Spatial & temporal disparities in air pollution exposure at Italian public 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. Here, I geocode addresses of approximately 23 thousand public elementary and middle schools in Italy and connect them with estimates on Particulate Matter 2.5 measured in µg/m3 at a 1x1km resolution from 2001 to 2018 provided by the Atmospheric Composition Analysis Group (ACAG). Moreover, I create an indicator of school SES using fine-grained information on the real estate price made available by the Italian Observatory of Real Estate Value. Results highlight three main findings. First, most schools show an improvement in air quality over time of around 30%. Secondly, the decrease is larger in absolute terms in the most polluted schools in 2001 but similar in proportional terms across the countty. Thirdly, SES shows a quadratic relationship with PM2.5. In conclusion, air quality has improved but schools in middle SES neighbourhoods are the most exposed to air pollution.

Introduction

Air pollution is not equally distributed over space and time and some individuals are more exposed than others (Manduca & Sampson, 2021; Colmer, Shimshack & Voorheis, 2020). Disparities in exposure between geographical areas are present and mostly map existing socioeconomic inequalities (Fairburn et al., 2019; Heblich, Trew & Zylberberger, 2021). 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., 2021). Similarly, the investigation of exposure at a specific public institution, such as schools, unravels critical environmental inequalities between neighbourhoods (Grineski & Collins, 2018).

Schools are a vital public institution where exposure to air pollution has important consequences (Grineski et al., 2020). For example, children exposed to high levels of air pollution are more likely to develop respiratory conditions such as asthma (Alexander & Schwandt, 2019; Buka, Koranteg, Osornio-Vargas, 2006; Currie, 2013; Kravitz-Wirtz et al., 2018). Moreover, air pollution has been largely found to hamper learning, decrease students' cognitive abilities, and increase their absences (Amazandeh, Vesal & Ardestani, 2020; Currie et al., 2009; Mullen, et al., 2020; Grineski et al., 2020; Heissel, Persico & Simon, 2019; Ebenstein, Lavy & Roth, 2016). Consequently, mapping inequalities at school premises is critical from a public health and environmental justice perspective (Grineski & Collins, 2018).

The main research questions we investigate are two: (1) How does exposure to air pollution at school premises vary over time? (2) How does the socioeconomic characteristics of the school's neighborhood explain spatial variation in exposure to air pollution? To do so, we focus on Italy collecting data on addresses of more than 23 thousand public schools and combine them with precise estimates of Particulate Matter 2.5 μg/m3 (PM2.5) from 2001 to 2018. In addition, we create an indicator for the SES of the schools using the average value of real estate in the neighbourhood in 2018.

Previous studies mostly focused on inequalities in exposure at a broader geographical level or on a single point in time, but exposure can largely vary within the lowest administrative boundaries and over time (Mangia et al., 2012; Colmer et al., 2020). 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; Manduca & Samson, 2021).

This study advances the literature on disparities in the population exposure to environmental risks and environmental justice 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 analysis (Grineski & Collins, 2018). Thirdly, we contribute to the literature on the socioeconomic disparities in the exposure to air pollution in Europe exposing a quadratic relationship between SES and PM2.5 in Italy.

Schools, spatial & temporal disparities in exposure to air pollution

Schools as critical institution

Schools are a critical institution where children's exposure to air pollutants could be particularly consequential for their health and academic success. Children are more vulnerable to air pollution compared to adults (Orellano et al., 2017). The World Health Organization (WHO) report on "Air pollution and child health: prescribing clean air" highlights how multiple physiological characteristics of children are responsible for their higher susceptibility (WHO, 2018). Compared to adults', 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, Sly & Knibbs, 2016). For example, higher levels of air pollution have been linked with reduced lung development and smaller lung volume (Barone-Adesi, et al., 2015; Gehring et al., 2013; Mudway et al., 2019). In addition, children are susceptible to develop asthma or worsened respiratory conditions when exposed to high levels of pollution lowering their school attendance (Darrow et al., 2014; Currie et al., 2009; Orellano et al., 2017). Similarly, toxic pollutants impair neurological development in infants and affect their cognitive abilities (Payne-Sturges et al., 2019; Amazandeh, Vesal & Ardestani, 2020). Several studies have shown air pollution to decrease test scores with short-term and long-term exposure (Amazandeh, et al., 2020; Mullen, et al., 2020; Heissel, Persico & Simon, 2019; Ebenstein, Lavy & Roth, 2016).

