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Poor air quality at school and educational inequality by family socioeconomic status in Italy

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ABSTRACT

This paper investigates social stratification in the context of poor air quality's impact on educational achievement in Italy, a country characterized by high levels of air pollution and significant geographical diversity. We address two primary questions: firstly, whether students from different socio-economic backgrounds vary in their exposure to high levels of particulate matter (PM2.5) at school, and secondly, if the effect of exposure to poor air quality on academic performance differs between children from high and low socio-economic status families. Utilizing a novel dataset comprising test scores in math and reading for 456,508 8th-grade students, collected nationally in Italy in 2019, we geocode the locations of 6882 schools based on their addresses and link the level of air pollution in the surrounding areas using PM2.5 data from the Atmospheric Composition Analysis Group. To address potential confounding factors, we estimate municipality and province fixed effects and control for indicators of school neighborhood characteristics and school quality. Our analysis yields three key findings. Firstly, students from higher socio-economic backgrounds tend to attend schools with higher PM2.5 levels. However, the positive association between SES and exposure to PM2.5 disappears when adding province and municipality fixed effects, suggesting that the positive association can be explained by selection into provinces and municipalities by SES. Secondly, we identify a small yet consistent negative effect of PM2.5 on math and reading test scores. Thirdly, this adverse impact is primarily observed among students from low socio-economic backgrounds. We conclude that the relationship between environmental risks and disparities in educational achievement based on social background in Italy is nuanced and critically influenced by the country's specific context.

1. Introduction

The quality of air surrounding schools is paramount as children spend extensive hours in these environments, where outdoor-origin pollutants, such as fine particulate matter (PM2.5), infiltrate and persist indoors (Chen & Zhao, 2011; Jones et al., 2000; Pallarés et al., 2019). Elevated pollution levels within school premises can detrimentally impact students' ability to focus and maintain attention, consequently affecting learning outcomes during instructional hours (Gignac et al., 2021) and performance in standardized tests (Amanzadeh et al., 2020). Furthermore, poor air quality exerts a negative influence on children's health and attendance (Currie et al., 2009; König & Heisig, 2023), potentially disrupting their educational trajectories throughout the academic term. Indeed, prior research indicates a deleterious effect of exposure to inadequate air quality at schools on children's educational attainment (Amanzadeh et al., 2020; Currie, 2013; Requia et al., 2022; Stenson et al., 2021).

The environmental justice literature extensively examines the intersection of socioeconomic inequalities and environmental risks (Mohai et al., 2009; Muller et al., 2018). Specifically, ethnic and racial minorities have consistently been identified as facing the highest exposure to major sources of environmental pollution across various contexts (Grineski & Collins, 2018; Rüttenauer, 2018). However, findings regarding socioeconomic status (SES) disparities in air pollution exposure are more nuanced, particularly within European contexts, prompting the need for further investigation (Mohai et al., 2009; Hajat, Hsia & O'Neill, 2015). Actually, the relationship between SES and air pollution in Europe has been found to be non-linear or even negative in certain regions. Moreover, there is limited research available on whether the consequences of exposure to air pollution differ among socioeconomic groups, particularly concerning parental SES.

Building upon insights from research on public health and

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environmental inequalities, this paper examines the potential negative impact of exposure to poor air quality at school on academic achievement. Furthermore, we explore whether this negative effect of poor air quality contributes to educational disparities associated with parental SES. Specifically, we investigate disparities in exposure to poor air quality at school based on parental SES and differences in the academic consequences of such exposure, also considering parental SES.

We prioritize the examination of exposure to poor air quality at school due to its significance as a pertinent environmental risk factor, considering that children spend a substantial portion of their daily hours in this environment. Additionally, in Italy, especially in urban areas, a significant proportion of children reside in close proximity, about 1.2 km based on a recent study, to the schools they attend (Mantovani et al., 2022). Therefore, our indicator of poor air quality at school is also likely to encompass exposure to poor air quality at home.

Our analysis utilizes a unique dataset containing math and reading test scores from a national evaluation conducted in 2019 among all 8th-grade Italian students. Italy, categorized as a high-income country, faces one of the highest levels of air pollution among OECD nations (OECD, 2023). We examine data from 456,508 students across 6882 schools. School locations are geocoded based on addresses, and we link air pollution levels in the surrounding areas using fine-grained measures of particulate matter with a diameter of 2.5 micrometers or smaller (PM2.5), obtained from the Atmospheric Composition Analysis Group (ACAG) (Hammer et al., 2020).

We start our investigation by examining disparities in exposure to air pollution at school based on parental SES. This initial analysis is descriptive, aiming to determine whether high and low SES students attend schools with differing levels of air pollution. Subsequently, we investigate the potential adverse effects of air pollution exposure at school on academic achievement, while also exploring whether these effects vary according to parental SES. The critical issue we must address in this second analysis is the potential bias arising from parents' selection of schools with different levels of pollution. In Italy, the selection of schools is closely linked to the choice of residential neighborhood, as most children attend schools in the vicinity of their homes. We will discuss the patterns of residential segregation and the admission rules of schools in Italy below. Methodologically, we employ two approaches to address endogeneity concerns inherent in the relationship between exposure to poor air quality at school and academic achievement. Firstly, we employ province and municipality fixed effects and capitalize on variations in air quality within these subnational geographic units. By incorporating province and municipality fixed effects, we control for sorting by SES across provinces and municipalities. Importantly, we know from previous studies that the most polluted areas in the northern region often overlap with affluent regions, where students also tend to demonstrate higher academic performance, on average (Conte Keivabu, 2023; Martini, 2010). Additionally, within provinces and municipalities air quality at schools may be correlated with various factors, including the quality of neighborhood and school quality, which can influence test score results. Critically the quality of the neighborhood might drive parental residential choices and, therefore, selection into certain schools. To address the non-random selection into schools based on factors that might be correlated with air quality and school achievement, we incorporate indicators of neighborhood and school characteristics into our analysis.

We contribute to the existing literature on environmental inequality by foregrounding the study of SES heterogeneities in the adverse consequences of exposure to poor air quality on educational achievement. Simultaneously, we add to social stratification research by demonstrating how environmental risk factors can exacerbate SES inequalities. This represents a relatively novel area of inquiry, with most findings originating from studies in the United States (US) (Wodtke et al., 2022; Manduca & Sampson, 2021). Consequently, our study extends this literature by providing evidence from an EU country, where patterns of residential and educational segregation concerning exposure to air pollutants differ from those observed in the US.

In the subsequent sections of the article, we first delve into the background literature and various explanations regarding whether and how exposure to PM2.5 can impact educational achievement. We differentiate between explanations for differences in exposure to air pollution and difference in the effects of exposure based on parental SES. We then present the data and methods used in the empirical analyses and our main findings. Finally, we discuss our results and provide some concluding remarks.

2. Air pollution, educational achievement and inequality: theoretical framework

Rich academic evidence exists on the negative effect of air pollution on children's educational achievement (Amanzadeh et al., 2020; Grineski, Heissel et al., 2020, 2020; Mullen et al., 2020; Persico & Venator, 2019; Stenson et al., 2021). The existing studies relate the impact of air quality on educational achievement to direct and indirect effects.

Direct effects of air pollution on educational achievement refer to the impact of air quality on cognitive development and performance. The dimensions of cognitive abilities affected by air pollution are manifold. For example, studies have found PM2.5 to hinder the development of working memory (Alvarez-Pedrerol et al., 2017), to determine differences in brain structure (Cserbik et al., 2020) and to reduce pattern construction (Milojevic et al., 2021). Also, students attending schools located in the proximity of industrial facilities, power plants and highways have a higher risk of neurological diseases (Kweon et al., 2018; Zhang et al., 2022).

Indirect effects of air quality on educational achievement relate to decreases in school attendance or sleep quality. Air pollution increases the severity of several respiratory diseases such as asthma (Alotaibi et al., 2019) and worsens lung functioning (Barone-Adesi et al., 2015) increasing the number of school-days lost by students (Currie et al., 2009; Marcon et al., 2014). Moreover, air pollution can have a negative impact on sleep quality reducing the cognitive performance of children (Heyes & Zhu, 2019).

In this study we ask whether these direct and indirect adverse effects of exposure to poor air quality for academic achievement documented by environmental, public health and social science studies, contribute to SES inequalities in academic achievement.[1] For the purpose of this paper we distinguish between *differences in exposure* to poor air quality by SES and *differences in the effect of exposure* on school results by parental SES. With regard to differential exposure to air pollution by SES we consider two mechanisms that are usually discussed in the literature (Mohai & Saha, 2015): selective siting and selective migration. With regard to the possible differences in the effect of exposure by parental SES we suggest two mechanisms that might account for a more detrimental effect for low SES students: differential sensitivity and differential parental responses. While we are not able test these mechanisms in our analyses, we discuss them to formulate expectations about inequalities in exposure to poor air at school and its effect on academic achievement by family SES.

