from more than 6.4 million students. The sample is evenly split by gender, and approximately 22% of students have at least one parent with tertiary education.

The average daily $PM_{2.5}$ concentration on exam days is 11.12 $\mu g/m^3$, while the 90th percentile exceeds 18 $\mu g/m^3$, well above the WHO 24-hour guideline of 15 $\mu g/m^3$.

Figure 1 illustrates the temporal and spatial variation in pollution exposure in our

[8] The MIUR data do not contain information on building height, precluding the analysis of potential heterogeneity in exposure across floors.

[9] With the exception of the 2019/20 school year, when tests were not administered due to school closures during the Covid-19 pandemic.

[10] As discussed in Section 3.1.2, English reading and listening tests are administered only in fifth grade and were introduced in the 2017/18 school year.

Table 1: Descriptive statistics

	Obs.	Mean	SD	p10	p50	p90
Standardized test scores						
Pooled	21,958,173	202.18	41.99	150.79	203.44	253.99
Literacy	8,854,131	201.97	41.64	150.79	203.60	252.20
Mathematics	8,731,079	202.42	41.65	151.76	203.03	253.84
English (reading)	2,187,307	201.04	41.42	148.66	204.22	255.63
English (listening)	2,185,656	203.18	45.14	148.55	205.13	257.52
Pollution and weather						
$PM_{2.5}$ ($\mu g/m^3$)	21,958,173	11.12	5.47	5.32	10.00	18.17
Temperature (K)	21,958,173	288.53	2.95	285.05	288.84	291.87
Precipitation (mm)	21,958,173	0.003	0.005	0	0.001	0.01
Students' demographics						
Female	21,958,045	0.49	0.49	0	0	1
High-educated parents	17,818,490	0.225	0.418	0	0	1

Notes: This table presents summary statistics for the variables used in the analysis, covering the school years from 2012/13 to 2022/23. The sample includes all students enrolled in second and fifth grade who were present on the test day.

sample. Panel A reports the distribution of $PM_{2.5}$ across municipalities and test dates, while Panel B maps the maximum recorded concentration for each municipality over the sample period. In Panel A, dashed lines indicate WHO pollution-risk thresholds. In Panel B, darker shades correspond to higher concentrations of $PM_{2.5}$.

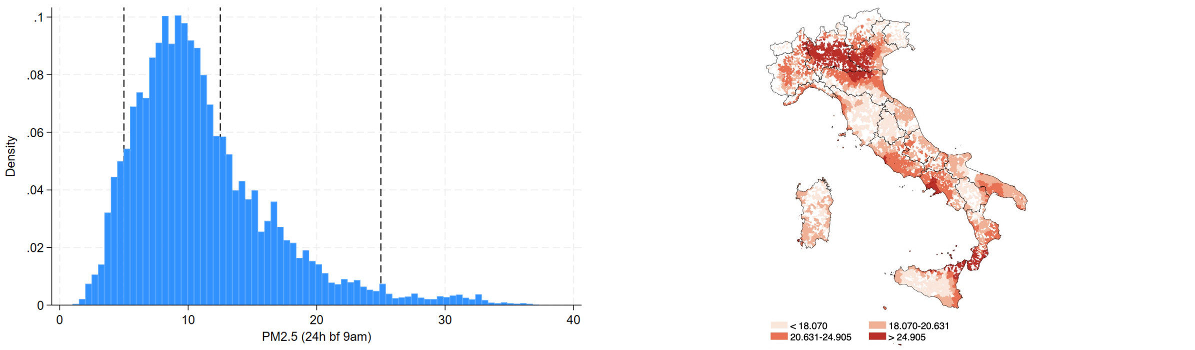
Two key insights emerge. First, $PM_{2.5}$ levels exhibit substantial variation across both time and space (Panel A), ranging from approximately 1 to 37 $\mu g/m^3$, with a non-negligible share of observations exceeding the WHO 24-hour guideline of 15 $\mu g/m^3$. Second, high pollution levels (top quartile) are geographically widespread, though particularly concentrated in the Po Valley and in urban and peri-urban areas surrounding Rome and Naples.

Figure 2 provides preliminary evidence on the relationship between test scores and $PM_{2.5}$ exposure. The figure plots residualized test scores against pollution concentrations after netting out individual fixed effects, thereby exploiting within-student variation over time.

Each point represents the average residual test score within bins of the $PM_{2.5}$ distribution, and the solid line reports the corresponding linear fit. The figure reveals a clear negative relationship: higher pollution exposure is associated with lower test performance.

Figure 1: $PM_{2.5}$ concentration variability

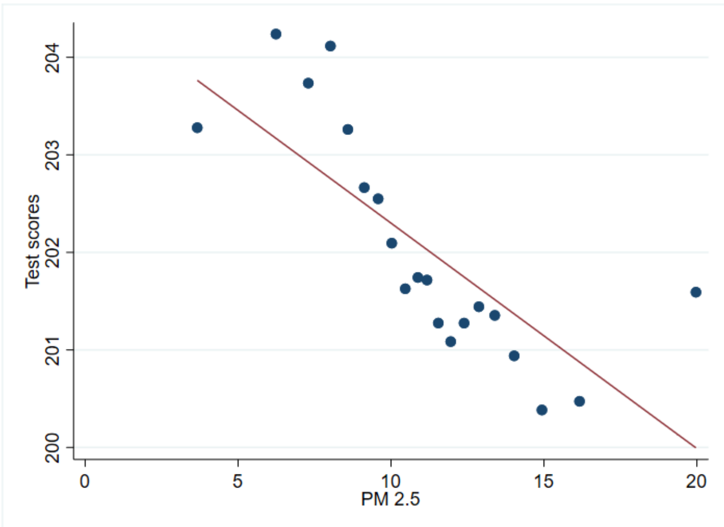
A. Across municipalities and test dates B. Across municipalities (max across test dates)



Notes: Panel A presents the dispersion of $PM_{2.5}$ across municipalities and test dates averaged over time. Panel B displays $PM_{2.5}$ concentration across municipalities. For each municipality, we record the registered maximum across test dates over time. Orange (red) areas depict municipalities with a lower (larger) concentration of $PM_{2.5}$.

Figure A3 in the Appendix replicates the analysis separately by subject and confirms that the negative relationship between test scores and $PM_{2.5}$ concentrations holds across all subjects. For Literacy and Mathematics, identification comes from within-student variation across grades and test days, while for English—assessed only in fifth grade—it relies on within-municipality variation across test dates.

Figure 2: Relationship between $PM_{2.5}$ and standardized test scores, conditional on students' fixed effects



Notes: The figure displays the relationship between test scores and $PM_{2.5}$ concentration, net of individual fixed effects.

4 Empirical Strategy and Identification

Our analysis investigates how exposure to air pollution affects student cognitive performance. To address this question, we exploit variation in pollution levels on test days and assess how these fluctuations influence student outcomes. Specifically, we estimate the following regression model:

$$\begin{aligned} y_{isgtm} = \beta_0 + \beta_1 PM2.5_{stm} + \beta_2 W_{stm} + \beta_3 X_{igtm} + \\ \delta_i + \theta_t + \omega_w + \lambda_{gs} + \varepsilon_{isgtm} \end{aligned} \tag{1}$$

where y_{isgtm} represents the test score of student i in subject s, grade g, year t, in municipality m. The main coefficient of interest is β_1, which captures the impact of exposure to particulate matter ($PM_{2.5}$) in municipality m in the 24 hours preceding the test of subject s in year t.[11] W_{stm} accounts for weather conditions, including temperature (in 2-degree-Celsius bins) and total precipitation, on the test day at the same location. The error term (ε_{isgtm}) represents idiosyncratic shocks at the student level.

The model includes several fixed effects to account for unobservable confounders. Year fixed effects (θ_t) capture any time-varying shocks that affect all students in a given year. Day-of-the-week fixed effects (ω_w) account for systematic weekly patterns in pollution and test performance, while grade-by-subject fixed effects (λ_{gs}) absorb permanent differences across subjects and grades.

The inclusion of individual fixed effects (δ_i) serves a dual purpose: beyond absorbing time-invariant individual characteristics such as innate ability and socioeconomic background, it addresses a potential source of selection bias arising from the effect of pollution on absenteeism. As we document in Section 7.2, higher pollution increases the likelihood of absence on test days, systematically altering the composition of students sitting the exam. Conditioning on individual fixed effects ensures that our estimates reflect within-student variation in performance rather than compositional changes in the test-taking population.

To account for spatial and temporal correlation in the error structure, we cluster standard errors at the level of 200 areas based on geographic proximity, determined

[11]More precisely, exposure is measured over the 24-hour window preceding the start of the school day, i.e., from 9 a.m. of the previous day to 9 a.m. of the test day.

using k-means clustering on latitude and longitude coordinates.[12]

Our identification strategy exploits within-student variation in test performance across subjects and grades, combined with temporal fluctuations in local pollution. The key identifying assumption is that, conditional on the fixed effects and weather controls, short-run variation in air pollution within municipalities across test dates is quasi-random.

While this setup mitigates concerns about endogenous school sorting and heterogeneous avoidance behavior (Ebenstein et al., 2016), two potential threats to identification remain. First, short-term fluctuations in air pollution may reflect increased traffic or industrial activity, which could independently impair student performance through noise or other channels, introducing omitted variable bias. Second, unobserved city-wide events — such as festivals or sporting competitions — could simultaneously raise emissions and divert students' attention on test days.

We address both concerns in Section 8. First, we show that our estimates are virtually unchanged when excluding schools located near road traffic or sources of noise pollution — precisely the schools most exposed to omitted variable bias — supporting the validity of our identifying assumption. Second, we trace the effect of $PM_{2.5}$ on test scores over a window spanning two days before and after the test. The association is driven entirely by pollution in the 24 hours preceding the exam, with no significant effects in the days before or after. This sharp temporal pattern is difficult to reconcile with confounding by discrete events, and supports a causal interpretation of our estimates.

5 Results

This section presents our estimates of the effects of outdoor air pollution on students' test performance. We begin by reporting results from our main specification and placing our findings within the existing literature (Section 5.1). We then turn to the mechanisms underlying the negative impact of pollution and explore potential sources of heterogeneity (Section 5.2).

[12]In Section 8, we show that our results are robust to alternative clustering specifications.

5.1 Main findings

Table 2 reports the results of our estimates of the causal effects of $PM_{2.5}$ exposure on students' test scores, based on the model specified in Equation 1. Columns (1)–(3) present estimates from specifications in which $PM_{2.5}$ enters linearly. Column (1) includes municipality, year, subject-by-grade, and day-of-week fixed effects. Column (2) augments this baseline specification with weather controls — specifically, daily average temperature bins and daily average precipitation. Column (3) further includes individual fixed effects, thereby exploiting within-student variation in pollution exposure across exam days and grades.

