WHO BEARS THE COST OF AIR POLLUTION? HOW POLLUTION SHOCKS WIDEN SOCIO-ECONOMIC GAPS IN EDUCATIONAL ACHIEVEMENT

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Who Bears the Cost of Air Pollution? How Pollution Shocks Widen Socio-Economic Gaps in Educational Achievement*

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Abstract

Who bears the educational cost of air pollution? Using administrative data on five million French students and wind-driven variation in $PM_{2.5}$, we show that exam-day pollution shocks lower exam scores by 4–7% of a standard deviation among disadvantaged students—equivalent to 10–25% of the socio-economic achievement gap—while leaving advantaged students unaffected. We trace this unequal vulnerability to socially stratified differences in cognitive resilience, defined as the capacity to perform under high-stakes conditions, for which we develop a novel individual-level measure. Pollution shocks therefore widen pre-existing educational inequalities. Yet vulnerability is not immutable: high value-added schools mitigate the effects of pollution among low-resilience students.

JEL classification: Q53 ; Q56 ; I24

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Introduction

Education is a central determinant of individual lifetime opportunities, shaping earnings, health, and social mobility (Blanden et al., 2023; Farquharson et al., 2024). Understanding the origins of educational inequality is essential to explaining the persistence of economic disparities across generations. A long tradition in social science emphasizes the intergenerational transmission of social, cultural, and economic capital (e.g., Bourdieu, 1986), while recent evidence also highlights the role of unequal school inputs, including differences in teacher quality and educational resources (Chetty et al., 2014; OECD, 2018).

This paper highlights a new mechanism that may contribute to educational inequality across socio-economic groups: differential vulnerability to air pollution. A growing literature in environmental justice documents systematic disparities in pollution exposure across socio-economic and ethnic groups (Hsiang et al., 2019; Cain et al., 2024; Colmer et al., 2020; Currie et al., 2023). By contrast, evidence on inequalities in environmental damages remains comparatively scarce. In particular, little is known about whether pollution shocks translate into unequal educational consequences, thereby reinforcing socio-economic disparities at critical stages of human capital formation. Our analysis addresses precisely this question by examining whether exposure to air pollution has differential effects on students' academic performance depending on their socio-economic background.

To investigate this question, we combine high-resolution air pollution data with exhaustive administrative records covering 5 million students enrolled in French secondary education over the 2010–2017 period. These data provide detailed information on students' socio-economic background and their performance in two national high-stakes examinations taken at the end of middle school and at the end of high school. Performance at these pivotal educational stages has well-documented long-term consequences for educational trajectories and labor market outcomes, affecting subsequent dropout decisions, access to and quality of higher education programs, and long-run earnings (e.g., Ebenstein et al., 2016; Canaan & Mouganie, 2018; Machin et al., 2020; Landaud et al., 2024).[1]

Our main analyses focus on the effect of fine particulate matter ($PM_{2.5}$), the pollutant responsible for the largest share of health and economic damages attributable to

[1] Canaan & Mouganie (2018) show, in particular, that performance in the *Baccalauréat* (end-of-high school exam) increases the quality of tertiary education accessed and raises earnings at ages 27–29 in the French context.

air pollution (Soares et al., 2025).[2] In addition to its severe health consequences, recent evidence shows that short-term exposure to $PM_{2.5}$ impairs cognitive performance and productivity (Aguilar-Gomez et al., 2022), with direct evidence that $PM_{2.5}$ reduces performance across multiple cognitive domains, including memory and problem solving (La Nauze & Severnini, 2025). Because the cognitive functions required for high-stakes examinations—attention, executive control, and stress regulation—are particularly sensitive to transient physiological disruptions, daily pollution spikes may translate into immediate performance losses.

A central empirical challenge is that exposure to pollution on exam days is not random. Students may sort across schools or municipalities in ways that correlate with both socio-economic background and academic performance. To address this concern, we take an instrumental variable approach that exploits day-to-day variation in wind direction to isolate short-term fluctuations in $PM_{2.5}$ concentration at the municipality level, building on Deryugina et al. (2019). Because wind transports pollutants across space in ways that are plausibly orthogonal to unobserved determinants of student performance, changes in wind direction generate quasi-exogenous variation in local pollution on exam days.

Our results reveal pronounced socio-economic heterogeneity in the impact of pollution shocks. For end-of-middle school exams, students receiving need-based scholarships experience a decline of approximately 4.5% of a standard deviation (SD) when taking an exam on a day in which $PM_{2.5}$ concentrations exceed 15 μg/m^3, which corresponds to the *World Health Organization* (WHO) recommended threshold for human health. This effect is substantial, representing 9% of the baseline achievement gap between disadvantaged and non-disadvantaged students. Because the end-of-middle school exam is nearly universal and takes place prior to major educational tracking, these results provide a comprehensive picture of how pollution shocks differentially affect students across the full socio-economic distribution.

The pattern is even stronger at the end of high school. Exposure to $PM_{2.5}$ above the WHO threshold lowers *Baccalauréat* scores by about 6–7% SD for disadvantaged students, corresponding to roughly 25% of the pre-existing achievement gap, while no significant effect is detected for more advantaged students. Taken together, these findings indicate that short-term pollution shocks do not uniformly depress performance, but instead disproportionately affect students who are already educationally and socio-economically vulnerable. By amplifying performance gaps at key stages of education,

[2]For example, the Environmental Protection Agency (EPA) estimates that $PM_{2.5}$ is responsible for over 90% of air pollution-related health damages in the US (US Environmental Protection Agency, 2011).

acute exposure to air pollution may therefore contribute to the persistence of long-run inequality.

Because a transitory pollution shock on exam day cannot alter the stock of accumulated knowledge, its impact must operate through short-run impairments in cognitive functioning—such as sustained attention, executive control, stress regulation, and cognitive endurance (Brown et al., 2025). To capture this dimension empirically, we construct a novel individual-level measure that compares performance in externally graded, high-stakes written examinations—taken over several long sessions concentrated within a few days—to continuous assessment grades obtained throughout the school year through lower-stakes classroom evaluations. By differencing these two measures within the same student, we isolate performance under stress and time pressure from accumulated academic knowledge.

This measure is strongly socially stratified: students from disadvantaged socio-economic backgrounds are significantly more likely to underperform in high-stakes exam conditions relative to their continuous assessment. Moreover, this within-student measure of cognitive resilience predicts vulnerability to pollution shocks three years later at the *Baccalauréat*. Students who underperform in high-stakes settings are significantly more affected by $PM_{2.5}$ exposure, while more resilient students are not. These findings suggest that acute pollution acts as a transitory cognitive shock that disproportionately harms students with lower cognitive resilience—who are themselves more likely to come from disadvantaged backgrounds.

Crucially, we further show that this vulnerability is not immutable. Students with a low cognitive resilience who attend a high value-added high school are no longer significantly affected by pollution shocks at the *Baccalauréat*, while comparable students in lower-quality schools remain vulnerable. This result is not driven by differential sorting, as access to high-quality schools is effectively identical across socioeconomic groups in our data. Together with recent experimental evidence that cognitive endurance can be improved through deliberate practice (Brown et al., 2025), these findings suggest that effective educational practices can build the cognitive resilience that shields students from adverse shocks.

This paper first contributes to the environmental justice literature. While a large body of research summarized in recent reviews by Hsiang et al. (2019), Cain et al. (2024) and Banzhaf et al. (2019) documents systematic socio-economic and racial disparities in *exposure* to environmental risks, evidence on inequalities in environmental *damages* remains comparatively limited. This imbalance likely reflects an important empirical challenge: documenting exposure disparities is largely descriptive, whereas identifying heterogeneous damages requires credible causal strategies. Yet exposure inequalities alone are insufficient to assess disparities in realized harms or welfare consequences (Hsiang et al., 2019). To our knowledge, this paper is the first to identify the mechanism through which short-term air pollution shocks contribute to socio-economic inequalities in education.

Second, this paper contributes to the growing literature examining how short-term pollution shocks affect cognitive performance and human capital.[3] A large body of evidence shows that temporary increases in air pollution reduce performance in high-stakes examinations and other cognitively demanding tasks, both in educational settings (Ebenstein et al., 2016; Carneiro et al., 2021; Graff Zivin et al., 2020; Balakrishnan & Tsaneva, 2021; Roth, 2022; Andersen et al., 2025) and in labor market contexts (Graff Zivin & Neidell, 2012; Aragón et al., 2017; Archsmith et al., 2018; Chang et al., 2019; Borgschulte et al., 2024). Yet this literature has largely focused on average effects.[4] We show that the educational consequences of pollution are highly unequal: short-term pollution shocks primarily affect disadvantaged students, thereby widening pre-existing educational gaps. Leveraging nationwide administrative records covering nearly five million students and the near-universe of French secondary schools, we provide some of the first large-scale evidence on the distributional consequences of short-term pollution exposure for human capital.[5] We further contribute to this literature by developing an individual-level measure of cognitive resilience. Our results suggest that cognitive resilience is a key determinant of vulnerability to pollution shocks, helping to explain why identical environmental exposures generate markedly different performance responses across individuals. We also provide evidence that higher-quality schools foster cognitive resilience, suggesting that susceptibility to environmental shocks is not fixed but can be shaped by the educational environment.

[3] A related strand of the literature, summarized by Nguyen (2026), documents adverse effects of chronic pollution exposure on academic achievement, school attendance, and student behavior. In companion paper (Briole & Salesse, 2026), we show that cumulative exposure to industrial emissions during middle school lowers *brevet* scores and reduces entry into the academic high-school track, with effects concentrated among disadvantaged students.

[4] A notable exception is Chung et al. (2025), who show that the effects of daily $PM_{2.5}$ exposure on absences and disciplinary incidents are concentrated among low-income, Black, and Hispanic students.

[5] Some recent contributions exploit administrative datasets, such as Carneiro et al. (2021), Graff Zivin et al. (2020) or Andersen et al. (2025), with typically 700,000–1,500,000 students and 50–150 geographical units. Our data cover approximately 6,800 middle schools and 2,400 high schools, providing substantially broader geographic and population coverage.

Third, while a large literature has documented the lasting consequences of pollution exposure during pregnancy and childhood for health, human capital, and later-life economic outcomes (Chay & Greenstone, 2003; Currie, 2011; Currie & Walker, 2011; Isen et al., 2017; Black et al., 2019; Colmer et al., 2021; Colmer & Voorheis, 2025), much less is known about the extent to which pollution exposure later in the life cycle contributes to the reproduction of socio-economic inequalities. Our findings suggest that environmental shocks remain an important source of inequality well beyond the early childhood period. This has important policy implications, as it suggests that efforts to reduce environmental inequality should not focus exclusively on early-life exposure but also consider how pollution affects individuals at later stages of the life cycle.

Finally, this paper contributes to the literature on school quality. A large body of research shows that access to effective schools is unequally distributed across students and has important long-run consequences for educational attainment, labor market outcomes, and social mobility (e.g., Chetty et al., 2014). More recent work has emphasized that school quality is multidimensional: beyond raising academic achievement, effective schools also foster a broad range of skills and behaviors, including socio-emotional and civic skills (Jackson et al., 2020; Cohodes & Feigenbaum, 2025; Briole et al., 2025) as well as cognitive endurance (Brown et al., 2025). We contribute to this literature by developing a novel measure of cognitive resilience—the ability to maintain cognitive performance under adverse conditions—and by providing evidence that this trait is shaped by the school environment. In particular, students attending higher value-added schools exhibit greater cognitive resilience and are less vulnerable to pollution shocks. These findings complement recent evidence on cognitive endurance (Brown et al., 2025) and suggest that schools may influence not only the accumulation of knowledge and skills, but also the capacity to maintain cognitive performance under adverse conditions. Such a capacity is likely to be valuable well beyond the classroom, as many labor-market settings require individuals to remain productive under pressure and in adverse environments.

The remainder of the paper is organized as follows. Section 1 presents the institutional setting and the data. Section 2 outlines the conceptual framework and our identification strategy. Section 3 reports the main results and robustness checks. Section 4 investigates mechanisms and discusses implications. Section 6 concludes.

1 Institutional Background and Data

1.1 School System and Educational Data

Secondary education in France consists of four years of lower secondary education in middle school (6th to 9th grade) followed by three years of upper secondary education in high school (10th to 12th grade). Schooling is compulsory until age 16. Students remain in the same class, with the same teachers, throughout the school year. Classes comprise approximately 25–30 students and constitute clearly defined entities.[6]

At the end of 9th grade, students take a national examination, the *Diplôme National du Brevet* (hereafter, DNB). The DNB, held in late June, covers mathematics, French language, and history–geography. All exam subjects are externally set (at the national level) and graded.

After middle school, students choose between an academic track and several vocational tracks. The academic track consists of three years of upper secondary education and prepares students for tertiary education. Students enrolled in the academic track specialize in one of three streams—*Science*, *Economics and Social Sciences*, or *Literature*—while some may switch to technological tracks in 11th grade. Vocational tracks are generally shorter and, in most cases, do not provide direct access to higher education.

At the end of 12th grade, students take the *Baccalauréat* (hereafter, Bac), a national examination specific to each track. Students completing an academic track are eligible for college enrollment, although the three streams provide access to distinct post-secondary opportunities. In our analysis of the Bac, we retain only exam subjects common across tracks (philosophy, history–geography, and mathematics), excluding optional or rescheduled exams.[7] All examinations are anonymized and externally graded.

Our analyses draw on a comprehensive administrative panel dataset covering all students enrolled in secondary education in France (*Fichier Anonymisé d'Elèves pour la Recherche et les Etudes*). The dataset reports annual enrollment status, basic student demographics (age, gender, nationality, scholarship status, and social origin),[8] and performance at national examinations (DNB and Bac), which is our main outcome of interest. Crucially, the dataset records the exact date of each examination, allowing us to merge

[6] School principals assign students and teachers to classes before the beginning of the school year.

[7] See Appendix C for details on subject formats, grading rules, and track-specific variations.

[8] Students are classified into four categories based on the socio-professional group of their reference parent: disadvantaged, middle, privileged, and highly privileged. This classification follows the standard occupational grouping used by the French Ministry of Education (DEPP).

individual exam outcomes with daily air pollution and weather data. Following Briole & Maurin (2022), we standardize scores by year, academic region, and subject.

1.2 Environmental Data

1.2.1 Air pollution data

Fine particulate matter ($PM_{2.5}$) is widely recognized as the air pollutant associated with the highest global health and economic costs (Aïchi & Husson, 2015; Deryugina et al., 2019; Aguilar-Gomez et al., 2022).[9] $PM_{2.5}$ represents a mixture of various particles with diameters of 2.5 micrometers or less, including nitrates, sulfates, ammonium, and carbon. These particles can be emitted directly as primary particles or formed in the atmosphere as secondary particles from the chemical reactions of gaseous pollutants. In 2022, the residential and tertiary sectors accounted for the vast majority (70%) of $PM_{2.5}$ primary emissions in France (Citepa, 2023), a trend that also holds at the European level, where the residential sector accounted for 58% of $PM_{2.5}$ emissions in 2020 (EEA, 2022).[10]

We match our educational data to daily $PM_{2.5}$ concentration ($\mu g/m^3$) data provided by the French National Institute for Industrial Environment and Risks (*INERIS*), available at the municipality level over the 2000-2020 period for all the French metropolitan territory. This data combines numerical modeling data from the *CHIMERE* chemistry-transport model (Menut et al., 2013) with measures of air quality from monitoring stations to correct for ground observations. It is computed by *INERIS* in order to build population-wide measures of background pollution exposure. Figure 1 shows the spatial distribution of annual average $PM_{2.5}$ concentration over the 2010-2017 period on the French territory. Importantly, this data makes it possible to compute the average daily concentration of $PM_{2.5}$ on the day of each exam for each student in our sample.

1.2.2 Weather data

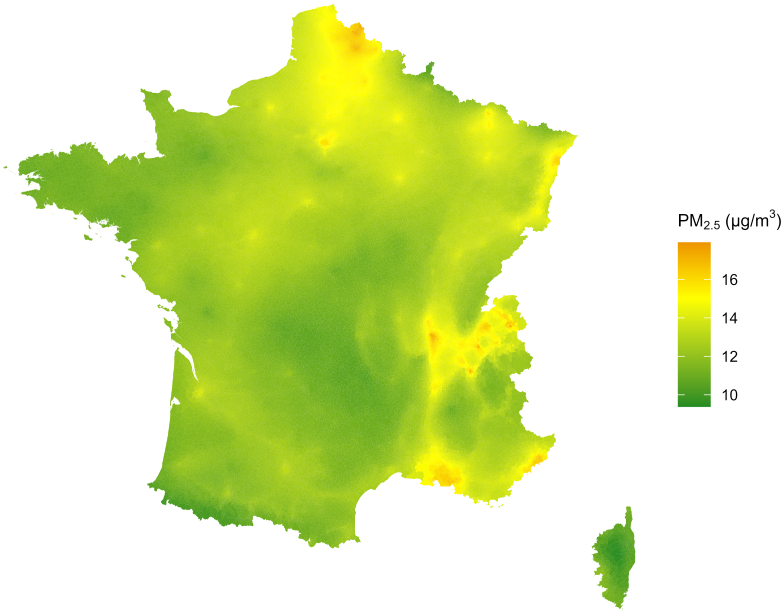
We also match our educational dataset with weather data from the French national institute for meteorological data monitoring (*Météo France*). Each municipality is matched to the closest weather station[11] and we use the daily wind direction data for each munic-

[9]For example, the U.S. Environmental Protection Agency (EPA) estimates that $PM_{2.5}$ is responsible for over 90% of air pollution-related health damages in the US (2011).