2.1. Differential exposure by parental SES

Selective siting refers to the placement of polluting facilities and infrastructure in impoverished areas where low socioeconomic status (SES) families and ethnic minorities are more likely to reside due to deliberate decisions, lower real estate prices or lower political power (Mohai & Saha, 2015). Conversely, selective migration refers to the

[1] Technically this question could be reformulated in terms of whether exposure to poor air quality *mediates* inequalities in achievement by family SES and/or whether family SES *moderates* the effect of exposure to poor air quality at school, so that – for instance – socioeconomic inequalities could be larger in case of exposure to poor air at school.

deliberate relocation of high SES households based on environmental considerations or the inability of low SES households to do so or opt for neighborhoods with better environmental quality due to higher prices, which can exacerbate disparities in exposure to air pollution (Best & Rüttenauer, 2018). Numerous studies have highlighted that ethnic minorities and communities of color often inhabit areas characterized by higher levels of air pollution (Neier, 2021; Rüttenauer, 2018). However, compared to the extensive literature on racial and ethnic disparities in exposure to air pollution, findings regarding the socioeconomic gradient are less consistent. Notably, within the European context, systematic reviews have revealed mixed results regarding the relationship between SES and exposure to air pollution (Fairburn et al., 2019; Hajat, Hsia & O'Neill, 2015).

When considering exposure to air pollution at school, we would expect to observe SES differences if, for example, students from high SES families attended schools with better air quality. This scenario could occur if high SES parents select schools based on air quality or other correlated characteristics. For instance, parents might opt for schools with modern facilities situated outside urban centers, closer to green spaces, and thus, offering better air quality. In accordance with the concept of selective migration, differential exposure may also occur if high SES families residing in neighborhoods with poor air quality choose to relocate to areas with better air quality, particularly to enroll their children in schools located in those areas (Best & Rüttenauer, 2018).

2.2. Differences in the effect of exposure by parental SES

One potential mechanism underlying heterogeneity in the effect of exposure to poor air quality is differential sensitivity. Certain children may be more susceptible to the adverse effects of polluted air due to pre-existing health conditions. Notably, poor air quality poses significant risks for children with respiratory conditions such as asthma, exacerbating existing health vulnerabilities (Guarnieri & Balmes, 2014; Jans et al., 2018). Of relevance to our study, available evidence indicates that children and adolescents from low SES families are more likely to suffer from asthma and have a higher prevalence of respiratory conditions (Gong et al., 2014; Kozyrskyj et al., 2010; Kuruvilla et al., 2019; Rocha et al., 2019). In Italy, a large-scale study also found that the prevalence of chronic cough and phlegm was higher among children of low-educated parents (SIDRIA, 1997). Consequently, low SES students may be more vulnerable to the negative effects of air pollution exposure, given the higher prevalence of chronic respiratory conditions among this demographic group (Gong et al., 2014).

Heterogeneity can also come about due to differential parental responses to exposure to poor air at schools. First, high SES parents might be more aware of the importance of good air for their children's development and health and have more resources to organize their free time to enjoy less polluted environments. High SES parents can then adopt avoidance behavior once they realize the hazards of air pollution. They might, for instance, enroll their children in extra-curricular activities in areas of the city with good air quality, spend more time during weekends and holidays in green areas or avoid visiting polluted locations (Yoo, 2021). Second, if the child has an existing respiratory condition, such as asthma they might seek medical care earlier (Stingone & Claudio, 2006) and use more often medication (Gong et al., 2014). In the case of Italy, there is evidence that high SES parents make more frequent use of healthcare facilities if their children suffer from asthma (SIDRIA, 1997). In this way high SES parents can improve the health conditions of their children and mitigate the negative consequences of exposure to poor air at school. Third, parental responses can be directly oriented towards school outcomes. In situations when exposure to poor air negatively affects educational performance, either indirectly through health condition or directly impairing cognitive development, high SES parents might take extra actions to favor their children learning and performance in school. For instance, if faced with a low performance of their children at school high SES parents have the specific knowledge to help them with their homework and/or can afford to hire private tutors (Bernardi & Graetz, 2015).

3. The Italian case

In Italy, the majority of students attend public schools. In lower secondary education (corresponding to the 8th graders that we study in this article) 96 per cent of students attend public schools,[2] and there is not a clear distinction between elite schools and non-elite schools, as it is the case for instance in US and UK (Reeves et al., 2017; Rahman Khan, 2016). Priority in admission to schools in lower secondary education is given to students living in the school neighborhood. As a result, children generally attend primary and lower secondary schools in the neighborhood where they live or close by. For example, a study on the cities of Bologna and Milan showed that children live on average at about 1.2 km from the school they attend (Mantovani et al., 2022). Therefore, the quality of air at school in most cases coincides with the quality of the air of the neighborhood where the children live.

With regard to air pollution, Italy is characterized by comparatively high levels of PM2.5 in the European context, with a very strong divide between the regions in the northern and southern part of the country. The regions in the North that are the richest of the country are also those with the highest level of air pollution (Conte Keivabu, 2023). In particular, the Po Valley, in North Italy, is densely inhabited and hosts a large number of industries, agricultural activities and has a high level of vehicle traffic. Moreover, air pollution is trapped within this territory as it is surrounded by two mountain ranges, in the north the Alps and in the south the Apennines (Raffaelli et al., 2020). Consequently, PM2.5 levels are much above the threshold recommended by the WHO of 5 μg/m3 and by the US of 12 μg/m3. For example, in the cities of Bergamo and Brescia PM2.5 yearly average level was recorded at a value above 27 μg/m3 in 2015 (Khomenko et al., 2021).

With regard to factors that might account for differences in exposure to air pollution, individuals with a higher socioeconomic status (SES) tend to reside in urban areas rather than rural ones, choosing locations characterized by greater economic activity and more employment prospects for those highly qualified. The Northern regions and big cities in the South, that are the most polluted areas in the country, offer more opportunities in this respect. However, SES residential segregation within cities is lower in Europe compared to the United States (US) (Andersson et al., 2018; Friedrichs et al., 2003). In Italy, high SES families often live in city centers and close to busy roads that are the most polluted areas, as for example shown for Rome and Milan (Cesaroni et al., 2010; Tammaru et al., 2020). Consequently, in Italy the association between SES and exposure to air pollution within each city is likely to be more mixed compared to the US, due to lower levels of urban residential segregation in Italy and generally Europe compared to US.

4. Hypotheses

Given the tendency of high SES individuals to live in large cities and in regions with high demand for high qualified employment that also tend to be the most polluted areas, one can expect to find a positive association between SES and air pollution at school at the national level (Hypothesis 1a). Nevertheless, due to low levels of urban residential segregation in Italy and school regulations that favor enrolment in schools in the neighborhood of residence, one can expect to not observe any substantial differences in exposure within municipalities (Hypothesis 1b).

At the same time, the varied sensitivity to the impact of poor air quality, influenced by prior health conditions, coupled with diverse parental reactions to school absences and academic underachievement

[2] Data retrieved from: http://dati.istat.it/Index.aspx?DataSetCode=DCIS_SCUOLE.

based on parental SES, may exacerbate the adverse effects of exposure to air pollution for students with a lower SES background. While we do not test these mechanisms in this article, we can still formulate the expectation that the effect of poor air will be stronger among students of socioeconomically disadvantaged families (Hypothesis 2).

5. Data, variables and methods

5.1. Data and variables

We use administrative data provided by the Italian National Institute for the Evaluation of Education (INVALSI) for 8th graders (ending lower secondary education) for the year 2019, amounting to 456,508 students and 6882 schools.[3] We geocode the location of the schools based on their postal addresses, using data provided by the Italian Ministry of Education. We then link school-level data on the levels of air pollution and quality of the neighborhood with the INVALSI data.

Our dependent variables are test scores in math and reading. These scores are scaled to have a mean of 200 and standard deviation of about 38, with a range from 66 to 366 in the case of math, and 35 to 364 for reading. The tests are low stake as that they do not contribute the final grades. Previous studies have however shown that the results of the INVALISI tests are strongly correlated to later educational attainment (Aktaş et al., 2022). School grades have shown to be prone to teacher biases in the assessment of competences in children due to discriminatory practices on students with certain characteristics (Dian & Triventi, 2021; Rangel & Shi, 2020). Consequently, for our purpose standardized tests as the one we use are a better outcome to capture learning in relation with air pollution, as done in previous studies focusing on the effect of heat exposure on educational achievement (Park, Behrer & Goodman, 2021).

Our key independent variable is parental socioeconomic status that is measured by the Economic, Social and Cultural Status (ESCS) index provided by INVALSI. The ESCS score is computed using the same international standards used by OECD for the PISA data. It combines into a single score different measures of resources that are available to the students (e.g.: books in the household, access to the Internet, availability of quiet place for studying) and on parental characteristics (e.g.: parents' educational attainment and occupational status) (Avvisati, 2020). The index is standardized with mean 0, standard deviation equal to 1, a range from approximately minus 3 to 2.