Table 2: Impact of air pollution on test scores

	Outcome: Test score					
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$ (24h bf 9am)	-0.120***	-0.094***	-0.183***			
	(0.036)	(0.034)	(0.049)			
High $PM_{2.5}$ ($PM_{2.5}$>10)				-1.564***	-1.319***	-1.545***
				(0.188)	(0.186)	(0.260)
Observations	22,178,506	22,178,506	21,879,514	22,178,506	22,178,506	21,879,514
Mean dep. var.	202.042	202.042	202.211	202.042	202.042	202.211
SD dep. var.	42.082	42.082	41.981	42.082	42.082	41.981
Municipality FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y	Y
Subject $\times$ grade FE	Y	Y	Y	Y	Y	Y
Weather controls	-	Y	Y	-	Y	Y
Individual FE	-	-	Y	-	-	Y

Notes: This table presents estimates of the impact of air pollution on test scores. Columns (1)–(3) use a continuous measure of $PM_{2.5}$, while Columns (4)–(6) use a dummy variable equal to 1 if $PM_{2.5}$ exceeds 10 $\mu g/m^3$ and 0 otherwise. Coefficients in Columns (1)–(3) are expressed in test score points per $\mu g/m^3$ of $PM_{2.5}$. Coefficients in Columns (4)–(6) are expressed in test score points. Columns (1)–(3) and (4)–(6) progressively add controls and fixed effects, as indicated in the bottom part of the table. Standard errors are clustered at the area level, where municipalities are grouped into 200 geographic areas using k-means clustering on latitude and longitude. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Across specifications, the estimated effect of $PM_{2.5}$ is consistently negative, statistically significant, and relatively stable in magnitude.

Notably, the estimated coefficient increases in absolute value when individual fixed effects are introduced in Column (3). This pattern is consistent with the evidence in Table 8, which shows that higher pollution increases student absences and induces compositional changes in test-taking. Indeed, by inducing selective exam participation, pollution may alter the composition of students who actually take the test, leading to biased estimates when this selection is not properly accounted for.

Specifically, the fact that the estimated effect becomes stronger once individual fixed effects are included suggests that, as expected, lower-performing or less motivated students are disproportionately more likely to be absent on high-pollution days. As a consequence, models that do not account for this selection underestimate the true impact of pollution, as they conflate its negative effect on performance with positive selection into test participation.

These findings highlight the importance of controlling for individual fixed effects when estimating the impact of air pollution on academic outcomes. When pollution disproportionately affects more vulnerable students, estimates that do not account for compositional differences will be biased toward zero and lead to a systematic underestimation of the true effect of pollution on academic outcomes.

Focusing on our preferred linear specification in Column (3), a one microgram per cubic meter increase in ambient $PM_{2.5}$ reduces test scores by 0.183 points. Given a standard deviation of test scores of approximately 42 points, this corresponds to a decline of about 0.44% of a standard deviation. A one standard deviation increase in $PM_{2.5}$ (approximately 5.5 $\mu g/m^3$), therefore, implies a reduction in test scores of roughly 2.4% of a standard deviation.

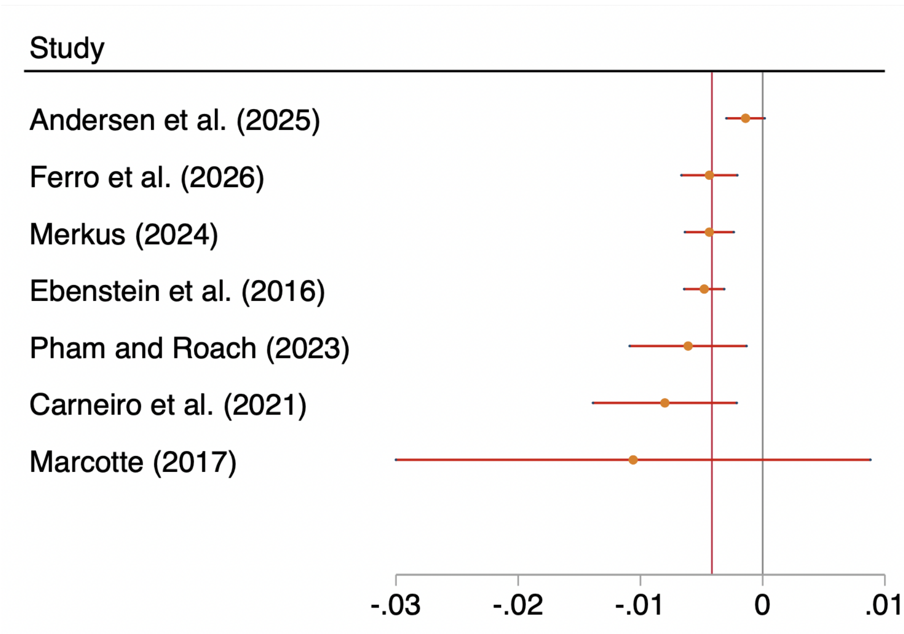
These magnitudes are economically meaningful and broadly consistent with the existing literature as reported in Figure 3, which compares our estimated effect size with findings from related studies in other countries.

To facilitate comparability, we express all estimates as the effect of a 1 $\mu g/m^3$ increase in $PM_{2.5}$ on test scores, measured in standard deviations. Most studies find relatively similar magnitudes. For example, Merkus (2024) estimate that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ reduces test scores by 0.44% of a standard deviation, while Ebenstein et al. (2016) report a decline of 0.48%. Slightly larger effects are documented by Pham and Roach (2023), who find a reduction of approximately 0.6% of a standard deviation in student learning, and by Carneiro et al. (2021), who estimate a decline of 0.8%.

Additional evidence from Marcotte (2017) shows that students perform about 1% of standard deviation worse on math and reading assessments, while Andersen et al. (2025) find that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ reduces test scores by 0.9% of a standard deviation.

In Columns (4)–(6), we replace the continuous measure of $PM_{2.5}$ with a binary indicator for high pollution exposure. We define high exposure as days in which $PM_{2.5}$ concentrations exceed 10 $\mu g/m^3$, corresponding to the median of the daily $PM_{2.5}$ distribution in our sample. The structure of the specifications mirrors that of Columns (1)–(3), with Column (6) including individual fixed effects and serving as our preferred specification in this panel. Again, estimates are roughly stable across specifications, with the inclusion of individual fixed effects leading to an increase in the coefficient, although this pattern is less pronounced than in the linear specification. The estimate in Column (6) indicates that test scores decline by approximately 1.5 points on days with high $PM_{2.5}$ exposure, corresponding to a reduction of about 3.7% of a standard deviation.

Figure 3: Comparing Our Estimates to Previous Findings



Notes: The forest plot depicts study-specific effects (orange circles) and 95% confidence intervals. The red vertical line highlights the study-specific deviations from the overall effect size, and the black vertical line highlights no-effect values. We included the studies focusing on the causal effect of air pollution changes on test scores. To allow comparability, each study-specific coefficient is computed as the test score effect of a 1 $\mu g/m^3$ increase in $PM_{2.5}$. Sources: Andersen et al. (2025), Carneiro et al. (2021), Ebenstein et al. (2016), Marcotte (2017), Merkus (2024) and Pham and Roach (2023).

Non linearities. To investigate non-linearities and identify potential thresholds, we replace the continuous measure of $PM_{2.5}$ with a set of indicator variables corresponding to 2 $\mu g/m^3$ bins of the $PM_{2.5}$ distribution. Figure 4 plots the estimated coefficients and 95% confidence intervals, using the 4–6 $\mu g/m^3$ range as the reference category.

The results reveal a clear monotonic relationship between pollution exposure and test performance: as $PM_{2.5}$ concentrations increase, estimated test scores progressively decline. While effects are small and statistically indistinguishable from zero at low pollution levels, they become increasingly negative as exposure rises, particularly beyond 8–10 $\mu g/m^3$. The largest declines—on the order of 4 to 5 points—are observed in the highest pollution categories, although confidence intervals widen at these levels. Overall, the figure provides evidence of fairly linear effects, with the adverse impact of $PM_{2.5}$ intensifying at higher concentrations.

This pattern suggests that short-run exposure to high levels of air pollution has disproportionately harmful effects on students' cognitive performance. For instance, Pham and Roach (2023) show that $PM_{2.5}$ concentrations begin to harm educational performance once average exposure exceeds approximately 9 $\mu g/m^3$, a level below both the U.S. Environmental Protection Agency's threshold for good air quality (12 $\mu g/m^3$) and the WHO guideline. Similarly, Ebenstein et al. (2016) find that very poor air quality on the day of an exam is associated with substantially larger declines in test performance than moderately polluted days, indicating that the adverse cognitive effects of pollution are driven primarily by exposure to high pollution levels.

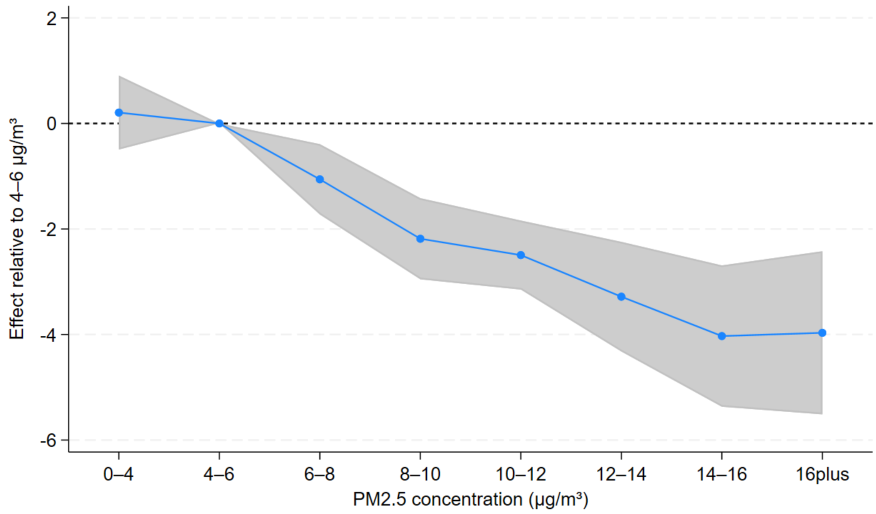
5.2 Mechanisms and heterogeneity

The negative effects documented in Table 2 raise two central questions: through which mechanisms do these effects operate, and which students are most affected? This section addresses these questions by examining (i) the cognitive processes and domains involved (knowledge versus reasoning), (ii) the role of question format (open-ended versus multiple-choice), and (iii) heterogeneity across student characteristics, including emotional factors.

Cognitive domains and question format. We begin by investigating the cognitive mechanisms underlying the estimated effects. *How* do they materialize? Specifically, does pollution primarily impair reasoning abilities or the retrieval of previously acquired knowledge? Moreover, does the effect vary with the question format?

