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Spatial and temporal disparities in air pollution exposure at Italian schools

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Abstract

Air pollution poses major threats to children's health and learning, making exposure at school particularly critical. However, some children are more exposed than others, especially depending on the socioeconomic status of their school's neighbourhood. In this study, we explore how exposure to air pollution varies across schools, over time and by the socioeconomic characteristics of the neighbourhood using data on approximately 23 thousand schools in Italy connected with estimates on Particulate Matter 2.5 measured in μg/m^3 at a 1×1 km resolution from 2002 to 2018 provided by the Atmospheric Composition Analysis Group (ACAG). Moreover, we create an indicator of school socioeconomic status (SES) using fine-grained information on the real estate value made available by the Italian Observatory of Real Estate Value. Results highlight three main findings. First, air quality at the location of the schools improved over time by about 35%. Secondly, SES shows an inverted U-curve with PM2.5 suggesting schools in middle SES neighbourhoods to be exposed to the highest levels of pollution. Thirdly, SES does not show a substantive association with a decrease in air pollution over time. In conclusion, air quality has improved over time in Italy, but schools still do not comply with the World Health Organization (WHO) standards and middle SES neighbourhoods remain the most exposed to air pollution.

Keywords: Air pollution, Schools, Children, SES, Italy

Introduction

Air pollution is not equally distributed over space and time and some individuals are more exposed than others (Colmer et al., 2020; Manduca & Sampson, 2021). Disparities in exposure between geographical areas are present and mostly map existing socioeconomic inequalities (Fairburn et al., 2019; Hajat et al., 2015). Moreover, analysis at a finer geographical level have shown how exposure can vary within cities and adjacent neighbourhoods (Demetillo et al., 2020; Heblich et al., 2020). Similarly, the investigation of exposure at specific public institutions, such as schools, unravelled critical environmental inequalities between children (Grineski & Collins, 2018).

Analysis of the spatial, temporal and sociodemographic inequality in the exposure to air pollution is particularly relevant from a population health perspective. For instance, research in Europe has demonstrated that geographic variations in air pollution exposure can result in differing rates of premature mortality across affected populations

(Khomenko et al., 2021). Also, temporal improvements in air quality could bring several benefits for the affected population increasing life expectancy (Conti et al., 2023). Importantly, as some sociodemographic groups are more vulnerable to air pollution, variations in air pollution could affect their outcomes more substantively (Jans et al., 2018).

Schools are a critical public institution where exposure to air pollution has important health and educational implications that can persist over time. For example, children exposed to high levels of air pollution are more likely to develop respiratory conditions such as asthma (Alotaibi et al., 2019; Currie, 2013; Kravitz-Wirtz et al., 2018). Air pollution has been largely found to hamper learning, decrease students' cognitive abilities, and increase their absences (Amanzadeh et al., 2020; Currie et al., 2009; Grineski et al., 2020; Mullen et al., 2020) with persisting effects over the life course (Ebenstein et al., 2016). Consequently, mapping sociodemographic inequalities at school premises is critical from a public health and environmental justice perspective (Grineski & Collins, 2018).

The main research questions we investigate are three: (1) How does exposure to air pollution at school premises vary over time? (2) How does the socioeconomic characteristic of the school's neighbourhood associate with exposure to air pollution? (3) How do the neighbourhood characteristics of the school associate with the change in air pollution between 2018 and 2002? To do so, we focus on Italy and collect data on addresses of more than 23 thousand public schools and combine them with precise estimates of Particulate Matter 2.5 μg/m^3 (PM2.5) from 2002 to 2018. In addition, we create an indicator for the SES of the schools using the average value of real estate in the neighbourhood.

Previous studies mostly focused on inequalities in exposure at a broader geographical level or at a single point in time, but exposure can largely vary within the lowest administrative boundaries and over time (Colmer et al., 2020; Mangia et al., 2013). For example, air pollution at critical public institutions, such as schools, could largely vary, but studies are so far limited (Grineski & Collins, 2018). In addition, studies on the relationship between socioeconomic status and exposure to air pollution have revealed contrasting results depending on the context or pollutants of analysis, limiting generalizability to different countries and types of toxic pollutants (Fairburn et al., 2019; Hajat et al., 2015).

This study advances the literature on disparities in the population exposure to environmental risks in three main ways. First, we bring novel evidence on inequalities at a detailed geographical level, and at a critical institution, public schools, improving on previous studies focused on larger administrative units. Secondly, the longitudinal data on air pollution brings new knowledge on the trends of exposure at school premises, where previous studies focused on cross-sectional data. Thirdly, we contribute to the literature on the socioeconomic disparities in the exposure to air pollution in Europe and on how neighbourhood characteristics are associated to the variation in air pollution over time providing evidence for Italy that hosts one of the most polluted areas in Europe.

The article is organized as follows: first, we describe the negative impact of air pollution on population health and why schools are a critical location of exposure to air pollution and illustrate the findings of previous literature inquiring spatial and temporal disparities in air quality. Also, we offer a deeper insight into our case study, Italy. In the following, we describe the data, the variables and the empirical strategy. We report the main results answering our research questions and we provide further analysis and robustness checks to substantiate our main results. Finally, we conclude with a discussion of the results and their implications.

Air pollution, schools and spatial and temporal disparities in exposure

Air pollution and population health

Air pollution stands as a critical factor affecting public health and of relevance for demographic research due to its multiple implications for population well-being, morbidity and mortality. Air pollutants are not merely of environmental concerns due to their contribution to climate change but they directly impact human health, exacerbating conditions like asthma, heart disease, and even affecting neurological development in children (Alvarez-Pedrerol et al., 2017; Buka et al., 2006; Deryugina et al., 2019; König & Heisig, 2023). Importantly, air pollution increases premature mortality (Khomenko et al., 2021), affects life expectancy (Conti et al., 2023) and is estimated to account for a larger share of global excess deaths than tobacco smoking (Lelieveld et al., 2020). Moreover, air quality can affect demographic patterns influencing migration trends (Chen et al., 2022). Also, the consequences of air pollution often disproportionately affect marginalized communities, amplifying existing health and social inequities (Mohai et al., 2009). Understanding the multifaceted impacts of air pollution is essential for informing policy decisions, healthcare interventions, and community planning, with profound consequences, long-term effects on both individual health outcomes and demographic trends.

Schools as critical locations of exposure

Schools are a critical institution as children's exposure to air pollution is particularly consequential for their health. Age related vulnerability to air pollution has been depicted as a U-curve as children and the elderly are the most susceptible (Johnson et al., 2021; Simoni et al., 2015). The World Health Organization (WHO) report on "Air pollution and child health: prescribing clean air" highlights how multiple physiological characteristics make children more susceptible to air pollution compared to adults (WHO, 2018). Children undertake a higher number of breaths, are less able to filter toxic particles and their lungs are more sensitive as still in a developmental phase (Goldizen et al., 2016). High levels of air pollution have been linked with reduced lung development, smaller lung volume (Barone-Adesi et al., 2015; Gehring et al., 2013; Mudway et al., 2019) and with an increased risk of developing respiratory conditions such as asthma or wheezing and to worsen such conditions when already present in children (Alotaibi et al., 2019; Darrow et al., 2014; Orellano et al., 2017). Also, toxic pollutants impair the neurological development, determine behavioural issues (Loftus et al., 2020) and increase the likelihood of experiencing attention deficiency (Thygesen et al., 2020) with repercussions on their academic achievement (Payne-Sturges et al., 2019).

Air quality at schools is consequential for children's academic achievement as it impairs students' cognitive abilities and increases their school absences. Air pollution has been documented to negatively affect cognitive abilities and productivity also in the adult population. For example, a decrease in cognitive performance with exposure to high levels of air pollution has been shown in observational studies looking at test scores in China (Zhang et al., 2018), decision-making in baseball players in the U.S. (Archsmith et al., 2018) and chess players in Germany (Künn et al., 2019). Moreover, air pollution has shown to lower labour productivity in members of parliament in Canada (Heyes et al., 2019), industrial workers in China (Chen & Zhang, 2021) and football players in Germany (Lichter et al., 2017). In children, the negative effects of air pollution on cognitive abilities are visible in their test scores and documented in several countries such as school districts in the U.S (Grineski et al., 2020), in Iran (Amanzadeh et al., 2020), in Utah, U.S. (Mullen et al., 2020), in Florida, U.S. (Heissel et al., 2019) and in Israel (Ebenstein et al., 2016). Moreover, the negative effects of air pollution on test scores are observed both with short-term exposure (Amanzadeh et al., 2020), during the day of the test and with long-term exposure (Mullen et al., 2020). One mechanism that explains the long-term effects of air pollution on test scores is a decrease in school attendance (Currie et al., 2011). In fact, some studies have highlighted air pollution to increase school absences in Italy, (Marcon et al., 2014), in Texas (Currie et al., 2009), in Utah (Hales et al., 2016) in India (Singh, 2020), and to increase attendance when there is an improvement in air quality (Conte Keivabu & Rüttenauer, 2022).