With regard to the level of air pollution at school we use estimates of PM2.5 provided by the ACAG (Hammer et al., 2020). The ACAG provides data on PM2.5 at 1 km x 1 km resolution computed using a combination of satellite observations, in-situ monitors, and chemical transport modelling. The data has been shown to present some measurement error in the United States, leading to both overreporting and underreporting compared to local stations (Fowlie et al., 2019). However, full reliability of data from local measurement stations is not assured either (Zou, 2021) and these are not equally present in all the Italian territory. Consequently, the ACAG data appears to be the most reliable data at our disposal. Importantly, this data has been widely used in existing similar studies and shows to highly resemble the true values when compared with local monitoring stations (Hammer et al., 2020). We compute the average yearly exposure to PM 2.5 μg/m3 in each 1 km x 1 km grid and assign the value to the school that corresponds to the grid where it is located. In our analyses we use both measures with linear values in μg/m3 from minimum of about 4 μg/m3 to a maximum of about 24 μg/m3 and in quintiles (Q1: 9.5 μg/m3; Q2: 13 μg/m3; Q3: 14 μg/m3; Q4: 18 μg/m3; Q5: 22 μg/m3). Note that the World Health Organization (WHO) recently lowered the threshold value for air quality standard from PM2.5 equal to 10 μg/m3 to 5 μg/m3 (Hoffmann et al., 2021). The US standard is 12 μg/m3, while in the European Union (EU) this is much higher, equal to 25 μg/m3, although recently a proposal has been issued by the EU Commission to lower the limit to 10 μg/m3.[4] This means that the level of pollution in the areas around Italian schools is below the previous less stringent limit recommended by WHO (10 μg/m3) in only about 20 per cent of schools (first quintile) and below or just above the recommended limit in US in about 40 per cent of schools (first and second quintiles). In other words, the great majority of Italian children attend schools where air pollution exceeds the limit set by the WHO and the US government, as well as that recently proposed by the EU Commission. One should note that PM2.5 is not the only harmful pollutant that could affect achievement. For example, Nitrogen Dioxide (NO2) and Ozone (O3) have been found to affect test scores to a similar extent (Lu, Hackman & Schwartz, 2021). Nevertheless, data on such pollutants is not available at the same geographical resolution in Italy and previous studies have shown a high correlation between PM2.5 levels with other pollutants such as Nitrogen Dioxide and Ozone (Fu et al., 2020). Also, PM2.5 is one of the most researched air pollutants in public health research as these fine particles are small enough to penetrate deep into the lungs and even enter the bloodstream, potentially causing significant health problems and common sources of PM2.5 are vehicle emissions, industrial processes, burning of fossil fuels, and natural sources such as wildfires.

5.2. Methods

In order to estimate inequality by SES in exposure to poor air at school we use simple OLS regression models with the school level of PM2.5 as dependent variable. In our first specification we do not include fixed effects or controls for the quality of the neighborhood where the school is located. We also estimate, however, the same model with province and municipality fixed effects. The first model with no fixed effect enables us to investigate overall inequalities in exposure by SES. With the province and municipality fixed effects models we analyze whether there are SES inequalities in exposure by accounting for selective sorting into provinces and municipalities by SES. In particular, the latter model with the municipality fixed effect allows us to discern whether among students who live in the same municipality there are SES inequalities in exposure. Nevertheless, the results of the municipality fixed effects should be interpreted cautiously due to the low number of schools in small municipalities. In more than 60% of the municipalities there is only one school and these cases are lost when we estimate a municipality fixed effect (Appendix: Figure A2). When running such model our sample is reduced from 456,508 to 277,038 students. Moreover, the variation in levels of PM2.5 within municipality is small. The intraclass correlation for PM2.5 within municipalities, as determined by a mixed effects model, is observed to be 0.97. This indicates that a mere 3% of the variation in air pollution levels occurs within municipalities. Conversely, at the provincial level the intraclass correlation is of 0.81 and the number of schools in each province range from 13 to 374 (Appendix: Figure A2).

When we investigate the effect of PM2.5 on achievement and its possible different effect by SES, a major concern is the endogeneity of air quality at school. For instance, it could be that the level of PM2.5 at school reflects whether the school is located in a rich area of the country where there are also more industries and more pollution and where test

[3] From 2018, the test is computer-based to minimize the risk of cheating and better capture of cognitive abilities. It is compulsory for all students and in 2019 took place between 1 and 18 April. The test does not contribute to the final grade of graduation from middle school but attendance is a requirement to be able to sit the final exam that takes place in summer.

[4] For the current EU limit value of PM2.5 set at 10 μg/m3 see: https://environment.ec.europa.eu/topics/air/air-quality/eu-air-quality-standards_en. In October 2022 the European Commission published a proposal to reduce the limit value for PM2.5 to 10 μg/m3, which is still double the limit suggested by WHO.

scores in the INVALSI evaluation are on average higher (Martini, 2010). The level of PM2.5 at school might also capture the quality of neighbourhood where the school is located. For example, the level of PM2.5 at a school might be higher in less affluent neighbourhoods, where there is also more exposure to violence and crime, more urban degradation and there are less institutions that favour learning, such as public libraries. The observed negative effect of air pollution on school achievement could then be spurious and capture the effect of other factors such as exposure to crime and urban degradation in the school environment that negatively affect educational achievement. In the Italian context, the opposite could also be true with higher levels of PM2.5 being observed in more affluent neighbourhoods, given the tendency of high SES families to still live in the centres of big cities. To deal with possible biases due to unobserved confounders we employ two strategies.

First, we estimate Ordinary Least Square (OLS) regression with province fixed effects (FE) (n = 107) with standard errors clustered at the school level. Using province FE, we exploit variation in the levels of PM2.5 within the same province. With this research design, we control for variations in the wealth levels of the provinces where schools are located, which are also associated with both the level of pollution and the average academic achievement of students. In the appendix, we also present results based on municipality fixed effects (n = 4446), which should be interpreted cautiously for the reasons explained above.

In Fig. 1 we present the average values of PM2.5 levels at school for each province and the average test score results for each province. Visually the maps in Fig. 1 show that in the northern area of the country both pollution and average test scores tend to be higher. Indeed, at the aggregate provincial level there is a positive correlation between average levels of PM2.5 and test score in math (r = 0.6) and reading (r = 0.5). There is also a positive although somehow weaker correlation between average levels of PM2.5 and average SES at the provincial level (r = 0.3).

Second, within provinces and municipalities, the air quality in schools may be associated with a range of factors, such as the neighborhood's quality and the overall standard of the school, which could also impact test score outcomes. In our FE models we control for these possible confounders with an indicator that directly measures the quality of the school neighbourhood. We use the average real estate value of the neighborhood where the school is located as an omnibus measure of the quality of the neighborhood, following common practices in urban studies. A high real estate value indicates that the school is likely proximate to valued goods, services, and social networks that provide additional access to material resources, knowledge, and skills (Ware, 2017).[5] We rely on administrative data on real estate values in the second semester of 2018 provided by the Italian fiscal agency.[6] Also, we control for the average socioeconomic status at the school, computing the average SES score of the students attending each school.

In all the analyses we also control for gender (Female=1), the student being non-native Italian (non-native=1, where non-native includes first and second generation immigrant students) and population density in the municipality of the school.[7] Summary statistics for the dependent and independent variables are presented in Table 1.

6. Results

6.1. Is there a SES gradient in exposure to PM2.5 at school?

Table 2 presents the beta coefficients of an OLS regression where the dependent variable is the average yearly level of PM2.5 in the area around a school. Considering SES, when estimating the model without fixed effects (model 1) or with province fixed effects (model 2) we observe a positive effect for SES. The positive effect of parental SES can be attributed to the propensity of high SES families to reside in wealthier areas of Italy and urban centers where the level of PM2.5 are also higher. The coefficient for SES notably declines in the province fixed effects model suggesting the spatial sorting by SES across macro areas of the country explain the large coefficient for SES in model 1. Within the same province (model 2), the effects for SES are small in size. For instance, a variation in two points of SES (i.e. two standard deviations since SES is standardized with mean 0 and standard deviation equal to 1) is associated with a variation in exposure of about 0.2 μg/m3 in PM2.5.[8]

Conversely, using municipality FE (model 3) we do not observe any substantial SES differences in exposure to air pollution. In other words, after accounting for socioeconomic status (SES) sorting across municipalities, we do not observe any SES gradient in exposure within them. This finding might be related to the relatively low level of residential segregation in Italian cities and to school regulations in Italy that favor enrolment in schools in the neighborhood of residence.

6.2. Does exposure to PM2.5 reduce educational achievement?

Table 3 presents the beta coefficients of a province fixed effect OLS model with test scores in math and reading. In this model we also control for the quality of the neighborhood and the quality of the school, including the real estate value in the area where the school is located and the average SES score of the students attending each school. We focus on the effects of PM2.5, observing that the associations of the other control variables are in line with what is known from previous literature.

Confirming previous studies that have documented a negative effect of the level of air pollution on academic achievement, we also find that students attending schools with a higher level of air pollution have a worse performance. Nevertheless, the effect is more robust for math compared to reading as found in a previous study (Amanzadeh et al., 2020). To better interpret the results, the beta coefficients for PM2.5 in Table 3 can be interpreted based on the impact of a 2 SD increase in air pollution (Appendix: Table A1). They would thus express the variation in math and reading score associated with a variation of 8.76 μg/m3 in PM2.5. In the case of math, a 2 SD increase in air pollution is associated

[5] In doing this, we follow recent proposals in urban studies. For instance: "Residences on the high end of the property value distribution are likely proximate to valued goods, services, and social networks that provide access to material resources, knowledge, and skills. Conversely, properties with low values are more likely to be in high-crime neighborhoods." (Ware, 2017).