Columns (1) and (2) of Table 3 examine differential impacts across cognitive do-

Figure 4: Estimated effect of $PM_{2.5}$ on test scores by pollution level



Notes: The figure displays the estimated coefficients and 95% confidence intervals for each 2 sized bins of the $PM_{2.5}$ distribution on test scores. The 4-6 $PM_{2.5}$ category is omitted and serves as the reference category. The regression includes the full set of controls described in Equation 1. Standard errors are clustered at the area level, where municipalities are grouped into 200 geographic areas using k-means clustering on latitude and longitude.

mains. Exploiting detailed item-level information, we distinguish between reasoning-intensive questions—which require abstraction, higher-order thinking, and sustained attention—and knowledge-based questions, which rely primarily on recall. Columns (3) and (4) instead focus on question format, distinguishing between open-ended and closed-ended items. All outcomes are measured as the share of correctly answered questions within each category.[13]

Two clear patterns emerge from Table 3. First, comparing Columns (1) and (2), we find that reasoning-intensive questions are the primary source of the adverse effect. Exposure to $PM_{2.5}$ does not significantly affect students' ability to retrieve factual knowledge (the coefficient is small and statistically insignificant), but it substantially impairs performance on tasks requiring concentration and cognitive effort. In other words, air pollution appears to disrupt executive functioning and fluid reasoning rather than long-term memory or crystallized knowledge.

This finding is consistent with evidence from both the psychological and economic

[13]Because tests differ in the relative weight assigned to knowledge and reasoning questions, Appendix Table A1 reports specifications weighted by the share of questions of the corresponding type in each test. This approach gives greater weight to tests that provide a more informative measure of performance in a given domain. For example, tests with a larger share of knowledge questions receive greater weight in the knowledge regressions and lower weight in the reasoning regressions, while the opposite applies to tests with a larger share of reasoning questions. The results are largely unchanged.

literature. For example, Bedi et al. (2021), using a controlled laboratory setting, show that acute exposure to high levels of $PM_{2.5}$ reduces performance on tasks involving higher-order cognitive processes, including fluid reasoning and complex problem-solving, while leaving basic attention, arithmetic processing speed, and working memory largely unaffected. Similarly, La Nauze and Severnini (2025) document that exposure to $PM_{2.5}$ significantly reduces performance across a wide range of cognitive exercises, with particularly pronounced effects on novel or unfamiliar tasks that rely heavily on fluid reasoning. Complementary evidence from high-stakes professional settings is provided by Künn et al. (2023), who show that poor indoor air quality impairs strategic decision-making under time pressure in professional chess tournaments, especially for cognitively demanding decisions. Taken together, this body of evidence supports the interpretation that pollution primarily disrupts complex reasoning and executive control rather than routine or memory-based tasks. To the best of our knowledge, our paper is the first to provide causal evidence of this mechanism in an educational context by systematically distinguishing between reasoning-intensive and knowledge-based items using large-scale administrative data on standardized test performance.

Turning to the question format, Columns (3) and (4) indicate that the negative effects of pollution are stronger for multiple-choice questions than for open-ended ones. At first glance, this may seem at odds with the stronger effects observed for reasoning-intensive questions; however, it reflects the interaction between question format and cognitive demands (Griselda, 2024). Multiple-choice items require students to evaluate several alternatives, rule out distractors, and make fine-grained comparisons—processes that place substantial demands on attention, executive functioning, and inhibitory control. In contrast, open-ended items are more based on recall and response production, which are less sensitive to short-term $PM_{2.5}$ exposure. This is consistent with the "paradox of choice" in behavioral research (Kida et al., 2010; Schwartz and Ward, 2004), showing that increasing available options can increase cognitive load and error rates.

In sum, our analysis demonstrates that the adverse effects of air pollution are not uniform across test content. Reasoning-intensive tasks and multiple-choice formats, which demand sustained attention, complex processing, and executive control, are particularly affected, highlighting the mechanisms through which environmental stressors undermine cognitive performance.

Table 3: Impact of Air Pollution by Cognitive Domain and Question Format

	Outcome: Share of Correct Answers			
	Cognitive Domain		**Question Format**	
	Knowledge (1)	Reasoning (2)	Open (3)	Closed (4)
$PM_{2.5}$	0.0075	-0.0791***	-0.1002***	-0.4025***
	(0.0361)	(0.0232)	(0.0297)	(0.0341)
Observations	17,485,649	17,485,649	18,375,902	21,882,951
Mean dep. var.	63.636	60.476	63.001	62.864
SD dep. var.	27.621	22.635	30.523	23.088
Year FE	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y
Subject $\times$ grade FE	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y

Notes: This table reports estimates of the impact of air pollution on the share of correct answers by cognitive domain—knowledge-intensive questions (Column 1) and reasoning-intensive questions (Column 2)—and by question format—open-ended questions (Column 3) and closed-ended questions (Column 4). All specifications include year, day-of-week, individual, and subject-by-grade fixed effects, as well as weather controls (temperature and total precipitation). Standard errors are clustered at the area level, where municipalities are grouped into 200 geographic areas using k-means clustering on latitude and longitude coordinates. The outcome is expressed as the share of correct answers (0–100). $PM_{2.5}$ is expressed in $\mu g/m^3$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Emotional perceptions of the test. Emotional perceptions and non-cognitive traits might interact non-trivially with air pollution in shaping students' performance.

We explore this mechanism using information from the INVALSI student background questionnaire, which includes four items capturing students' emotional states and self-perceived performance on the day of the Mathematics test.

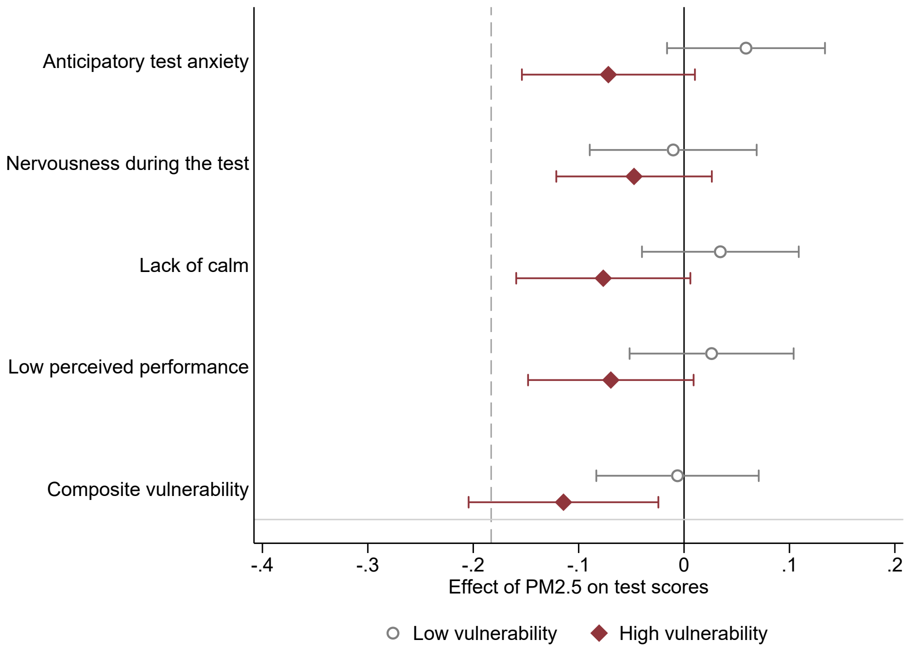
Students are asked — on a four-point Likert scale ranging from ″strongly disagree″ to ″strongly agree″ — whether they (i) were worried before taking the test, (ii) felt so nervous during the test that they could not find the answers, (iii) had the impression of performing poorly while answering the questions, or (iv) felt calm during the test (see Table A2 in the Appendix for the exact wording of the questions). We construct binary indicators for each emotional dimension, classifying students as having high (low) levels of nervousness during the test, anticipatory test anxiety, lack of calm and low self-confidence if they respond ″agree″ or ″strongly agree″ (″disagree″ or ″strongly disagree″) to the corresponding statement. In addition, we define a composite indicator equal to one if a student agrees or strongly agrees in all four items, capturing a broader condition of emotional vulnerability during the assessment.

Figure 5 presents heterogeneous estimates of the effect of air pollution on test scores by levels of these emotional perceptions. For each dimension, the figure reports separate coefficients for students with low and high levels of the corresponding trait.

A caveat is worth emphasizing. While we interpret emotional perceptions as pre-existing traits that moderate the effect of pollution, these measures are collected on the day of the Mathematics test in fifth grade and may themselves respond to testing conditions, including, potentially, pollution exposure. To the extent that pollution directly increases emotional distress—or does so indirectly through its impact on performance—our heterogeneity estimates may partly capture endogenous emotional responses rather than purely differential susceptibility. Disentangling these channels is difficult with the available data. Nevertheless, two considerations support our interpretation. First, the heterogeneity patterns are remarkably consistent across all emotional dimensions. Second, the heterogeneity extends to all subjects, not only Mathematics, even though emotional perceptions are measured during the Mathematics assessment. Taken together, these patterns suggest that our estimates primarily capture differences in emotional vulnerability rather than purely transitory reactions to test-day conditions.

One plausible mechanism is that pollution exacerbates stress-related physiological responses, further impairing attention, working memory, and problem-solving abilities during the test (Barnor, 2025). Students who already experience anxiety or insecurity during evaluative settings may therefore be particularly susceptible to environmental stressors. This finding complements Ballatore et al. (2025), who document that adverse testing conditions—in their case, high temperatures—increase anxiety and reduce self-esteem, ultimately leading to poorer cognitive performance.

Figure 5: Heterogeneity by emotional perceptions



Notes: The figure reports estimates and 95% confidence intervals of Equation 1 by students' emotional perceptions. For each dimension, coefficients are shown separately for students with low and high vulnerability; the final pair refers to a composite indicator equal to one for students reporting high vulnerability in all four domains. The sample is restricted to 5th-grade students in 2012/13–2016/17. All specifications include individual, year, grade, subject, subject-by-grade, and day-of-week fixed effects, as well as weather controls. Standard errors are clustered at the area level, where municipalities are grouped into 200 geographically proximate areas using k-means clustering on latitude and longitude.

Other heterogeneity: gender, parental education, grade, and subject. We next examine additional dimensions of heterogeneity and assess how the effects vary across the performance distribution. Table 4 reports estimates of our baseline specification on subsamples defined by gender and parental education, the latter serving as a proxy for family socioeconomic status. We analyze heterogeneity along these dimensions both in isolation (Panel A) and jointly with other relevant margins, namely test subject (Panel B) and school grade (Panel C).

Overall, the results reveal substantial heterogeneity in the effects of $PM_{2.5}$ on test scores across subjects, grades, gender, and family background. First, Panel A suggests limited heterogeneity by gender on average (Columns 2 and 3). However, a more nuanced pattern emerges in Panel B. In particular, each gender appears to be more adversely affected in subjects where its baseline performance is relatively weaker: male students exhibit larger declines in language-related subjects—where females tend to outperform—while the effects are smaller in mathematics, a domain in which males typically perform better.

Second, although the estimated effects on native language scores are generally small and imprecise, exposure to $PM_{2.5}$ has sizable and statistically significant negative impacts on mathematics and English outcomes, with English listening emerging as the most affected outcome in the full sample. This pattern is consistent with our earlier findings that air pollution primarily impairs performance in cognitively demanding domains requiring sustained attention and information processing, such as mathematics and foreign language, rather than more knowledge-based domains such as native language (see for example Brill-Schuetz and Morgan-Short (2014)). At the same time, English is only assessed in Grade 5, where overall effects are also stronger, which may partly account for the larger estimated impacts for English outcomes.