[10]The transport, industrial, and agricultural sectors are the other main contributors to $PM_{2.5}$ emissions, each sector accounting individually for 6–11% of primary emissions in France in 2022. See Briole & Lavaine (2026) for more details on the origins of $PM_{2.5}$ in France and Europe.

[11]Wind direction data come from Météo-France's climatological stations, which record daily wind direction (in degrees). Our dataset includes 494 stations across metropolitan France. The median

Figure 1: $PM_{2.5}$ average annual concentration in France (2010-2017)



Note: This figure illustrates the spatial distribution of annual average $PM_{2.5}$ concentrations in France over the 2010-2017 period, based on INERIS data.

ipality. We build binary variables for each of four directions where the wind comes from: North (below 45° or above 315°), East (between 45° and 135°), South (between 135° and 225°) and West (between 225° and 315°). We also use daily weather data (temperature, wind speed, humidity and rain) from the E-OBS database produced by Copernicus EU based on observations from meteorological stations throughout Europe. Wind direction and strength are used to create instrumental variables. Temperature, humidity and rainfall are used as controls.

distance between a school and its nearest wind station is 9.2 km; the mean distance is 13.3 km and over 82% of schools are located within 20 km of the nearest station.

1.3 Sample Characteristics

1.3.1 9th Grade Student Sample

To assess the effect of air pollution on school performance, we matched administrative panel data of 9th and 12th grade students, with daily $PM_{2.5}$ and weather data. Our 9th grade sample comprises students from 7 cohorts (2010-2016), totaling 4,818,985 students distributed across 6,854 middle schools. Table A1 provides the average characteristics of these students: 21.5% receive a need-based scholarship, determined by parental income, and 31.6% come from low socio-economic status (SES) families, as defined by parental occupational classification. As shown in Table A2, students from low-SES families and those receiving need-based scholarships perform significantly worse on end-of-9th grade exams compared to their peers, with a performance gap of 0.52 SD of a test score. Students in our 9th grade sample are exposed to 12.69 $\mu g/m^3$ on average on the days of the exam (Table A1), and about 29% of exam days in the corresponding municipality have $PM_{2.5}$ levels exceeding the threshold recommended by the *World Health Organization* for daily average concentration, which is set at 15 $\mu g/m^3$ (WHO, 2021). Importantly, these figures are virtually identical across socioeconomic groups: the share of exam days exceeding the WHO threshold is 28.8% for low-SES students and 29.3% for others, and conditional on exceeding the threshold, the average $PM_{2.5}$ level is nearly the same—19.10 versus 19.07 $\mu g/m^3$ (Table A3). Disadvantaged students are thus neither more frequently exposed to pollution shocks on exam days, nor exposed to more intense shocks when they occur.

1.3.2 12th Grade Student Sample

Our main sample of 12th grade students includes students from 5 cohorts (2013-2017), totaling 1,459,260 students, distributed across 2,386 schools. Regardless of the criteria used, the proportion of students from socially disadvantaged backgrounds is lower in this sample compared to the 9th grade sample (Table A1). This is largely because these students are more likely to pursue shorter, non-academic educational tracks or drop out after 9th grade. In the 12th grade sample, 14% of students receive a need-based scholarship and 18.5% come from low-SES families, as defined by parental occupation. As shown in Table A4, students from socially disadvantaged backgrounds also perform significantly worse on BAC exams compared to their peers, with a performance gap of 0.25 SD of a test score. Students in the 12th grade sample, who belong to more recent cohorts, are exposed to lower levels of $PM_{2.5}$ on the days of the exam than students from the 9th grade sample:[12] on average, they are exposed to 9 $\mu g/m^3$ (Table A1) and for about 8.2% of exam days the level of $PM_{2.5}$ is above the WHO threshold. As for the 9th grade sample, these exposure patterns do not differ meaningfully across socioeconomic groups: the share of exam days above the WHO threshold is 8.1% for low-SES students versus 8.2% for others, and conditional on exceeding the threshold, average $PM_{2.5}$ levels differ by less than 0.2 $\mu g/m^3$ (Table A3). It implies that any heterogeneous effect of exam-day pollution across SES groups reflects differences in vulnerability to the same exposure, not differences in exposure itself.

2 Conceptual Framework and Empirical Strategy

Our objective is to estimate the causal effect of a pollution shock on the day of an exam on student performance in that exam. We begin by discussing the short-run mechanisms through which a pollution shock on the day of an exam may affect performance (Section 2.1), before turning to our identification strategy (Section 2.2).

2.1 $PM_{2.5}$ Shocks and Student Performance: Expected Mechanisms

Chronic exposure to air pollution—and in particular to $PM_{2.5}$—may affect academic performance through learning impairments over extended periods.[13] By contrast, a transitory pollution spike on the exam day cannot, by definition, alter the stock of skills and knowledge available to the student at the time of taking the exam. Instead, it may affect performance quasi-immediately through an *impairment of cognitive resilience*. In cognitive psychology and neuroscience, the relevant functions include sustained and selective attention (maintaining focus while filtering distractions), executive control (planning, reasoning, and problem-solving), working memory (holding and manipulating information), inhibitory control (preventing impulsive responses and errors), and the regulation

[12] $PM_{2.5}$ concentration in France is slightly but continuously decreasing over the 2010-2017 period, in line with the global trends observed in European countries (Salesse, 2022) and in the US (Currie et al., 2023).

[13] Such long-run impacts may operate through health, school attendance, and neurodevelopmental pathways.

of stress and effort under time pressure (Diamond, 2013; Miyake et al., 2000; Gawryluk et al., 2023).[14]

$PM_{2.5}$ penetrate deeply into the lungs, trigger inflammatory responses, and affect the circulatory system by altering blood flow and oxygen delivery (Mills et al., 2009; Pope III & Dockery, 2006). Since the brain is highly oxygen-dependent, even short-term disruptions in oxygen delivery and systemic inflammation may impair cognitive functioning. This suggests that acute exposure—such as a daily pollution spike—can affect performance immediately. Consistent with this mechanism, recent studies demonstrate that short-term exposure to $PM_{2.5}$ impairs specific cognitive abilities essential for academic performance. Controlled experiments document declines in selective attention and executive control within hours (Faherty et al., 2025). Faherty et al. (2025) reports significant impairments four hours post-exposure, while Shehab & Pope (2019) detects declines in global cognitive function immediately following one-hour exposures. These laboratory findings are corroborated at scale by La Nauze & Severnini (2025), who exploit exogenous variation in $PM_{2.5}$ across brain-training sessions in the US and document significant impairments in memory and problem solving. These findings are corroborated by experimental brain imaging evidence. In a randomized controlled study, Gawryluk et al. (2023) show that brief exposure to traffic-related air pollution temporarily reduces functional brain connectivity in regions associated with memory and cognitive performance.

In this paper, we test these mechanisms in a real-world setting, leveraging a natural experiment and focusing on high-stakes examinations that have meaningful long-term consequences for students' educational trajectories. The cognitive functions affected by short-run $PM_{2.5}$ exposure are precisely those required during national high-stakes examinations. First, these exams are high-stakes and therefore intrinsically involve stress regulation. Second, exam sessions are concentrated over a few consecutive days, which increases the importance of cognitive endurance and fatigue management. Third, the nature of the tasks in core subjects directly relies on attention and executive control: in mathematics, students must comprehend problem statements, formulate solution strategies, and avoid computational errors; in French, they must analyze texts, organize essays, and proofread carefully; and in history-geography, they must evaluate multiple documents, establish connections, and synthesize evidence. These features make it particularly

[14] These dimensions relate to the concept of *cognitive endurance*—the ability to sustain cognitive effort over time and resist fatigue (Brown et al., 2025)—while also encompassing broader self-regulatory capacities often discussed in economics as non-cognitive skills (e.g., perseverance, motivation, and self-confidence).

plausible that contemporaneous pollution shocks translate into lower exam performance through short-run disruptions in cognitive functioning.

2.2 Empirical strategy

Our main identification challenge is that students' exposure to pollution on exam days is not random. A naive OLS estimator of the effect of $PM_{2.5}$ on academic performance would suffer from two distinct sources of bias, which we address sequentially.

A first source of bias arises from static sorting. Time-invariant characteristics of students and their environments—family background, neighborhood, school quality—are correlated with their average exposure to pollution. For instance, disadvantaged students are more likely to live and attend school in more polluted municipalities (Banzhaf et al., 2019). To address this concern, we exploit a central feature of our setting, in which each student takes the *Brevet* (and later the *Baccalauréat*) over several consecutive days within a single examination week, with subject scheduled on different days. This institutional design generates day-to-day variation in $PM_{2.5}$ exposure within the same student-week. Including student fixed effects allows us to absorb all time-invariant individual and contextual characteristics—family background, school attended, residential location—and to identify β from short-run, plausibly random fluctuations in pollution across the subject-days of a same student.

A second concern stems from dynamic confounders. Even within the same student-week, daily $PM_{2.5}$ concentrations may covary with other day-level factors that independently affect performance, such as local traffic intensity, urban events, transportation disruptions, or ambient noise. To address this bias, and following Deryugina et al. (2019), we instrument the daily concentration of $PM_{2.5}$ with day-to-day variation in wind direction. The underlying idea is that wind transports pollution across space in ways that are plausibly orthogonal to local unobserved determinants of student performance. Because wind direction has heterogeneous effects across regions depending on local geography, and because pollution dispersion also depends on wind speed, we construct instruments by interacting four wind direction dummies (North, South, East, West) with regional indicators (*Départements*) and wind speed. We estimate the following first stage regression:

$$PM2.5_{imst} = \sum_j \sum_r \tau \cdot Dir^j_{mst} \times Region^r_m \times Speed_{mst} + \theta \cdot X_{mst} + \mu_i + \delta_t + \gamma_s + \eta_{mst} \quad (1)$$

where $PM2.5_{imst}$ is a dummy indicating a daily mean concentration of $PM_{2.5} > 15\mu g/m^3$ in the municipality of student i's school during the day of subject s' exam.[15] Each student belongs to a single school, which is itself located in a given municipality. The variable Dir^j_{mst} denotes the main wind direction ($j \in \{N, S, E, W\}$), $Region^r_m$ indicates the *Département*,[16] and $Speed_{mst}$ measures average daily wind speed. Weather controls X_{mst} include daily mean temperature, precipitation, and humidity. For Baccalauréat, it further includes dummies for the three academic tracks in high school. The specification also incorporates student fixed effects μ_i, year fixed effects δ_t, and subject fixed effects γ_s. Note that, given that students are observed in a single municipality within a given year, student fixed effects also capture municipality-by-year fixed effects (θ_{mt}).

The second stage equation then estimates the causal effect of pollution on exam performance:

$$Y_{imst} = \beta \cdot \widehat{PM2.5}_{imst} + \theta \cdot X_{mst} + \mu_i + \delta_t + \gamma_s + \varepsilon_{imst} \tag{2}$$

where Y_{imst} is the standardized test score of student i in subject s in year t in a school located in municipality m. Standard errors are clustered at the municipality level, the level at which our instrument varies.

Robustness. Because our main IV strategy relies on a large number of instruments (approximately 380), we assess the potential role of many-instrument bias by comparing 2SLS estimates with those obtained using the Limited Information Maximum Likelihood (LIML) estimator and more parsimonious instrument sets. Appendix B1 presents the methodology and results in detail and confirms that our findings are not driven by the many-instrument bias.

As a complementary check, we also implement a simple within-student fixed-effects strategy, in the spirit of Ebenstein et al. (2016), which uses day-to-day variations in outdoor fine particulate matter across exam days to estimate its causal effect on student test scores. We estimate the following equation.

[15] In our main specification, $PM2.5_{mst}$ is a binary variable indicating whether $PM_{2.5}$ concentration exceeds the WHO's recommended threshold for human health. We check the robustness of our results to using a continuous measure of $PM_{2.5}$ and to applying a lower threshold of $10\mu g/m^3$ in Appendix B.

[16] The *Département* is an intermediate administrative division in France, situated between the municipality and the larger region. It provides a relatively fine level of spatial disaggregation. France has 96 metropolitan *Départements* (excluding overseas territories), each with its own local government, including a prefecture (administrative center) and a departmental council.

$$Y_{imst} = \alpha + \beta \cdot PM2.5_{mst} + \theta \cdot X_{mst} + \mu_i + \delta_t + \gamma_s + \varepsilon_{imst} \tag{3}$$

Notation follows Equation (2). The key identifying assumption is that unobserved shocks affecting exam performance across subjects are uncorrelated with subject-specific pollution levels. While this design helps address concerns of sorting across schools or regions, it remains vulnerable to time-varying confounders correlated with pollution. We therefore treat this approach as a complementary robustness check rather than our main identification strategy. Results are presented in Appendix B.

3 The effect of $PM_{2.5}$ on student performance

3.1 End-of-middle school exams

Table 1 presents the main estimates of the impact of $PM_{2.5}$ on student test scores in end-of-9th grade exams over the period 2010-2016, based on the instrumental variables approach. As shown in the top panel of the table, our results indicate no significant effect when considering the full sample of students, although the estimated coefficients is negative. However, this non-significant average result masks a strong heterogeneity based on students' socio-economic backgrounds. While students not receiving need-based scholarships are not significantly affected by $PM_{2.5}$ shocks in our setting, those who do receive such scholarships are significantly impacted: taking an exam on a day when $PM_{2.5}$ levels exceed WHO recommendations results in a 4.5% SD decrease in scores for these students. Similarly, while students from average or advantaged social backgrounds are not significantly affected by $PM_{2.5}$ shocks in our data, those from disadvantaged social backgrounds are significantly affected. For these students, exposure to $PM_{2.5}$ levels above WHO recommendations results in a 3.9% SD decrease in test scores. These are substantial effects, equivalent to a decrease of one hour in weekly instructional time in the exam subject throughout the school year (Briole, 2026).

These findings, illustrated in Figure 2, highlight that students from disadvantaged socio-economic backgrounds are disproportionately vulnerable to air pollution shocks when taking high-stakes examinations at the end of middle school. A consequence of this result is that pollution shocks significantly widen the performance gap between disadvantaged students and their more advantaged peers. Exposure to a pollution shock on the exam day increases the socioeconomic achievement gap by 9% relative to its level under normal conditions (Figure 3). Because performance in these exams has long-term implications for students' academic trajectories and, ultimately, their labour market outcomes, pollution shocks may contribute to the persistence of economic inequalities in the long run. In the next section, we examine whether similar results are obtained for end-of-high school examinations, which directly condition access to higher education (Section 3.2).

Table 1: Effects of $PM_{2.5}$ on Student Performance: End-of-middle School Exams

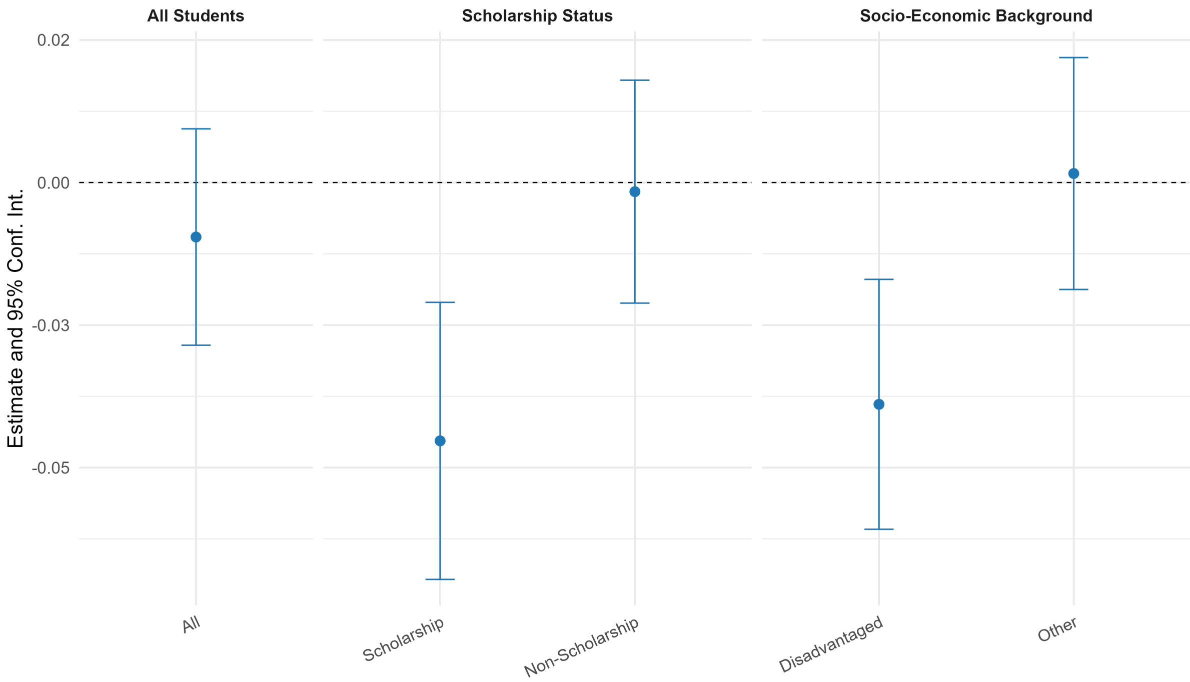
	IV (1)
All Students (N=11,703,685)	
$PM_{2.5} > 15$	-0.0096
	(0.0097)
Scholarship Students (N=2,371,171)	
$PM_{2.5} > 15$	-0.0453***
	(0.0124)
Non-Scholarship Students (N=9,332,514)	
$PM_{2.5} > 15$	-0.0016
	(0.0100)
Disadvantaged socio-economic background (N=3,434,794)	
$PM_{2.5} > 15$	-0.0389***
	(0.0112)
Other socio-economic background (N=7,966,589)	
$PM_{2.5} > 15$	0.0016
	(0.0104)
Student Fixed Effects	Yes
Year Fixed Effects	Yes
Subject Fixed Effects	Yes
Weather Controls	Yes

Note: This table reports IV estimates of the effect of $PM_{2.5}$ on student performance in end-of-middle school examinations, based on Equation (2). The key regressor is a binary indicator equal to one if daily $PM_{2.5}$ concentration exceeds 15 $\mu g/m^3$ (WHO daily threshold). Each panel corresponds to a separate regression. Standard errors, clustered at the municipality of school level, are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

3.2 End-of-high school exams

Table 2 reports the impact of $PM_{2.5}$ exposure on student performance in end-of-high school exams (*Baccalauréat*) over the period 2013-2017, using our IV strategy. As for the end-of-middle school exams, we find no significant effect for the overall population, although the point estimates are consistently negative. Here again, this average masks pronounced heterogeneity across socio-economic groups. Scholarship students experience a strong and statistically significant decline in performance: taking an exam on a day when $PM_{2.5}$ levels exceed WHO recommendations lowers their score by about 6.6% SD.