[6] In Italy there are large geographical differences in the average cost of real estate. For instance, an average value of 3000 euros per square meter corresponds to a relatively poor neighborhood in the province of Milan, in the north of the country, while a value of 2000 euros per square meter corresponds to a relatively rich neighborhood in the province of Bari in the south (In Appendix Figure A1 we report the distribution of average of these values at schools' premises by province). However, using province fixed effects we are able to account for such geographical variations.

[7] Since non-native families are concentrated in the low part of the SES distribution, and migrants might attend schools with worse air quality, it is important to control for this variable to avoid that the effect of family SES on exposure to PM2.5 captures the effect of being non-native. We include gender as control in order to benchmark the effect of PM2.5. Moreover, the replication of the well-known opposite effect of gender on math and reading adding credibility to our findings.

[8] At the national level, without adjusting for covariates, the average level of PM2.5 for natives is 15.2 μg/m3 and 17.38 μg/m3 for non-natives. This suggests a starker difference in exposure between native and non-native students, when considering the spatial distribution of migrants across the country.

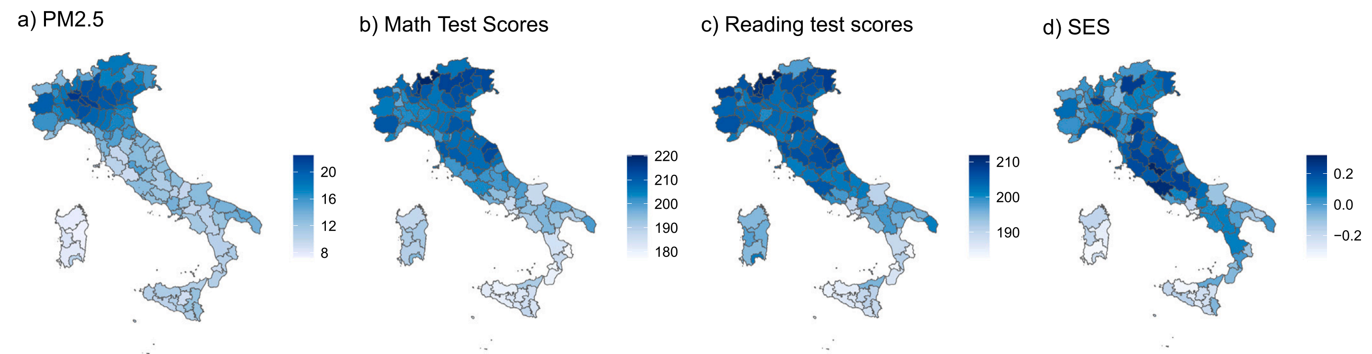

Fig. 1. Average PM2.5, math and reading test scores and average SES in schools in Italian provinces. Note: in panel a) we report the average PM2.5 values at the provinces included in the analysis measured in μg/m3. In panel b) we report average math test scores at the provinces in Italy. In panel c), we report the average reading test scores. In panel d) we report the average SES based on the standardized ESCS index. All measures are based on values at the school locations and weighted by the number of students in each province.

Table 1
Descriptive statistics for the key variables used in the empirical analysis.

Variable	Mean	Std. Dev.	Min	Max
Math	200.64	38.19	66.51	366.08
Reading	200.46	36.5	35.2	363.57
PM2.5	15.42	4.38	3.6	23.7
Female	.49	.5	0	1
Non-native	.1	.31	0	1
SES	.04	1	-3.06	2.15
Real Estate Value	1580.97	896.44	217.5	13000
School SES	.02	.4	-2.42	1.39
Municipality Population density	1398	1913	3.5	12,147
Tot. observations	456,508			

Table 2
The association between parental SES and the level of PM2.5 of the school (exposure to air pollution at school).

	Model 1	Model 2	Model 3
	PM2.5	PM2.5	PM2.5
SES	0.496 *	0.112 *	0.002
	(0.007)	(0.010)	(0.007)
Female	-0.003	0.002	-0.002
	(0.013)	(0.006)	(0.003)
Non-Native	2.428 *	0.229 *	0.062 *
	(0.021)	(0.019)	(0.013)
Province fixed effects	NO	YES	NO
Municipality fixed effects	NO	NO	YES
Observations	456,508	456,508	277,038

Note: Coefficients of an OLS model where the dependent variable is the level of PM2.5 of the school that the child attends. In column 2 we add province fixed effects and standard errors clustered at the school level. In column 3, we use municipality fixed effects. Due to municipalities with only one school, the observations with municipality fixed effects are lower. Standard errors in parentheses. * $p < 0.05$

with a 2.02 points reduction in the test score, while in the case of reading the reduction is equal to 0.56 points. These effects are not extremely large in size if one considers that the standard deviation in math score is 38. In the case of math, the estimated effect is therefore about 1/20 of a standard deviation. Still the effect is not trivial either. For instance, the 2.02-point reduction in math score associated with a variation of 8.76 μg/m3 in PM2.5, is about 55% of the observed gap in math test score for girls compared to boys. When using categories for quintiles of exposure to PM2.5 the results show that the effect is concentrated in the 5th quintile, suggesting some non-linearity in the effect of PM2.5 (Appendix: Table A2).

Table 3
The association between test scores and the level of PM2.5 of the school (consequences of exposure).

	(1)	(2)
VARIABLES	Math	Reading
PM2.5	-0.231 *	-0.064
	(0.060)	(0.050)
Female	-3.834 *	8.529 *
	(0.113)	(0.105)
Non-native	-8.203 *	-16.937 *
	(0.214)	(0.224)
SES	10.982 *	11.378 *
	(0.064)	(0.062)
Real estate value	0.082 *	0.062 *
	(0.021)	(0.019)
School SES	7.546 *	6.842 *
	(0.387)	(0.371)
Municipality Population density	-0.033 *	-0.015
	(0.010)	(0.009)
Observations	456,508	456,478

Note: Coefficients of an OLS model where the dependent variables are test scores, with province fixed effects and standard errors clustered at the school level. Coefficients for real estate value and municipality population density are multiplied by 100. Standard errors in parentheses. * $p < 0.05$

6.3. Does the effect of PM2.5 on educational achievement vary by family SES?

In the next step of our analysis, we include an interaction term between PM2.5 and SES. In Fig. 2, we plot the average marginal effect of PM2.5 for different values of SES (coefficients reported in Table A3 also in the Appendix). From Fig. 2, we see that the negative average marginal effect of PM2.5 reduces for higher SES levels for both math and reading. Most importantly, for the highest level of SES (values between 1 and 2), the effect of PM2.5 is almost 0. This means that high SES students are largely sheltered against the negative effect of exposure to PM2.5, while the observed negative effect of exposure to PM2.5 at school is concentrated among low SES students. For someone whose family SES is equal to − 2, a variation of 10 μg/m3 in the level of PM2.5 at school is associated with a reduction of about 4 points in math test scores. The same variation entails no change in math test scores of high SES students. Crucially, our findings reveal a widening achievement gap in math and reading between low SES students and high SES students when exposed to worst air at school, within the same province of residence (Appendix: Figure A3 reports the predictive margins for each grouped ESCS values). For instance, the SES gap in math test score, comparing those having parental SES equal to – 2 and those having a parental SES equal to 2, increases from 39 points when air pollution levels are low, at 3.5 μg/m3 of PM2.5, to approximately 48 points at the highest observed air