Third, students from less-educated families experience larger negative effects than those from more-educated backgrounds. For several subjects—most notably English reading and listening—the estimates are attenuated and often statistically insignificant among students with highly educated parents (Column 4), while they are larger and more precisely estimated among students from less advantaged families (Column 5). This pattern is consistent with prior evidence that socioeconomic resources can mitigate the adverse consequences of pollution exposure (e.g. Ebenstein et al., 2016).

Finally, Panel C shows that the effects increase markedly with grade level. While

$PM_{2.5}$ exposure already negatively affects outcomes in Grade 2, the estimated effects are substantially larger in Grade 5 across all subsamples. Given that assessments at higher grade levels place greater emphasis on problem-solving, reasoning, and other higher-order cognitive skills—rather than purely knowledge-based competencies—this pattern is again consistent with our earlier evidence that air pollution disproportionately impairs attention and information processing.

Taken together, these results indicate that the detrimental effects of air pollution on academic performance are concentrated in more cognitively demanding subjects, at higher grade levels, and among more vulnerable student groups. These patterns are internally consistent and closely align with the cognitive mechanisms highlighted in our main analysis.

Finally, we assess heterogeneity across the performance distribution, following the approach of Andersen et al. (2025) and estimating unconditional quantile treatment effects (Firpo et al., 2009). For this purpose, we rely on the estimators proposed by Borgen et al. (2021), which allow both high-dimensional fixed effects and continuous treatments.

Figure 6 presents the estimates and shows quantile treatment effects of air pollution on test scores. At the upper end of the test score distribution, the impact of air pollution is minimal, less than one-quarter of the baseline estimate. The treatment effects increase steadily when moving toward lower quantiles. At the bottom decile, a one $\mu g/m^3$ increase in air pollution reduces test scores by 0.25 points — about five times the effect at the top of the distribution. This result differs from those of Andersen et al. (2025) and Graff Zivin and Neidell (2012), who find stronger pollution effects at the top of the test score distribution, but aligns with Carneiro et al. (2021) and Ebenstein et al. (2016), who document larger effects among lower-performing students.

Importantly, these results are consistent with the heterogeneity patterns discussed above: just as students appear less affected in subjects where they have a relative strength, higher-performing students may be better able to compensate for pollution-induced cognitive impairments. In contrast, students at the lower end of the performance distribution—who plausibly require more sustained cognitive effort to answer the questions—experience substantially larger adverse effects.

Overall, these findings indicate that air pollution disproportionately worsens educational outcomes for already disadvantaged students, and thus contributes to exacer-

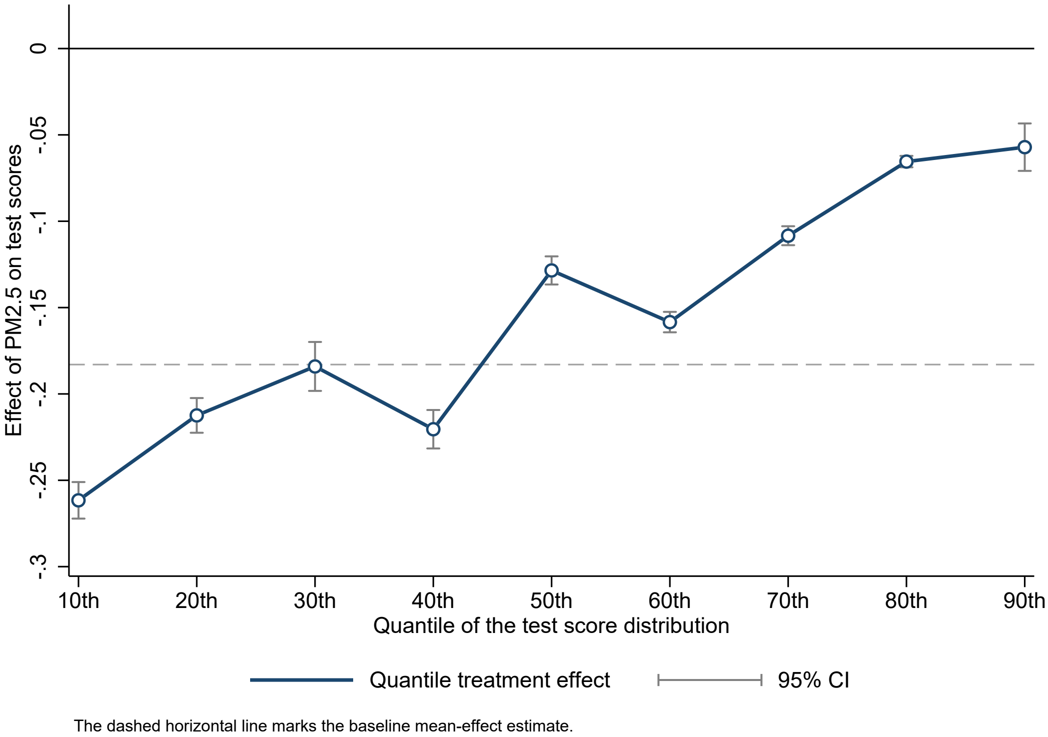
Table 4: Effects of $PM_{2.5}$ on Test Scores by Subject and Grade

	(1) Full	(2) Females	(3) Males	(4) High educ	(5) Low educ
Panel A: All Grades and Subjects					
$PM_{2.5}$	-0.183***	-0.1864***	-0.1793***	-0.0813**	-0.1612***
	(0.049)	(0.0520)	(0.0466)	(0.0385)	(0.0439)
Panel B: Interaction by subject					
$PM_{2.5} \times$ Language	-0.0525	-0.0318	-0.0722**	-0.0295	-0.0405
	(0.0330)	(0.0349)	(0.0316)	(0.0306)	(0.0303)
$PM_{2.5} \times$ Math	-0.1862***	-0.2302***	-0.1421***	-0.1095***	-0.1801***
	(0.0400)	(0.0401)	(0.0404)	(0.0394)	(0.0329)
$PM_{2.5} \times$ English (reading)	-0.4021***	-0.4342***	-0.3687***	-0.2342*	-0.3269***
	(0.1081)	(0.1131)	(0.1041)	(0.1192)	(0.1051)
$PM_{2.5} \times$ English (listening)	-0.4730***	-0.4020***	-0.5407***	-0.0683	-0.3995***
	(0.1348)	(0.1498)	(0.1218)	(0.1136)	(0.1254)
Panel C: Interaction by grade					
$PM_{2.5} \times$ Grade 2	-0.1024***	-0.1016**	-0.1036***	-0.0390	-0.0921***
	(0.0381)	(0.0398)	(0.0367)	(0.0339)	(0.0330)
$PM_{2.5} \times$ Grade 5	-0.2557***	-0.2616***	-0.2473***	-0.1268**	-0.2191***
	(0.0619)	(0.0656)	(0.0583)	(0.0505)	(0.0555)
Observations	21,879,514	10,814,250	11,065,224	3,949,701	13,522,925
Mean dep. var.	202.211	202.552	201.878	215.514	198.878
Year FE	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y
Subject $\times$ grade FE	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y

Notes: This table reports estimates of Equation 1 of the impact of air pollution on test scores across different subgroups. Panel A presents average effects across all grades and subjects. Panel B reports interaction effects by subject. Panel C reports interaction effects by grade. Column (1) uses the full sample; Columns (2) and (3) split the sample by gender (females and males, respectively); Columns (4) and (5) split the sample by parental education, where a student is classified as having highly educated parents if at least one parent has completed tertiary education. All specifications include year, grade, subject, day-of-week, individual, and subject-by-grade fixed effects, as well as weather controls (temperature and total precipitation). Standard errors are clustered at the area level, where municipalities are grouped into 200 geographic areas using k-means clustering on latitude and longitude. Coefficients are expressed in test score points per $\mu g/m^3$ of $PM_{2.5}$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

bating pre-existing educational inequalities.

Figure 6: Quantile regression of $PM_{2.5}$ on test scores



Notes: The figure plots quantile treatment effects of $PM_{2.5}$ on test scores across deciles of the test score distribution, estimated following (Borgen et al., 2021). Markers report point estimates and vertical bars indicate 95% confidence intervals. The dashed horizontal line marks the baseline mean-effect estimate from Equation 1. All specifications include individual, year, grade-by-subject, and day-of-week fixed effects, as well as weather controls. Standard errors are clustered at the area level, where municipalities are grouped into 200 areas based on geographic proximity, determined using k-means clustering on latitude and longitude data.

6 Coping strategies

This section examines whether school infrastructure and location mitigate the detrimental effects of air pollution.

Mechanical ventilation and air conditioning systems. While the previous results establish that contemporaneous exposure to air pollution significantly impairs cognitive performance and reduces student test scores, the effectiveness of school-level mitigation strategies remains an open policy question. In this section, we examine whether these adverse effects are attenuated in schools equipped with mechanical ventilation and air conditioning systems. Such systems can reduce indoor concentrations of particulate matter through two main channels: built-in filters in the air handling units, and reduced reliance on natural ventilation (i.e., opening windows), which limits the infiltration of polluted outdoor air. Evidence suggests that well-designed ventilation and filtration configurations can substantially attenuate indoor exposure to ambient pollutants (Polidori et al., 2013).

To this end, we exploit detailed school building–level data from the Ministry of Education (MIUR) to test for differential effects of pollution across schools with different infrastructure. Specifically, we use a binary indicator of whether the school building is equipped with a mechanical ventilation or air conditioning system.[14] The analysis is restricted to the subset of schools successfully matched to the MIUR database for which this information is available (see Section 3.3).

Table 5 reports estimates based on Equation 1. Column (1) presents results for the matched sample, while Columns (2) and (3) report estimates separately for schools without and with mechanical ventilation and air conditioning systems, respectively. The coefficient in Column (1) is slightly larger than in the baseline specification, likely reflecting differences in sample composition. In particular, the MIUR data cover the period from 2017 onward, excluding earlier years in which the impact of pollution may have been smaller. Additionally, starting from the 2017/18 school year, the introduction of English reading and listening tests increased the cognitive load of fifth-grade assessments—expanding from two to four subjects—which may have heightened students' sensitivity to environmental stressors during testing.

Comparing Columns (2) and (3), the results indicate that the presence of a ventilation or air conditioning system substantially mitigates the negative effects of pollution on academic performance. The estimated coefficient for schools equipped with such systems is approximately half the size of that observed in schools without them, although it remains negative and only marginally significant.

Two factors likely explain why the effect is attenuated but not eliminated. The first, and arguably most important, is that school infrastructure can only shield students during school hours: exposure during the commute, at home, and in other environments remains unaffected, and the cumulative pollution load on cognitive performance reflects all these sources. In addition, standard ventilation and air conditioning

[14]The MIUR indicator is binary and is recorded conditional on the building being equipped with a heating system. It does not provide information on filter quality, system maintenance, or actual operation during school hours, which likely attenuates the estimated moderating effect.

systems include filters of variable quality and are not designed primarily for fine particulate removal, unlike dedicated HEPA-grade air purifiers.