Figure 2: Effects of $PM_{2.5}$ on Student Performance: End-of-middle School Exams



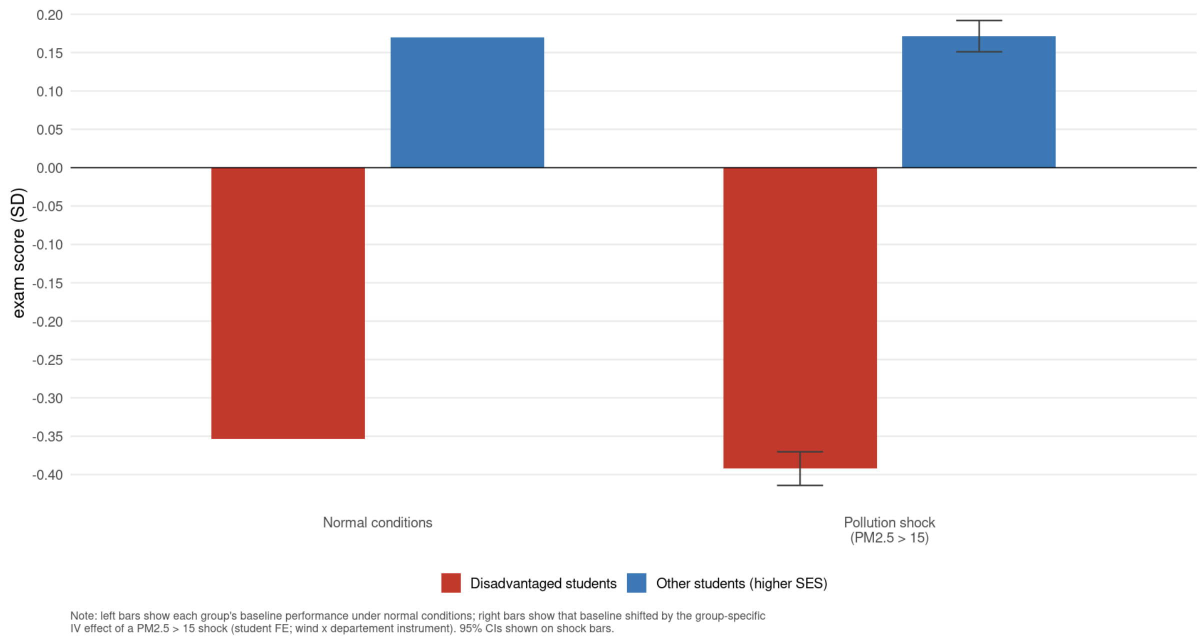
Note: This figure shows IV estimates of the effect of $PM_{2.5}$ on student performance in end-of-middle school examinations. The regressor of interest is a binary indicator equal to one if daily $PM_{2.5}$ concentration exceeds 15 $\mu g/m^3$ (WHO daily threshold). Each coefficient is estimated from a separate regression for the group indicated. Vertical bars represent 95% confidence intervals, with standard errors clustered at the municipality of school level.

Likewise, students from disadvantaged socio-economic backgrounds suffer a 6.2% SD decrease in test scores, while those from more advantaged backgrounds remain unaffected, as illustrated in Figure 4.

These effects are economically meaningful and imply a substantial increase in educational inequalities at a critical stage of the schooling process. As shown in Figure 5, exposure to a pollution shock on the exam day increases the socioeconomic achievement gap by 25% relative to its level under normal conditions. Performance in the *Baccalauréat* has far-reaching consequences. Obtaining this diploma is a prerequisite for admission to higher education, so failing the exam substantially limits access to university and, consequently, educational attainment. Moreover, Canaan & Mouganie (2018) show that *Baccalauréat* performance affects the quality of tertiary education accessed and increases earnings at ages 27–29. Our findings therefore suggest that short-term pollution shocks can reinforce long-term socioeconomic inequalities by disproportionately affecting the educational opportunities of disadvantaged students.

Strikingly, the results mirror those obtained for the end-of-middle-school examination. In both middle- and high-school exams, students from disadvantaged backgrounds

Figure 3: Effects of $PM_{2.5}$ on the Socioeconomic Achievement Gap in End-of-Middle-School Examinations



Note: This figure illustrates how the performance gap between disadvantaged and higher-SES students widens under a pollution shock in end-of-middle school examinations. For each group, the left bar reports the baseline mean performance (in standard deviations); the right bar shifts this baseline by the group-specific IV effect of a pollution shock, defined as a binary indicator equal to one when daily $PM_{2.5}$ concentration exceeds 15 $\mu g/m^3$ (WHO daily threshold), with 95% confidence intervals on the shock effect.

experience large and significant losses, whereas their more advantaged peers are not significantly affected. This consistency suggests that the mechanisms driving the unequal effects of short-term air pollution exposure are not specific to a particular age or examination, but operate throughout key stages of the educational trajectory. We explore these mechanisms in Section 4. Before doing so, the next section examines the robustness of our main findings (Section 3.3).

3.3 Robustness checks

3.3.1 Alternative Specifications

Tables B1 and B2 assess the robustness of our main results to alternative specifications. In both tables, Column (1) reports IV estimates including more flexible weather controls, allowing for interactions between temperature, humidity, and rainfall. Results are virtually unchanged, with disadvantaged and scholarship students remaining significantly affected by pollution shocks. Second, Column (2) tests the sensitivity of our results to a lower threshold, using $PM_{2.5} > 10\,\mu g/m^3$ as the key regressor. This exercise

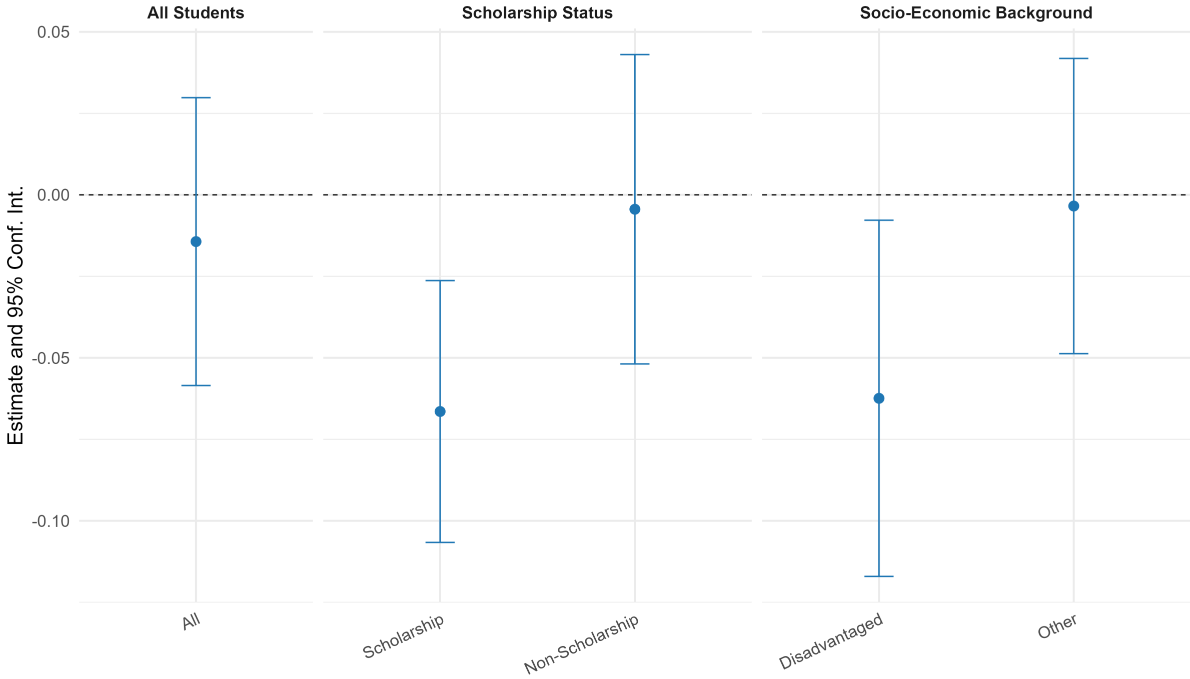
Table 2: The Effects of $PM_{2.5}$ on Student Performance: End-of-high School Exams

	IV (1)
All Students (N=3,462,332)	
$PM_{2.5} > 15$	-0.0143
	(0.0225)
Scholarship Students (N=468,180)	
$PM_{2.5} > 15$	-0.0665***
	(0.0205)
Non-Scholarship Students (N=2,994,152)	
$PM_{2.5} > 15$	-0.0044
	(0.0242)
Disadvantaged socio-economic background (N=622,986)	
$PM_{2.5} > 15$	-0.0624**
	(0.0279)
Other socio-economic background (N=2,780,165)	
$PM_{2.5} > 15$	-0.0034
	(0.0231)
Student Fixed Effects	Yes
Year Fixed Effects	Yes
Subject Fixed Effects	Yes
Academic Track Fixed Effects	Yes
Weather Controls	Yes

Note: This table reports IV estimates of the effect of $PM_{2.5}$ on student performance in end-of-high school examinations (*Baccalauréat*), based on Equation (2). The key regressor is a binary indicator equal to one if daily $PM_{2.5}$ concentration exceeds 15 $\mu g/m^3$ (WHO daily threshold). Each panel corresponds to a separate regression. Standard errors, clustered at the municipality of school level, are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

is motivated by recent evidence suggesting that even relatively low levels of pollution may affect cognitive outcomes (e.g., Andersen et al., 2025). While all types of students are affected with this specification, we find a pattern that is consistent with our main findings: scholarship and disadvantaged students are significantly more affected than other students. Note that with this specification, coefficients tend to be smaller but more precisely estimated than in the main specification, in line with $PM_{2.5}$ level above 10 $\mu g/m^3$ being both more frequently observed and less harmful than $PM_{2.5}$ level above 15 $\mu g/m^3$. Column (3) uses continuous $PM_{2.5}$ concentration (in $\mu g/m^3$) as the key regressor. Results remain consistent with our main findings, as scholarship and disadvantaged students are significantly more affected than other students for the Baccalauréat, while the evidence is weaker for the Brevet with no subgroup significantly affected. The overall attenuation of results with the continuous measure suggests that pollution must exceed a critical concentration level to meaningfully impair short-term cognitive function, consistent with a nonlinear dose–response relationship. Column (4) shows that the results are

Figure 4: Effects of $PM_{2.5}$ on Student Performance: End-of-high School Exams

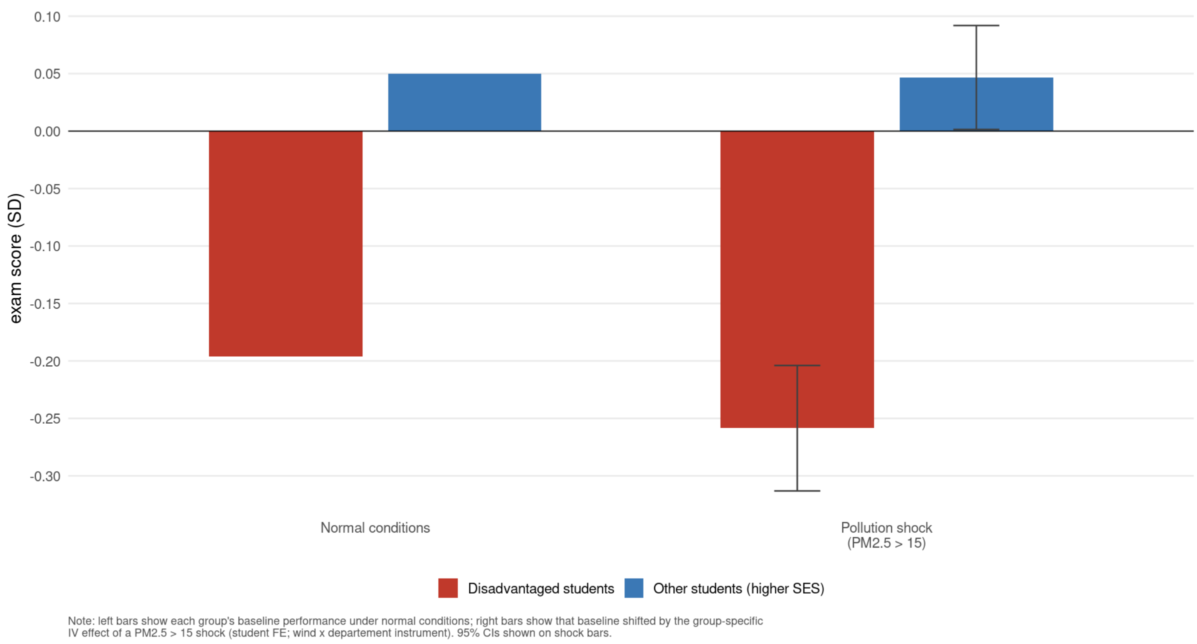


Note: This figure shows IV estimates of the effect of $PM_{2.5}$ on student performance in end-of-high school examinations. The regressor of interest is a binary indicator equal to one if daily $PM_{2.5}$ concentration exceeds 15 $\mu g/m^3$ (WHO daily threshold). Each coefficient is estimated from a separate regression for the group indicated. Vertical bars represent 95% confidence intervals, with standard errors clustered at the municipality of school level.

robust to measuring pollution exposure at the municipality of residence rather than the municipality of school. The estimated effects remain very similar to the baseline specification, both quantitatively and qualitatively, with sizeable negative impacts concentrated among disadvantaged students. Finally, Column (5) presents OLS estimates using the binary $PM_{2.5} > 15\,\mu g/m^3$ variable. Although this approach does not fully address potential endogeneity, it provides a useful comparison with the IV estimates. Consistent with Ebenstein et al. (2016), we exploit within-student variation across subjects taken on different exam days in the same week. The resulting pattern broadly corresponds to our main findings, with disadvantaged groups being the most affected by pollution shocks, and the size of the coefficients being very similar to that in our main specification.

Overall, the robustness checks confirm that our main conclusions hold across a variety of specifications: short-term exposure to $PM_{2.5}$ slightly - if anything - affects the performance of more advantaged students, but it has sizeable and significant negative effects on students from disadvantaged socio-economic backgrounds.

Figure 5: Effects of $PM_{2.5}$ on the Socioeconomic Achievement Gap in End-of-High-School Examinations



Note: This figure illustrates how the performance gap between disadvantaged and higher-SES students widens under a pollution shock in end-of-high school examinations. For each group, the left bar reports the baseline mean performance (in standard deviations); the right bar shifts this baseline by the group-specific IV effect of a pollution shock, defined as a binary indicator equal to one when daily $PM_{2.5}$ concentration exceeds 15 $\mu g/m^3$ (WHO daily threshold), with 95% confidence intervals on the shock effect.

3.3.2 The Role of NO_2

While our main focus is on $PM_{2.5}$, the pollutant with the highest documented health and economic costs, it is also informative to examine whether similar effects arise for nitrogen dioxide (NO_2). NO_2 is a key traffic-related pollutant, and recent evidence from the United States shows that exposure to traffic pollution can negatively affect students' cognitive performance (e.g., Heissel et al., 2022). Moreover, NO_2 is closely linked to fine particulate matter, as it contributes to the formation of secondary particles. Consistent with this, we observe a correlation of 0.37 between daily $PM_{2.5}$ and NO_2 concentrations in our data.

To investigate this issue, we replicate our main analysis using NO_2 as the key regressor, defined as a dummy equal to one if daily concentrations exceed the WHO guideline of 25 $\mu g/m^3$. Table B3 shows that, unlike for $PM_{2.5}$, we find no significant effect of NO_2 exposure on student performance in end-of-middle school exams, either for the full population or for specific socio-economic subgroups. By contrast, the pattern observed for $PM_{2.5}$ is also observed for NO_2 when looking at performance in end of high school exams

(Table B4). Overall, these results support our focus on $PM_{2.5}$ as the primary pollutant of interest, both because of its larger health burden and because it partly captures the influence of other pollutants such as NO_2 through secondary particle formation.