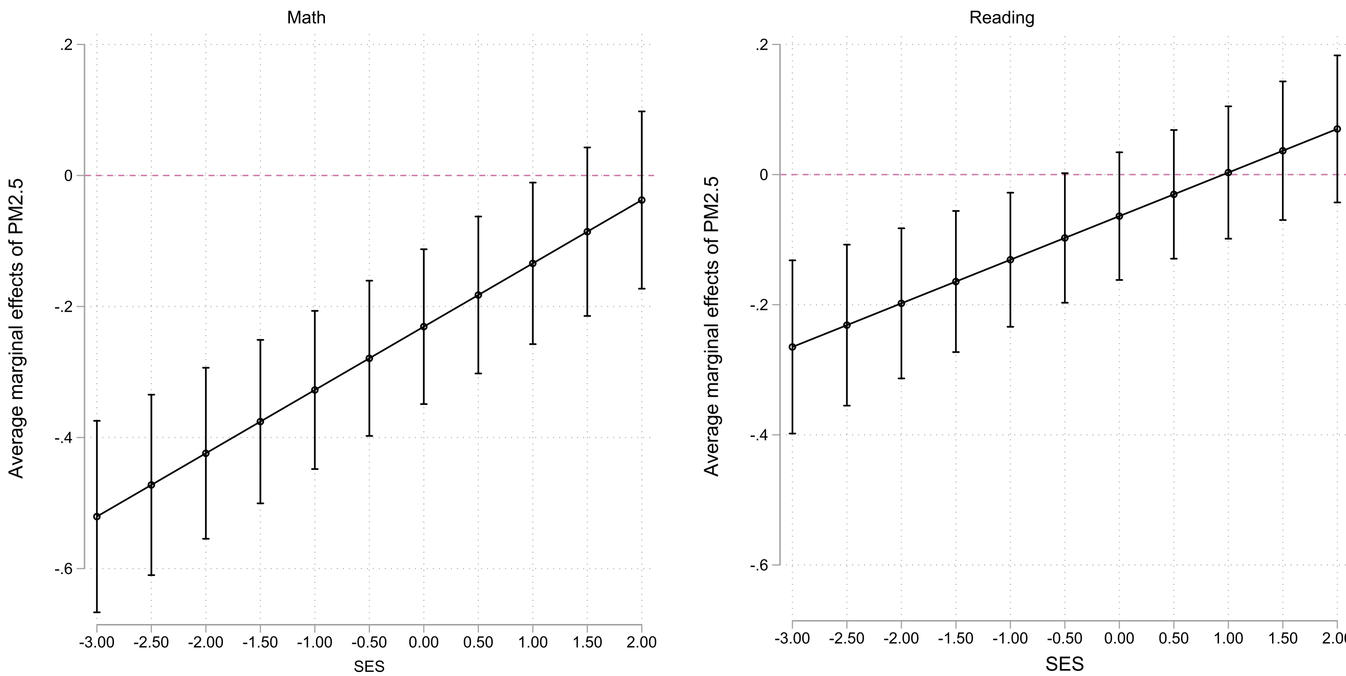

Fig. 2. Average marginal effects and 95% confidence intervals of PM2.5 on test scores in math and reading by SES (differences in the consequences of exposure by SES). Note: Figure is based on an OLS model where the dependent variable is test scores, with province FE and control variables for gender, migration status, real estate value, SES of the school and municipality population density. Number of students in the analysis 456,508 for math and 456,478 for reading in 6882 schools. 95% confidence intervals.

pollution levels of 23.5 μg/m3. These results underscore that improvements in air quality are associated with a decrease in the SES gap in math of about 17%.[9]

6.4. Supplementary analyses

In this section we present results from additional analysis. First, we test alternative measures of SES. In our main analysis, we used a continuous measure of SES based on the ESCS index constructed by INVALSI. We provide results using quintiles for the ESCS index, to test if the association between PM2.5 and SES is not linear. Considering disparities in exposure, we observe highest exposure to PM2.5 at the highest quintiles of SES (Appendix: Table A4). When interacting PM2.5 with SES we observe the effect of PM2.5 on math and reading to be largest at the 1st and 2nd quintiles of the ESCS measures for both math and reading (Appendix: Figure A4). The ESCS index is based on several dimensions of socioeconomic status that we explained above. INVALSI also asks the students about their parents' occupation. We leverage information on parental occupation collected by INVALSI from the students and construct six occupational categories: 1) not in paid employment (including those who are retired, unemployed and homemaker), 2) working class (including unskilled manual and non-manual workers), 3) self-employed (including self-employed agricultural workers), 4) white collars (that include teacher, office workers and professional employees (5) Upper class (that includes managers, university professors, high rank public employees and entrepreneurs). INVALSI collects information on the occupation of both fathers and mothers, and we employ a dominance criterion to determine the student' occupational class, selecting the highest class from either the father or the mother. For about 18% of the sample, this information is missing. In general, the results confirm the findings presented in the main analysis. We find that exposure to air pollution is lower for the working class and in particular for the self-employed (who include also agricultural workers) and higher for white collars and upper class, at the national level and within provinces. Within municipality we do not find any differences as we did not find for the continuous measure of SES (Appendix: Table A5). When we interact the occupational categories with PM2.5 we observe that the protective effect found for high SES is concentrated among the upper class, also in line with the finding using SES in quintiles (Appendix: Table A6). A similar pattern is observed for reading.

We further test the robustness of our results with different model specifications. We add an interaction not only between SES and PM2.5 but also between migration background and PM2.5. The results closely resemble those of the main analysis (Appendix: Table A7). We also replicate the results without including gender as a covariate (Appendix: Table A8). Also, in this case, we do not observe any major differences in the results.

Finally, we replicate the results in Table 3 using municipality fixed effects instead of province fixed effects (Appendix: Table A9). In spite of the low contribution of the variation in PM2.5 levels across schools within the same municipality to the overall variation in PM2.5, the pattern of results is very similar to that found in the main analysis using province FE. Most importantly, also within municipalities we find that exposure to PM2.5 at school is less negatively associated to test scores for high SES students. We have also restricted the analysis only to large municipalities (i.e. with more than 10 schools) and, again, we find the same results (Appendix: Table A10).

7. Discussion and conclusion

In this paper we explored whether exposure to air pollution affects school achievement and whether it contributes to inequalities in school achievement by parental SES. Inspired by the environmental justice literature, we first analyzed how the socioeconomic status of family of origin in Italy stratifies children's exposure to the air pollutant PM2.5 at school. We find that in Italy, high SES students tend to be exposed to

[9] The predicted score in Marth for SES= −2 at PM2.5 = 3.5 is 183 and for SES = 2 is 222. The corresponding values for PM2.5 = 23.5 are 174 and 222, respectively. The corresponding SES gaps are 39 and 48.

higher levels of PM2.5 at school at the national level and to a lesser extent, within provinces but not within the same municipality. The observed positive association between SES and exposure to PM2.5 notably shrinks when adding province FE and disappears completely when we estimate municipality fixed effects, suggesting that the positive association can be explained by selection into provinces and municipalities by SES. Our results based on municipality FE require cautiousness since students living in small municipalities with only one schools are excluded. Still they are informative of the relationship between SES and PM2.5 exposure in larger municipalities, with at least two schools, where more than 60 per cent of the students live.

These results differ from the findings from previous studies in US (Cheeseman et al., 2022) on the relationship between schools' sociodemographic characteristics and air pollution that show that low SES students attend schools that are on average exposed to higher levels of air pollution. In Europe, studies on the association between SES and exposure to air pollution based on the neighborhood of residence have found mixed results (Fairburn et al., 2019; Hajat, Hsia & O'Neill, 2015). Our results have to be interpreted in light of the specifics of the Italian context. There is a significant disparity in PM2.5 levels across areas of the country, with the highest levels of pollution observed in the northern part of the country and in large cities, areas where individuals with high SES are more likely to reside, as demonstrated in a recent article (Conte Keivabu, 2023). At the same time, within big cities the level of segregation is less acute compared to US and this is likely to explain why we do not find SES differences in exposure when looking at the variation within municipalities.

Additionally, we inquired how air quality differently affects math and reading test scores of students based on their SES. Estimating province fixed effects and controlling for the quality of the neighborhood and of the school composition, we find air pollution to be consequential for test scores. Our results show that a variation of 2 SD in PM2.5 (i.e. of about 9 μg/m3) is associated to a variation of 2.02 points in math test scores and 0.56 in reading. While these average effects are not large in size, we find the effect to be largely concentrated among low SES students. These results are in line with a study in Barcelona (Sunyer et al., 2015) focused on traffic related pollution and with a study on wildfire smoke in the US (Wen & Burke, 2022).[10]

With regard to the interplay of environmental risks and social background inequalities our results are then mixed. On the one hand, we find that high SES students tend to attend school with poorer air quality. On the other hand, we also find that the negative effect of exposure on test score is concentrated among low SES students. The relationship between environmental risks and social background inequalities is then nuanced and critically related to different specificities of the country investigated, Italy in this case. For instance, the observation that high SES students attend school with poorer air quality is true at the aggregate national level and province level but not within municipalities where we do not find any difference in exposure by SES. If the research question refers to the overall contribution of exposure to air pollution to observed SES inequalities, the correct model specification is the one without fixed effect. Still, it is also interesting to observe that within municipalities we do not observe differences in exposure by SES, possibly due to the relatively low level of urban residential segregation in European cities.

This study is not without limitations, and addressing these limitations points to promising future avenues of research. First, our measure of air pollution is not ideal as it captures air quality in the year prior, but not during the full school year and it can be biased by over- or under-reporting (Fowlie et al., 2019). Nevertheless, air pollution has been shown to persist in the same neighborhoods over time (Colmer et al., 2020) making it unlikely for our estimates to change in relative terms. Moreover, fine-grained data provided by measurement stations is not available for the whole territory in Italy but is of increasing availability and could be leveraged in future research. Second, our data are cross-sectional and it would be important to expand our research using longitudinal data and measures of exposure over time. Using such design could allow to disentangle the role of exposure during an extended period of time or just during one school-year. Also, as air pollution levels have been shown to slightly fluctuate year-to-year, but with a constant downward trend over time in Italy (Conte Keivabu, 2023), a longitudinal analysis could help to uncover the benefits of improvements in air quality on performance. Third, we are not able to disentangle PM2.5 levels at home compared to the levels experienced at school. As most students live in the proximity of schools, what we are actually studying is then the cumulated effect of exposure at school and at home. These limitations could be overcome in future studies with repeated over time information on educational achievement, the students' school and home address and more geographically fine-grained information on pollution level.