Beyond explaining the residual negative coefficient, this reasoning has a substantive implication for the interpretation of our main results. If pollution affected cognitive performance primarily through cumulative or lagged exposure, then school infrastructure would have limited scope to attenuate the effect, since it can only act on a fraction of daily exposure. The fact that the coefficient roughly halves in schools equipped with ventilation and air conditioning is therefore consistent with the hypothesis that the impact of $PM_{2.5}$ on test performance is largely contemporaneous, operating through short-run physiological channels active at the time of the test, rather than through the slow accumulation of past exposure. This interpretation is corroborated by the dynamic analysis in Section 8, which shows that the effect is driven entirely by exposure in the 24 hours preceding the test.

A potential concern is that schools with and without ventilation and air conditioning systems may differ systematically along several dimensions, including student composition, baseline performance, local pollution, weather conditions, or broader resource availability. If so, the observed heterogeneity could partly reflect these underlying differences rather than the moderating role of ventilation and air conditioning per se. To address this issue, in Panel B of Table 5 we implement a reweighting approach based on propensity score matching, ensuring comparability between schools with and without such systems across a rich set of observable characteristics. These include pollution exposure, weather conditions, student composition, and baseline academic outcomes.

Reassuringly, the results remain very similar in the reweighted sample: the negative impact of pollution is still substantially smaller in schools equipped with ventilation and air conditioning systems, suggesting that the attenuation effect is unlikely to be driven by systematic differences in school characteristics.

These findings are consistent with a broader literature on the benefits of investments in indoor air quality. Most closely related, Biasi et al. (2025) document that investments in heating, ventilation, and air conditioning (HVAC) systems in U.S. schools yield substantial gains in student performance, in part by mitigating the adverse effects of air pollution and extreme temperatures. Although our infrastructure indicator captures only ventilation and air conditioning, not heating, the relevant channel for indoor $PM_{2.5}$ mitigation—mechanical air handling with filtration, which can reduce both

Table 5: Impact of air pollution on test scores in schools with and without ventilation and air conditioning systems

	All schools (year>2017) (1)	Schools without VACS (year>2017) (2)	Schools with VACS (year>2017) (3)
	Panel A: raw comparison		
$PM_{2.5}$	-0.3141***	-0.3205***	-0.1997*
	(0.0748)	(0.0757)	(0.1143)
Observations	8,105,091	7,744,358	359,040
Mean dep.	202.323	202.36	201.569
	Panel B: PSM reweighted comparison		
$PM_{2.5}$	-0.2743***	-0.3092***	-0.2041*
	(0.0765)	(0.0762)	(0.1143)
Observations	8,252,538	7,739,949	357,928
Mean dep. var.	202.459	202.879	201.57
Year FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Subject × grade FE	Y	Y	Y
Weather controls	Y	Y	Y
Individual FE	Y	Y	Y

Notes: This table presents estimates of Equation 1 on test scores for schools without and with ventilation or air conditioning systems (VACS) for the school years 2017/18–2022/23 (Columns 2 and 3). Column (1) reports estimates of Equation 1 in the pooled sample of schools matched to MIUR administrative characteristics, with and without such systems. Panel A reports baseline estimates obtained from the full, unweighted sample. Panel B reports estimates obtained after reweighting schools using propensity score matching to improve comparability. Propensity scores are estimated at the school level using kernel matching and include average temperature, total precipitation, $PM_{2.5}$ concentration, average test scores, socioeconomic status (ESCS), gender composition, share of foreign students, and school size decile. The resulting weights are applied to construct a reweighted sample where treated and control schools are balanced along these observable characteristics. Each specification controls for year, grade-by-subject, day-of-week, and individual fixed effects, and for weather conditions (temperature and total precipitation). Standard errors are clustered at the area level, where municipalities are grouped into 200 areas based on geographic proximity, determined using k-means clustering on latitude and longitude data. Coefficients are expressed in test score points per $\mu g/m^3$ of $PM_{2.5}$. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

infiltration of outdoor pollutants and the need to open windows—is common across system types.[15] Additional evidence comes from studies on dedicated air purifiers, a related but distinct technology: Gilraine (2023) shows that HEPA air filters significantly improve classroom environments and student test scores, while Persico and Fuller (2025) document gains in test scores and reductions in chronic absenteeism following filter installations in North Carolina. In the Italian context, Bonan et al. (2025) exploit the random allocation of air purifiers across primary schools in Milan and find significant reductions in indoor pollutant concentrations and student absenteeism.

Although we do not claim a fully causal interpretation of these effects, the consistency of our findings with this literature suggests that school infrastructure can play an important role in buffering environmental shocks.

These results carry important policy implications. They suggest that relatively low-cost investments in school infrastructure can effectively shield students from environmental risks and help reduce inequalities in academic achievement, consistent with broader evidence on the returns to educational spending (Jackson and Mackevicius, 2024; Pavese and Rubolino, 2023). Importantly, since standard ventilation and air conditioning installations are not optimized for fine particulate removal, even larger gains may be achievable through targeted investments in dedicated air filtration technology, particularly in areas with persistently poor air quality. Such interventions not only protect student health but also represent a promising tool for reducing inequality in educational outcomes.

School location and environmental quality. The previous analysis suggests that school infrastructure can act as an important mitigating factor. However, both the effectiveness of such defenses and students' underlying vulnerability may also depend on the baseline environmental conditions in which schools are located.

A priori, it is unclear whether the marginal impact of pollution on test day is more pronounced in urban areas—characterized by persistently higher pollution levels—or in rural areas, where baseline exposure is typically lower. On the one hand, the hypothesis of "dose-response" (see Graff Zivin and Neidell (2013)) implies that in urban

[15] A residual concern is that the MIUR indicator does not distinguish between mechanical ventilation systems (designed to operate continuously regardless of temperature) and air conditioning units (typically used only during warm periods). Since INVALSI tests are administered in May, the moderating effect we estimate may be driven primarily by schools with continuous mechanical ventilation. To the extent that some units are inactive during testing, our estimates likely understate the moderating effect of fully operational systems.

environments, where cumulative exposure is greater, an additional increase in $PM_{2.5}$ on the test day may push students beyond a critical cognitive threshold, leading to greater detrimental effects. On the other hand, the "adaptation" hypothesis posits that children in more polluted areas may develop physiological or behavioral resilience to poor air quality, potentially attenuating the impact of marginal fluctuations relative to students in cleaner environments, for whom such pollution spikes may represent a more acute shock (Neidell, 2009).

To test these competing hypotheses, we re-estimate Equation 1 separately for urban and rural municipalities, using the degree of urbanization classification provided by the Italian National Institute of Statistics (ISTAT). Following ISTAT's methodology, "urban" areas include densely populated cities and urban centers, while "rural" areas encompass small towns, suburban areas, and sparsely populated zones.[16]

The results are reported in the first three columns of Table 6. Column (1) reproduces the baseline estimate for the full sample, while Columns (2) and (3) present the estimates for urban and rural schools, respectively.

The findings indicate that the adverse effects of air pollution are substantially more pronounced in urban settings. Students in urban areas experience stronger cognitive impairment: the estimated coefficient is 56% larger in magnitude than the baseline effect (Column 1) and approximately 2.4 times larger than the effect observed in rural areas (Column 3). These results provide support for the "dose–response" mechanism, suggesting that the cognitive costs of pollution are amplified in environments with persistently poor air quality, rather than attenuated through adaptation.

Similarly, in Columns (4)–(7) of Table 6, we investigate whether the detrimental effects of $PM_{2.5}$ exposure are more pronounced in schools located in disadvantaged or environmentally high-risk areas. Following the same sample restriction adopted in the air ventilation analysis—focusing on the subset of schools successfully matched with the MIUR database - Column (4) reports results for the matched sample of schools for which detailed local area characteristics are available. Columns (5) through (7) present disaggregated estimates of the impact of $PM_{2.5}$ on student test scores based on schools' proximity to waste sites, polluting firms, and degraded urban areas, respectively.

Although the subsamples in Columns (5)–(7) are relatively small and the resulting

[16] Additional details on the geographic classification of Italian municipalities are available in ISTAT website at https://www.istat.it/classificazione/principali-statistiche-geografiche-sui-comuni/

estimates less precise, the results consistently indicate that the negative impact of air pollution on academic performance is substantially amplified in environmentally degraded contexts. For schools located near polluting firms (Column 6), the estimated adverse effect of $PM_{2.5}$ is more than twice as large as the matched-sample estimate baseline (-0.827 compared to -0.310). This finding suggests the presence of a ”cumulative burden” effect: students already exposed to chronic localized stressors are more vulnerable to acute spikes in ambient $PM_{2.5}$ on test days, because the body's compensatory mechanisms are already exhausted.

These findings are closely related to the "urban penalty" discussed above, as schools in densely populated areas are more likely to be located near traffic hubs or environmentally degraded zones. More broadly, they highlight the importance of the local environmental context for student outcomes. Consistent with this interpretation, Persico and Venator (2021) show, using a difference-in-differences design, that acute exposure to industrial pollution can lead to large declines in test scores. Similarly, Facchinello (2024) document significant reductions in cognitive performance following exposure to PFAS contamination in the Italian context, reinforcing the view that environmental hazards can have substantial and persistent cognitive effects. These results also carry important policy implications, particularly when considered alongside our findings on school infrastructure. Schools located near polluting firms or in degraded urban environments—where the cognitive costs of pollution are largest—represent priority targets for interventions aimed at improving indoor air quality, such as the installation of air filtration systems. In the absence of such measures, the interaction between poor outdoor environmental quality and inadequate indoor protection is likely to exacerbate disparities in academic outcomes between students in more and less advantaged environments.

Table 6: Impact of Air Pollution on Test Scores: Heterogeneity by Location and Environmental Exposure

	Urban vs. Rural			Environmental Exposure			
	Full	Urban	Rural	Full (Matched)	Near Waste	Near Polluting Firm	Degraded Area
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PM_{2.5}$	-0.186***	-0.291***	-0.123***	-0.310***	-0.460*	-0.827***	-0.481**
	(0.050)	(0.099)	(0.027)	(0.074)	(0.246)	(0.254)	(0.199)
Observations	21,656,980	7,690,100	13,886,035	8,253,665	54,460	91,003	75,426
Mean dep. var.	202.253	202.283	202.239	200.430	202.350	202.410	196.811
Year FE	Y	Y	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y	Y	Y
Subject × grade FE	Y	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y

Notes: This table reports estimates of Equation 1 on test scores. Columns (1)–(3) present results for the full sample and separately for urban and rural schools. Column (4) reports results for the full matched sample with MIUR data. Columns (5)–(7) report estimates by proximity to environmental hazards (waste sites, polluting firms, and degraded areas). All specifications include year, grade, subject, day-of-week, and individual fixed effects, and control for weather conditions (temperature and precipitation). Standard errors, reported in parentheses, are clustered at the area level (200 areas defined via k-means clustering on latitude and longitude). Coefficients are expressed in test score points per $\mu g/m^3$ of $PM_{2.5}$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

7 Additional Outcomes

The effects of air pollution may extend well beyond test scores. This section examines two margins of behavioral adjustment induced by pollution exposure: the incidence of cheating during tests and the likelihood of test attendance.