Considering the negative effects of air pollution on children health and academic achievement, mapping exposure at school premises becomes critical from a public health perspective. Nevertheless, air pollution is not equally distributed over space and some socioeconomic groups might be more exposed than others.

Spatial disparities in air pollution

Spatial disparities in the exposure to air pollution often map existing societal inequalities. In the U.S. context, individuals with low socioeconomic status (SES) and racial and ethnic minorities inhabit neighbourhoods with the highest levels of toxic pollutants (Colmer et al., 2020; Manduca & Sampson, 2021). A study focused specifically on public schools in the U.S. documented large racial disparities in the exposure to several pollutants but no significant association with the SES of the school (Grineski & Collins, 2018). Similar results for ethnic minorities have been found also in Germany where they are more exposed to industrial pollutants than natives (Best & Rüttenauer, 2018; Rüttenauer, 2018).

The SES of a neighbourhood has failed to consistently predict higher exposure to air pollution in several studies and literature reviews focused on the European context (Deguen & Zmirou-Navier, 2010; Fairburn et al., 2019; Hajat et al., 2015). In Asturias, Spain, no SES gradient has been observed (Fernández-Somoano & Tardon, 2014). Conversely, in Strasbourg, France, the results are quadratic suggesting an inverted U-curve with middle SES individuals being exposed to the highest levels of air pollution (Havard et al., 2009). Nevertheless, the majority of the findings denote low SES individuals being more exposed to high levels of air pollution (Hajat et al., 2015) as for example in Malmö, Sweden (Chaix et al., 2006), London (Heblich et al., 2020) or in 16 European cities (Temam et al., 2017). The contrasting findings could be related to three main factors.[1] First, studies have been using differing operationalizations of neighbourhood SES and air pollution. Secondly, methodological choices could determine biases in the estimation of

[1] For a more detailed discussion, we refer to Bailey et al., (2018) and Hajat et al., (2015).

the relationship between air pollution and SES (Hajat et al., 2015). For example, models accounting for spatial autocorrelation and non-linear associations should be preferred and potential confounding factors such as population density included in the analysis (Bailey et al., 2018; Hajat et al., 2015). Thirdly, results are often context dependent and generalizability of associations to other geographical contexts or units with differing spatial resolution should be done cautiously (Bailey et al., 2018).

The spatial understanding of SES disparities in the exposure to air pollution is critical to comprehend the root causes of existing social inequalities. Exposure to air pollution has shown to be an independent predictor of intergenerational mobility in the US (Manduca & Sampson, 2019, 2021). Additionally, the negative effects of air pollution are also multigenerational and transmitted by grandparents to grandchildren (Colmer & Voorheis, 2020). Similarly, in utero exposure to air pollution has shown to be causally associated with lower educational attainment and higher poverty in the U.S. (Persico, 2020). Moreover, the negative effects of air pollution during the school years could persist throughout the life course. For example, lower test scores determined by air pollution have shown to reduce future educational attainment and income (Ebenstein et al., 2016). Consequently, it is relevant from a public health and environmental justice perspective to map spatial disparities in the exposure to air pollution at school premises as it could help to explain the existence of socioeconomic inequalities and shape policymaking to help the most exposed individuals.

The temporal persistence of air pollution

Air pollution endures in the same geographical area over time. In London, poor air quality has persisted in the Eastern part of the city from the eighteenth century to current days (Heblich et al., 2020). Also, this part of the city is to these days mostly inhabited by low SES individuals highlighting the intergenerational transmission of environmental inequalities. In the U.S., the decline in air pollution from 1981 to 2016 has been highest in areas with a higher proportion of high SES and white inhabitants (Colmer et al., 2020). The persisting sociodemographic disparities in air pollution are often explained by selective siting and selective migration (Best & Rüttenauer, 2018; Ehler et al., 2023; Mohai & Saha, 2015). Selective siting proposes that low SES neighbourhoods suffer the persistence or the inflow of new sources of pollution contrary to high SES neighbourhoods (ibid.). Selective migration suggests that high SES individuals might relocate to less polluted areas and that low SES individuals might choose to live in more polluted neighbourhoods as these could have cheaper housing (ibid.). Another possible explanation could be the higher capabilities of high SES individuals to promote public policies that reduce air pollution in their neighbourhood (Aldred et al., 2021). Nevertheless, research on SES and variation of air pollution over time suffers from similar contrasting findings highlighted for the spatial cross-sectional association. For instance, in Scotland the association between deprivation and air pollution has shown to not be stable over time in the same locality (Bailey et al., 2018). Overall, the persistence of inequalities in air quality over time is concerning from an environmental justice perspective and it unravels how environmental inequalities do not differ from other SES inequalities in how they persist in the society.

Italy and air pollution

Air pollution is a big concern for Italian citizens especially for those living in the Po Valley, in the Northern part of the country. This region suffers the presence of several factors determining high air pollution. The area is densely populated, hosts several highly polluting industrial facilities and air pollution is trapped in the territory by natural factors such as rare wind and the presence of mountains surrounding the area (Raffaelli et al., 2020). The high level of pollution in this area is particularly consequential and accounts for one of the highest pollution-related death tolls in Europe (Khomenko et al., 2021). However, high pollution is not only affecting the northern parts of the country as densely inhabited and industrialized areas in the south suffer from poor air quality. For example, Taranto a city in the South of Italy hosts a highly polluted industrial facility negatively affecting the air quality in the neighbouring area (Leogrande et al., 2019; Mangia et al., 2013).

Research on the association between SES and exposure to air pollution in Italy, is limited. One study, in Rome, showed high SES individuals to be more exposed to higher levels of pollution as inhabiting the central areas of the city that have a higher incidence of traffic (Forastiere et al., 2007). A study on several European cities included for Italy the urban areas of Pavia, Verona and Turin showing a negligible role of SES for Pavia and Turin. Conversely, contrasting findings were found for Verona where individual level SES was positively associated with air pollution, but neighbourhood SES was negatively associated with it (Temam et al., 2017).[2] Consequently, the Italian case is no different from other European contexts in showing contrasting findings in the association between air pollution and SES.

Dataset, variables and empirical strategy

Dataset

In this study, we employ five main sources of data for Italy. (1) We use school addresses provided by the Italian Ministry of Education; (2) information on PM2.5 air pollution is provided by the Atmospheric Composition Analysis Group (ACAG); (3) the average value of the real estate collected by the Italian National Observatory of the Real Estate Market (Osservatorio del Mercato Immobiliare—OMI) and provided by the Italian Agency of Public Finances (Agenzia delle Entrate); (4) we measure population density at the school premises using the Global Human Settlement Layer (GHSL); and (5) we collected data on the Leaf Area Index (LAI), as a measure of vegetation, available in the Copernicus Data Store (CDS).

School addresses are publicly accessible in the national database provided by the Italian Ministry of Education. However, the location of the schools is not publicly available. Consequently, to capture the longitude and latitude of the schools we geocoded the addresses for the schoolyear 2020–2021 using the HERE API.[3] The total number of elementary and middle schools present are 26,205 but we lose approximately 2 thousand schools, of which 771 are determined by unavailable addresses and the remaining are

[2] However, the study uses differing conceptualizations of individual and neighbourhood SES. The former was captured by the educational level of the individual and the latter by the unemployment rate.

[3] More information on HERE API is provided in their website: https://www.here.com/.

related to missing information on the other variables. Consequently, the sample of geo-coded schools comprises 23,981 public and private elementary and middle schools. The elementary schools are attended by pupils aged 6 to 11 and the middle schools in the age 12 to 14. These schools are also a proxy of the neighbourhood in which the students live, as attendance is often determined based on residence in the school district and most students live at about 1.5 km from the school (Mantovani et al., 2022). Nevertheless, in certain cases, parents can select a school that is settled in another neighbourhood for their children, as for example a private school.

Data on yearly average PM2.5 μg/m^3 air pollution from 2002 to 2018 is provided by the ACAG that combines satellite, chemical transport modelling and in situ observations to achieve a resolution of a 1×1 km (Hammer et al., 2020). Using this pollutant, we follow previous studies that used PM2.5 due to the harmful effects it has shown to bring on human health (Colmer et al., 2020; Darrow et al., 2014; Xing et al., 2016). Moreover, the level of outdoor air pollution is a good proxy of indoor exposure, as it has been shown to be positively correlate with it (Amato et al., 2014; Raysoni et al., 2011; Rivas et al., 2014). The ACAG dataset has several advantages compared to using either satellite observations or measurement stations. On one hand, satellite observations have the advantage of providing reliable information on average levels of pollutants, but often lack precise geographic resolution. On the other hand, measurement stations achieve high territorial resolution but miss homogeneous coverage in the territory, are susceptible to cheating (Zou, 2021) and might not monitor air pollution continuously over time. Consequently, the ACAG modelling of observations from different data sources permits to achieve the best compromise between accuracy and geographical resolution (Hammer et al., 2020). However, this dataset is not free from caveats. In fact, some studies have shown that pollution estimates constructed using satellite observations and chemical transport modelling might in some cases overestimate or underestimate the actual levels of pollution measured by the local measurement stations determining biases (Fowlie et al., 2019).