3.3.3 Many instrument bias

Because our identification relies on a large number of excluded instruments (roughly 380), a natural concern is that the 2SLS estimates could be biased toward OLS (Bound et al., 1995; Bekker, 1994). We test this formally in Appendix B1 along two complementary lines. First, we re-estimate our main specifications using the Limited Information Maximum Likelihood (LIML) estimator, which is not subject to many-instrument bias (Bekker, 1994; Anderson et al., 2010). LIML and 2SLS estimates are virtually indistinguishable, as the effect of crossing the $PM_{2.5} > 15\ \mu g/m^3$ threshold for scholarship students is -0.045 SD for end-of-middle school exams and -0.067 SD for end-of-high school exams under both estimators, with differences negligible across all subgroups. Second, we replicate the results with a parsimonious instrument set ($\sim$50 instruments) that interacts wind direction with 13 administrative regions rather than 95 *départements*. Here again, point estimates remain stable in sign and magnitude—for instance -0.049 ($p < 0.10$) versus -0.067 for scholarship students for end-of-high school exams—with the expected loss of precision as the first stage weakens.

4 Why Are Disadvantaged Students More Vulnerable?

In this section, we examine the mechanisms underlying the greater vulnerability of socioeconomically disadvantaged students to air pollution shocks. We structure the analysis around the conceptual framework introduced in Section 2.1. A transitory pollution shock on exam day cannot alter the stock of skills and knowledge (H) that a student brings to the exam. Instead, it may impair cognitive functioning under adverse conditions—the capacity to sustain attention, manage stress, resist fatigue, and exert executive control under time pressure. We denote this capacity by θ.

This concept builds on the notion of cognitive endurance introduced by Brown et al. (2025), which emphasizes the ability to sustain cognitive effort and maintain performance over time despite fatigue. We extend this framework by considering any type of adverse conditions that may impair performance, including not only fatigue, but also stress, time pressure, heat, or air pollution exposure. Throughout the remainder of the paper, we therefore refer to θ as *cognitive resilience*: the ability to maintain performance under stressful and cognitively demanding conditions.[17]

We first investigate whether differences in θ can account for the unequal effects of pollution across socioeconomic groups. To do so, we construct a measure of θ, examine its social distribution, and test whether students with lower cognitive resilience (i.e., greater cognitive vulnerability) are more affected by pollution shocks. We then explore whether cognitive resilience is malleable by studying the role of school quality in shaping it. Finally, we assess competing explanations based on inequalities in chronic pollution exposure and health vulnerability.

4.1 Cognitive Resilience and Pollution Vulnerability

4.1.1 Measuring Cognitive Resilience

We construct an individual-level measure of cognitive resilience by exploiting the fact that, for each student in 9th grade, we observe two distinct assessments of academic performance: continuous assessment (CA) grades obtained throughout the school year and written examination scores at the end-of-middle school exam. These two measures capture fundamentally different dimensions of student ability.

The CA grade reflects knowledge accumulated through regular, low-stakes evaluations administered by the student's own teacher throughout the year. Because these evaluations are frequent, short, and conducted in a familiar environment, they arguably provide a good proxy for students' stock of human capital H—the knowledge and skills they have acquired through learning. By contrast, performance in the written exams depends not only on H but also on students' cognitive resilience θ, since these exams expose students to demanding conditions that are largely absent from continuous assessment: high stakes (the exam is consequential for their educational trajectory), time pressure (sessions lasting up to three hours), sustained effort (exams concentrated over two consecutive days), and external grading (eliminating teacher familiarity effects).

Building on this notion, we define our measure of cognitive resilience as:

$$\theta_i = \bar{Z}_i^{\text{exam}} - \bar{Z}_i^{\text{CA}} \tag{4}$$

[17] The concept of θ also relate to the broader literature on non-cognitive skills, including perseverance, self-regulation, and grit, as well as to the cognitive psychology literature on executive function (Diamond, 2013) and neuroscience evidence on brain connectivity (Gawryluk et al., 2023).

where $\bar{Z}_i^{\text{exam}}$ is the average of student i's standardized scores across the three end-of-middle school written subjects—French, mathematics, and history-geography. Each score is standardized within year × academic region × subject cells, as in our main analysis, and then averaged at the student level. $\bar{Z}_i^{\text{CA}}$ is the student's overall continuous assessment grade (the average of all classroom evaluations received throughout the school year), standardized within class × year cells.[18] The within-class standardization is essential: teachers may grade students relative to their own classroom expectations, introducing systematic variation across classrooms within the same school. By standardizing at the class level, we ensure that our measure is not confounded by differences in grading practices across teachers.[19]

Lower values of θ_i reflect lower cognitive resilience, meaning that the student performs relatively worse in the high-stakes examination than would be predicted by her continuous assessment performance. Higher values of θ_i reflect greater cognitive resilience, indicating a stronger ability to maintain performance under demanding exam conditions[20].

4.1.2 The Socioeconomic Gradient in Cognitive Resilience

A necessary condition for cognitive resilience to explain socioeconomic differences in pollution vulnerability is that it itself be unequally distributed across socioeconomic groups. Figure 6, which plots kernel density estimates of cognitive resilience by socioeconomic status, strongly supports this prediction[21]. The entire distribution of cognitive resilience is shifted to the left for disadvantaged students relative to their more advantaged peers, indicating systematically lower levels of cognitive resilience throughout the distribution. This pattern suggests that socioeconomic differences in cognitive resilience are not driven solely by a small group of particularly vulnerable students, but instead reflect a broad shift affecting disadvantaged students as a whole.

Table 3 provides further evidence of this socioeconomic gradient in cognitive resilience. The mean value of θ is -0.136 for disadvantaged students, compared to $+0.062$ for other students—a gap of 0.198. The point-biserial correlation between θ and the disadvantaged

[18] In the French system, classes constitute clearly defined entities of approximately 25–30 students with the same teachers throughout the year. The within-class standardization absorbs both systematic differences in grading leniency across establishments and teacher-specific grading patterns within schools, while preserving meaningful variation in relative standing among classmates who share the same instructional environment.

[19] As a robustness check, we recompute θ_i by standardizing $\bar{Z}_i^{\text{CA}}$ within school × year cells instead, and show that our results are robust to this alternative standardization (see Table B6 and Table B8)

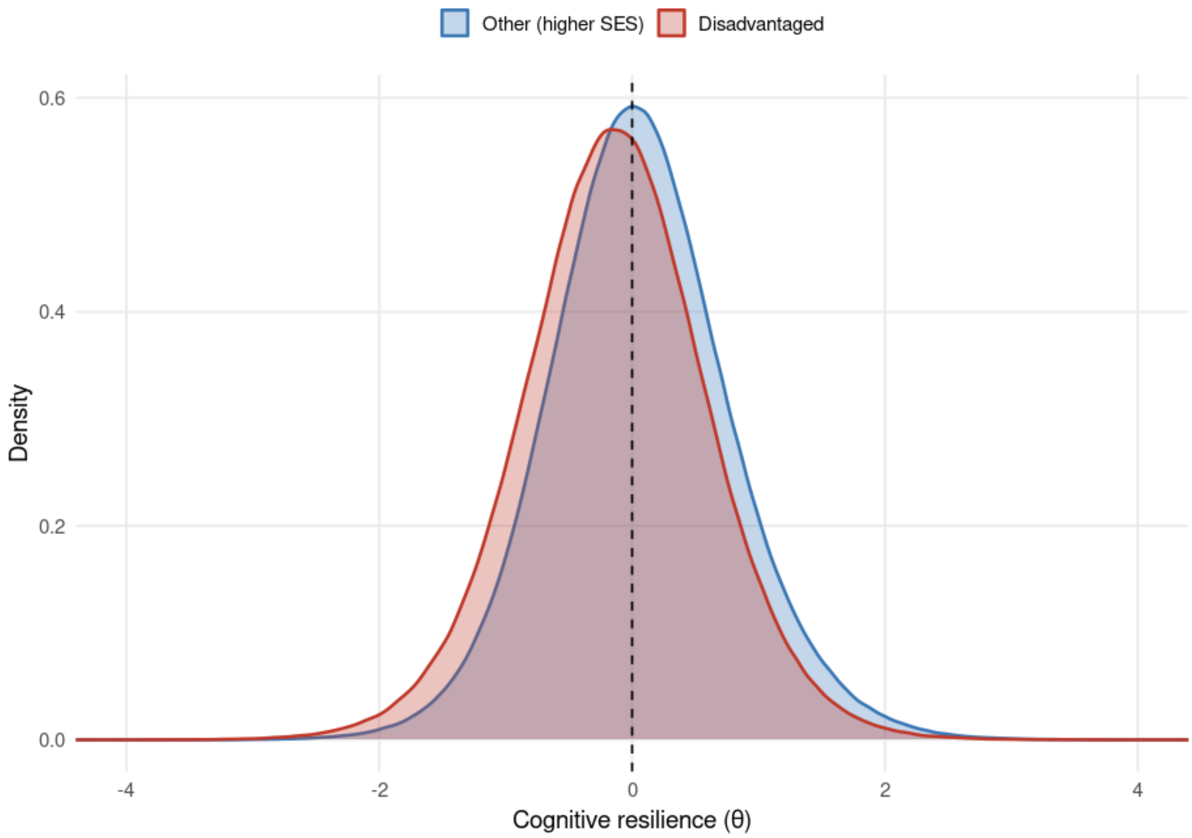
[20] See distribution of θ_i in appendix Figure A1

[21] Same pattern hold using scholarship status instead of SES see Figure A2 and Figure A3

indicator is $r = -0.125$. Consistent with this pattern, disadvantaged students are substantially overrepresented among students with low levels of cognitive resilience: 27.7% of students in the bottom quintile of θ come from disadvantaged backgrounds, compared with only 11.9% in the top quintile. These results confirm a pronounced socioeconomic gradient in cognitive resilience.

This pattern is consistent with the broader literature documenting socioeconomic disparities in cognitive endurance (Brown et al., 2025) and in the development of non-cognitive skills (Fletcher & Wolfe, 2016). More importantly for our purposes, it suggests that cognitive resilience is a plausible candidate mechanism through which air pollution may generate larger performance losses among disadvantaged students.

Figure 6: Distribution of Cognitive Resilience (θ) by Socio-Economic Background: 9th Grade



Note: This figure plots kernel density estimates of the distribution of cognitive resilience (θ) separately for students from disadvantaged and other (higher-SES) socio-economic backgrounds in 9th grade.

4.1.3 Cognitive Resilience and Pollution Vulnerability at the End-of-High School Exam

We now test whether θ, measured at the end of 9th grade, predicts individual vulnerability to pollution shocks during the *Baccalauréat* examinations three years later, at the end of 12th grade. To do so, we divide students into quintiles of θ and re-estimate our main IV specifications separately for each group.[22]

Table 4 and Figure 7 provide strong evidence that cognitive resilience, as captured by θ, predicts vulnerability to pollution shocks. Students in the lowest quintile of cognitive resilience (Q_1) experience a statistically significant decline of -0.058 SD ($p < 0.05$) when exposed to $PM_{2.5}$ levels above WHO recommendations. By contrast, students in all other quintiles (Q_2 through Q_5) show no significant effect, with point estimates close to zero. The concentration of the entire effect among students with the lowest levels of cognitive resilience is consistent with the view that pollution acts as a cognitive stressor that primarily affects those who are most cognitively vulnerable under adverse conditions.

This pattern is robust across a wide range of specifications. First, OLS estimates with student fixed effects reveal a similar gradient in pollution vulnerability (Appendix Table B5). The estimated effect is largest for students in the lowest quintile of cognitive resilience (-0.054 SD, $p < 0.01$) and declines steadily across the distribution, reaching -0.014 SD and becoming statistically insignificant in the highest quintile. The magnitude for the least resilient students is remarkably similar across OLS and IV specifications (-0.054 and -0.058, respectively). The results are robust to using continuous rather than threshold-based pollution exposure (Figure B1). Finally, Appendix B1 shows that the findings are not driven by concerns related to the large number of instruments used in our main specification. Estimates remain virtually unchanged when using the Limited Information Maximum Likelihood (LIML) estimator and when relying on a substantially more parsimonious instrument set. In both cases, the adverse effect of pollution remains concentrated among students with the lowest levels of cognitive resilience.

[22] The measure θ is available for 89.6% of students in our 12th-grade sample.

Table 3: Cognitive function (θ) by socioeconomic status (SES)

	N	Mean θ	SD
Other	3,260,461	0.062	0.721
Disadvantaged	1,475,253	-0.136	0.738
Tests			
Difference in means (Other $-$ Disadvantaged)			0.198
Welch t-statistic			271.35
Correlation $\theta \times$ Disadvantaged SES (r)			-0.125

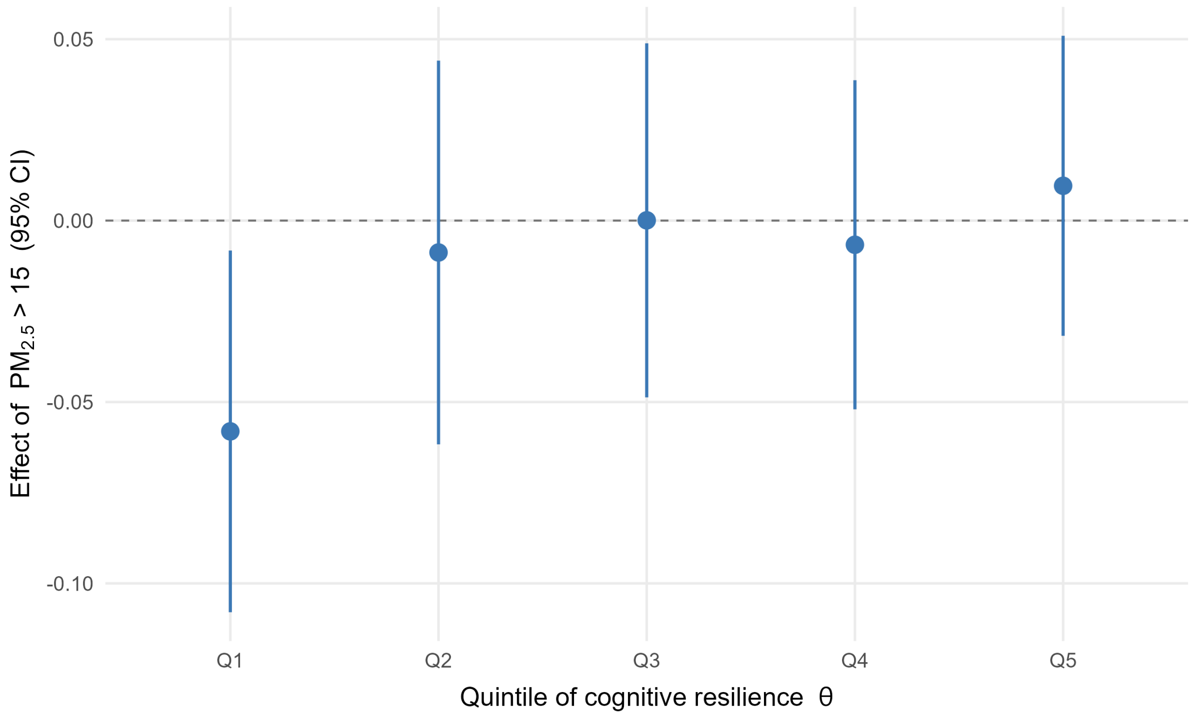
Notes: θ_i is defined as the difference between standardized high-stakes end-of-middle school exam scores and continuous assessment grades obtained throughout 9th grade standardized within class $\times$ year cells. The first correlation is the point-biserial correlation between θ_i and a binary indicator for disadvantaged SES. All tests have $p < 2 \times 10^{-16}$.

Table 4: Effect of $PM_{2.5} > 15$ on Bac performance by quintile of cognitive resilience (θ)

	Q_1 (Low θ)	Q_2	Q_3	Q_4	Q_5 (High θ)
$PM_{2.5} > 15$	-0.0581^{**}	-0.0088	0.0001	-0.0067	0.0096
	(0.0254)	(0.0269)	(0.0249)	(0.0231)	(0.0211)
Observations	616,919	671,459	668,725	645,307	595,812
Mean θ	-0.97	-0.38	-0.01	0.36	1.03
% Disadvantaged SES	27.7	20.9	17.8	15.3	11.9

Note: This table reports IV estimates of the effect of $PM_{2.5} > 15$ (daily concentration above 15 $\mu g/m^3$) on standardized *Baccalauréat* scores, based on Equation (2), estimated separately by quintile of cognitive resilience (θ). Cognitive resilience is measured in 9th grade as the difference between standardized DNB exam scores and continuous assessment grades. Q_1 denotes the least resilient students and Q_5 the most resilient. "% Disadvantaged SES" reports the share of disadvantaged students in each quintile. All regressions include student, year, subject, and track fixed effects as well as weather controls. Standard errors clustered at the municipality-of-school level are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure 7: Effect of $PM_{2.5} > 15$ on Bac performance by quintile of cognitive resilience (θ)



Note: The figure reports point estimates and 95% confidence intervals of the effect of $PM_{2.5} > 15$ on standardized Bac score, estimated separately within quintiles of cognitive resilience θ_i. Q_1 contains the students with lowest cognitive resilience; Q_5 the highest cognitive resilience. θ_i is measured at the DNB (three years before the Bac) as the difference between standardized exam scores and continuous assessment standardized within class $\times$ year cells. Standard errors are clustered at the municipality-of-school level.

4.2 Can Schools Build Cognitive Resilience?

Having identified cognitive resilience (θ) as a key driver of the unequal effect of air pollution on student performance in high-stakes exams, an important question is whether it can be shaped by public policies and, in particular, by the school environment. We investigate this question by interacting θ with an independent measure of school quality: the value-added (VA) of the high school attended. A large literature in economics uses value-added measures to capture the causal contribution of schools to student achievement, and a growing body of evidence suggests that the gains generated by high value-added educational environments translate into improved outcomes in adulthood (see e.g. Angrist et al., 2023, for a review)

In practice, we use the *Indicateurs de Valeur Ajoutée des Lycées* (IVAL), produced by the French Ministry of Education's statistical office (DEPP), which measure a school's contribution to student success relative to what would be expected given its student intake.[23] We classify students into four groups based on whether their cognitive resilience measure (θ) is above or below the sample median and whether the VA of the high school they attend is above or below the median. We then re-estimate our main specifications separately for each subgroup.