7.1 Cheating

Beyond its direct effect on cognitive performance, air pollution may induce compensatory behaviors that affect measured test scores. In particular, teachers and students may respond to pollution shocks by increasing cheating during examinations.

A distinctive feature of our data is that it provides class-level measures of cheating for the full population of primary-school classes across all academic years included in our analysis. As detailed in Angrist et al. (2017), and Battistin et al. (2017), the probability of score manipulation is estimated by INVALSI using a set of class-level indicators: the mean and standard deviation of test scores, response patterns, and the proportion of missing items (see Quintano et al. 2009 for details). Based on this estimated probability, INVALSI constructs a correction factor that adjusts the class average scores as the degree of suspected cheating increases. In the analysis that follows, we collapse data at the class level and use the complement to one of this correction factor (multiplied by 100), as the outcome variable of Equation 1, to investigate whether teachers and students compensate for the detrimental effects of pollution by altering their cheating behaviors.

Table 7 reports the results of this exercise. Column (1) shows that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ levels increases the cheating index by 0.08. In terms of magnitude, this implies that a one–standard-deviation increase in $PM_{2.5}$ results in a 2.6% of a SD increase in score manipulation.

Importantly, we do not interpret this as evidence of overt or deliberate misconduct. Rather, pollution-induced stress and cognitive impairment may lead teachers to engage in more lenient invigilation or to unconsciously assist students, and students to be more susceptible to copying from peers, without any explicit intent to manipulate scores. We interpret the cheating response as an involuntary coping mechanism triggered by environmental stress rather than as a deliberate strategic choice.

To quantify differences in cheating behavior across contexts more or less exposed to air pollution, Columns (2) and (3) re-estimate Equation 1 separately for urban and rural municipalities. The effect is larger in urban areas, where the impact of pollution on test scores is also stronger, consistent with the "dose–response" pattern documented earlier and with cheating functioning as a coping mechanism under heightened environmental stress.

Overall, these results suggest that pollution affects test scores not only by impairing students' cognitive performance during the tests, but also by triggering compensatory behaviors from teachers and students that increase the incidence of cheating.

7.2 Students' absences

We next examine whether test participation responds to changes in air quality. Because we only observe students who sit the test, individual-level absences cannot be directly computed. We therefore conduct the analysis at the school level, investigating whether the number of students taking the test varies with pollution levels.

Table 7: Impact of air pollution on cheating

	Outcome: Cheating		
	Full	Urban	Rural
	(1)	(2)	(3)
$PM_{2.5}$	0.0779***	0.1109***	0.0648***
	(0.0138)	(0.0087)	(0.0244)
Observations	1,339,772	448,407	891,365
Mean dep. var.	5.081	5.901	4.668
Year FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Subject × grade FE	Y	Y	Y
Weather controls	Y	Y	Y
Individual FE	Y	Y	Y

Notes: This table reports estimates of Equation 1 using the factor used to correct for cheating as the outcome variable. Data are collapsed at the class level. Column (1) shows results for the full sample of classes in our analysis. Columns (2) and (3) show results for urban and rural areas, respectively. The model includes fixed effects for year, grade, subject, day of the week, school, and subject-by-grade. Weather controls include temperature and precipitation. Standard errors are clustered at the area level, where municipalities are grouped into 200 areas based on geographic proximity, determined using k-means clustering on latitude and longitude data. Coefficients are expressed in cheating index points per $\mu g/m^3$ of $PM_{2.5}$. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

We compute the total number of students taking each test at the school–grade–subject–test date level and estimate a Poisson pseudo–maximum likelihood (PPML) model with high-dimensional fixed effects. PPML is well suited to our count outcome (number of test-takers) and is preferable to OLS when the assumptions of homoskedasticity and normally distributed errors do not hold (Cameron and Trivedi, 2013). The specification follows Equation 1, replacing individual fixed effects with school fixed effects to reflect the change in unit of analysis.

Results are reported in Table 8. In Column (1), the dependent variable is the total number of students participating in the test; Columns (2)-–(9) replicate the analysis for different subgroups of the student population. According to our estimates, a 1 SD increase in $PM_{2.5}$ is associated with a 1.1% reduction in the number of students taking the test. This effect is stronger among older students (grade 5) and foreign students, while we find no meaningful heterogeneity by gender or socioeconomic status.

These findings are consistent with prior evidence that air pollution reduces school attendance (Currie et al., 2009; Liu and Salvo, 2018; Mendoza et al., 2020; Chung et al., 2025), and the estimated magnitudes are broadly in line with the existing literature.

Beyond documenting an additional margin of adjustment, these results carry an important methodological implication. Since air pollution differentially affects the composition of students sitting the test, estimates that do not account for this selection may conflate changes in student composition with true effects on performance. This underscores the importance of individual fixed effects in obtaining credible causal estimates of pollution's effect on test scores.

Table 8: Impact of air pollution on students' participation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		By Grade		Gender		By SES		By Origin	
	All students	Grade 2	Grade 5	Females	Males	High	Low	Native	Foreign
$PM_{2.5}$	-0.011***	-0.007**	-0.015***	-0.011***	-0.011***	-0.017***	-0.018***	-0.008**	-0.012*
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.003)	(0.007)
Observations	395,311	198,068	197,243	395,229	395,225	197,149	197,231	395,207	393,871
Mean dep. var.	45.277	22.679	22.598	22.344	22.936	11.232	11.077	38.303	6.978
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Subject $\times$ grade FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
School FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes: This table present estimates of the effect of $PM_{2.5}$ on the number of students taking a test. The unit of observation is school-test, and the dependent variable is the count of students sitting the test in each school. Estimates are obtained using a Poisson pseudo–maximum likelihood (PPML) model, and coefficients should be interpreted as the expected change, on the log scale, in the number of students per 1 SD increase in $PM_{2.5}$. Each specification controls for year, grade, subject, day of the week, school and subject-by-grade fixed effects and controls for weather conditions captured by temperature and total precipitations. Standard errors are clustered at the area level where municipalities are grouped into 200 areas based on geographic proximity, determined using k-means clustering on latitude and longitude data. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

8 Robustness tests

This section tests the robustness of the results to potential confounders and addresses remaining threats to identification.

Potential confounders. One of the possible threats to our identification strategy is the presence of confounding factors that may simultaneously correlate with air pollution and affect students' test performance, thus biasing our estimates. For instance, road traffic is a major source of short-term fluctuations in ambient pollution levels. Increases in traffic-related pollution may coincide with higher noise exposure, which could independently impair students' concentration and performance. Similarly, variations in industrial activity may influence pollution air quality while also affecting local economic conditions or background noise.

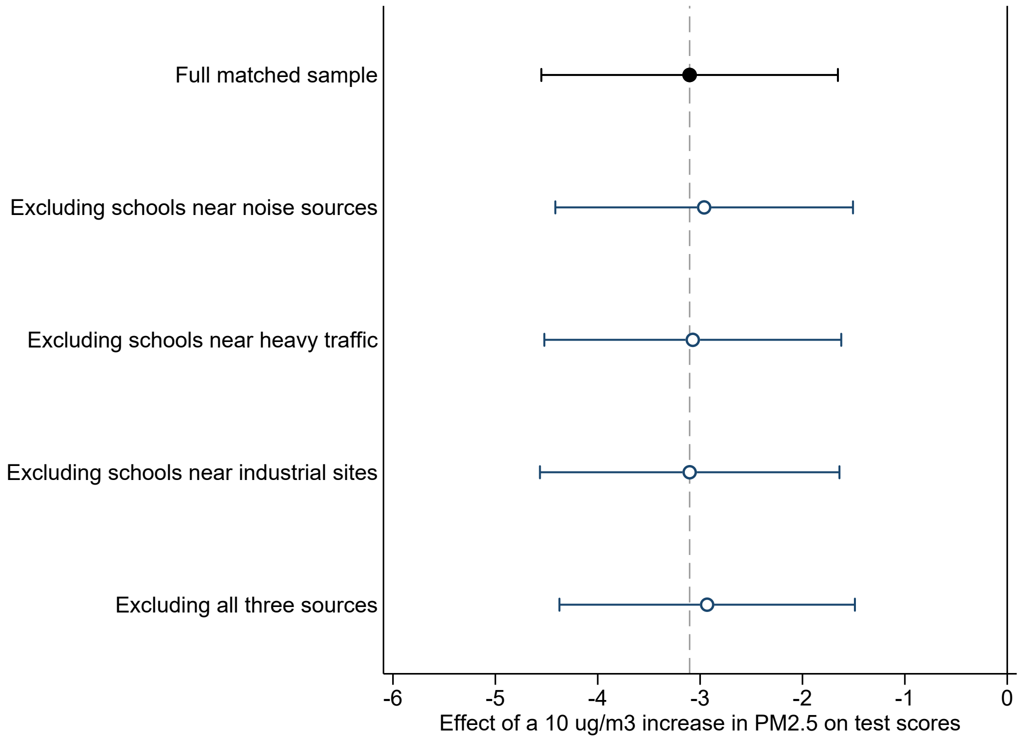
Although it is reasonable to expect the confounding role of these factors to be minor - for example, Andersen et al. (2025) show that OLS estimates of the effect of $PM_{2.5}$ on test scores in Denmark are virtually identical to those obtained using an instrumental variable approach based on wind direction- it is nevertheless important to discuss and rule out these concerns. To address this issue, in Figure 7, we replicate our main specification after excluding schools located near major sources of potential confounding shocks, such as noise pollution, road traffic, or polluting industrial facilities. We also present results applying all these exclusions simultaneously (label "Not near any").

The results of these tests confirm that our findings are not driven by proximity to environmental externalities that may jointly influence pollution levels and student performance. The estimates obtained after excluding all potentially affected schools are only slightly smaller in magnitude than those based on the full sample. Importantly, this exercise should not be interpreted as evidence that these confounding factors do not affect students. Indeed, the estimated effect is stronger for schools located near traffic, noise sources, or polluting industrial plants—a pattern consistent with these factors exerting additional adverse effects on students. The exercise therefore suggests that, while proximity to such sources may amplify the overall impact of environmental conditions on learning, it does not constitute a meaningful source of bias for our identification strategy.

Dynamic effects. To estimate the effect of air pollution on test scores, we use $PM_{2.5}$ concentrations measured on the test day. Figure 8 examines the dynamic pattern of this effect using a more flexible specification that includes leads and lags for the two days preceding and the two days following the test. The results indicate that the negative impact of air pollution on performance is driven primarily by $PM_{2.5}$ exposure in the 24 hours preceding the test. Exposure on the previous day has a much smaller magnitude and is not statistically significant at the 95% confidence level, supporting the validity of the identifying variation.