We capture the socioeconomic status (SES) of a school, using administrative data provided by OMI. The dataset is available yearly and by semester and for the purpose of this study we used the data on the second semester of 2018. Provided are the minimum and maximum values of the real estate measured as euros per square metre and divided in detailed geographical areas for the whole national territory. The use of the real estate value is justified by previous studies finding it to be strongly correlated with student's socioeconomic status and their math achievements (Ware, 2019).

The GHSL population density maps provide accurate information on the total population at fine geographic resolution (Schiavina et al., 2019). The data are available for the years 1975, 1990, 2000 and 2015 and we use the latest available. Moreover, we select the dataset with the highest resolution of 250 m for each grid cell. The total population in each grid cells is computed by GHSL using administrative census data at the local level and disaggregated to each cell based on the Global Human Satellite Built dataset that captures information on the built environment using satellite data.[4]

[4] For more information, please refer to the following website: https://ghsl.jrc.ec.europa.eu/ghs_bu_s2_2018.php.

The leaf area index (LAI) is a widely used indicator of vegetation. More precisely, it leverages remote sensing technologies to measure the amount of leaf material in a specific territory (Fang et al., 2019). We used the version v3.0 of the CDS that is constructed by the Copernicus Climate Change Service(C3S) using satellite data and sophisticated algorithms to estimate the effective LAI and capturing the clumping of leaves within a 1-km grid. The satellite observations are taken every 10 days and we collected data from January to December 2018 that has been gathered three times per month either on the 10th, 20th, 28th, 30th or 31st calendar day.

Variables

The dependent variable of our interest is PM2.5 at the school location. The variable represents the yearly average level of PM2.5 $\mu g/m^3$ measured at the grid cell of the school location. Our main independent variable is the socioeconomic status of the school computed using the OMI dataset on the average price of the real estate at the location of the school. More precisely, we used binary values for the deciles of the real estate value computed within provinces to better capture the local variations in real estate value at the school location in 2018. For population, we used the value of the population residing in the 250-m grid cell provided by the GHSL, in which the school is located. The LAI is computed averaging the daily values to the yearly level for 2018. Moreover, we include two dummy variables retrieved from the administrative data on the schools. Respectively, we introduce one variable to denote that a school is private (private = 1) and that it is a middle school (middle school = 1). The total number of private schools in the sample is 1938 (8.08% of the total sample) and the middle schools are 7751 (32.3% of the total sample).

Empirical strategy

The empirical strategy is divided in three main parts. First, we answer our first research question providing simple descriptive statistics on the trends in PM2.5 from 2002 to 2018 at the location of the schools. Secondly, we employ ordinary least squared regression (OLS) with province fixed effects (FE) to observe how school SES is associated with PM2.5 in 2018. Thirdly, we apply the province FE model on the rank change of PM2.5 as our outcome and use the rank change in SES and the control variables[5] between two points in time 2018 and 2002, to inquire the factors that are associated with a decrease in air pollution over time.

We implement an OLS model with FE to analyse how SES is associated with PM2.5 in 2018 that is described in Eq. (1):

$$PM_{ip} = D_{ip} + X_{ip} + \alpha_p \, e_{ip}. \tag{1}$$

Here, the outcome variable *PM* is the logarithm of PM2.5 measured at school *i*, and province *p*. *D* is a vector of dummy variables representing the province specific deciles of the real estate value at school *i*, and province *p*. We use such measurement of SES to capture non-linearities in the relationship between SES and air pollution as suggested

[5] For population, we use the values for 2000 as the GHSL does not provide data for 2002.

Table 1 Summary statistics

Variable	N	Mean	Std	Min	Max
PM2.5 μg/m^3 in 2018	23,981	14.23	4.54	3.6	24
PM2.5 μg/m^3 in 2002	23,981	22.12	6.63	5.7	35.2
% Change in PM2.5	23,981	− 35.53	7.39	− 63.35	9.09
Estate value in € per m^2 in 2018	23,981	1,398.48	856	170	13,000
Estate value in € per m^2 in 2002[a]	18,972	747.3	521.19	85	10,000
% Change in estate value	18,972	107.28	90.63	− 70.43	910.64
Population in 2015	23,981	341.66	349.57	0	4524.58
Population in 2000	23,981	345.6	354.19	0	4572.41
% Change in population	23,981	6.32	101.99	− 67.71	7142.24
Leaf area index (LAI) in 2018	23,981	0.46	0.27	0	1.47
Leaf area index (LAI) in 2002	23,981	0.39	0.22	0	1.29
% Change in LAI	23,981	63.38	3,154.97	− 99.03	464,540
Private schools	23,981	0.08	0.28	0	1
Middle schools	23,981	0.32	0.47	0	1

It presents summary statistics on the main variables and the percentage differences between the values in 2018 and 2002

[a] Missing values are related to Trentino Alto Adige for which we do not have available data for 2002

in previous research (Bailey et al., 2018; Hajat et al., 2015). X is a vector comprising the school-level control variables described in the preceding section. We include α_p as province FE in the analysis, that are in total 107 and we cluster standard errors at the regional level, that are 20, to account for spatial autocorrelation.

We inquire the factors explaining change in PM2.5 over time using the FE model on the rank change in PM2.5. More precisely, we compute the rank change for the dependent and the independent variables subtracting the ranking of schools in 2018 from the rank in 2002. We prefer the use of rank change based on previous studies that employed a similar approach (Chetty et al., 2014; Colmer et al., 2020). For this analysis, the sample is reduced to 18,972 as we lack information on real estate value for 2002 for the autonomous region of Trentino Alto-Adige.

Results

Disparities in exposure to air pollution across space and time

In Table 1, we show the summary statistics for the main variables in the analysis for 2018, 2002 and the percentage change between these years. In 2018, the average value of PM2.5 at 14.23 μg/m^3 highlights that most Italian schools do not comply with the WHO guidelines of PM2.5 annual levels below 10 μg/m^3 (Krzyzanowski & Cohen, 2008) or the newest guidelines proposing a limit of 5 μg/m^3. However, there is high heterogeneity in the level of air pollution at the school premises with the lowest value of 3.6 μg/m^3 recorded in the municipality of Pescasseroli (2200 inhabitants), located in a natural reserve in the province of L'Aquila in the region Abruzzo and the highest of 24 μg/m^3 in the municipality of Gorgonzola (20,400 inhabitants), located in the outskirts of the city of Milan, in the region Lombardia, where several high polluting industrial facilities are located. Moreover, compared to 2002 we observe a decrease of about 35% in air pollution. In Fig. 1, we show the trend in air pollution in the 90th, 50th and 10th percentile from 2002 to 2018 and we observe an overall decline in air pollution over time.

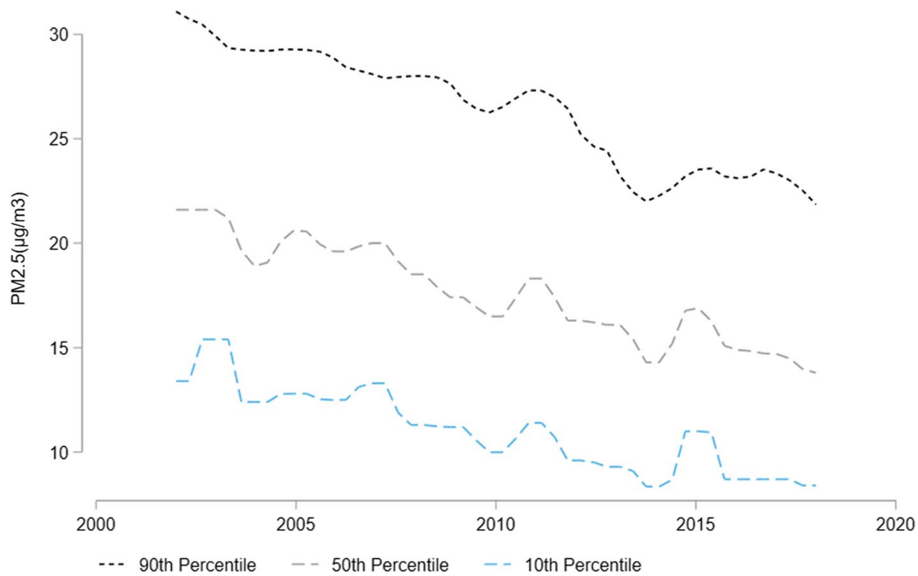

Fig. 1 Air pollution at schools from 2002 to 2018. The figure shows the level of PM2.5 µg/m^3 at the schools at the 90th, 50th and 10th percentile in the PM2.5 from 2002 to 2018

Moreover, we investigate the absolute and proportional change in PM2.5 in 2018 compared to 2002 based on deciles computed using PM2.5 in 2002 (Appendix 1: Fig. 5). The most polluted school neighbourhoods in 2002 experienced the highest absolute reduction in pollution. However, the relative change in pollution is more homogeneous across deciles. In fact, the correlation of the school rank in air pollution in 2002 and 2018 is of 0.96, suggesting high persistence over time. Looking at the other variables in Table 1, we observe a substantial increase in real estate value,[6] population and leaf area index (LAI) suggesting on average higher real estate value, population density and greener neighbourhoods.