A clear pattern emerges in Figure 8. Among students with low cognitive resilience, exposure to pollution significantly reduces performance only when they attend a low-VA high school, with an IV estimate of -0.069 SD, significant at the 5% level (Table 5). By contrast, students with similarly low cognitive resilience but enrolled in high-VA schools are not significantly affected. Among students with high cognitive resilience, we find no significant effect of pollution regardless of school quality. These results are robust to using an OLS specification with student fixed effects (Table B7). They are also robust to standardizing continuous assessment grades ($\bar{Z}_i^{\text{CA}}$) at the school $\times$ year level (Table B8). The results are also robust to using continuous rather than threshold-based pollution exposure (Figure B2). These findings indicate that high-quality schools mitigate the vulnerability of students with low cognitive resilience to acute pollution shocks.

[23] The IVAL methodology and school-level results are publicly available at `https://www.education.gouv.fr/les-indicateurs-de-resultats-des-colleges-et-des-lycees-377729`. The indicators compare observed outcomes to those predicted by a statistical model controlling for student characteristics (age, sex, socioeconomic background, prior achievement) and school composition. They are computed separately for each school $\times$ academic track combination. We focus on the value-added measure based on the *mention* (honors) rate, which captures a school's ability to promote high performance in the *Baccalauréat*.

Ruling out differential sorting. Importantly, this result is not driven by differential sorting of students across schools. As shown in Table 6, access to high-quality high schools is identical across socioeconomic groups: 44% of both advantaged and disadvantaged students attend a high VA high school. The table further shows that access to high VA high schools varies little with cognitive resilience. Specifically, 43.1% of students with low cognitive resilience attend a high VA high school, compared with 45.1% of students with high cognitive resilience, a difference of only 2pp. This suggests that differential sorting into high-quality schools is unlikely to explain why students with low cognitive resilience are no longer affected by pollution when attending a high VA high school.

Interpretation and policy implications. Our results indicate that differences in cognitive resilience is a key driver of the socioeconomic gradient in vulnerability to air pollution shocks. The gap in cognitive resilience does not appear to be generated by differential access to school quality during secondary education. Disadvantaged students attend high VA middle schools at similar or slightly higher rates than their peers,[24] and access to high VA high schools is also remarkably similar across groups (Table 6). Likewise, students with low cognitive resilience are only slightly less likely to attend a high value-added high school than students with high cognitive resilience. These patterns suggest that neither school assignment nor differential sorting into effective schools can account for the observed disparities in cognitive resilience.

The origins of these differences therefore likely lie upstream, before students enter secondary education. A large body of evidence shows that socioeconomic gaps in both cognitive and non-cognitive skills emerge early in childhood and are strongly influenced by family environments and early investments (e.g., Cunha & Heckman, 2007). In France, recent longitudinal evidence indicates that inequalities by parental background are already visible at age three in language, early numeracy, and executive functioning (DEPP, 2025). These early differences persist throughout the schooling process (Murat, 2024) and, according to our results, ultimately translate into differential vulnerability to environmental shocks during high-stakes examinations.

At the same time, our findings show that these initial disadvantages are not immutable. Students with low cognitive resilience who attend a high value-added high school are no longer significantly affected by pollution shocks, whereas otherwise similar students enrolled in low value-added schools remain highly vulnerable. This pattern sug-

[24] Specifically, disadvantaged students are 50.3% likely to attend a high VA middle school, while other students are 48.0% likely to do so.

gests that effective schools can partly compensate for lower levels of cognitive resilience. More broadly, it is consistent with the view that cognitive resilience is not fixed but can be strengthened through educational experiences and pedagogical practices (Brown et al., 2025). It also echoes recent evidence showing that effective schools generate particularly large long-run benefits for disadvantaged students and that these benefits extend beyond test-score gains (Jackson et al., 2024).

Table 5: Effect of $PM_{2.5}$ on *Baccalauréat* Performance by Cognitive Resilience (θ) and High School Value-Added

	Low cognitive resilience		High cognitive resilience	
	Low VA	High VA	Low VA	High VA
$PM_{2.5} > 15$	-0.0692^{**}	0.0194	-0.0162	0.0215
	(0.0320)	(0.0250)	(0.0287)	(0.0267)
Observations	971,969	668,694	886,932	651,850
% Disadvantaged SES	22.3	23.6	14.7	13.7

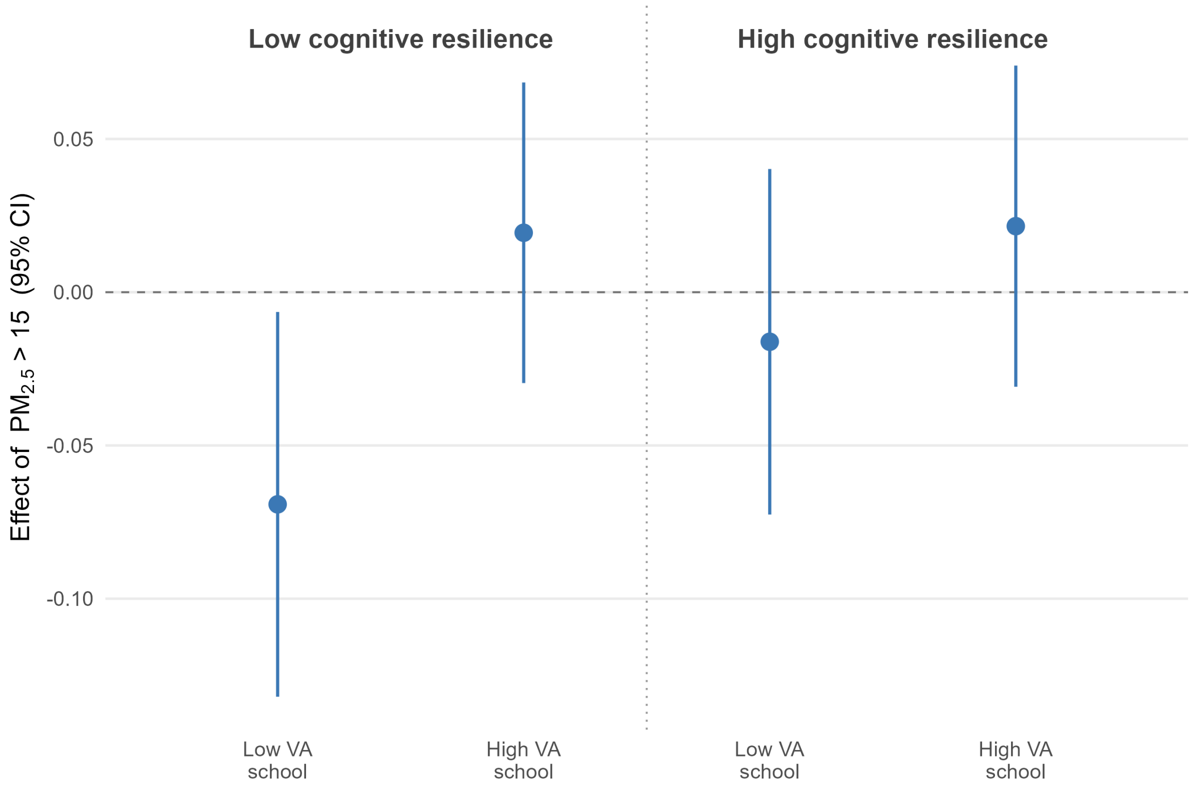
Note: This table reports IV estimates of the effect of $PM_{2.5} > 15$ (daily concentration above 15 $\mu g/m^3$) on standardized *Baccalauréat* scores. Students are classified according to whether their cognitive resilience (θ) and the value-added of the high school they attend are above or below 0. "% Disadvantaged SES" reports the share of disadvantaged students in each subgroup. All regressions include student, year, subject, and track fixed effects as well as weather controls. Standard errors clustered at the municipality-of-school level are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6: High Value-Added High Schools by Socioeconomic Status and Cognitive Resilience

	N	% High VA
By socioeconomic status		
Disadvantaged	263,847	44.0
Other	1,167,869	44.1
By cognitive resilience (θ)		
Low cognitive resilience ($\theta < 0$)	734,247	43.1
High cognitive resilience ($\theta \geq 0$)	697,469	45.1

Notes: This table reports the share of students enrolled in high value-added (VA) high schools, by students SES and cognitive resilience. High VA is defined as a positive VA on the *mention* rate (*Indicateurs de Valeur Ajoutée des Lycées*). The measure is computed by the French Ministry of Education and adjusts for student composition. Students with $\theta_i < 0$ are classified as low cognitive resilience, while those with $\theta_i \geq 0$ are classified with high cognitive resilience.

Figure 8: Effect of $PM_{2.5} > 15$ on *Baccalauréat* Performance by Cognitive Resilience (θ) and High School Value-Added



Note: The figure reports point estimates and 95% confidence intervals of the effect of $PM_{2.5} > 15$ on standardized *Baccalauréat* scores, estimated separately within groups defined by cognitive resilience (θ_i) and school value-added (VA). Left panel: low cognitive resilience students ($\theta_i < 0$); right panel: high cognitive resilience students ($\theta_i \geq 0$). Within each panel, estimates are shown for students in low VA schools (VA < 0) and high VA schools (VA ≥ 0). VA is the value-added on the *mention* rate, computed by the French Ministry of Education for each school $\times$ track. Standard errors are clustered at the municipality-of-school level.

4.3 Ruling Out Alternative Mechanism

Disadvantaged students tend to be in poorer health (Currie, 2011; Castillo et al., 2025), which could make them physiologically more sensitive to acute $PM_{2.5}$ shocks—for instance through pre-existing respiratory inflammation or reduced pulmonary capacity. This health vulnerability could stem from cumulated damage due to chronic air pollution exposure, or from other socioeconomic determinants of health such as nutrition, access to healthcare, or chronic stress. We assess each channel in turn.

4.3.1 Does chronic pollution exposure amplify sensitivity to acute shocks?

A first concern is that disadvantaged students, if chronically more exposed to $PM_{2.5}$, may have accumulated respiratory or cardiovascular damage that renders them more sensitive to acute pollution spikes on exam day. We address this in two steps.

We first show that the premise does not hold in our data: chronic exposure gaps across socioeconomic groups are negligible. Tables 7 and 8 compare average annual $PM_{2.5}$ concentrations across SES groups. In our 9th grade sample, the difference between disadvantaged and other students ranges from 0.054 to 0.090 $\mu g/m^3$—less than 0.6% of the mean exposure level. In our 12th grade sample, the gap is even smaller and sometimes reversed: disadvantaged students attending the general track are exposed to slightly lower levels of $PM_{2.5}$ than their peers[25].

We then directly test whether chronic exposure amplifies sensitivity to acute shocks. We classify students into three groups based on the average annual $PM_{2.5}$ concentration in their school municipality (bottom 25%, middle 50%, top 25%) and re-estimate our main specification within each group. If sustained pollution exposure damaged health in ways that amplified the cognitive impact of acute shocks, students in more polluted areas should exhibit larger exam-day effects. They do not. For both end-of-middle school and end-of-high school exams, the effect of exam-day $PM_{2.5}$ is similar across the three groups (Figure B3). Results are unchanged when chronic exposure is measured at the residence municipality (Figure B4). The absence of any gradient, together with the absence of strong exposure differential by student SES, rule out the chronic-exposure-to-health channel.

[25] See other descriptive statistics of exposure year by year Table A5 and Table A6

Table 7: Inequalities in $PM_{2.5}$ exposure by socioeconomic background – Brevet

	Disadvantaged (μg/m^3)	Other (μg/m^3)	Gap (μg/m^3)	p-value
Panel A: Scholarship status				
School municipality	15.068	15.005	0.063	< 0.001
Residence municipality	15.083	14.994	0.090	< 0.001
Panel B: Socioeconomic status (SES)				
School municipality	15.059	15.004	0.054	< 0.001
Residence municipality	15.067	14.991	0.076	< 0.001

Notes: Entries report average annual $PM_{2.5}$ concentration over the school year for students taking the *brevet* exam (2010–2016). In Panel A, the columns correspond to *Scholarship* and *Non-scholarship* students, respectively. In Panel B, they correspond to Disadvantaged SES and Other SES students, respectively. Gap is the difference between the first and second column in each panel. P-values test equality of means.

Table 8: Inequalities in $PM_{2.5}$ exposure by socioeconomic background – Baccalauréat

	Disadvantaged (μg/m^3)	Other (μg/m^3)	Gap (μg/m^3)	p-value
Panel A: Scholarship status				
School municipality	13.291	13.265	0.026	< 0.001
Residence municipality	13.222	13.146	0.076	< 0.001
Panel B: Socioeconomic status (SES)				
School municipality	13.208	13.282	-0.074	< 0.001
Residence municipality	13.121	13.163	-0.042	< 0.001

Notes: Entries report average annual $PM_{2.5}$ concentration over the school year for students taking the *baccalauréat* exam (2013–2017). In Panel A, the columns correspond to Scholarship and Non-scholarship students, respectively. In Panel B, they correspond to Disadvantaged and Other students, respectively. Gap is the difference between the first and second column in each panel. P-values test equality of means.

4.3.2 Does health vulnerability unrelated to air pollution explain differential sensitivity?

A broader concern remains: disadvantaged students may be in poorer health for reasons unrelated to air pollution—worse nutrition, limited healthcare access, disrupted sleep, or chronic psychosocial stress—and this could independently increase their physiological sensitivity to acute $PM_{2.5}$. We cannot test this directly, as we do not observe individual health status. We therefore rely on external evidence.

The most direct evidence comes from Andersen et al. (2025), who leverage Denmark's population-wide health registries—covering the complete history of hospital diagnoses for every individual, regardless of cause—to examine whether pre-existing health conditions moderate the cognitive impact of air pollution on test scores. They find that diagnosed asthma, chronic respiratory diseases, and other recorded conditions do not amplify the effect of acute pollution on cognitive performance. Their null finding strongly suggests that the cognitive effects of acute pollution operate independently of baseline health status.

This conclusion is reinforced by experimental evidence. Several controlled experiment studies show that acute $PM_{2.5}$ exposure significantly impairs executive functions, selective attention, and global cognitive performance even among healthy young adults with no pre-existing conditions (Faherty et al., 2025; Shehab & Pope, 2019). These results demonstrate that acute pollution impairs cognition through a direct neurophysiological pathway—involving systemic inflammation, oxidative stress, and disrupted cerebral oxygen delivery (Mills et al., 2009; Pope III & Dockery, 2006)—rather than by exacerbating pre-existing health vulnerabilities.

Taken together, the evidence suggests that health vulnerability is unlikely to be the primary mechanism behind the differential impact of acute $PM_{2.5}$ shocks on disadvantaged students. Our empirical tests rule out the chronic-exposure channel, while existing evidence indicates that acute cognitive effects operate largely independently of baseline health (Andersen et al., 2025; Faherty et al., 2025; Shehab & Pope, 2019). Instead, the results point to cognitive resilience (θ) as the main source of differential vulnerability. We cannot, however, fully exclude a residual role for health-related mechanisms.

Finally, these results imply that the two channels through which air pollution can harm academic outcomes operate independently. Chronic exposure may reduce accumulated knowledge (H) over time through health-related absenteeism and impaired learning capacity (Currie et al., 2009), while acute exposure disrupts cognitive functioning on exam day.

5 Discussion

5.1 Long-Term Consequences of Pollution Shocks during Exam Days

A relevant question is whether the transitory effects on exam performance documented in this paper have lasting consequences. We argue that they can, through two distinct channels: students' educational opportunity sets and students' aspirations and beliefs about their academic ability.

First, performance in high-stakes examinations directly affects students' educational opportunity sets. The *Baccalauréat* is a prerequisite for enrollment in higher education in France, and the specific grade obtained conditions access to selective programs. Canaan & Mouganie (2018) show that performance at the *Baccalauréat* increases the quality of tertiary education accessed and raises earnings at ages 27–29 in the French context, while a growing literature provides further evidence that high school GPA has long-run consequences for educational attainment and labor market outcomes (Machin et al., 2020; Landaud et al., 2024). Even marginal differences in exam scores can shift outcomes for students near critical thresholds, where a pollution-induced decline of a few percentage points of a standard deviation may mean the difference between passing and failing, or between admission and rejection.

Second, exam results may influence students' beliefs about their own ability and, consequently, the choices they make within their available opportunity set. Grades obtained in high-stakes examinations provide an important signal of academic potential and can therefore shape future educational decisions. Students who perform below expectations may revise downward their beliefs about their ability, reduce effort, or opt for less ambitious educational tracks. A growing body of evidence shows that negative academic signals can trigger persistent behavioral responses and alter students' educational trajectories (Avery et al., 2018; Tan, 2023), especially for low-income students (Papay et al., 2016). One possible mechanism is the psychological effect that perceived failure has on self-evaluation: students may interpret poor performance as evidence of limited ability even when it partly reflects transitory factors beyond their control. This channel may be particularly important for disadvantaged students. Recent evidence from France shows that socially disadvantaged students systematically underestimate their academic ability and hold lower educational aspirations than equally performing advantaged students, and that these lower aspirations are associated with poorer subsequent educational outcomes (Guyon & Huillery, 2021).