Spatial disparities to air pollution

Disparities in exposure between geographical areas are critical and often map existing societal inequalities, but the SES of a neighborhood has failed to consistently predict higher exposure to air pollution (Fairnburn et al., 2019; Hajat et al., 2015). On one hand, in the U.S. context, low SES and ethnic minorities are disproportionately exposed to high levels of air pollutants (Colmer et al., 2020; Grineski & Collins, 2018; Samson & Manduca, 2021). And this is the case also in London (Heblich et al., 2021). On the other hand, the European context, has failed to show consistent results in the relationship between SES and exposure to air pollution (Fairnburn et al., 2019; Hajat et al., 2015). For example, in Rome, in Italy, high SES individuals are more exposed to higher levels of pollution as living in the central areas of the city that have a higher incidence of traffic (Forastiere et al., 2007). Moreover, it is relevant to distinguish between types of air pollutants as these can be produced from different sources exposing populations to separate or additive risks (Urman et al., 2014). For example, in the U.S. the air pollutants PM10, PM2.5, NO2, CO and lead, are heterogeneously distributed in the territory (Samson & Manduca, 2021). However, these sources of pollution are always found to be the most prevalent in the more deprived communities. Consequently, the relationship between SES and air pollution might differ depending on the country context and on the type of pollutant analyzed.

Air pollution over time

Air pollution has shown to persist in the same geographical area over time (Colmer et al., 2020). For example, in London, higher air pollution has persisted in the Eastern part of the city from the 18th century to the current days (Heblich et al., 2021). Also, this part of the city is mostly inhabited by low SES individuals highlighting the persistence of environmental inequalities over generations. Similarly, in the U.S., the decline in air pollution has been highest in areas with a higher proportion of high SES and white inhabitants (Colmer et al., 2020). These findings can be explained by selective migration as high SES individuals might relocate to less polluted areas (Best & Rüttenauer, 2018). Another explanation could be the higher capabilities of high SES populations to promote policies that reduce air pollution in their neighborhood (Aldred et al., 2021; Hajat et al., 2015). Overall, the persistence of inequalities in air quality over time is concerning from an environmental justice perspective.

Datasets & variables

In this study, we focus on Italy and employ five main sources of data. (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) (Schiavina et al., 2019). (5) Finally, we collected data on the Leaf Area Index (LAI) available in the Copernicus Data Store[1].

School addresses are publicly accessible in the national database provided by the Italian Ministry of Education. However, the location is not publicly available. Consequently, to capture the longitude and latitude of the schools we geocoded the addresses using the HERE API[2]. The sample of geocoded schools comprises the elementary and middle public and private schools for which addresses are available comprising a total of 23,211 observations. The elementary schools are attended by pupils aged 6 to 11 and the middle schools in the age 11 to 14. These school are a good proxy of the neighbourhood in which the students live, as attendance is often determined based on residence in the school district. Nevertheless, 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/m3 air pollution from 2001 to 2018 is provided by the ACAG that combines satellite, chemical transport modelling and in-situ observations to achieve a resolution of a 1x1km (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 (Darrow et al., 2014; Xing et al., 2016; Colmer et al., 2020). 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, Rubin & Walker, 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

[1] The dataset is freely available in the website: https://cds.climate.copernicus.eu/#!/home.

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

data on the second semester of 2018. Provided are the minimum and maximum values of the real estate measured as euros per square meter 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. The data available is 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 250meters[3] 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].

The Leaf Area Index (LAI) is a widely used indicator of "greenness" of a selected area. More precisely, it uses remote sensing technologies to measure the amount of leaf material in a specific territory[5]. Here, 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 the log value of PM2.5. 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 and we use the logarithm of the average value at the school location in 2018. For population density, we use the log value of the population in the 250m grid cell in which the school is located. The LAI is computed averaging the daily values to the monthly averages and averaged at 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 of 1,925(8.3% of the total sample) and the middle schools are 7,496(32.3% of the total sample).

Empirical Strategy

The empirical strategy is divided in two main parts.

[3] The GHLS also provides data at a 1km resolution, but we used the information at 250 meters for higher accuracy.
[4] For more information please refer to the following website: https://ghsl.jrc.ec.europa.eu/ghs_bu_s2_2018.php .
[5] A more detailed description of the metric is provided in the Copernicus Data Store (CDS) : https://cds.climate.copernicus.eu/cdsapp#!/dataset/satellite-lai-fapar?tab=overview

First, we answer our first research question providing simple descriptive statistics on the exposure to PM2.5 from 2001 to 2018 at the location of the schools. Secondly, we employ a Spatial Lag of X(SLX) with fixed effects (FE) to observe how school SES is associated with PM2.5 in 2018.