In Fig. 2, we map the level of PM2.5 in 2018 to better visualize the heterogeneous spatial distribution of air pollution. Air pollution looks to be particularly concentrated in the northern parts of the country, in the Po Valley. The Po Valley is one of the most polluted areas of Europe as it is densely populated, it hosts several industrial facilities and natural factors such as rare wind and the presence of mountains surrounding the area impede air pollution to get dispersed (Raffaelli et al., 2020). However, high pollution is not only affecting the northern parts of the country as densely inhabited and industrialized areas in the south suffer from poor air quality (Leogrande et al., 2019). Also, we map the % change in air pollution between 2018 and 2002 (Appendix 1: Fig. 6). Here, we observe a heterogeneous pattern in the north, a larger decrease in the centre, and a relatively lower decrease in air pollution in the southern parts of the country.

Air pollution and SES inequalities

In Fig. 3 (we display results also in Appendix 1: Table 3), we explore our second research question. Here, we can observe an inverted U-curve in the relationship between the

[6] The real estate prices are not adjusted for inflation.

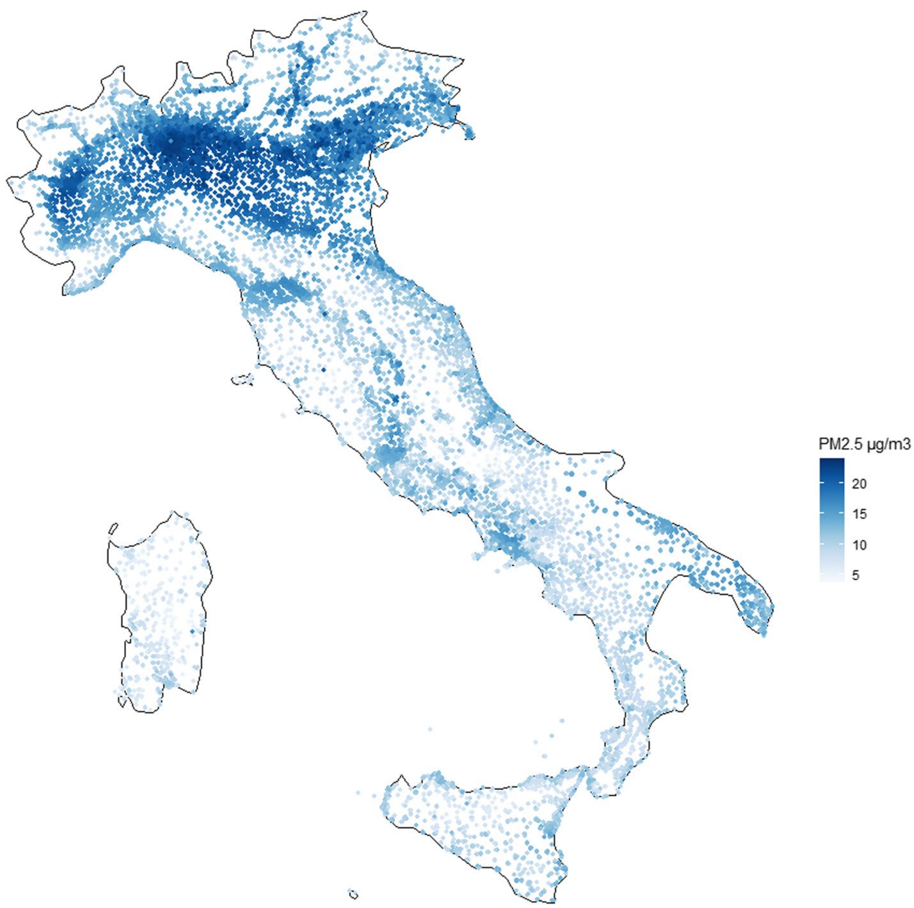

Fig. 2 PM2.5 µg/m^3 air pollution at schools in 2018. The figure shows the level of PM2.5 µg/m^3 at school locations in 2018

province specific deciles in school's real estate value and log PM2.5. Also, we observe a similar pattern in a model without the provincial FE (Appendix 1: Table 3). Considering the control variables, private schools show a positive coefficient but that is not statistically significant. Middle schools are less exposed to pollution compared to elementary schools, a higher population count is positively associated with air pollution and the LAI is negatively associated with PM2.5.

In Table 2, we show the results of the relationship between the rank change in air pollution and the rank change in the independent variables between 2018 and 2002. In column (1), the model suggests a positive relationship between an increased rank in real estate value and rank in air pollution. However, in column (2) the relationship becomes negligible when we add province fixed effects. Nevertheless, we observe private schools to be positively associated with increased pollution, likely, as they are more present in large urban areas. Conversely, an increase in the rank in the LAI reduces air pollution.

Macro-regional heterogeneities

Italy has large geographical differences in air pollution and economic development that could determine heterogeneities in the associations we have observed in the previous analysis. Moreover, a study on Scotland has highlighted how theoretical

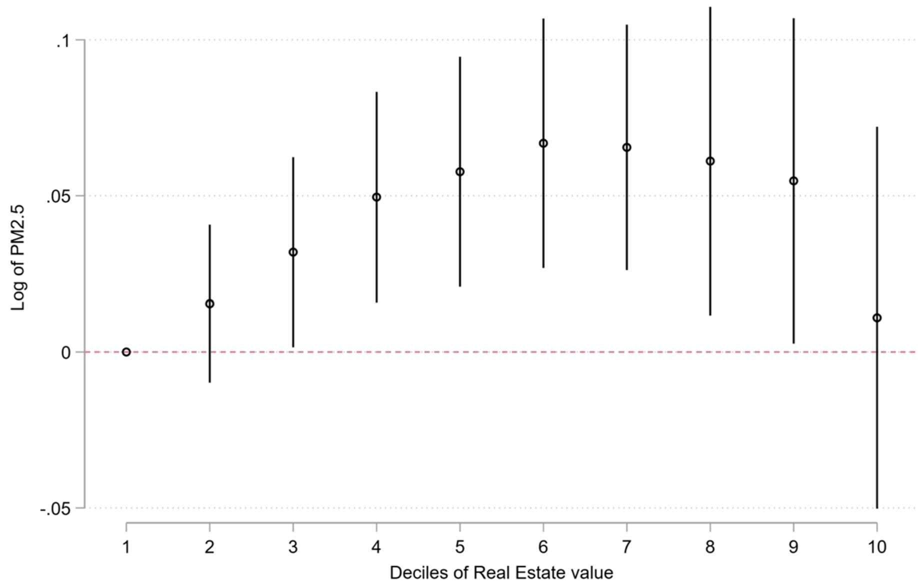

Fig. 3 Relationship between school SES and air pollution. This shows the relationship between the deciles of real estate value computed at the provincial level and the Log of PM2.5. The model includes control variables described in Eq. (1) and province FE. Standard errors clustered at the regional level. The 1st decile is set at the reference level. 95% confidence intervals

Table 2 Rank change in air pollution and SES

	(1) OLS	(3) OLS and FE
Real estate rank change	0.032*** (0.003)	0.004 (0.011)
Private school	0.011*** (0.002)	0.016** (0.005)
Middle school	− 0.001 (0.001)	− 0.001 (0.001)
Rank change population density	− 0.015 (0.015)	0.050 (0.037)
Rank change LAI	− 0.041*** (0.006)	− 0.048*** (0.012)
Observations	18,972	18,972
Province FE	No	Yes

It shows the results of two models. In column (1), are exposed the results of the OLS model without province fixed effects. In column (2), are the results of the OLS model with FE for provinces and standard errors clustered at the regional level

Constant present but not reported

Significance levels: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

expectations on the association between air pollution and neighbourhood deprivation do not replicate in different regions due to the complexity of the association (Bailey et al., 2018). We replicated analysis in Fig. 3 and Table 2 separately by three macro-areas: North, Centre and South. In Fig. 4, the associations for 2018 show an inverted U-curve between SES and PM2.5 in the North, a linear relationship in the centre and the lack of an association in the South. When inquiring rank change over time the results do not substantively differ between regions and resemble those of the pooled sample (Appendix 1: Table 4).