5.2 Policy Implications

Our findings point to two complementary policy levers: reducing exposure and strengthening resilience. First, reducing exposure during critical moments is the most direct response to limit students' exposure to $PM_{2.5}$ during high-stakes examinations. General pollution reduction policies, such as low-emission zones, have been shown to improve air quality and health outcomes in urban areas (Pestel & Wozny, 2021; Margaryan, 2021; Klauber et al., 2024). More targeted interventions could focus specifically on exam-day conditions, for example by improving indoor air quality in examination rooms through the use of air purifiers and air-quality monitoring systems. Given that the effects we document are concentrated among disadvantaged students, such measures would likely have a progressive distributional impact.

Our mechanism analysis shows that cognitive resilience is not a fixed trait. Students with low cognitive resilience in 9th grade who attend a high value-added school are no longer significantly affected by pollution shocks at the end of high school (Section 4.2). This finding is consistent with experimental evidence from Brown et al. (2025), who show that cognitive endurance can be improved through deliberate practice. Their results indicate that higher-quality schools already incorporate strategies that develop sustained cognitive effort, while schools attended by less privileged students typically do not. Diffusing such pedagogical practices—including more frequent timed assessments, longer in-class problem-solving sessions, or structured practice in sustained concentration—across schools serving disadvantaged populations could strengthen students' capacity to perform under adverse conditions. Evidence from high-performing schools in low-income settings in the United States supports this view (Angrist et al., 2013; Dobbie & Fryer Jr, 2013), as does a broader literature showing that related socio-emotional skills can be fostered through school-based interventions (Jackson et al., 2020).

6 Conclusion

This paper provides causal evidence that short-term air pollution shocks can amplify educational inequalities. Using nationwide administrative data and exogenous variation in $PM_{2.5}$ induced by wind patterns, we show that pollution spikes on examination days significantly reduce performance among socioeconomically disadvantaged students, while leaving more advantaged students largely unaffected. These effects are substantial and occur in high-stakes examinations that shape subsequent educational opportunities.

Our findings suggest that these unequal effects operate through differences in vulnerability rather than differences in exposure. While the environmental justice literature has primarily emphasized inequalities in pollution exposure, we show that even when students face similar pollution levels, the educational consequences of pollution can differ markedly across socioeconomic groups. Our mechanism analysis points to cognitive resilience as a key driver of this heterogeneity. Disadvantaged students display systematically lower levels of cognitive resilience and are disproportionately represented among the students most vulnerable to pollution shocks. At the same time, our results suggest that cognitive resilience is not fixed. Students with low cognitive resilience who attend high value-added schools are no longer significantly affected by pollution shocks, indicating that educational environments can partly compensate for initial vulnerabilities.

These findings have implications for both environmental and education policy. A first priority is to reduce exposure during critical moments of human capital formation, for example through improved air filtration in examination rooms or broader policies that reduce ambient pollution. A second priority is to strengthen students' capacity to perform under adverse conditions. Our results suggest that educational practices that build cognitive resilience may reduce vulnerability to environmental shocks and thereby limit the extent to which such shocks translate into educational inequality.

More broadly, our analysis identifies a striking and previously overlooked source of educational inequality: a pronounced socioeconomic gradient in vulnerability to short-term pollution shocks. Yet this mechanism is likely only one part of the broader relationship between air pollution and educational inequality. As suggested by Isen et al. (2017), sustained exposure to pollution can impair cognitive development and human capital accumulation in the long run. Understanding which students are most affected by long-term exposure, through which mechanisms, and at what stages of the educational process remains an important challenge for future research. Addressing these questions is essential for assessing the full contribution of air pollution to the intergenerational persistence of socioeconomic inequality.

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Appendix A Descriptive statistics

Table A1: Sample Characteristics

	N	Mean	Std. Dev.	Min	Max
9th grade sample: Student characteristics					
Gender (Male)	4,818,985	0.495	0.500	0	1
Need-based scholarship holder	4,818,985	0.215	0.411	0	1
Disadvantaged socio-economic group	4,818,985	0.316	0.465	0	1
Middle socio-economic group	4,818,985	0.327	0.469	0	1
Advantaged socio-economic group	4,818,985	0.127	0.333	0	1
Highly-advantaged socio-economic group	4,818,985	0.229	0.420	0	1
Exam sensitivity (θ)	4,866,299	−0.001	0.734	−5.517	6.906
9th grade sample: Exam characteristics					
$PM_{2.5} > 15$	14,445,186	0.291	0.454	0	1
Air pollution $PM_{2.5}$ (µg/m^3)	14,445,186	12.697	4.835	4.270	37.860
Temperature (°C)	13,532,826	20.714	3.726	−0.300	29.500
Humidity (%)	13,526,375	67.101	11.394	35.500	95.200
Rain (mm)	13,532,826	1.087	3.051	0.000	68.300
12th grade sample: Student characteristics					
Gender (Male)	1,459,260	0.432	0.495	0	1
Need-based scholarship holder	1,459,260	0.140	0.347	0	1
Disadvantaged socio-economic group	1,459,260	0.185	0.389	0	1
Middle socio-economic group	1,459,260	0.298	0.457	0	1
Advantaged socio-economic group	1,459,260	0.152	0.359	0	1
Highly-advantaged socio-economic group	1,459,260	0.365	0.481	0	1
Exam sensitivity (θ)	1,499,961	0.002	0.703	−5.517	5.509
12th grade sample: Exam characteristics					
$PM_{2.5} > 15$	4,184,412	0.082	0.275	0	1
Air pollution $PM_{2.5}$ (µg/m^3)	4,184,412	9.036	3.727	1.850	34.940
Temperature (°C)	3,914,740	19.026	3.783	0.700	30.300
Humidity (%)	3,911,748	70.997	11.953	32.500	95.200
Rain (mm)	3,914,740	2.573	5.342	0.000	60.300

Note: This table reports descriptive statistics for the 9th and 12th grade samples used in the analysis. Student characteristics include gender, scholarship status, and socio-economic group. Exam characteristics refer to the environmental conditions on exam days, including whether $PM_{2.5}$ levels exceeded the 15 μg/m^3 WHO threshold, as well as temperature, humidity, and rainfall at the municipality level. The unit of observation for student variables is the individual; for exam-day variables, it is subject-level exam sittings. $PM_{2.5}$ concentrations are measured in μg/m^3, temperature in °C, humidity in percent, and rain in mm.

Table A2: Standardized (Brevet) test scores by student social origin

Social origin	**Score**	**Difference**	**p-value**
Disadvantaged social background	-0,35		
Other social background	0,17	-0,52	0.00
Scholarship holder	-0,40		
Non-scholarship holder	0,11	-0,51	0.00

Notes: This table reports the mean standardized *Brevet* (DNB) exam score by student social origin.

Table A3: Acute $PM_{2.5}$ Exposure on Exam Days by Socioeconomic Status

	Brevet (DNB)			*Baccalauréat*		
	Disadv.	Other	Gap	Disadv.	Other	Gap
Panel A: By parental occupation						
% days $> 15\ \mu g/m^3$	28.80	29.29	-0.49^{***}	8.14	8.24	-0.10^{***}
Mean $PM_{2.5}$ when $> 15\ \mu g/m^3$	19.10	19.07	0.03^{***}	17.75	17.59	0.16^{***}
Panel B: By scholarship status						
% days $> 15\ \mu g/m^3$	28.37	29.29	-0.92^{***}	8.80	8.12	0.67^{***}
Mean $PM_{2.5}$ when $> 15\ \mu g/m^3$	19.29	19.02	0.27^{***}	17.72	17.60	0.12^{***}
Obs. (student $\times$ subject)		14,710,815			4,334,280	

Notes: This table compares acute $PM_{2.5}$ exposure on exam days across socioeconomic groups. The first row of each panel reports the share of student $\times$ subject observations for which daily $PM_{2.5}$ exceeds the WHO threshold of 15 $\mu g/m^3$. The second row reports mean $PM_{2.5}$ (continuous) conditional on exceeding this threshold. In Panel A, "Disadv." refers to students from disadvantaged families as defined by parental occupation. In Panel B, it refers to students receiving a need-based scholarship. Differences are tested using Welch's t-tests. *** $p < 0.01$.

Table A4: Standardized (Bac) test scores by student social origin

Social origin	**Score**	**Difference**	**p-value**
Disadvantaged social background	-0.20		
Other social background	0.05	-0.25	0.00
Scholarship holder	-0.22		
Non-scholarship holder	0.04	-0.26	0.00

Notes: This table reports the mean standardized *Baccalauréat* (Bac) exam score by student social origin, using two alternative definitions of social disadvantage.

Table A5: PM2.5 exposure trends by socioeconomic characteristics - Baccalauréat

	By SES		By scholarship	
Year	Disadv.	Other	Scholar.	Non-scholar.
2013	15.18	15.26	15.20	15.25
2014	12.56	12.68	12.69	12.65
2015	13.57	13.64	13.63	13.62
2016	11.30	11.43	11.45	11.40
2017	13.39	13.44	13.46	13.42

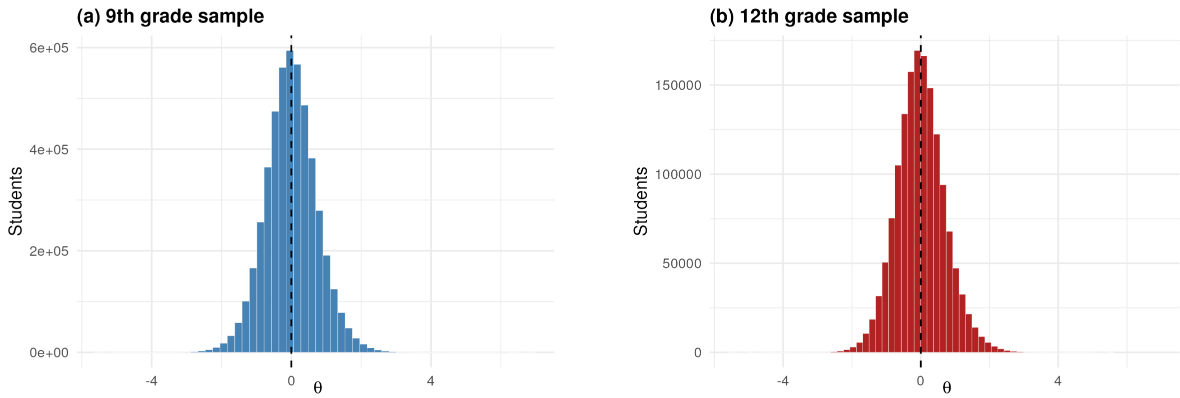
Notes: Average annual PM2.5 concentration (µg/m³) at school municipality. "Disadv." = disadvantaged socioeconomic status; "Scholar." = scholarship recipient.

Table A6: PM2.5 exposure trends by socioeconomic characteristics - Brevet

	By SES		By scholarship	
Year	Disadv.	Other	Scholar.	Non-scholar.
2010	18.31	18.44	18.40	18.40
2011	18.34	18.22	18.42	18.22
2012	16.76	16.77	16.92	16.73
2013	15.08	15.05	15.12	15.05
2014	12.46	12.51	12.58	12.48
2015	13.48	13.43	13.55	13.41
2016	11.22	11.27	11.35	11.23

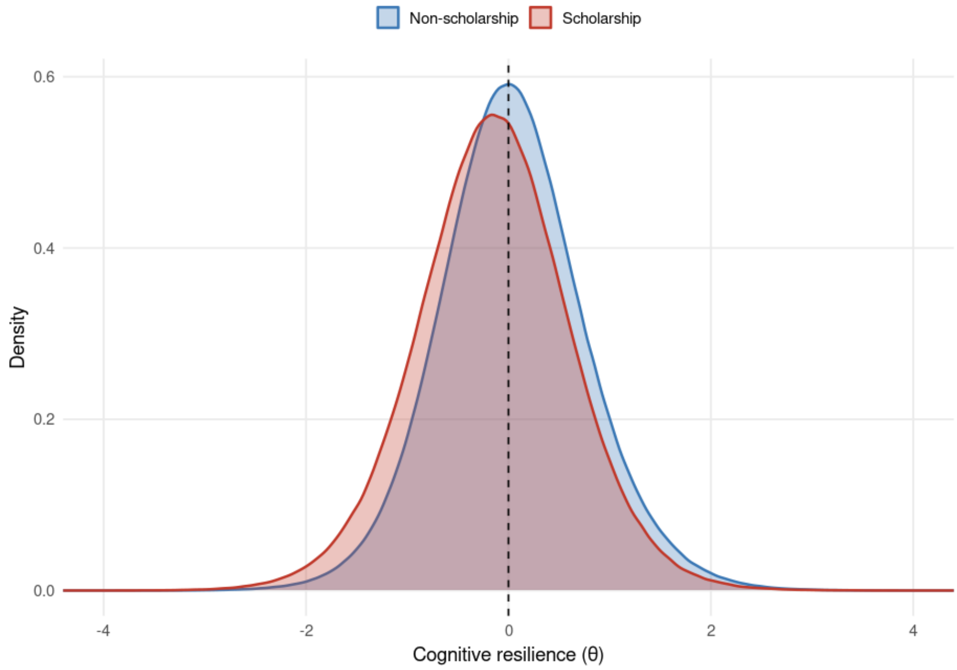
Notes: Average annual PM2.5 concentration (µg/m³) at school municipality. "Disadv." = disadvantaged socioeconomic status; "Scholar." = scholarship recipient.

Figure A1: Distribution of θ across students



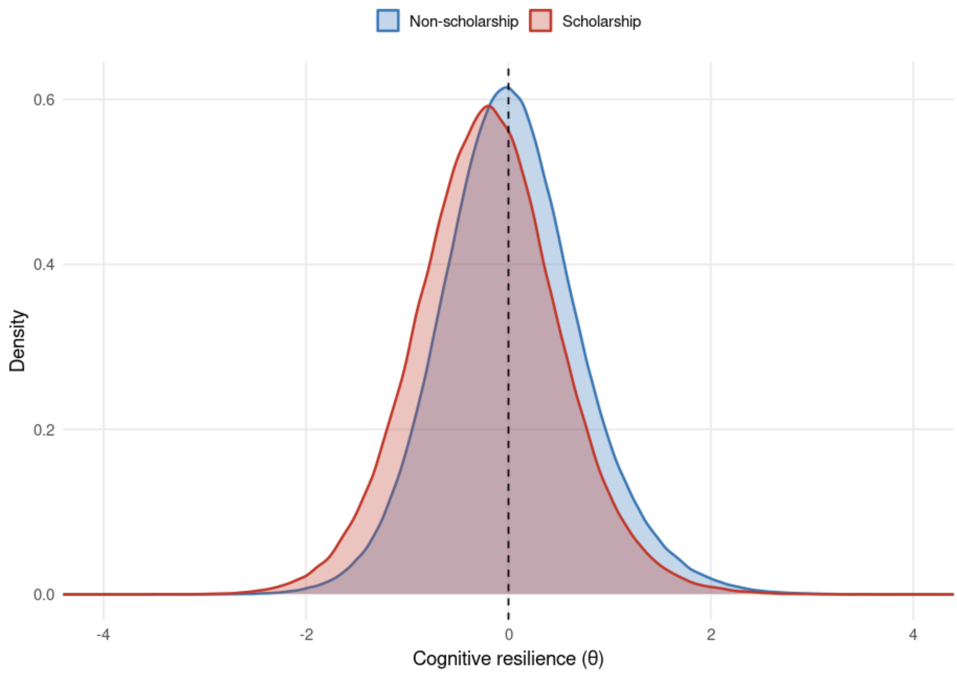
Notes: The figures display the distribution of θ (exam resilience). Panel (a) shows the 9th grade sample (DNB); panel (b) shows the 12th grade sample (Baccalauréat).

Figure A2: Distribution of Cognitive Resilience (θ) by Scholarship Status: 9th Grade



Note: This figure plots kernel density estimates of the distribution of cognitive resilience (θ) separately for scholarship and non-scholarship students in 9th grade.

Figure A3: Distribution of Cognitive Resilience (θ) by Scholarship Status: 12th Grade



Note: This figure plots kernel density estimates of the distribution of cognitive resilience (θ) separately for scholarship and non-scholarship students in 12th grade.