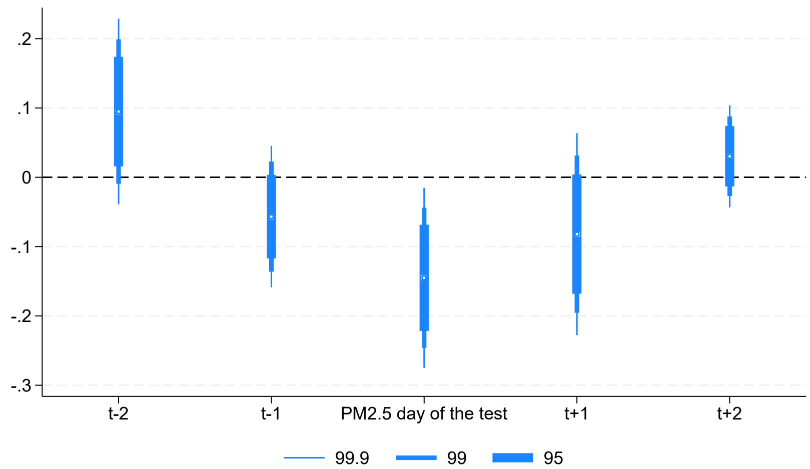
Reassuringly, Figure 8 shows no statistically significant effects of $PM_{2.5}$ in the two days following the test, providing additional support for our baseline specification.

Figure 7: Robustness test: excluding schools near noise pollution or industrial production



Notes: The figure reports estimates and 95% confidence intervals of Equation 1 after excluding schools located near selected sources of potential confounding environmental exposure. Coefficients are scaled to represent the effect of a 10 µg/m3 increase in PM2.5 on test scores. The dashed vertical line marks the estimate for the full matched sample. All specifications include individual, year, grade-by-subject, and day-of-week fixed effects, as well as weather controls. Standard errors are clustered at the area level, where municipalities are grouped into 200 geographically proximate areas using k-means clustering on latitude and longitude.

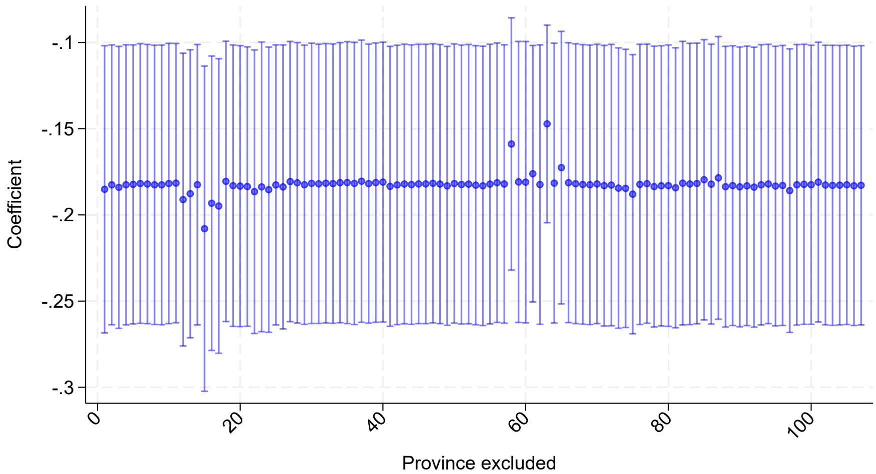
Figure 8: Dynamic effect



Notes: This figure shows the dynamic effects of air pollution on test scores, using estimates from our preferred specification. It plots the estimated coefficients for the association between test scores measured on day t and $PM_{2.5}$ levels from day t-2 to t+2. Dots represent point estimates; boxes indicate 90%, 95%, and 99% confidence intervals.

Leave-one-province-out. To ensure results are not driven by any single province, we re-estimate the baseline specification sequentially excluding one province at a time. Figure 9 reports point estimates and 90% confidence intervals for each of the resulting estimates. The coefficients are stable across all exclusions, ranging between -0.20 and -0.15, and remain statistically significant throughout. No province exerts undue influence on the main finding.

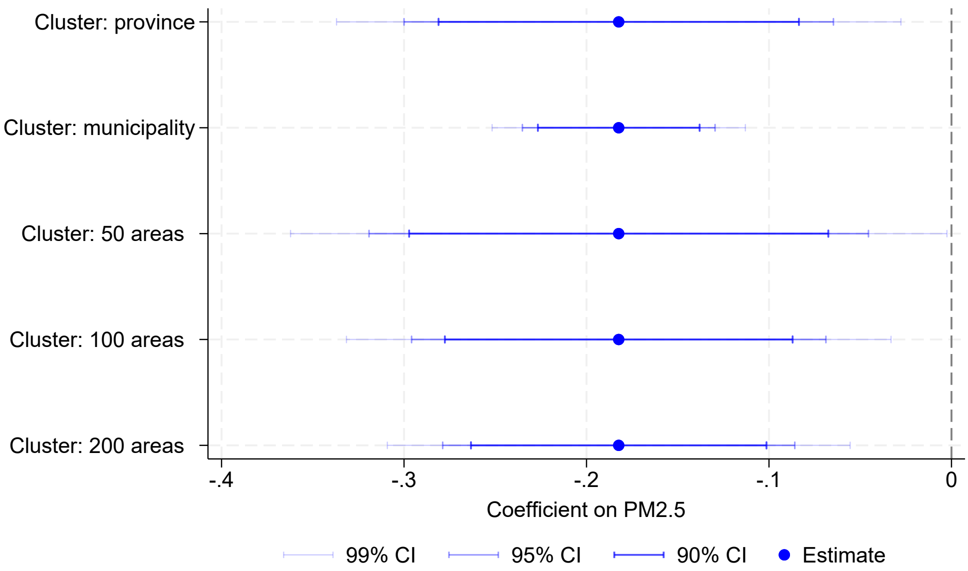
Figure 9: Leave-one-province-out estimates (90% CI)



Notes: Each point corresponds to an OLS estimate of the baseline specification obtained after dropping the indicated province. Bars are 90% confidence intervals. Standard errors are clustered at the area level, where municipalities are grouped into 200 geographically proximate areas using k-means clustering on latitude and longitude.

Alternative Standard Error Clustering Specifications. In our preferred specification, we cluster standard errors using 200 clusters of municipalities based on geographical proximity to account for the spatial and temporal correlation of $PM_{2.5}$ exposure. However, this choice is inherently arbitrary: the relevant geographic scope of correlation is unknown, and different clustering levels may capture different dimensions of error dependence. Figure 10 shows that the baseline estimate is robust to alternative assumptions about the clustering structure of standard errors. Across five clustering specifications, the coefficient of $PM_{2.5}$ remains statistically significant at conventional levels and standard errors appear stable across these alternative specifications.

Figure 10: Robustness to Alternative Standard Error Clustering Specifications



Notes: The figure reports the estimated coefficient on $PM_{2.5}$ concentration under alternative standard error specifications. Horizontal lines represent 90%, 95% and 99% confidence intervals. Clustering specifications group observations by geographic grid cells, where municipalities are grouped into geographically proximate areas using k-means clustering on latitude and longitude (200, 100, and 50 cells), by municipality, and by province. All specifications include school, temperature bin, day-of-week, grade-subject, and year fixed effects.

9 Conclusions

Pollution imposes substantial costs on society. It negatively affects health, reduces worker productivity, and has adverse consequences for cognition and behavior (Aguilar-Gomez et al., 2022). In recent years, the effects of pollution on children have attracted growing attention, with a growing body of literature consistently documenting negative effects on student performance.

We build on this literature by providing rigorous causal evidence on the impact of air pollution on student achievement and on the mechanisms underlying this relationship. We show that pollution significantly reduces academic performance, with effects primarily driven by impairments in higher-order cognitive functions—such as attention, reasoning, and decision-making—rather than by difficulties in recalling previously acquired knowledge. These effects are heterogeneous: lower-achieving and emotionally vulnerable students are disproportionately affected, and they are particularly pronounced in urban schools and in those located near polluting sources, where baseline environmental conditions are already poor. Schools equipped with ventilation and air conditioning systems exhibit substantially attenuated effects, suggesting a meaningful role for infrastructure as a buffer against environmental shocks.

Beyond direct effects on cognition, we document that pollution induces compensatory behavioral responses—including increased cheating and reduced test attendance—which further complicate the measurement of its full impact on learning. This finding also carries an implication for empirical work: because pollution induces selective absenteeism, estimates that do not account for compositional changes and for the endogenous response in strategic cheating, systematically underestimate its true effect on academic performance.

The impact of pollution is likely to have meaningful implications for human capital accumulation. Our estimates capture the contemporaneous effect of pollution on test-day performance: a one standard deviation increase in $PM_{2.5}$ exposure (about 5.5 $PM_{2.5}$ in our sample) — broadly comparable to the gap between a municipality at the median of the Italian distribution (e.g., Florence) and one near the 95th percentile (e.g., Milan) — generates a cognitive cost equivalent to approximately 2.4% of a standard deviation in test scores. Under the assumption that a permanent increase in exposure translates into a permanent reduction in cognitive ability, this is roughly comparable to the effect of a one-student increase in class size, based on the estimates in Chetty et al. (2011). If long-run consequences scale proportionally, this further implies a reduction of approximately 0.8 percentage points in college attendance and a 0.6% of a standard deviation decline in a summary index of adult outcomes.

Our estimates are obtained in a setting characterized by moderate pollution levels, and are therefore informative about the cognitive costs of pollution in contexts with comparable exposure, such as much of Europe and other high-income regions. Three caveats apply. First, in line with standard practice in the literature, our pollution measure relies on municipal-level data, which approximate but do not perfectly capture individual exposure: we do not observe time spent outdoors or possible defensive behaviors on high-pollution days. Still, municipal-level exposure is also the relevant margin for policy, since regulations typically impose area-wide restrictions to limit ambient pollution rather than targeting individual exposure behavior. Second, our design isolates the contemporaneous effects of pollution on test-day performance and is not informative about the cumulative effects of prolonged exposure. Our estimates thus capture only part of the social costs of pollution that operate through human capital formation, and should be complemented with evidence on long-run exposure. Third, our infrastructure indicator is binary and does not capture variation in system quality or operation, likely understating the true moderating role of indoor air quality interventions.

Taken together, these findings contribute to a growing literature on the non-health consequences of pollution by highlighting cognitive channels, particularly higher-order reasoning, and the unequal distribution of its effects across students. The results suggest that pollution may exacerbate existing educational inequalities along two reinforcing dimensions: lower-achieving students bear the largest cognitive costs, and schools located in more environmentally degraded areas—where exposure is already higher—experience the most pronounced effects. Pollution thus disproportionately harms those already at a disadvantage, both in terms of academic preparation and environmental conditions.

The cognitive costs of pollution can be effectively mitigated through dedicated air filtration, a targeted and low-cost intervention that has been shown to substantially reduce indoor pollutant concentrations and student absenteeism in Italian primary schools (Bonan et al., 2025). Our results suggest that the scope for mitigation is even broader: even general-purpose ventilation and air conditioning systems—not specifically designed to filter fine particulates—meaningfully attenuate the cognitive effects of pollution. This points to a useful synergy. The same infrastructure that moderates indoor temperature also reduces exposure to ambient pollutants, and since heat itself impairs cognitive performance and emotional regulation during testing (Ballatore et al., 2025), investments in ventilation and climate control deliver compounding gains by addressing both environmental stressors at once (Biasi et al., 2025). Investments of this kind are therefore likely to be more cost-effective than single-purpose alternatives.