Finally, we are unable to test the mechanisms underlying the differences in the effect of air pollution by SES that we have documented. We have mentioned that higher prevalence of existing respiratory conditions among low SES children in Italy (SIDRIA, 1997) might make them more sensitive to the exposure to air pollution. Moreover parental responses might compensate for the negative effect of air pollution on learning in the case of high SES children (Bernardi, 2014). Consequently, future studies could shed light on whether disparities in sensitivity or parental responses determine the stratified impact of PM2.5 by family SES documented by our results. In this respect gaining information on students' health related school absences would be crucial.

To conclude, in this article we provide evidence on the impact of air pollution at school on students' test scores and its stratified effect by SES, with the negative effect of exposure to pollution being largely concentrated among low SES students. Most importantly, our results also show that SES inequalities are smaller where PM2.5 is low (Fig. 2). With the caveat of the limitations just highlighted, most notably that we have not investigated the mechanisms that allow high SES students to be more sheltered against the negative effects of PM2.5, the important implication of our results is that policies to improve air quality at schools might benefit low SES students in particular, especially those attending schools with high levels of PM2.5. We know that policies such as congestion charges and infrastructure interventions at schools can be successful in reducing exposure to PM2.5 at school (Conte Keivabu & Rüttenauer, 2022). Our results suggest, then, that these policies could be most beneficial in terms of test score results for low SES students whose achievement is more negatively associated with levels of pollution. Providing information on air quality to limit outdoor exposure and early advice from health professionals (Iriti et al., 2020; Wynes, 2022) could also mitigate the negative effects of PM2.5 on test scores, as low SES families are more likely to lack such information and early diagnosis of respiratory diseases.

CRediT authorship contribution statement

Fabrizio Bernardi: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Funding acquisition, Conceptualization, Data curation, Formal analysis, Project administration, Software, Supervision. **Risto Conte Keivabu:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

No competing interests to declare.

[10] The results for the wildfire smoke showed to be more consequential also in high SES neighborhoods, but with a low prevalence of White students.

Acknowledgements

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Appendix

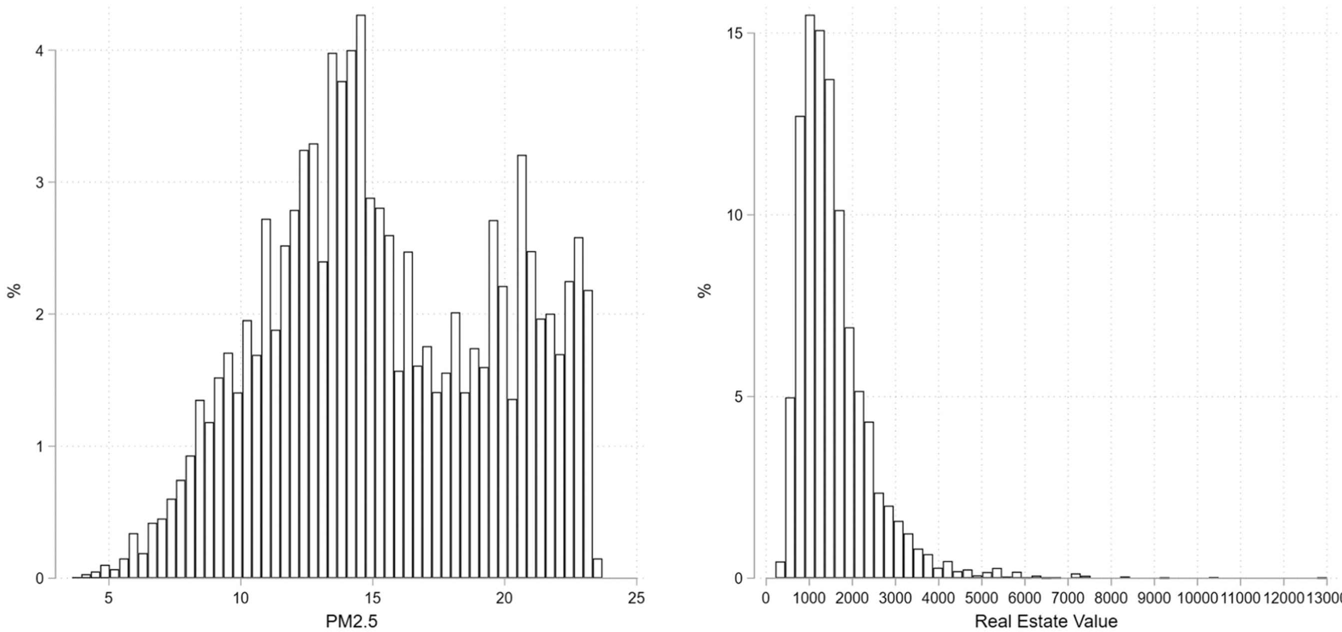

Fig. A1. Distribution of values of PM2.5 and Real Estate Value at middle school premises. Note: in the left figure we depict the percentage of schools exposed to each value of PM2.5 reported on the x-axis. On the right figure, we report the same but for the real estate values.

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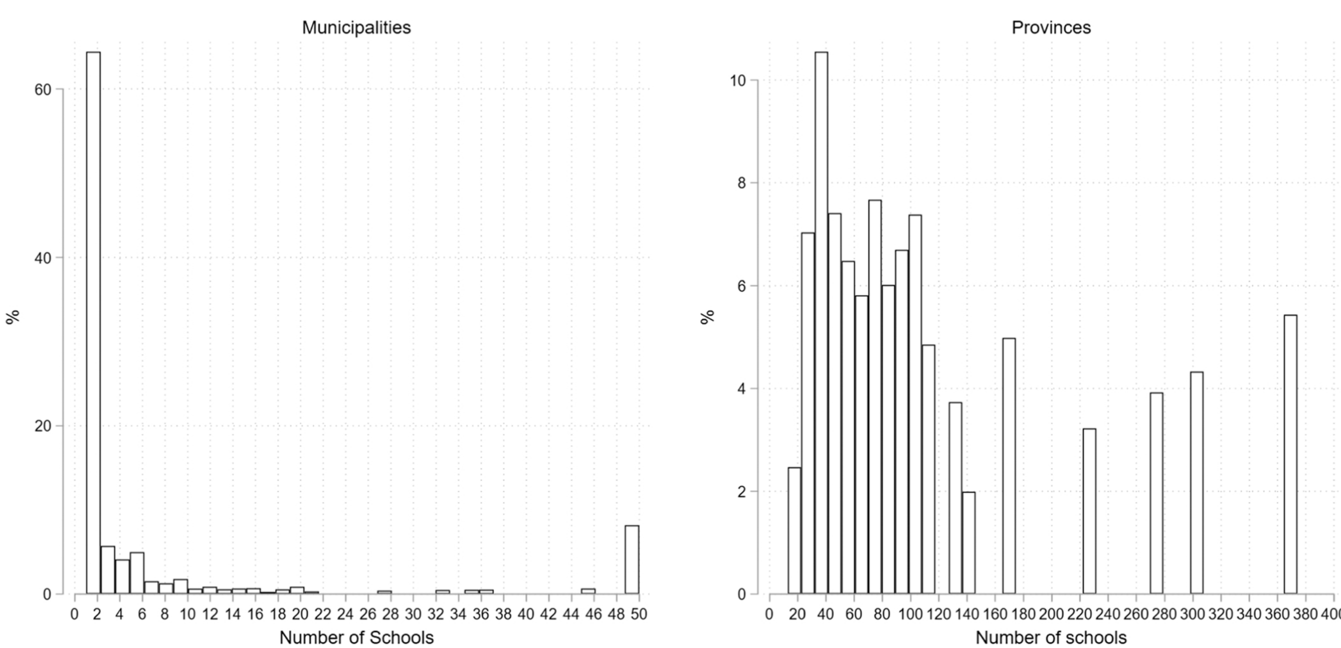

Fig. A2. Distribution of the number of schools within municipalities and provinces. Note: in the left panel we depict the distribution in the number of schools reported on the x-axis within municipalities. To better visualize the distribution, we collapsed the values above 50. On the right panel, we report the same but for provinces. Here we report all the values.