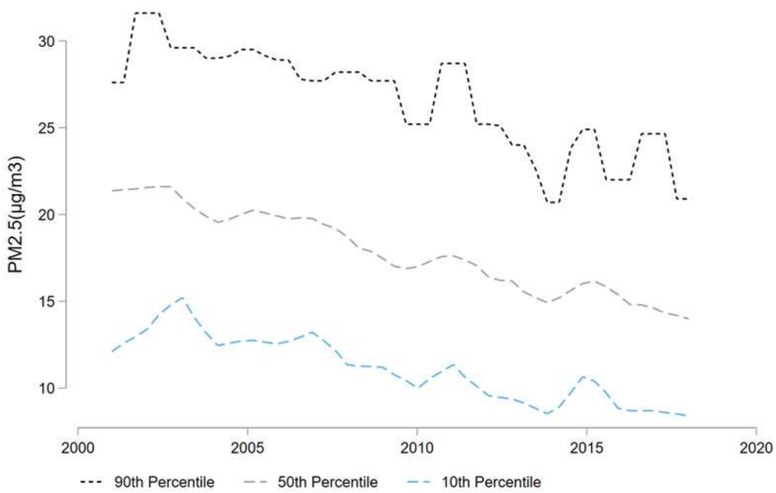
More precisely, to answer our second research question we proceed in four steps. In the first step, we use simple Ordinary Least Squared Regression described in Equation (1) to investigate the relationship between air pollution and SES of the school. Here, the outcome variable *PM* is the log value of PM2.5 measured at school *i*, *SES* is the real estate value at the school *i* and *X* is a vector comprising the control variables described in the preceding section.

$$1)\quad Log\ (PM_i) = SES_i + X_i + e_i$$

In the second step, we add to the Equation (1) spatial weights to correct for spatial clustering. We do so using the SLX model for the advantages it has shown in previous research that compared it to other spatial models (Ruttenauer, 2018; Ruttenauer, 2019). We construct our Weight matrix using the K-Nearest Neighbors (KNN) approach with 12 Nearest Neighbors. In the third step, we include municipality FE in the analysis, that are in total 6,150. In the fourth step, we include a quadratic term for school SES to capture non linearities in the relationship between SES and air pollution, as previous studies in Europe have shown a nonlinear relationship, highlighting middle SES individuals to be more exposed to air pollution (Richardson et al., 2013).

Results

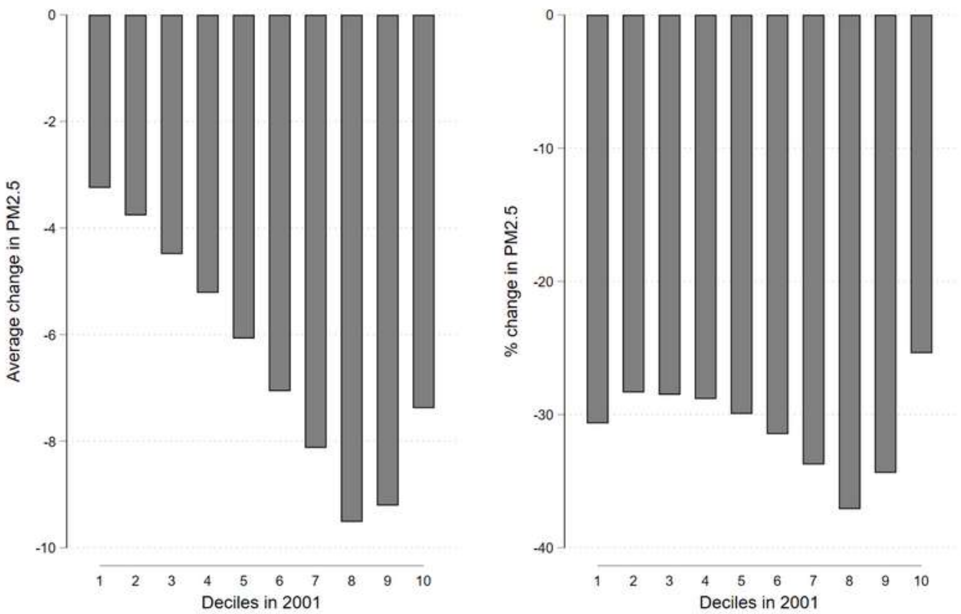
Figure 1. Air pollution at schools from 2001 to 2018



Note: The figure shows the level of PM2.5 µg/m3 at the schools at the 90th, 50th and 10th percentile in the PM2.5 distribution from 2001 to 2018.