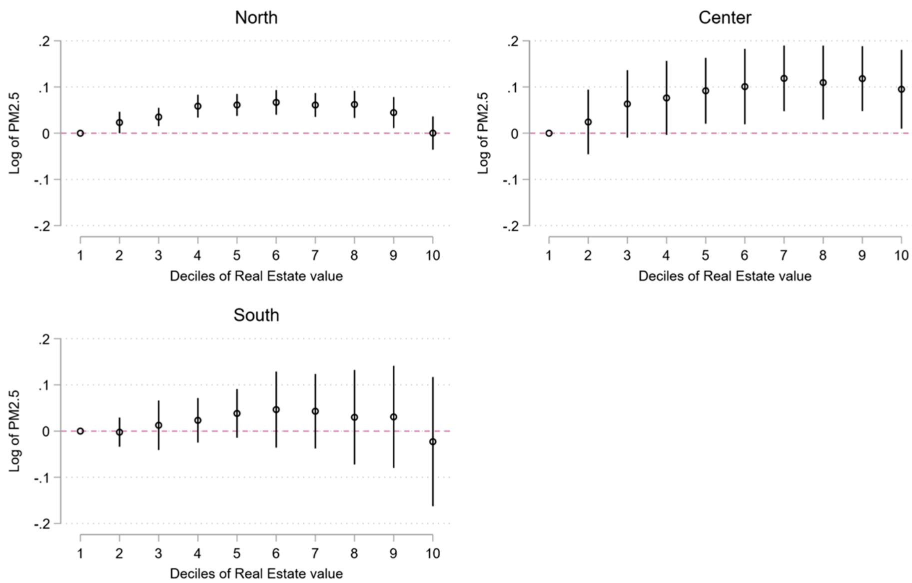

Fig. 4 Relationship between school SES and air pollution by macro-areas. This shows the relationship between the deciles of real estate value computed at the provincial level and the Log of PM2.5 by macro-areas. The model includes control variables described in Eq. (1) and province FE. Standard errors clustered at the provincial level. The 1st decile is set at the reference level. 95% confidence intervals

Supplementary analysis and robustness checks

In our main analysis, we focused on a specific type of pollutant, but different results could be found when inquiring other sources of air pollution. For example, previous research on the U.S. has found that the air pollutants PM10, PM2.5, NO2, CO and lead, are heterogeneously distributed in the territory, but to be always most prevalent in the most deprived communities (Manduca & Sampson, 2021). We further inquired exposure to air pollution collecting data from the European Pollutant Release and Transfer Register (E-PRTR) dataset for 2018 on the location of toxic industrial facilities in Italy. We classify a school as residing close to the industrial facility if it is settled within a 2 km buffer calculated around it and construct a binary variable (0–1). We choose a 2 km boundary based on previous studies for the US showing pollution from industrial sites to affect air quality within a buffer of approximately one mile (Currie et al., 2015). The schools residing close to an industrial facility are 3317 comprising 14% of the total sample. We run a Linear Probability Model (LPM) with the binary variable Industry (1 = school close to the industry) without and with province FE and control variables used in the previous analysis (Appendix 1: Table 5). The results show a negative coefficient for real estate value at the national level for the 8th and 10th decile, but introducing provincial level FE, all coefficients are not significant and small. However, the relationship might vary depending on the macro-area of interest, especially as 76% of these industries are in the North. Nevertheless, when repeating the analysis by the three macro-areas, we do not observe differing patterns by macro-areas (Appendix 1: Fig. 7).

Different results could be expected when using alternative operationalizations of neighbourhood SES. Additional fine-grained indicators of neighbourhood SES are not of easy access for Italy. Nevertheless, the Italian Ministry of Finance makes accessible information on taxable income by zip code for a restricted sample of Italian cities. We use information on taxable income for the year 2019 on 605 zip codes located in 41 municipalities matched with 2847 schools and run analysis as in Fig. 3.[7] Also, in this analysis, we compute the deciles for taxable income by province and use fixed effects at the provincial level. The results (Appendix 1: Fig. 8) show no substantive association between taxable income and air pollution.[8] The correlation between taxable income of the zip code and real estate value is of 0.76 and we could expect similar results when using real estate value with the restricted sample for which we have information for income. We replicated results using the real estate value for the smaller sample (Appendix 1: Fig. 9) and observe a similar pattern seen in Appendix 1: Fig. 8, bringing further validity on the SES measure we are using in our main analysis.

We run some robustness checks. First, we replicated results in Fig. 3 and Table 2 using the more restrictive municipality FE instead of provincial fixed effects, showing a weakened association compared to the results of Fig. 3 but similar results to Table 2 (Appendix 1: Fig. 10 and Table 6). Secondly, we replicated results of Fig. 3 using deciles of real estate value computed at the national level and results show to resemble those observed in the main analysis (Appendix 1: Fig. 11). Thirdly, we used percentage change in air pollution instead of rank change in air pollution to test how sensitive the results are to the measurement of variation over time (Appendix 1: Table 7). Results show null effects as in Table 2 for all variables except private schools. Also, we used the non-log transformed values of PM2.5 to replicate Fig. 3 and found similar results (Appendix 1: Fig. 12). Finally, we reproduced the analysis in Fig. 3 using the variables for 2002 to observe if the relationship observed for 2018 was already previously present (Appendix 1: Fig. 13). Here, we observe similar relationships to Fig. 3 suggesting a persistence over time of the relationship between SES and air pollution.

Discussion and conclusion

In this article, we exposed disparities in the exposure to PM2.5 air pollution at school premises in 2018 and the variation over time in Italy. There are three main findings. First, the location at which Italian schools are located shows an improvement in air quality of about 35% in 2018 relative to 2002, but 81% of the schools are still above the old WHO guidelines of yearly average PM2.5 below 10 $\mu g/m^3$ and 99% are above the stricter requirement of PM2.5 below 5 $\mu g/m^3$ introduced in 2021. Secondly, in 2018, we observe a non-linear relationship between SES and PM2.5 with schools in middle SES neighbourhoods exposed to higher levels of air pollution. However, we observed some differences based on the three Italian macro-areas as the non-linear pattern is present mostly in the North, linear in the Centre and no differences by SES are observed in the South. Thirdly, we do not observe the rank change in SES to be significantly associated with a rank change in PM2.5, but the higher the increase in vegetation in the neighbourhood the largest the decline in air pollution in 2018.

The steady decrease over time of air pollution in Italy confirms previous findings for other country contexts. For example, the reduction in PM2.5 over time shows a pattern

[7] We are not able to replicate the analysis of Table 2 using taxable income as data by zip code are available only for the years 2011, 2015, 2019, 2020.

[8] Similar results for the fixed effects model are observed also when running the analysis by macro-areas.

that is similar to the United States (Colmer et al., 2020). For Italy, the high levels of air pollution in the Po Valley have been previously depicted and have been targeted by policies to improve the air quality of the citizens (Raffaelli et al., 2020; Stafoggia et al., 2019). However, to our knowledge, this is the first time that the improvements in PM2.5 from 2001 to 2018 are exposed for Italy at a fine geographic resolution and for schools. The decline on air pollution has several important implications for public health and population outcomes. Importantly, a recent study documented how the decline in air pollution from 1990 to 2019 in Italy translates in a substantive decrease in the burden of disease related to air pollution (Conti et al., 2023). For example, enhanced air quality is believed to have led to improvements in multiple public health indicators, including mortality rates, Disability-Adjusted Life Years (DALYs), Years Lived with Disability (YLD), and cardiorespiratory conditions such as strokes or chronic obstructive pulmonary diseases.

The results on the relationship between SES and air pollution highlight how this can differ depending on the context and within a country. In the U.S., the poorest neighbourhoods are the most exposed to high levels of air pollution (Colmer et al., 2020; Manduca & Sampson, 2021). However, in Europe, the results look more mixed (Hajat et al., 2015) and previous findings on SES and air pollution have found a positive relationship in Italy, in Rome, when observing citizens' exposure to traffic-related air pollution in the end of the twentieth century (Forastiere et al., 2007). Here, we have shown SES to have a non-linear relationship with PM2.5 implying higher exposure to air pollution for individuals attending schools in middle SES neighbourhoods. However, this appears to be the case mostly in the North of the country. When looking at an alternative measure of air pollution, proximity to industrial plants, we did not find a substantive association with SES. Additionally, the restricted urban sample for which we have information on taxable income per zip code showed no association with air pollution. Overall, the findings suggest middle SES schools to be the most exposed to PM2.5 in Italy, but with differences determined by the macro-area, source of air pollution and SES indicator.

Air pollution is geographically concentrated in the same neighbourhood over time. We observed a high correlation of 0.96 in the school rank in air pollution in 2018 and 2002, we found rank change in real estate value to not be related to a decrease in air pollution over time and the association in 2018 to be peculiar to the one observed in 2002. Interestingly, a factor that shows to reduce air pollution is an increase in the LAI, suggesting vegetation to be relevant in increasing air quality in a neighbourhood.