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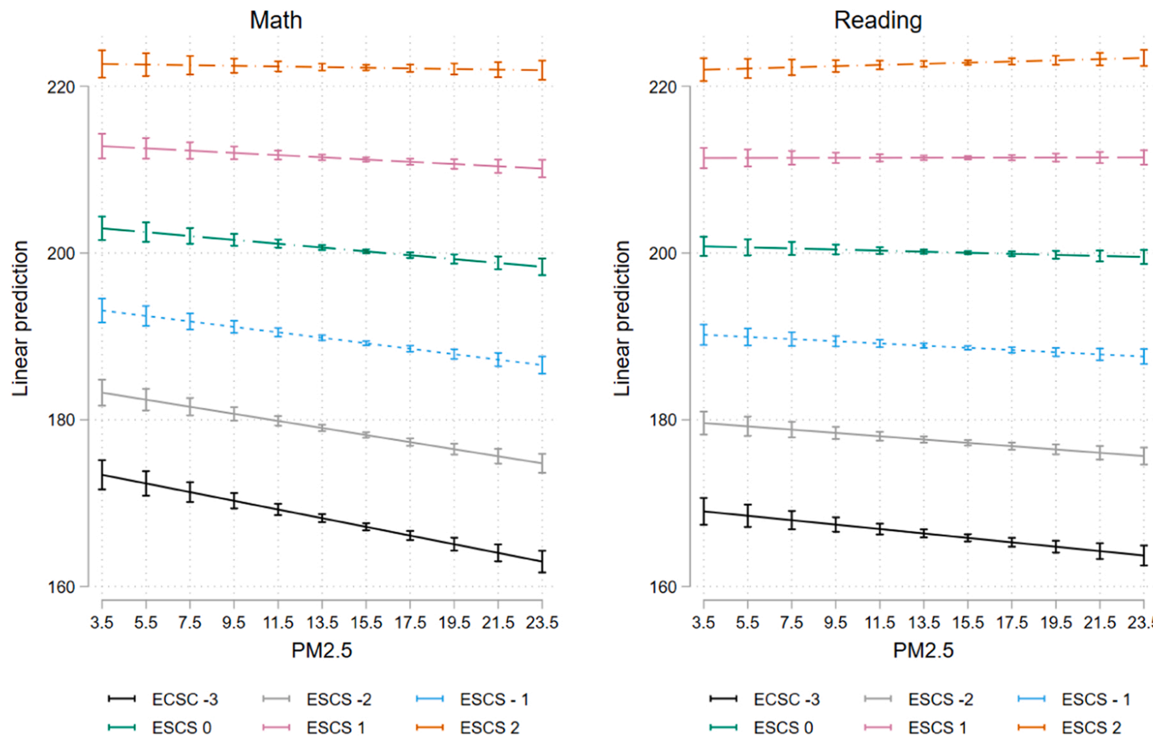

Fig. A3. Linear prediction of test scores at different values of PM2.5 and SES. Note: Each panel is based on an OLS models with province FE and control variables for gender, migration status, real estate value, SES of the school, municipality population density and the interaction between SES and PM2.5 on math and reading. Number of students in the analysis 456,508 for math and 456,478 for reading in schools 6882. Standard errors clustered at the school level. 95% confidence intervals.

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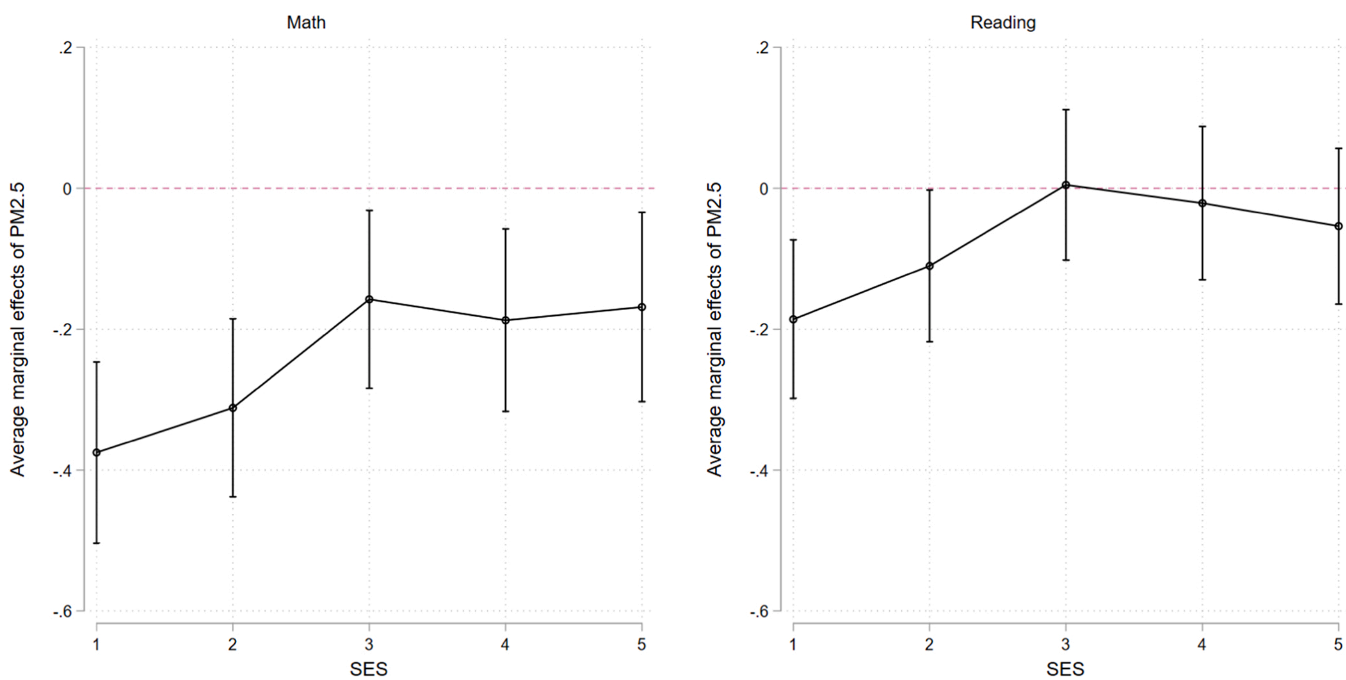

Fig. A4. Average marginal effect and 95% confidence intervals of PM2.5 on test scores in math and reading by quintiles of SES. Note: Each panel is based on an OLS models with province FE and control variables for gender, migration status, real estate value, SES of the school, municipality population density and the interaction between SES and PM2.5 on math and reading. Standard errors clustered at the school level. Number of students in the analysis 456,508 for math and 456,478 for reading in schools 6882. 95% confidence intervals.

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Table A1
The association between PM2.5 and math and reading scores with standardized values of PM2.5.

	(1) Math	(2) Reading	(3) Standardized Math	(4) Standardized Reading
Female	-3.834 *	8.529 *	-0.100 *	0.234 *
	(0.113)	(0.105)	(0.003)	(0.003)
Non-native	-8.203 *	-16.937 *	-0.215 *	-0.464 *
	(0.214)	(0.224)	(0.006)	(0.006)
SES	10.982 *	11.378 *	0.288 *	0.312 *
	(0.064)	(0.062)	(0.002)	(0.002)
Real Estate Value	0.082 *	0.062 *	0.002 *	0.002 *
	(0.021)	(0.019)	(0.001)	(0.001)
School SES	7.546 *	6.842 *	0.198 *	0.187 *
	(0.387)	(0.371)	(0.010)	(0.010)
Standardized values of PM2.5	-1.011 *	-0.280	-0.026 *	-0.008
	(0.264)	(0.219)	(0.007)	(0.006)
Municipality population density	-0.033 *	-0.015	-0.001 *	-0.000
	(0.010)	(0.009)	(0.000)	(0.000)
Observations	456,508	456,478	456,508	456,478

Note: Coefficients of an OLS model where the dependent variables are test scores for math and reading. In column 3 and 4 we use values standardized at 0 for math and reading. All models have province FE and standard errors clustered at the school level. Coefficients for estate and municipality population density are multiplied by 100. Standard errors in parentheses. * $p < 0.05$

Table A2
The association between PM2.5 and math and reading scores with PM2.5 measured in quintiles.

	(1) Math	(2) Reading
Female	-3.835 *	8.528 *
	(0.113)	(0.105)
Non-native	-8.206 *	-16.932 *
	(0.214)	(0.224)
SES	10.982 *	11.378 *
	(0.064)	(0.062)
Real Estate Value	0.079 *	0.061 *
	(0.020)	(0.019)
School SES	7.566 *	6.864 *
	(0.385)	(0.370)
Quintile 2 of PM2.5	-0.597	-0.074
	(0.414)	(0.359)
Quintile 3 of PM2.5	-0.239	0.261
	(0.483)	(0.420)
Quintile 4 of PM2.5	-0.810	-0.021
	(0.576)	(0.487)
Quintile 5 of PM2.5	-2.786 *	-1.060
	(0.696)	(0.588)
Municipality population density	-0.032 *	-0.013
	(0.010)	(0.009)
Observations	456,508	456,478

Note: Coefficients of an OLS model where the dependent variables are test scores for math and reading. All models have province FE and standard errors clustered at the school level. Coefficients for estate and municipality population density are multiplied by 100. The first quintile of PM2.5 is at the reference level. Standard errors in parentheses. * $p < 0.05$

Table A3
The interaction between PM2.5 and SES on math and reading scores.