Our findings further indicate where such investments would have the highest returns. The cognitive costs of pollution are greatest in urban areas, in schools located near polluting sources, and among lower-achieving students—groups that often overlap. The flip side of this heterogeneity is that the marginal benefit of indoor air quality interventions is largest precisely where exposure and vulnerability are highest, making these contexts a natural target for prioritization. Evaluating the relative cost-effectiveness of these interventions, and of mitigation versus prevention more broadly, remains an important area for future research.

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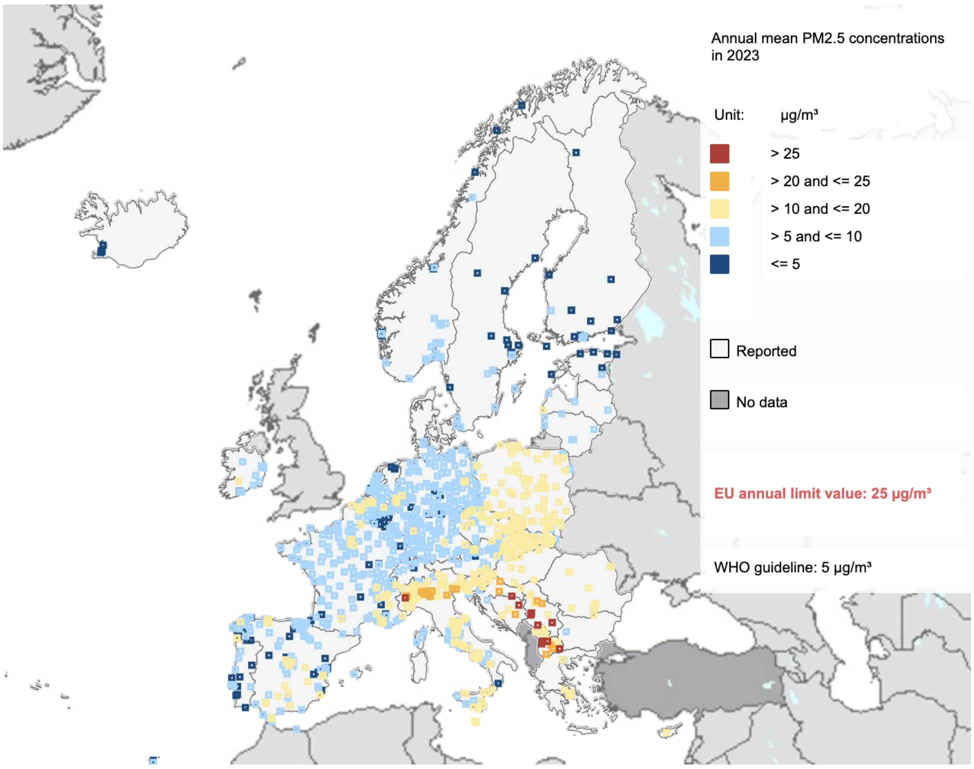
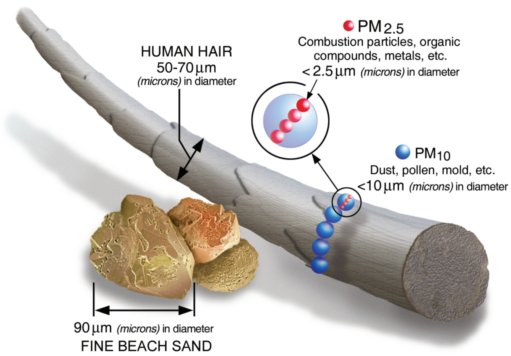
Appendix

Figure A1: Map of 2023 $PM_{2.5}$ Concentrations in European countries.



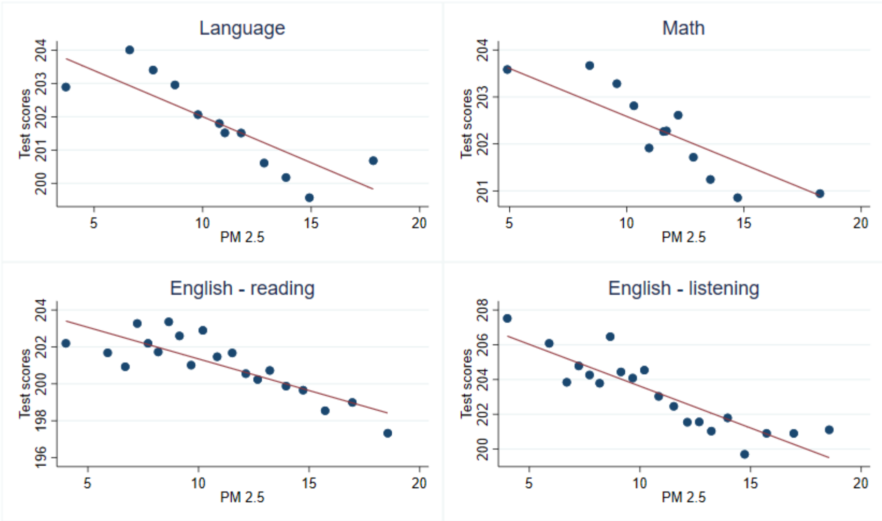
Notes: The Figure reports the concentrations of $PM_{2.5}$ in 2023 relative to the EU annual limit value and the WHO annual guideline level. Source: European Environment Agency (Europe's air quality status).

Figure A2: $PM_{2.5}$ scale



Notes: This figure compares $PM_{2.5}$ scale with the scale of a human hair and of fine beach sand.

Figure A3: Relationship between $PM_{2.5}$ and standardized test scores, conditional on student and municipal fixed effects, by subjects



Notes: The figure displays the relationship between test scores and $PM_{2.5}$ concentration, net of individual fixed effects (for Language and Math) and municipal fixed effects (for English).

Table A1: Impact of Air Pollution by Cognitive Domain and Question Format

	Outcome: Share of Correct Answers			
	Cognitive Domain		**Question Format**	
	Knowledge (1)	Reasoning (2)	Open (3)	Closed (4)
$PM_{2.5}$	-0.0409 (0.0274)	-0.0767*** (0.0214)	-0.0700*** (0.0190)	-0.0933*** (0.0216)
Observations	17,485,649	17,485,649	18,375,902	21,882,951
Mean dep. var.	63.64	60.48	61.74	59.86
SD dep. var.	27.62	22.63	30.57	22.41
Year FE	Y	Y	Y	Y
Day-of-week FE	Y	Y	Y	Y
Subject × grade FE	Y	Y	Y	Y
Weather controls	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y

Notes: This table reports estimates of the impact of air pollution on the share of correct answers by cognitive domain—knowledge-intensive questions (Column 1) and reasoning-intensive questions (Column 2)—and by question format—open-ended questions (Column 3) and closed-ended questions (Column 4). All specifications include year, grade, subject, day-of-week, individual, and subject-by-grade fixed effects, as well as weather controls (temperature and total precipitation). Regressions are weighted by the share of questions of the corresponding type in the test to account for the varying relative importance of knowledge and reasoning components across assessments. Standard errors are clustered at the area level, where municipalities are grouped into 200 geographic areas using k-means clustering on latitude and longitude. The outcome is expressed as the share of correct answers (0–100). $PM_{2.5}$ is expressed in $\mu g/m^3$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A2: Students' emotional responses during the INVALSI test.

Thinking about the INVALSI tests in Literacy and Mathematics How much do you agree with the following statements?					
		Strongly disagree	**Disagree**	**Agree**	**Strongly agree**
A.	I was already worried about taking the tests before they started.				
B.	I was so nervous that I couldn't find the answers.				
C.	While answering, I had the impression that I was doing poorly.				
D.	While answering, I felt calm.				

Examples of Question Types – 5th Grade

Knowledge Questions

C10. Read the following sentence:

"Anna was holding the dog on the leash."

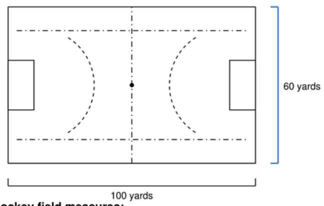
How many syllables does the sentence contain?

Total number of syllables: ....

A. Literacy

D7. In the United States of America, the yard is used as the unit of measurement for length.

10 yards correspond to 9.144 metres.
A field hockey pitch has a playing area with the dimensions shown in the figure.



The perimeter of the hockey field measures:

A. ☐ 160 m
B. ☐ between 160 m and 200 m
C. ☐ between 270 m and 300 m
D. ☐ 320 m

B. Math

Reasoning Questions

B11. This paragraph contains the following information:

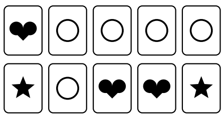
- Italians place little value on physical activity
- Young people are very attracted to new technologies
- Sports facilities are not adequate

This information represents

A. ☐ the solutions to a problem
B. ☐ the consequences of a problem
C. ☐ the conclusions of a problem
D. ☐ the causes of a problem

A. Literacy

D24. Luca has these 10 cards.



Luca puts the cards in a bag, mixes them up, and draws one card at random.
Complete the following sentence by inserting in place of the dots one of the following expressions:

greater than	less than	equal to

For Luca, the probability of drawing a card with a heart is 50%

B. Math

Close Questions

A12. "One day, playing the old pieces, he managed to make the violin sing." (lines 73-74). What does the author mean when he writes "managed to make the violin sing"?

It means that Alessandro manages

A. ☐ to sing a song while playing the violin

B. ☐ to produce a tuneful melody from the violin

C. ☐ to produce with the violin a sound more beautiful than the human voice

D. ☐ to produce from the violin a sound that resembles a human voice

A. Literacy

D34. The figures show a wind turbine at two different moments.

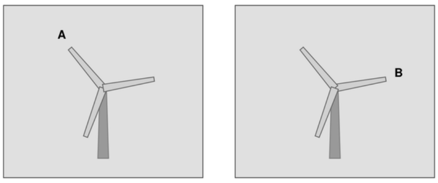


Figure A   Figure B

To go from position A to position B, by how many degrees has the blade rotated clockwise?

A. ☐ About 120°

B. ☐ About 90°

C. ☐ About 240°

D. ☐ About 180°

B. Math

Open Questions

B4. "The salt of life" (line 15) is a figurative expression used as the title of the third paragraph and referring to emotions. To clarify why emotions are considered the "salt of life", complete the following sentence
<u>with words from the text.</u>

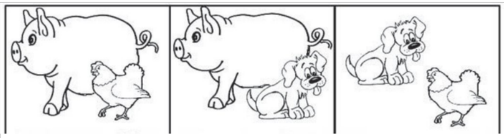
Just as salt serves to give flavour to food, so emotions serve

____

____

A. Literacy

D17. Look at the pictures.



Together they weigh **30 kg**	Together they weigh **34 kg**	Together they weigh **10 kg**

How much does the dog weigh?

Answer: .... kg

B. Math