The study has several limitations. First, the descriptive results presented should be cautiously interpreted as we do not estimate a causal association between PM2.5 and SES and we are not able to account for reverse causality in the observed relationship. Additionally, other confounding factors such as the presence of local amenities at the school location could be influencing our findings. Reverse causality could be a problem as previous studies have shown air quality to affect housing prices (Sager & Singer, 2022) and policies affecting traffic-related air pollution in cities such as congestion charges have shown to increase housing value in London (Tang, 2021) but to decrease them in Milan (Percoco, 2014). Secondly, results should not be generalized to other country contexts, air pollutants and SES measures as the observed relationships could widely vary as shown in previous studies (Hajat et al., 2015). Thirdly, the choice of focusing on schools as a unit of analysis could be debatable. On one hand, the attention on schools increases awareness on the environmental hazards encountered by a vulnerable population and permits to analyse a more fine-grained geographical unit. On the other hand, schools limit generalizability to other social groups and might not perfectly capture the differences in exposure experienced by students at home. Thirdly, this study does not present information on other relevant characteristics of the schools, the neighbourhoods, student's outcomes, or air pollutants. This limits our analysis to school locations and not schoolchildren as done in previous studies (Grineski & Collins, 2018) and does not allow us to weight our estimates by the number of pupils in a school. Also, we are unable to account for the closure or relocation of schools in previous years as information on school addresses is available only from 2015. Moreover, we were limited in the use of the real estate value as a proxy of school SES for lack of similarly fine-grained level data on SES for the whole of Italy. However, previous studies have shown real estate value to be highly correlated with other SES measures (Ware, 2019) and we found that to be the case for a restricted sample for which we have information on taxable income. Similarly, we inquired PM2.5 as fine-grained data are only available for this pollutant but other toxic air pollutants such as PM10, ozone, nitrogen dioxide or lead could highlight the existence of other environmental risks. Nonetheless, PM2.5 is often cited as the most important air pollutant for public health (Colmer et al., 2020) and we complemented the analysis exploring the relationship between SES and proximity to industrial facilities.

Further analysis could build on the evidence exposed here investigating three main promising research opportunities. First, studies could use a panel data analysis or test the impact of policy changes such as congestion charges to provide a more robust estimate of how changes in neighbourhood SES over time affect PM2.5 in Italy. Second, it could be inquired which are the sources of pollution that determine a larger exposure to PM2.5. Third, by gathering data on pupil characteristics and school outcomes, we could shift our focus from estimating air pollution exposure at the school level to understanding its impact on individual schoolchildren. Also, such data would enable us to analyse how air pollution specifically influences test scores and attendance rates. Fourth, the same approach used in this article could be extended to other country contexts or public institutions. For example, analysing the same relationship in developing countries could reveal different relationships between SES and PM2.5 and inform about the environmental risk children face. Additionally, analysing the same association at other critical institutions such as hospitals could uncover other relevant locations of exposures that are consequential for public health (El-Sharkawy & Noweir, 2014).

In conclusion, despite a constant improvement in air quality, air pollution continues to pose a threat for the Italian population at large and children in particular. The level of PM2.5 still exceeds the WHO guidelines or the institutional recommendations set by the UNESCO Chair on Health Education and Sustainable Development & the Italian Society of Environmental Medicine (Pulimeno et al., 2020). Given the existing evidence on the public health benefits of lower air pollution, policymakers have the important task of designing policies targeting locations that suffer from low air quality and enhance population health.

Appendix 1

See Tables 3, 4, 5, 6, 7 and Figs. 5, 6, 7, 8, 9, 10, 11, 12, 13.

Table 3 Air pollution, school SES and different model specifications

	(1) OLS	(2) OLS and FE
2nd decile of real estate value	0.036*** (0.009)	0.015 (0.012)
3rd decile of real estate value	0.042*** (0.008)	0.032* (0.015)
4th decile of real estate value	0.043*** (0.009)	0.050** (0.016)
5th decile of real estate value	0.052*** (0.009)	0.058** (0.018)
6th decile of real estate value	0.066*** (0.009)	0.067** (0.019)
7th decile of real estate value	0.065*** (0.009)	0.066** (0.019)
8th decile of real estate value	0.046*** (0.009)	0.061* (0.024)
9th decile of real estate value	0.051*** (0.009)	0.055* (0.025)
10th decile of real estate value	− 0.017 (0.010)	0.011 (0.029)
Private school	0.078*** (0.008)	0.010 (0.006)
Middle school	− 0.015*** (0.004)	− 0.009*** (0.002)
Population in 250 m (per 1000)	− 0.095*** (0.007)	0.030** (0.009)
LAI	− 0.541*** (0.009)	− 0.420*** (0.039)
Observations	23,981	23,981
Province FE	NO	YES

This shows the results of two models. In column (1), are exposed the results of an OLS model without province FE. In column (2), we present results for the OLS with province FE with clustered standard errors at the regional level

Constant present but not reported

The 1st decile is set at the reference level. Significance levels: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 4 Rank change in air pollution and real estate value by macro-area

	(1) North	(2) Centre	(3) South
Real estate rank change	− 0.014 (0.009)	0.034 (0.011)	0.010 (0.025)
Private school	0.017* (0.007)	0.018* (0.003)	0.011 (0.011)
Middle school	0.001 (0.001)	0.001 (0.002)	− 0.002* (0.001)
Rank change population	0.020 (0.043)	− 0.030 (0.061)	0.121 (0.059)
Rank change LAI	− 0.037** (0.007)	− 0.023 (0.022)	− 0.074* (0.028)
Observations	8672	3290	7010
Province FE	Yes	Yes	Yes

This shows the results for the OLS model with province FE and standard errors clustered at the regional level

Constant present but not reported

Significance levels: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 5 Proximity to industry and real estate value

	(1) LPM	(2) LPM and FE
2nd decile of real estate value	0.014 (0.009)	0.009 (0.014)
3rd decile of real estate value	0.011 (0.009)	0.008 (0.015)
4th decile of real estate value	0.014 (0.009)	0.003 (0.016)
5th decile of real estate value	− 0.006 (0.010)	− 0.003 (0.022)
6th decile of real estate value	0.022* (0.010)	0.008 (0.022)
7th decile of real estate value	− 0.013 (0.010)	− 0.025 (0.019)
8th decile of real estate value	− 0.022* (0.010)	− 0.030 (0.021)
9th decile of real estate value	− 0.013 (0.010)	− 0.033 (0.022)
10th decile of real estate value	− 0.032** (0.011)	− 0.040 (0.026)
Private school	0.028*** (0.008)	0.013 (0.010)
Middle school	0.006 (0.005)	0.004 (0.002)
Population in 250 m (per 1,000)	− 0.042*** (0.007)	0.024 (0.014)
LAI	− 0.233*** (0.010)	− 0.237*** (0.046)
Observations	23,981	23,981
R-squared	0.028	0.194
Province FE	No	Yes

This shows the results of the LPM with province level deciles of real estate value. In column (2), we show the results of the LPM with FE for provinces and clustered standard errors at the regional level

The 1st decile is set at the reference level

Constant present but not reported

Significance levels: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 6 PM2.5 and rank change in PM2.5 with municipality FE

	(1) Rank change PM2.5
Rank change estate value	− 0.005 (0.006)
Rank change population density	0.039 (0.020)
Rank change LAI	− 0.031*** (0.007)
Private school	0.003 (0.002)
Middle school	0.002*** (0.000)
Population within 250 m	
Observations	17,529
Municipality FE	Yes

This shows the results of the OLS model for rank change with municipality FE and standard errors clustered at the provincial level

The total sample is reduced as singleton observations are dropped

Constant present but not reported

Significance levels: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 7 Percentage change in PM2.5 and SES

	OLS	(2) OLS and FE
% change in real estate value	− 0.001* (0.001)	− 0.002 (0.002)
Private school	1.044*** (0.196)	1.411*** (0.328)
Middle school	0.024 (0.115)	0.040 (0.052)
% change in population density	− 0.001 (0.001)	− 0.000 (0.000)
% change in LAI	0.000 (0.000)	− 0.000 (0.000)
Observations	18,972	18,972
Province FE	No	Yes

This shows the results of the OLS model with and without province FE

Standard errors clustered at the regional level

Constant present but not reported

Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

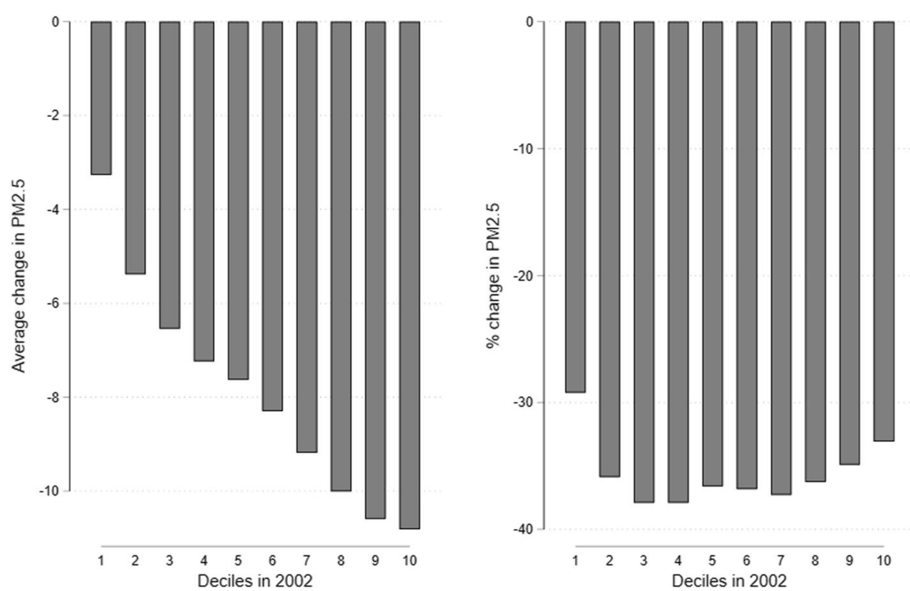

Fig. 5 Absolute and relative decline in air pollution at schools. In the left, can be observed the absolute reduction in pollution in 2018 compared to 2002, based on deciles computed for pollution at schools in 2002. In the right graph, can be observed the proportional change in air pollution