In Figure1, we can observe large decrease in air pollution over time. However, the decline in air pollution might be more pronounced in certain locations. In Figure 2, I investigate the absolute and proportional change in PM2.5 in 2018 compared to 2001 based on deciles computed using PM2.5 in 2001. The most polluted schools in 2001 experienced the highest absolute reduction in pollution. However, the relative change in pollution is more homogeneous across deciles.

Figure 2. Absolute and relative decline in air Pollution at Schools



Note: In the left graph, can be observed the absolute reduction in pollution in 2018 compared to 2001, based on deciles representing the most polluted schools in 2001. In the right graph, can be observed the proportional change in air pollution.

In Table 1, we show the summary statistics for the main variables in the analysis. The average value of PM2.5 at 13.31µg/m3 highlights that in 2018 most Italian public schools do not comply with the WHO (World Health Organization) guidelines of PM2.5 annual levels below 10 µg/m3 (Krzyzanowski & Cohen, 2008). However, there is high heterogeneity in the level of air pollution at the school premises with the lowest value of 3.6 µg/m3 and highest of 24 µg/m3. In Figure 3, we map the level of PM2.5 to better visualize the heterogeneous spatial distribution. 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).

Table 1. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
PM2.5	23211	14.31	4.53	3.6	24
Estate value in €	23211	1,421.29	863.89	170	13,000
Private schools	23211	.08	.28	0	1
Middle schools	23211	.32	.47	0	1
Density	23211	349.65	344.61	0	4524.58
Leaf area index (LAI)	23211	.46	.27	0	1.47

Note: The table presents summary statistics on the main variables.

Figure 3. PM2.5 µg/m3 Air Pollution at Schools in 2018

Note: The figure shows the level of PM2.5 µg/m3 at each school location in 2018.

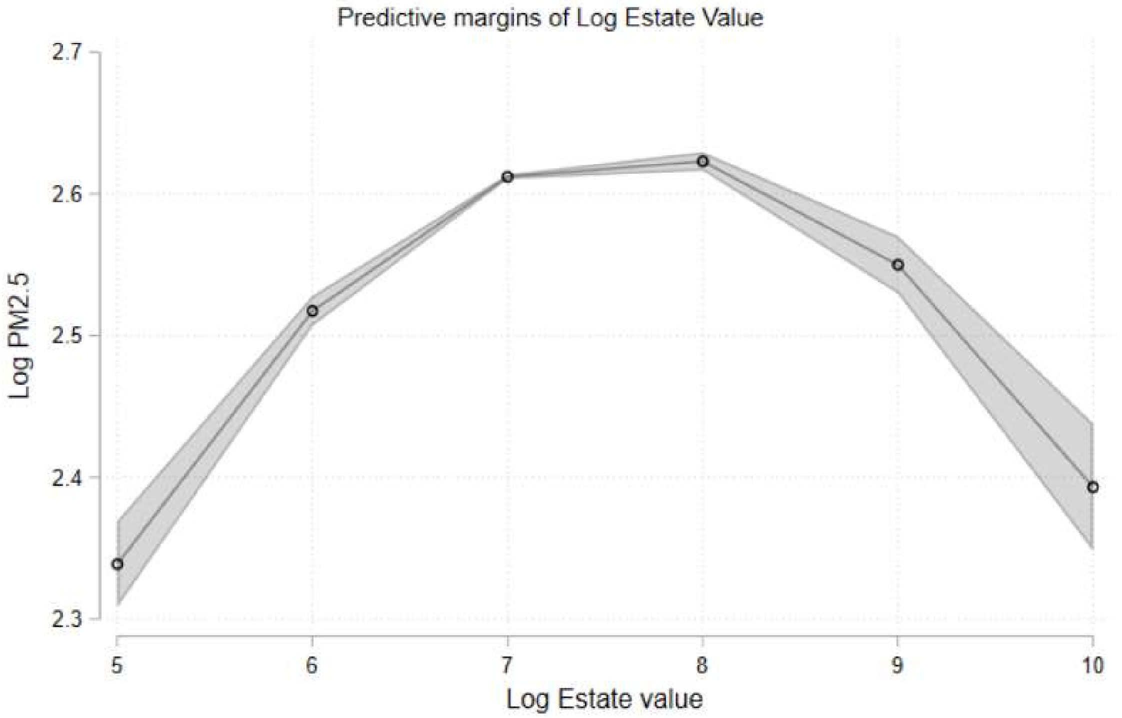
Table 2. Air pollution, School SES and different model specificiations