Appendix B Robustness Checks and Additional Results

Table B1: Robustness Checks: Effects of $PM_{2.5}$ on Student Performance (End of Middle School Exams)

	IV				OLS
	$PM_{2.5} > 15$	$PM_{2.5} > 10$	Continuous	Residence	$PM_{2.5} > 15$
	(1)	(2)	(3)	(4)	(5)
All Students					
N=11,703,685	-0.0135	-0.0092*	-0.0012	-0.0091	-0.0058
	(0.0097)	(0.0050)	(0.0010)	(0.0095)	(0.0042)
Scholarship Students					
N=2,371,171	-0.0474***	-0.0157**	-0.0014	-0.0448***	-0.0228***
	(0.0124)	(0.0076)	(0.0014)	(0.0122)	(0.0072)
Non-Scholarship Students					
N=9,332,514	-0.0060	-0.0083*	-0.0014	-0.0010	-0.0012
	(0.0100)	(0.0050)	(0.0010)	(0.0098)	(0.0040)
Disadvantaged					
N=3,434,794	-0.0414***	-0.0119*	-0.0014	-0.0380***	-0.0161***
	(0.0113)	(0.0067)	(0.0013)	(0.0110)	(0.0058)
Other background					
N=7,966,589	-0.0025	-0.0085	-0.0014	0.0020	-0.0011
	(0.0104)	(0.0052)	(0.0011)	(0.0102)	(0.0042)
Fixed-effects and controls					
Student (FE)	Yes	Yes	Yes	Yes	Yes
Year (FE)	Yes	Yes	Yes	Yes	Yes
Subject (FE)	Yes	Yes	Yes	Yes	Yes
Weather Controls	Flexible	Yes	Yes	Yes	Yes

Note: This table assesses the robustness of the main estimates. The dependent variable is the standardized Brevet exam score. Each panel corresponds to a separate regression for the indicated subgroup. "Disadvantaged" refers to students from disadvantaged socio-economic backgrounds; "Other background" refers to students from other socio-economic backgrounds. Column (1) reports IV estimates using a binary indicator for $PM_{2.5} > 15\,\mu g/m^3$ (WHO threshold) with flexible weather controls (temperature, humidity, rainfall, and their pairwise interactions). Column (2) uses a lower threshold ($PM_{2.5} > 10\,\mu g/m^3$). Column (3) uses continuous $PM_{2.5}$ exposure (in $\mu g/m^3$). Column (4) reports IV estimates using pollution exposure measured in the municipality of residence rather than the municipality of school. Column (5) reports OLS estimates using the binary $PM_{2.5} > 15\,\mu g/m^3$ variable. The N reported in the row headers corresponds to the sample used in Column (1); sample sizes differ slightly across specifications because of data availability. All regressions include student, year, and subject fixed effects. Standard errors clustered at the municipality-of-school level are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table B2: Robustness Checks: Effects of $PM_{2.5}$ on Student Performance (End of High School Exams)

	IV				OLS
	$PM_{2.5} > 15$	$PM_{2.5} > 10$	Continuous	Residence	$PM_{2.5} > 15$
	(1)	(2)	(3)	(4)	(5)
All Students					
N=3,462,332	-0.0231	-0.0350**	-0.0038*	-0.0138	-0.0277***
	(0.0221)	(0.0144)	(0.0020)	(0.0231)	(0.0102)
Scholarship Students					
N=468,180	-0.0686***	-0.0536***	-0.0071***	-0.0652***	-0.0412***
	(0.0196)	(0.0167)	(0.0023)	(0.0215)	(0.0123)
Non-Scholarship Students					
N=2,994,152	-0.0137	-0.0314**	-0.0031	-0.0031	-0.0249**
	(0.0239)	(0.0150)	(0.0021)	(0.0247)	(0.0107)
Disadvantaged					
N=622,986	-0.0684***	-0.0429**	-0.0060**	-0.0650**	-0.0441***
	(0.0258)	(0.0168)	(0.0025)	(0.0290)	(0.0144)
Other background					
N=2,780,165	-0.0118	-0.0324**	-0.0030	-0.0014	-0.0240**
	(0.0232)	(0.0154)	(0.0020)	(0.0235)	(0.0103)
Fixed-effects and controls					
Student (FE)	Yes	Yes	Yes	Yes	Yes
Year (FE)	Yes	Yes	Yes	Yes	Yes
Subject (FE)	Yes	Yes	Yes	Yes	Yes
Track (FE)	Yes	Yes	Yes	Yes	Yes
Weather Controls	Flexible	Yes	Yes	Yes	Yes

Note: This table assesses the robustness of the main estimates. The dependent variable is the standardized *Baccalauréat* exam score. Each panel corresponds to a separate regression for the indicated subgroup. "Disadvantaged" refers to students from disadvantaged socio-economic backgrounds; "Other background" refers to students from other socio-economic backgrounds. Column (1) reports IV estimates using a binary indicator for $PM_{2.5} > 15\,\mu g/m^3$ (WHO threshold) with flexible weather controls (temperature, humidity, rainfall, and their pairwise interactions). Column (2) uses a lower threshold ($PM_{2.5} > 10\,\mu g/m^3$). Column (3) uses continuous $PM_{2.5}$ exposure (in $\mu g/m^3$). Column (4) reports IV estimates using pollution exposure measured in the municipality of residence rather than the municipality of school. Column (5) reports OLS estimates using the binary $PM_{2.5} > 15\,\mu g/m^3$ variable. The N reported in the row headers corresponds to the sample used in Column (1); sample sizes differ slightly across specifications because of data availability. All regressions include student, year, subject, and academic track fixed effects. Standard errors clustered at the municipality-of-school level are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table B3: Effects of NO_2 on Student Performance: End-of-middle School Exams

	IV (1)
All Students (N=11,703,685)	
$NO_2 > 25 \mu g/m^3$	0.0092
	(0.0106)
Scholarship Students (N=2,371,171)	
$NO_2 > 25 \mu g/m^3$	0.0089
	(0.0174)
Non-Scholarship Students (N=9,332,514)	
$NO_2 > 25 \mu g/m^3$	0.0086
	(0.0118)
Disadvantaged socio-economic background (N=3,434,794)	
$NO_2 > 25 \mu g/m^3$	0.0126
	(0.0154)
Other socio-economic background (N=7,966,589)	
$NO_2 > 25 \mu g/m^3$	0.0049
	(0.0122)
Student Fixed Effects	Yes
Year Fixed Effects	Yes
Subject Fixed Effects	Yes
Weather Controls	Yes

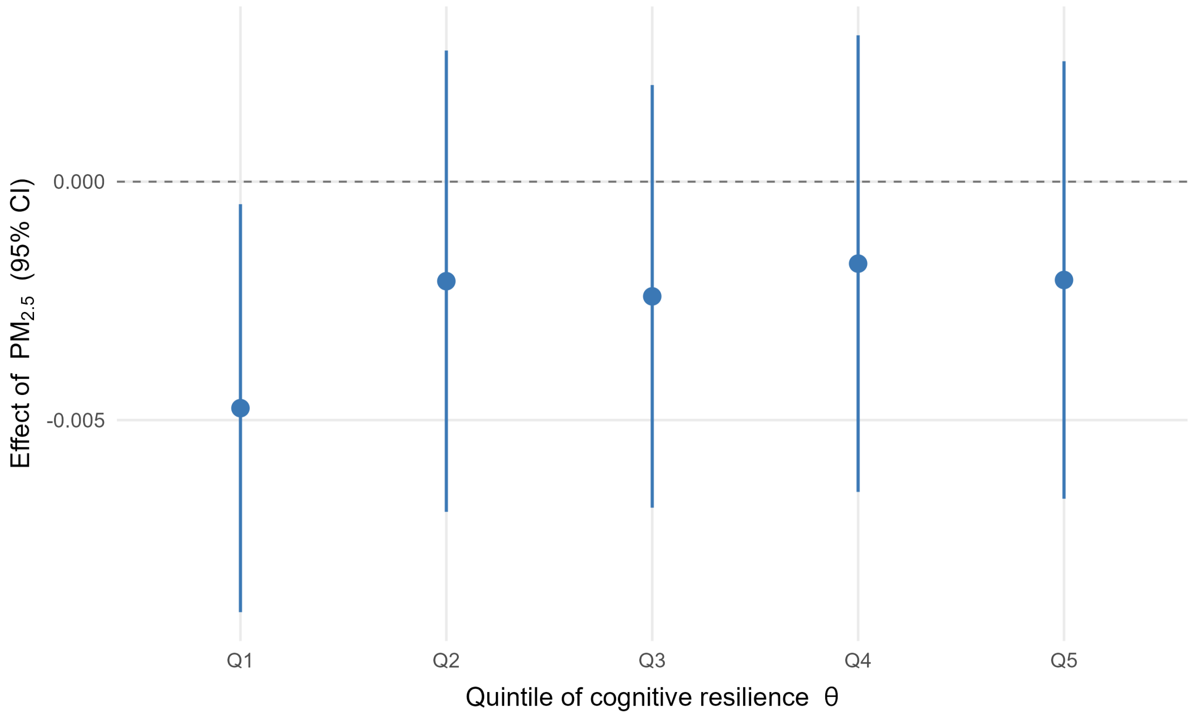
Note: This table reports IV estimates of the effect of NO_2 on student performance in end-of-middle school examinations. The key regressor is a binary indicator equal to one if daily NO_2 concentration exceeds the 2021 WHO daily guideline (25 $\mu g/m^3$). Each row corresponds to a separate regression. Standard errors, clustered at the municipality of school level, are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table B4: Effects of NO_2 on Student Performance: End-of-high School Exams

	IV (1)
All Students (N=3,462,332)	
$NO_2 > 25\mu g/m^3$	-0.0417*
	(0.0229)
Scholarship Students (N=468,180)	
$NO_2 > 25\mu g/m^3$	-0.1089***
	(0.0329)
Non-Scholarship Students (N=2,994,152)	
$NO_2 > 25\mu g/m^3$	-0.0295
	(0.0193)
Disadvantaged socio-economic background (N=622,986)	
$NO_2 > 25\mu g/m^3$	-0.1199***
	(0.0382)
Other socio-economic background (N=2,780,165)	
$NO_2 > 25\mu g/m^3$	-0.0333*
	(0.0175)
Student Fixed Effects	Yes
Year Fixed Effects	Yes
Subject Fixed Effects	Yes
Academic Track Fixed Effects	Yes
Weather Controls	Yes

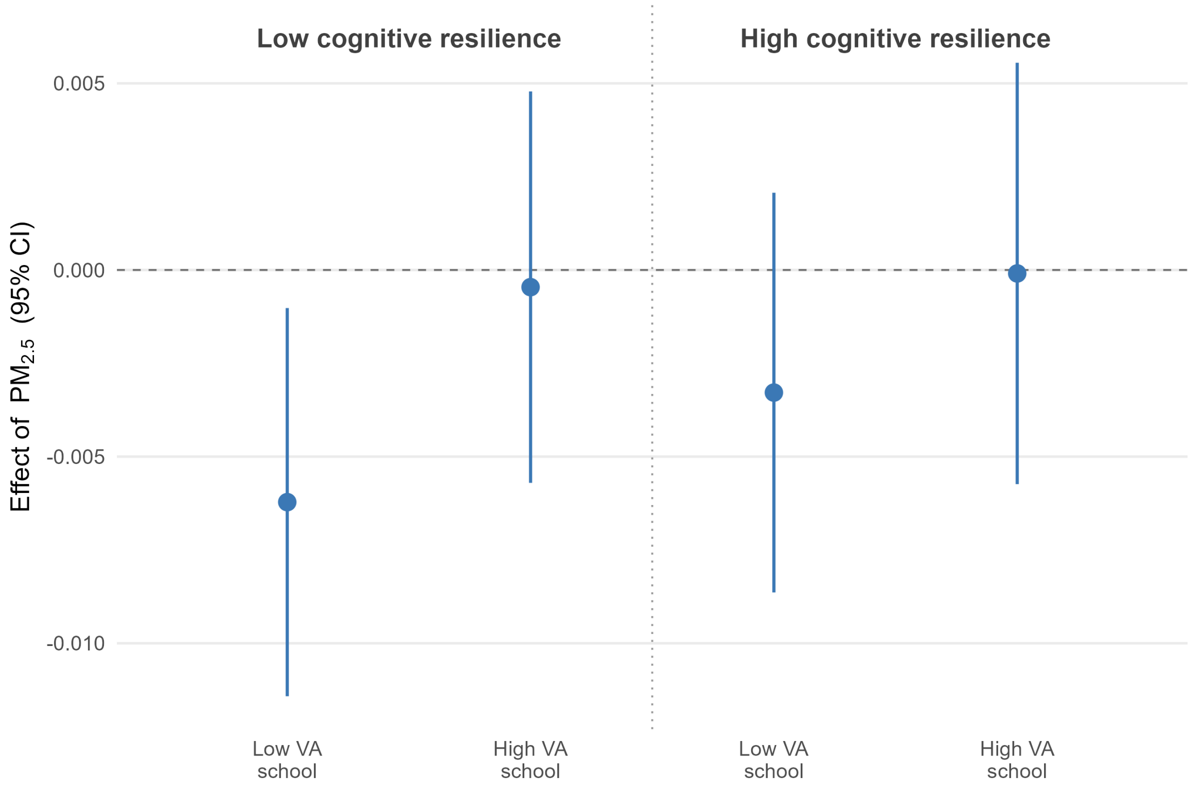
Note: This table reports IV estimates of the effect of NO_2 on student performance in end-of-high school examinations. The key regressor is a binary indicator equal to one if daily NO_2 concentration exceeds the 2021 WHO daily guideline (25 $\mu g/m^3$). Each row corresponds to a separate regression. Standard errors, clustered at the municipality of school level, are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Figure B1: Effect of continuous $PM_{2.5}$ on Bac performance by quintile of cognitive resilience (θ)



Note: The figure reports point estimates and 95% confidence intervals of the effect of a one μg/m^3 increase in $PM_{2.5}$ on standardized Bac score, estimated separately within quintiles of cognitive resilience θ_i. Q_1 contains students with low cognitive resilience; Q_5 with high cognitive resilience. θ_i is measured at the DNB (three years before the Bac) as the difference between standardized exam scores and continuous assessment standardized within class $\times$ year cells. Standard errors are clustered at the municipality-of-school level.

Figure B2: Effect of continuous $PM_{2.5}$ on *Baccalauréat* Performance by Cognitive Resilience (θ) and High School Value-Added



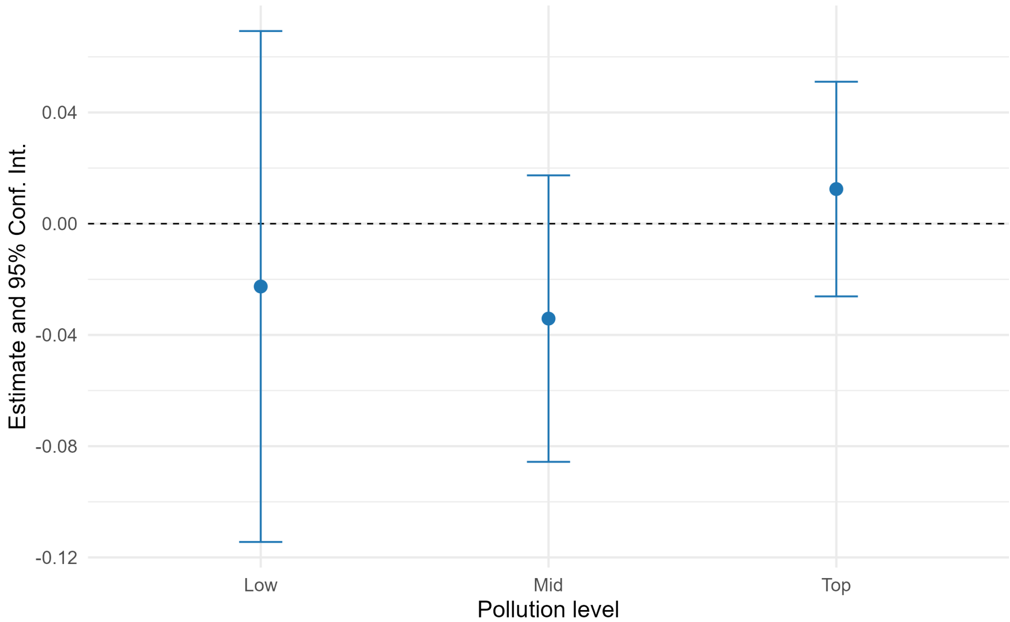
Note: The figure reports point estimates and 95% confidence intervals of the effect of a one μg/m^3 increase in $PM_{2.5}$ on standardized *Baccalauréat* scores, estimated separately within groups defined by cognitive resilience (θ_i) and school value-added (VA). Left panel: low cognitive resilience students ($\theta_i < 0$); right panel: high cognitive resilience students ($\theta_i \geq 0$). Within each panel, estimates are shown for students in low VA schools (VA < 0) and high VA schools (VA ≥ 0). VA is the value-added on the *mention* rate, computed by the French Ministry of Education for each school $\times$ track. Standard errors are clustered at the municipality-of-school level.