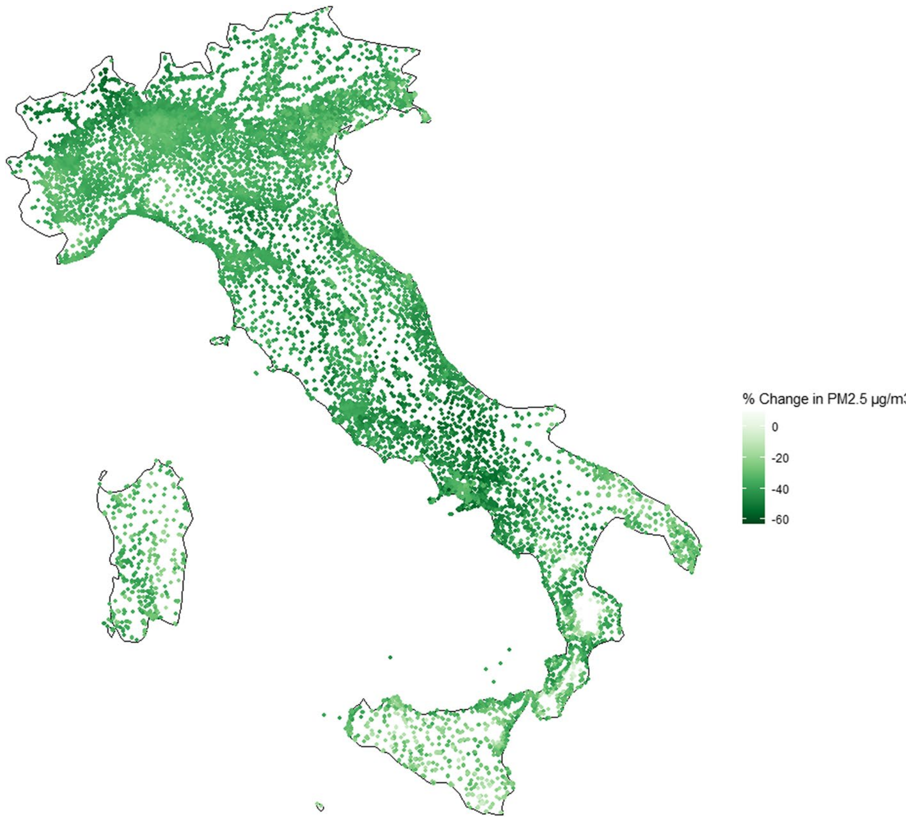

Fig. 6 Percentage change in air pollution between 2018 and 2002. In the map, can be observed the % change in air pollution in 2018 compared to 2002

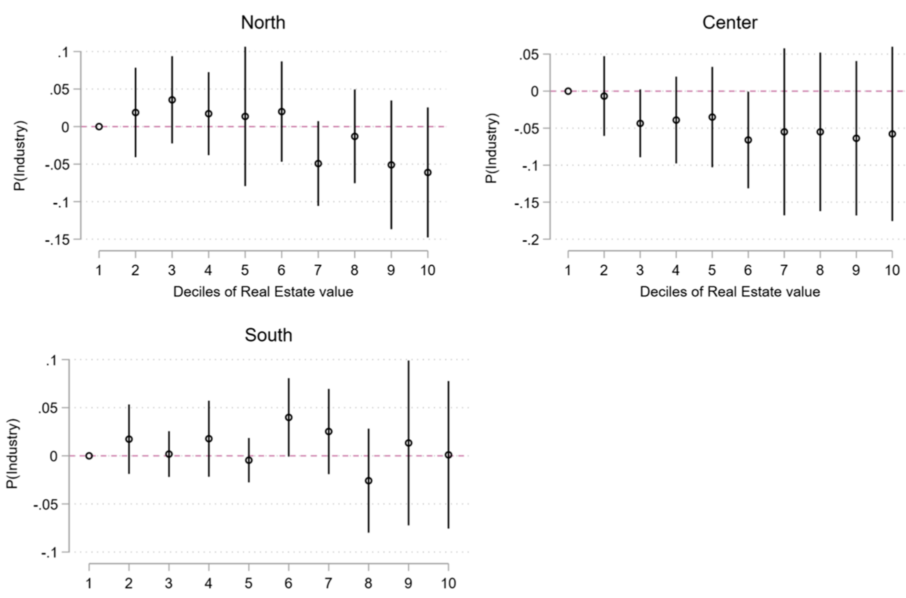

Fig. 7 Probability of proximity to an industry and SES by macro-area. This shows the relationship between the deciles of real estate value computed at the provincial level and the probability of the school being close to an industry by macro-areas. The model includes control variables described in Eq. (1) and province FE. Standard errors clustered at the provincial level. The 1st decile is set at the reference level. 95% confidence intervals

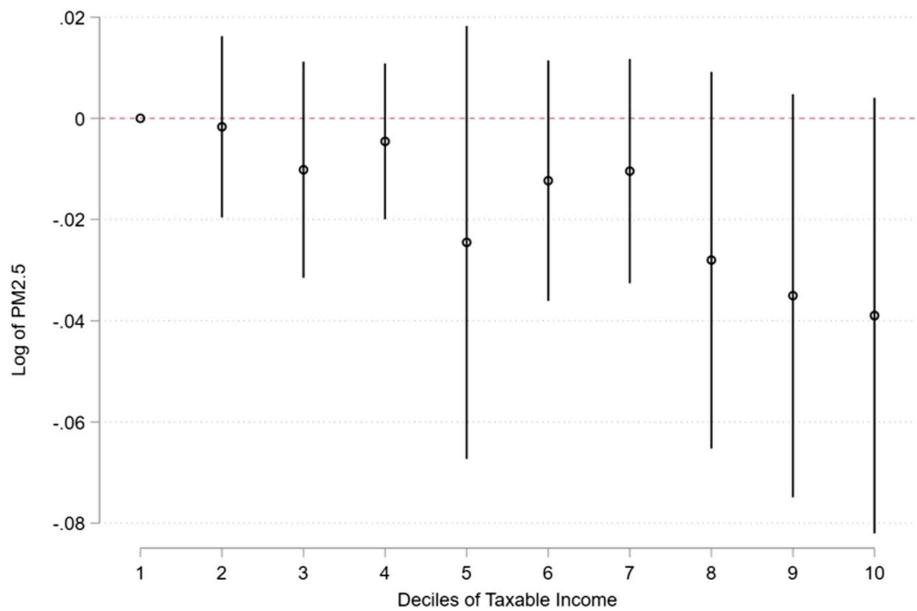

Fig. 8 PM2.5 and taxable income. This shows the relationship between the deciles of taxable income computed at the provincial level and log PM2.5. The model includes control variables described in Eq. (1) and municipality FE. Standard errors clustered at the provincial level. The 1st decile is set at the reference level. 95% confidence intervals

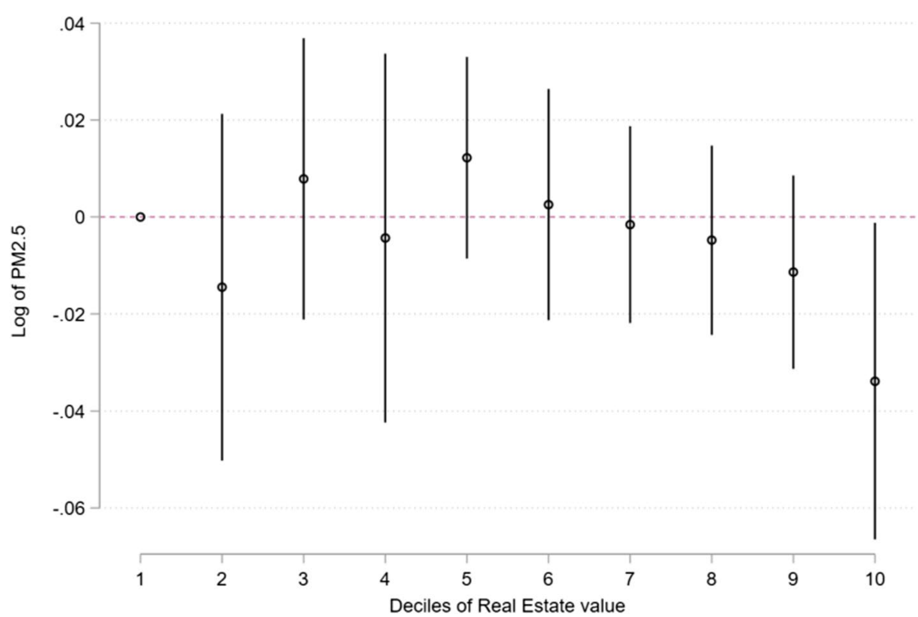

Fig. 9 PM2.5 and SES in the restricted sample. This shows the relationship between the deciles of real estate value computed at the provincial level and log PM2.5. The model includes control variables described in Eq. (1) and municipality FE. Standard errors clustered at the provincial level. The 1st decile is set at the reference level. 95% confidence intervals