	(1) Math	(2) Reading
Female	-3.834 *	8.529 *
	(0.113)	(0.105)
Non-native	-8.021 *	-16.811 *
	(0.214)	(0.223)
SES	9.515 *	10.360 *
	(0.244)	(0.237)
Real Estate Value	0.079 *	0.060 *
	(0.021)	(0.019)
School SES	7.543 *	6.840 *
	(0.387)	(0.372)
PM2.5	-0.231 *	-0.064
	(0.060)	(0.050)
SES*PM2.5	0.097 *	0.067 *
	(0.016)	(0.015)

(*continued on next page*)

Table A3 (*continued*)

Municipality population density	-0.034 *	-0.015
	(0.010)	(0.009)
Observations	456,508	456,478

Note: The coefficients are based on a regression where the dependent variables are test scores, with province FE. Standard errors clustered at the school level. Coefficient for estate and municipality population density are multiplied by 100. Standard errors in parentheses. * p < 0.05

Table A4
The association between parental SES and the level of PM2.5 of the school, with SES as quintiles.

	(1) PM2.5	(2) PM2.5	(3) PM2.5
Female	-0.001	0.003	-0.002
	(0.013)	(0.006)	(0.003)
Non-native	2.391 *	0.217 *	0.061 *
	(0.021)	(0.019)	(0.013)
1st Quintile SES (ref. cat.)			
2nd Quintile SES	0.588 *	-0.023	-0.001
	(0.020)	(0.013)	(0.009)
3rd Quintile SES	0.796 *	0.013	-0.006
	(0.020)	(0.016)	(0.011)
4th Quintile SES	1.014 *	0.118 *	-0.009
	(0.020)	(0.020)	(0.015)
5th Quintile SES	1.427 *	0.359 *	0.006
	(0.021)	(0.028)	(0.020)
Observations	456,508	456,508	277,038

Note: Coefficients of an OLS model where the dependent variable is the level of PM2.5 of the school that the child attends. In column 2 we add province FE and standard errors clustered at the school level. In column 3, we use municipality FE. Due to municipalities with only one school, the observations with municipality Fixed Effects are lower. Standard errors in parentheses. * p < 0.05

Table A5
The association between parental occupation and the level of PM2.5 of the school.

	(1) PM2.5	(2) PM2.5	(3) PM2.5
Female	0.004	0.005	-0.001
	(0.014)	(0.006)	(0.003)
Non-native	2.500 *	0.267 *	0.047 *
	(0.025)	(0.021)	(0.012)
Working class (ref. cat.)			
Not in paid employment	-1.743 *	0.123 *	0.007
	(0.039)	(0.028)	(0.018)
Self Employed	-0.294 *	-0.039 *	-0.010
	(0.023)	(0.015)	(0.009)
White collar	0.953 *	0.302 *	-0.012
	(0.019)	(0.019)	(0.012)
Upper Class	1.171 *	0.292 *	-0.003
	(0.027)	(0.026)	(0.015)
Observations	363,059	363,059	213,437

Note: Coefficients of an OLS model where the dependent variable is the level of PM2.5 of the school that the child attends. In column 2 we add province FE and standard errors clustered at the school level. In column 3, we use municipality FE. Due to municipalities with only one school, the observations with municipality Fixed Effects are lower. Also, compared to the main analysis we lose observations due to missing observations in the occupation variable. Manual as the reference group. Standard errors in parentheses. * p < 0.05

Table A6
The interaction between PM2.5 and parental occupation on math and reading scores.

	(1) Math	(2) Reading
Female	-3.792 *	8.678 *
	(0.128)	(0.120)
Non-native	-8.055 *	-17.077 *
	(0.251)	(0.274)
Working class (ref. cat.)		
Not in paid employment	-4.447 *	-6.396 *
	(1.224)	(1.233)
Self Employed	2.926 *	3.425 *
	(0.693)	(0.677)
White collar	15.270 *	16.331 *
	(0.604)	(0.592)

(*continued on next page*)

Table A6 (*continued*)

Upper class	7.817 *	8.445 *
	(0.914)	(0.876)
PM2.5	-0.419 *	-0.149 *
	(0.067)	(0.057)
Not in paid employment * PM2.5	-0.060	0.052
	(0.085)	(0.085)
Self Employed * PM2.5	0.132 * **	0.007
	(0.045)	(0.043)
White Collar * PM2.5	0.073	-0.041
	(0.038)	(0.036)
Upper class * PM2.5	0.531 * **	0.376 * **
	(0.056)	(0.054)
School SES	12.282 * **	11.952 * **
	(0.399)	(0.384)
Real Estate Value	0.078 * **	0.066 * **
	(0.022)	(0.021)
Municipality population density	-0.027 * **	-0.010
	(0.011)	(0.009)
Observations	363,059	363,033

Note: Coefficients of an OLS model where the dependent variables are test scores, with province fixed effects, an interaction between occupational categories and PM2.5 and standard errors clustered at the school level. The category working class is set at the reference level. Coefficients for real estate value and municipality population density are multiplied by 100. Standard errors in parentheses. * $p < 0.05$

Table A7
The interaction between PM2.5 and SES and migration background and PM2.5 on math and reading scores.

	(1) Math	(2) Reading
Female	-3.832 *	8.532 *
	(0.113)	(0.105)
Non-native	-3.345 *	-9.763 *
	(0.850)	(0.857)
PM2.5	-0.204 *	-0.023
	(0.061)	(0.051)
Non-Native*PM2.5	-0.276 *	-0.416 *
	(0.049)	(0.049)
SES	9.807 *	10.801 *
	(0.246)	(0.238)
SES*PM2.5	0.077 *	0.038 *
	(0.016)	(0.015)
School SES	7.500 *	6.776 *
	(0.387)	(0.371)
Real Estate Value	0.081 *	0.062 *
	(0.021)	(0.019)
Municipality population density	-0.032 *	-0.013
	(0.010)	(0.009)
Observations	456,508	456,478

Note: The coefficients are based on a regression where the dependent variables are test scores, with province FE. Standard errors clustered at the school level in parenthesis. Coefficient for real estate and municipality population density are multiplied by 100. * $p < 0.05$

Table A8
The interaction between PM2.5 and SES on math and reading scores without gender as control.

	(1) Math	(2) Reading
Non-native	-8.014 *	-16.826 *
	(0.214)	(0.223)
SES	9.500 *	10.393 *
	(0.244)	(0.240)
PM2.5	-0.231 *	-0.064
	(0.060)	(0.050)
SES*PM2.5	0.097 *	0.066 *
	(0.016)	(0.015)
School SES	7.557 *	6.808 *
	(0.387)	(0.374)
Real Estate Value	0.078 *	0.061 *
	(0.021)	(0.019)
Municipality population density	-0.034 *	-0.015
	(0.010)	(0.009)
Observations	456,508	456,478

Note: The coefficients are based on a regression where the dependent variables are test scores, with province FE. Standard errors clustered at the school level in parenthesis. Coefficient for real estate and municipality population density are multiplied by 100. * $p < 0.05$

Table A9
The association between PM2.5 and SES on math and reading scores and the interaction between PM2.5 and SES **with municipality FE**.

	(1) Math	(2) Reading	(3) Math	(4) Reading
Female	-4.232 *	8.045 *	-4.229 *	8.049 *
	(0.146)	(0.137)	(0.146)	(0.137)
SES	11.651 *	12.785 *	8.919 *	8.877 *
	(0.085)	(0.093)	(0.341)	(0.349)
PM2.5	-0.380	-0.400 *	-0.382	-0.403 *
	(0.196)	(0.167)	(0.195)	(0.166)
SES*PM2.5			0.174 *	0.249 *
			(0.021)	(0.022)
School SES	8.419 *	8.106 *	8.443 *	8.139 *
	(0.461)	(0.467)	(0.460)	(0.465)
Real Estate Value	0.878 *	0.883 *	0.817 *	0.796 *
	(0.304)	(0.310)	(0.304)	(0.311)
Observations	277,038	277,019	277,038	277,019

Note: The coefficients are based on a regression where the dependent variables are test scores, with municipality FE. Standard errors clustered at the school level in parenthesis. Coefficient for real estate are multiplied by 100. * $p < 0.05$

Table A10
PM2.5 and SES on math and reading scores and interaction between PM2.5 and SES **with municipality FE for municipalities with more than 10 schools**.

	(1) Math	(2) Reading	(3) Math	(4) Reading
Female	-4.603 *	7.669 *	-4.599 *	7.673 *
	(0.243)	(0.224)	(0.243)	(0.224)
Non-native	-6.356 *	-17.778 *	-6.038 *	-17.465 *
	(0.470)	(0.537)	(0.465)	(0.534)
SES	11.172 *	11.650 *	9.250 *	9.758 *
	(0.141)	(0.148)	(0.662)	(0.638)
PM2.5	-0.578	-0.535 *	-0.591	-0.548 *
	(0.311)	(0.262)	(0.310)	(0.262)
SES*PM2.5			0.119 *	0.117 *
			(0.040)	(0.037)
School SES	8.293 *	7.316 *	8.400 *	7.421 *
	(0.612)	(0.609)	(0.604)	(0.602)
Real Estate Value	0.001 *	0.001 *	0.001 *	0.001 *
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	99,601	99,594	99,601	99,594

Note: The coefficients are based on a regression where the dependent variables are test scores, with municipality FE. Only municipalities with more than 10 schools are included in the analysis. Standard errors clustered at the school level in parenthesis. Coefficient for real estate are multiplied by 100. * $p < 0.05$

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