Table B5: Effect of $PM_{2.5} > 15$ on Bac performance by quintile of cognitive resilience (θ): OLS estimates

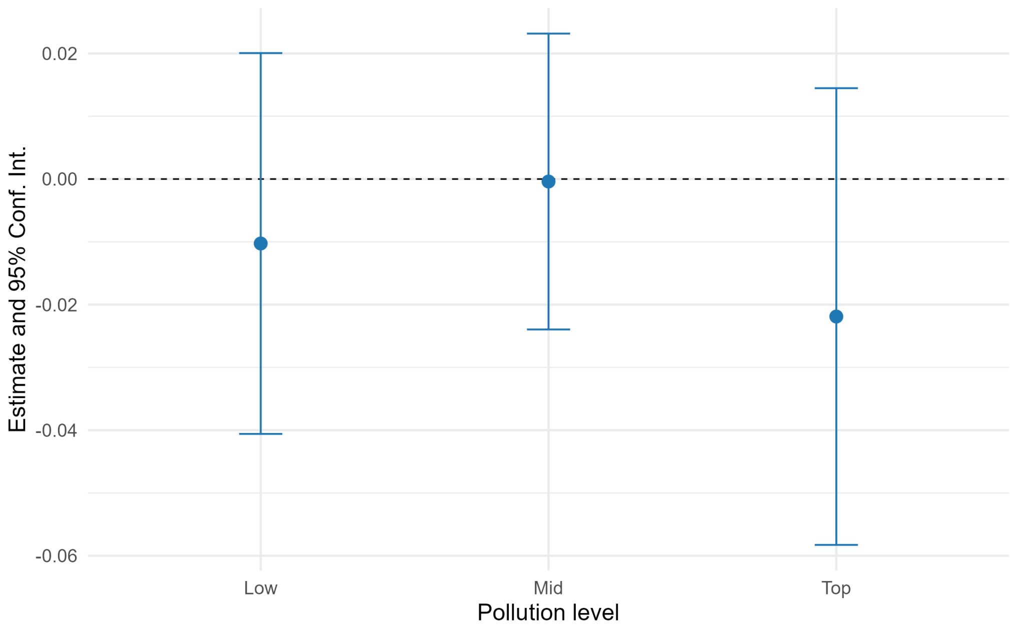
	Q_1 (Low θ)	Q_2	Q_3	Q_4	Q_5 (High θ)
$PM_{2.5} > 15$	-0.0540^{***}	-0.0302^{**}	-0.0203^{*}	-0.0213^{**}	-0.0139
	(0.0152)	(0.0123)	(0.0105)	(0.0108)	(0.0116)
Observations	693,560	750,618	747,691	721,395	669,461
Mean θ	-0.97	-0.38	-0.01	0.36	1.03
% Disadvantaged SES	27.7	20.9	17.8	15.3	11.9

Note: This table reports OLS estimates of the effect of $PM_{2.5} > 15$ (daily concentration above 15 $\mu g/m^3$) on standardized *Baccalauréat* scores, estimated separately by quintile of cognitive resilience (θ). Cognitive resilience is measured in 9th grade as the difference between standardized DNB exam scores and continuous assessment grades. Q_1 denotes the least resilient students and Q_5 the most resilient. "% Disadvantaged SES" reports the share of disadvantaged students in each quintile. All regressions include student, year, subject, and track fixed effects as well as weather controls. Standard errors clustered at the municipality-of-school level are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure B3: Effects of $PM_{2.5}$ on End-of-Secondary Exams by School-Level Pollution



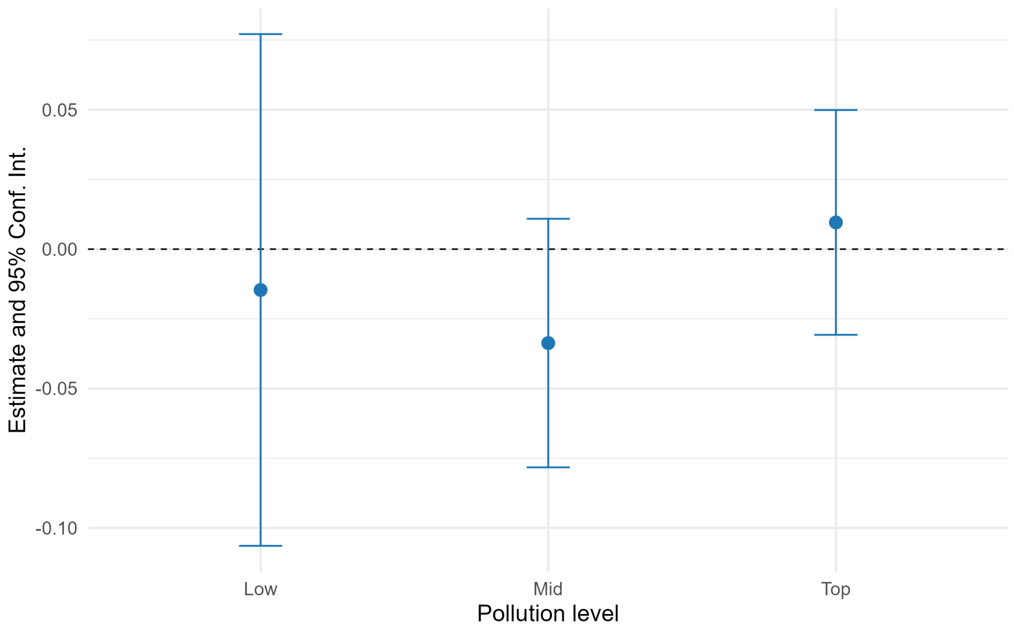
(a) Baccalauréat — All students



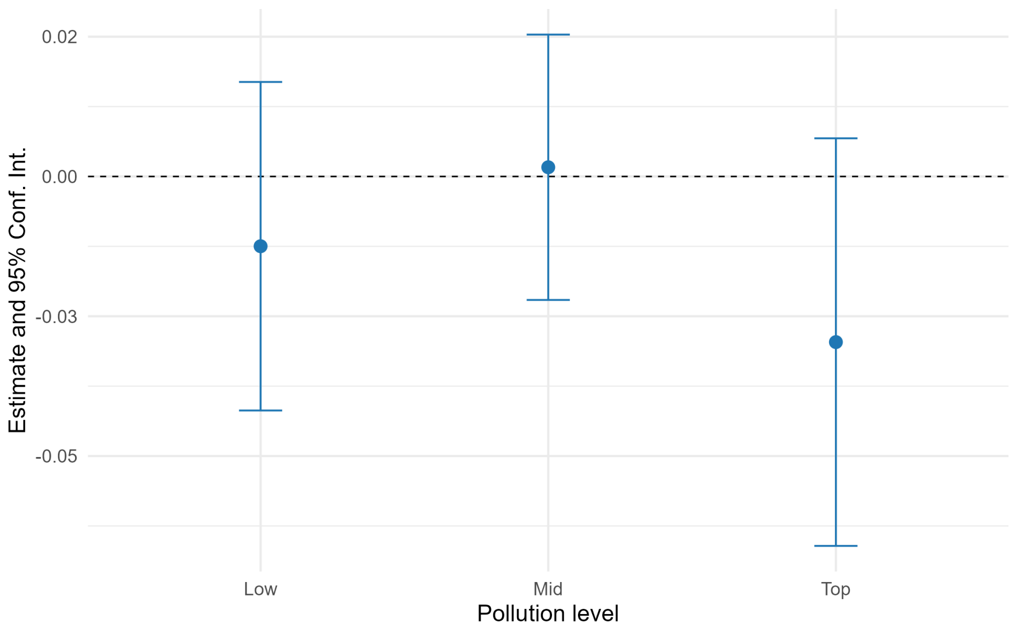
(b) Brevet — All students

Note: This figure reports estimates of the effect of $PM_{2.5} > 15\,\mu g/m^3$ on standardized exam scores, by school-level long-run pollution: bottom 25% (Low), middle 50% (Mid), and top 25% (High) of the school-level $PM_{2.5}$ distribution. Each coefficient comes from a separate regression for the group indicated. Panel (a) reports results for the Baccalauréat; Panel (b) reports results for the Brevet. Vertical bars represent 95% confidence intervals. Standard errors are clustered at the municipality of school level.

Figure B4: Effects of $PM_{2.5}$ on End-of-Secondary Exams by Pollution at the Municipality of Residence



(a) Baccalauréat — All students



(b) Brevet — All students

Note: This figure reports estimates of the effect of $PM_{2.5} > 15\,\mu g/m^3$ on standardized exam scores, by long-run pollution in the municipality of residence: bottom 25% (Low), middle 50% (Mid), and top 25% (High) of the municipality-of-residence $PM_{2.5}$ distribution. Each coefficient comes from a separate regression for the group indicated. Panel (a) reports results for the Baccalauréat; Panel (b) reports results for the Brevet. Vertical bars represent 95% confidence intervals. Standard errors are clustered at the municipality of residence level.

Table B6: Effect of $PM_{2.5}$ on Bac performance by quintile of cognitive resilience (θ): Robustness to standardizing $\bar{Z}_i^{\text{CA}}$ within school $\times$ year cells

	Q_1	Q_2	Q_3	Q_4	Q_5
$PM_{2.5} > 15$	-0.0467^{*}	-0.0291	0.0055	0.0075	0.0040
	(0.0253)	(0.0262)	(0.0306)	(0.0238)	(0.0226)
Observations	676,582	703,049	673,563	622,347	523,837

Note: This table replicates Table 4 under an alternative construction of cognitive resilience θ_i. The only change is the reference cell used to standardize continuous assessment grades: the z-score is computed within *school* $\times$ year cells, instead of *class* $\times$ year cells in the baseline; the sample of exams is otherwise identical. Recomputed θ_i correlates at 0.87 with the baseline measure. The dependent variable is the standardized Bac score; the regressor is a binary indicator $PM_{2.5} > 15$ (daily concentration above 15 $\mu g/m^3$), estimated separately within quintiles of θ_i measured at the DNB. Standard errors clustered at the municipality-of-school level are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table B7: Effect of $PM_{2.5}$ on *Baccalauréat* Performance by Cognitive Resilience (θ) and High School Value-Added: OLS estimates

	Low cognitive resilience		High cognitive resilience	
	Low VA	High VA	Low VA	High VA
$PM_{2.5} > 15$	-0.0494^{***}	-0.0271	-0.0148	-0.0173
	(0.0127)	(0.0169)	(0.0127)	(0.0123)
Observations	1,073,709	763,805	974,741	748,637
% Disadvantaged SES	22.3	23.6	14.7	13.7

Note: This table reports OLS estimates of the effect of $PM_{2.5} > 15$ (daily concentration above 15 $\mu g/m^3$) on standardized *Baccalauréat* scores. Students are classified according to whether their cognitive resilience (θ) and the value-added of the high school they attend are above or below to 0. "% Disadvantaged SES" reports the share of disadvantaged students in each subgroup. All regressions include student, year, subject, and track fixed effects as well as weather controls. Standard errors clustered at the municipality-of-school level are reported in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table B8: Effect of $PM_{2.5}$ by Cognitive Resilience (θ) and School Value-Added: Robustness to standardizing $\bar{Z}_i^{\mathrm{CA}}$ within school $\times$ year cells

	$\theta < 0$		$\theta \geq 0$	
	Low VA	High VA	Low VA	High VA
$PM_{2.5} > 15$	-0.0695^{**}	0.0156	-0.0121	0.0259
	(0.0306)	(0.0258)	(0.0300)	(0.0268)
Observations	1,048,061	722,269	811,488	598,766

Note: This table replicates Table 5 under an alternative construction of θ_i, where continuous assessment grades are standardized within *school* $\times$ year cells instead of *class* $\times$ year cells; the sample is otherwise identical. The dependent variable is the standardized Bac score; the regressor is a binary indicator $PM_{2.5} > 15$. Standard errors clustered at the municipality-of-school level are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

B1 Many-Instrument Bias

A well-known concern with many-instrument designs is that the 2SLS estimator may be biased toward the OLS estimate (Bound et al., 1995), and that this bias worsens as the number of instruments increases relative to the strength of the first stage (Bekker, 1994). By contrast, the LIML estimator does not suffer from this bias (Bekker, 1994; Anderson et al., 2010), making it a diagnostic. In our setting, the ratio of excluded instruments to observations is extremely small—approximately $380/465{,}000 \approx 0.0008$ for the smallest Baccalauréat subsamples—suggesting that many-instrument bias should be negligible *a priori*. We nevertheless assess this formally using two complementary approaches.

LIML estimation We re-estimate our main IV specifications using the Limited Information Maximum Likelihood (LIML) estimator. Results are reported alongside the main 2SLS estimates in Table B9. Across all specifications, LIML and 2SLS estimates are virtually identical. For scholarship students at the Bac, the LIML coefficient is -0.0668 (s.e. 0.0211), compared to -0.0665 (s.e. 0.0205) for 2SLS. The same convergence holds for students from disadvantaged backgrounds (-0.0627 vs. -0.0624), for the most exam-sensitive quintile of θ (-0.0580 vs. -0.0581), and for exam-sensitive students in low value-added schools (-0.0695 vs. -0.0692). Differences are negligible across all subgroups. The same pattern holds for the end-of-middle school exam: the LIML estimate for scholarship students is -0.0455 (s.e. 0.0125), compared to -0.0453 (s.e. 0.0124) for 2SLS, and -0.0390 (s.e. 0.0113) vs. -0.0389 (s.e. 0.0112) for disadvantaged students.

Parsimonious instrument set As a complementary check, we replicate our main IV estimates using a more parsimonious instrument set that interacts wind direction with 13 administrative regions (instead of 95 *départements*) and wind speed, reducing the number of instruments to approximately 50. Point estimates remain stable in sign and magnitude across both instrument sets. For the Bac, the parsimonious estimate for scholarship students is -0.0494 ($p < 0.10$), compared to -0.0665 ($p < 0.01$) in the main specification; for disadvantaged students, it is -0.0547 ($p < 0.10$) vs. -0.0624 ($p < 0.05$). For the Brevet, parsimonious estimates are -0.0501 ($p < 0.01$) and -0.0447 ($p < 0.01$) for scholarship and disadvantaged students, respectively. The analysis by quintile of θ yields a consistent pattern: the point estimate for the most exam-sensitive students (Q_1) is -0.041 with the parsimonious set, compared to -0.058 in the main specification, while estimates for Q_2 through Q_5 remain close to zero. Similarly, the coefficient for exam-sensitive students in low VA schools is -0.058 ($p < 0.10$), compared to -0.069 ($p < 0.05$) in the main specification, while all other groups show point estimates close to zero. The attenuation in precision is expected: with fewer interactions, the instrument captures less of the spatial heterogeneity in how wind direction affects local pollution, resulting in a weaker first stage and larger standard errors.

Taken together, the near-identical LIML and 2SLS estimates confirm that many-instrument bias is negligible in our setting. The stability of point estimates across both instrument sets further supports the robustness of our main conclusions.

Table B9: Robustness to Many-Instrument Bias

	Main 2SLS (∼380 instr.)		LIML (∼380 instr.)		Parsimonious 2SLS (∼50 instr.)	
	Coef.	(SE)	Coef.	(SE)	Coef.	(SE)
Panel A: End-of-middle school (DNB)						
Scholarship	-0.0453^{***}	(0.0124)	-0.0455^{***}	(0.0125)	-0.0501^{***}	(0.0163)
Disadvantaged	-0.0389^{***}	(0.0112)	-0.0390^{***}	(0.0113)	-0.0447^{***}	(0.0147)
Panel B: End-of-high school (Baccalauréat)						
Scholarship	-0.0665^{***}	(0.0205)	-0.0668^{***}	(0.0211)	-0.0494^{*}	(0.0296)
Disadvantaged	-0.0624^{**}	(0.0279)	-0.0627^{**}	(0.0287)	-0.0547^{*}	(0.0298)
Panel C: Baccalauréat by quintile of cognitive resilience (θ)						
Q_1 (Exam-sensitive)	-0.0581^{**}	(0.0254)	-0.0580^{**}	(0.0260)	-0.0407	(0.0272)
Q_2	-0.0088	(0.0269)	-0.0084	(0.0275)	0.0038	(0.0298)
Q_3	0.0001	(0.0249)	0.0003	(0.0254)	0.0118	(0.0285)
Q_4	-0.0067	(0.0231)	-0.0064	(0.0236)	-0.0043	(0.0283)
Q_5 (Exam-resilient)	0.0096	(0.0211)	0.0100	(0.0216)	0.0062	(0.0323)
Panel D: Baccalauréat by θ × school value-added						
Exam-sens. / Low VA	-0.0692^{**}	(0.0320)	-0.0695^{**}	(0.0329)	-0.0581^{*}	(0.0313)
Exam-sens. / High VA	0.0194	(0.0250)	0.0208	(0.0258)	0.0396	(0.0365)
Exam-resil. / Low VA	-0.0162	(0.0287)	-0.0162	(0.0295)	-0.0253	(0.0337)
Exam-resil. / High VA	0.0215	(0.0267)	0.0225	(0.0276)	0.0260	(0.0425)
Student Fixed Effects	Yes		Yes		Yes	
Year Fixed Effects	Yes		Yes		Yes	
Subject Fixed Effects	Yes		Yes		Yes	
Track Fixed Effects	Yes (Bac)		Yes (Bac)		Yes (Bac)	
Weather Controls	Yes		Yes		Yes	

Note: This table assesses the sensitivity of the main IV results to many-instrument bias. All regressions use a binary indicator for $PM_{2.5} > 15$ $\mu g/m^3$ as the key regressor. The first two columns report two-stage least squares (2SLS) estimates from the main specification, which interacts four wind direction dummies with 95 *département* indicators and wind speed (∼380 excluded instruments). The next two columns report Limited Information Maximum Likelihood (LIML) estimates using the same instrument set. The last two columns report 2SLS estimates using a parsimonious instrument set replacing *départements* with 13 administrative regions (∼50 instruments). Each row corresponds to a separate regression. Standard errors clustered at the municipality-of-school level are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Appendix C Examination details

The *Diplôme National du Brevet* (DNB) is taken by 9th grade students in late June and marks the completion of middle school. It comprises three national subject tests: Mathematics, French language, and History–Geography. The mathematics exam consists of a series of problem-solving questions. The French language exam is divided into two parts—reading comprehension and writing exercises—each allotted the same amount of time. The history–geography exam combines factual questions with the analysis of historical and geographical documents. All DNB exams are graded out of 40 points. The content is set annually at the national level. In most years, the mathematics and French language tests are held on the same day (Thursday), followed by the history–geography test on the next day (Friday). The DNB has no make-up session. The final DNB grade combines the scores on the national written exams with continuous assessment grades awarded by teachers throughout the school year.

The *Baccalauréat* (Bac) examinations take place in June at the end of upper secondary education. This study focuses on the three academic tracks: **L** (Literary), **S** (Scientific), and **ES** (Economics & Social Sciences). While each track has its own set of subjects and weighting coefficients, three subjects are common to all: Philosophy, History–Geography, and Mathematics. We exclude Mathematics for the L track, where it is optional and taken by only a small minority of students, and we include History–Geography for the S track only from 2015 onwards, since in earlier years it was taken one year prior to the final examination. The Bac examinations generally extend over three days. Students who fail the written session may sit oral make-up exams (*épreuves de rattrapage*) held approximately two weeks later; we retain only scores from the main June session.