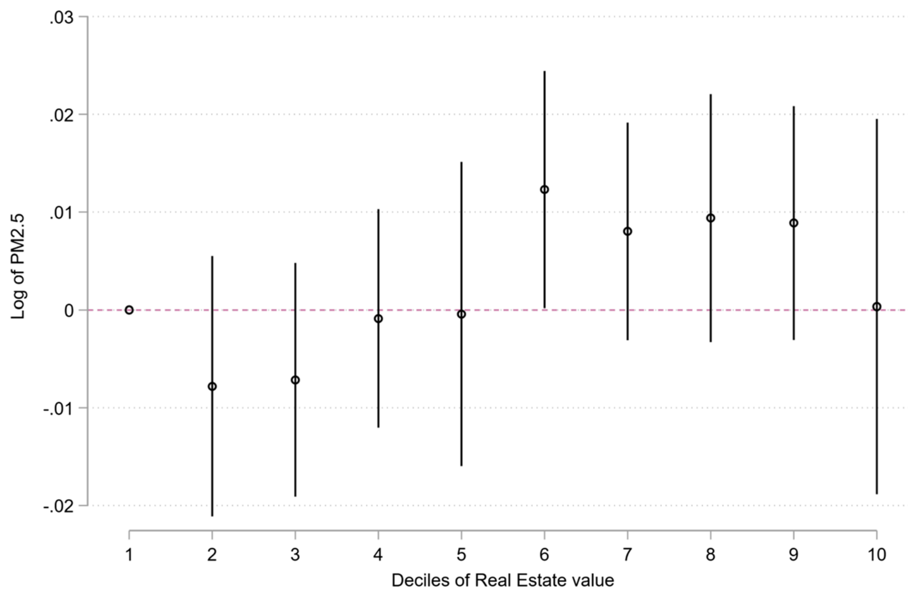

Fig. 10 PM2.5 and SES with municipality FE. This shows the relationship between the deciles of real estate value computed at the provincial level and log PM2.5. The model includes control variables described in Eq. (1) and municipality FE. Standard errors clustered at the provincial level. The 1st decile is set at the reference level. 95% confidence intervals

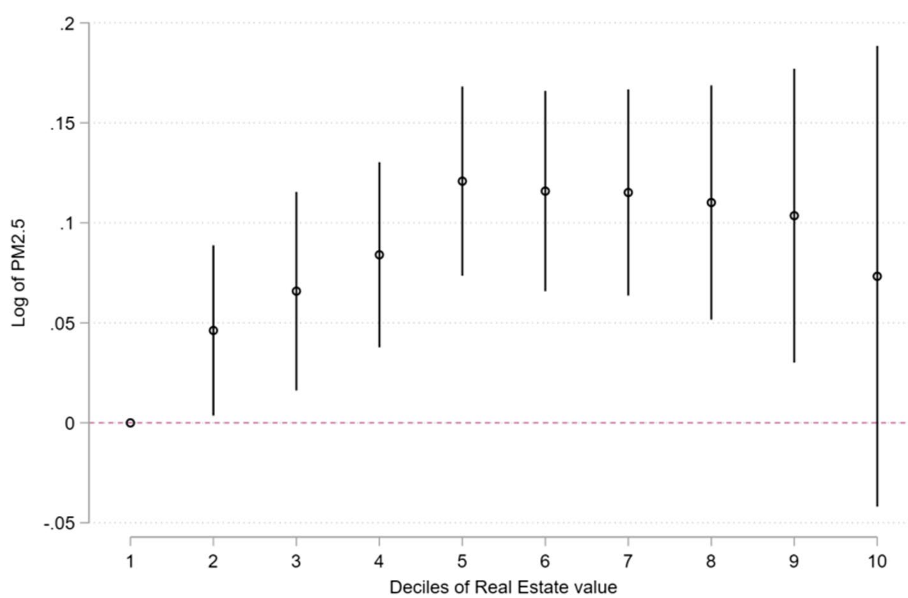

Fig. 11 PM2.5 and real estate values computed at the national level. This shows the relationship between the deciles of real estate value computed at the national level and log PM2.5. The model includes control variables described in Eq. (1) and province FE. Standard errors clustered at the regional level. The 1st decile is set at the reference level. 95% confidence intervals

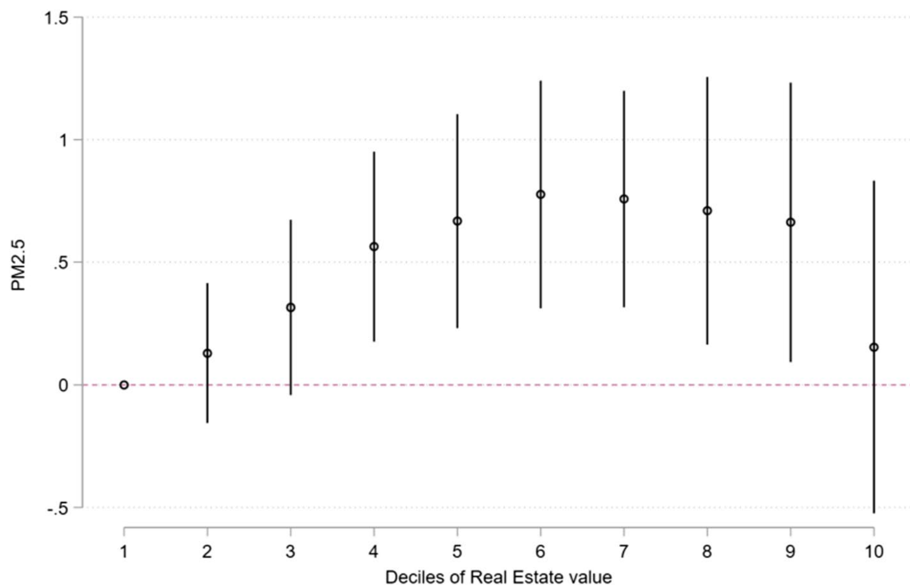

Fig. 12 Non-log PM2.5 and SES. This shows the relationship between the deciles of real estate value computed at the national level and PM2.5. The model includes control variables described in Eq. (1) and province FE. Standard errors clustered at the regional level. The 1st decile is set at the reference level. 95% confidence intervals

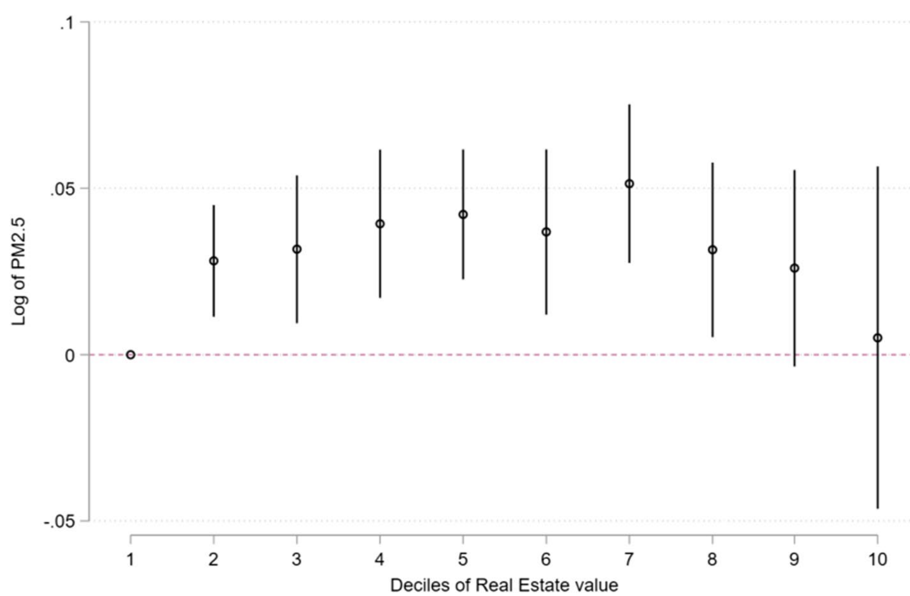

Fig. 13 Relationship between school SES and air pollution in 2002. This shows the relationship between the deciles of real estate value computed at the provincial level and PM2.5 with data for 2002. The model includes control variables described in Eq. (1) and province FE. Standard errors clustered at the regional level. The 1st decile is set at the reference level. 95% confidence intervals

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Author contribution
The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation. Both authors read and approved the final manuscript.

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Data available upon request to the authors.

Declarations

Competing interests
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