	(1)	(2)	(3)	(4)
Dependent Variable: Log PM2.5	OLS	SLX	SLX & FE	SLX & FE
Log Real Estate Value	0.233***	0.017	0.031***	0.640***
	(0.004)	(0.011)	(0.004)	(0.041)
Private school	0.046***	0.020**	-0.001	-0.001
	(0.008)	(0.008)	(0.002)	(0.002)
Middle School	-0.008	-0.012**	0.004***	0.004***
	(0.004)	(0.004)	(0.001)	(0.001)
Log Density	0.006***	0.007***	0.009***	0.008***
	(0.001)	(0.001)	(0.000)	(0.000)
Log LAI	-0.028***	-0.043***	-0.023***	-0.023***
	(0.002)	(0.004)	(0.001)	(0.001)
W [Log Real Estate Value]		0.019***	-0.000	0.003***
		(0.001)	(0.000)	(0.001)
W [Private school]		0.024***	-0.004***	-0.004***
		(0.002)	(0.001)	(0.001)
W [Middle School]		-0.012***	-0.001	-0.001
		(0.002)	(0.001)	(0.001)
W [Log Density]		-0.001**	0.002***	0.002***
		(0.000)	(0.000)	(0.000)
W [Log LAI]		0.002***	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
Log Estate * Log Estate				-0.042***
				(0.003)
Observations	23,211	23,211	23,211	23,211
R-squared	0.172	0.199	0.970	0.970
Municipality FE	NO	NO	YES	YES

Note: Table 2 shows the results of four models. In column (1), are exposed the results of the naïve OLS model. In column (2), are the results of the SLX model. In column (3), we show the results of the SLX with FE. In column (4), we present results for the SLX with FE with a quadratic term for the estate value. Significance levels: *** $p<0.001$, ** $p<0.01$, * $p<0.05$.

In table 2, we explore how the SES of the school is associated to PM2.5 in 2018. First, in column (1) can be observed a positive relationship between school's real estate value and PM2.5 . However, in column (2) the introduction of spatial weights for the independent variables substantially reduces the size of the effect and statistical significance. In column (3), we introduce the municipality FE and observe a slightly larger coefficient compared to column (2). In column (4), we add a quadratic term that reveals a statistically significant and negative coefficient. We further inquire the quadratic relationship in figure

Figure 4. Quadratic relationship between school SES and Air pollution



Note: Figure 4 shows the quadratic relationship between the log of the Real Estate value and PM2.5. 95% Confidence Intervals.

Discussion and conclusion

In this article, we exposed disparities in the exposure to PM2.5 air pollution at school premises in Italy. There are three main findings. First, Italy shows a high geographical variation in the levels of PM2.5, but a constant improvement in air quality since 2001. Secondly, air quality in absolute terms improved more in the already polluted areas, but the proportional change is more homogeneous across schools and High SES schools have experienced a higher reduction in air pollution. Thirdly, school SES is positively associated with PM2.5, but the introduction of a quadratic term unravels a quadratic relationship.

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 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 residents (Stafoggia et al., 2019; Raffaelli et al., 2020). However, to our knowledge, this is the first time that the improvements in PM2.5 from 2001 to 2018 is exposed for Italy at a fine geographic resolution.

The results on the relationship between SES and air pollution highlight how this can differ depending on the country context (Richardson et al., 2013). In the U.S., the poorest neighbourhoods are the most exposed to high levels of air pollution (Colmer, et al., 2020; Manduca & Samson, 2021). However, in Europe, the results look more mixed (Richardson et al., 2013). For Italy, we have shown SES to be quadratic with PM2.5 implying higher exposure to air pollution for individuals attending schools in middle SES neighbourhoods. In comparison, previous findings on SES and air pollution have found a positive relationship in Italy, in Rome when observing citizens' exposure to air pollution (Forastiere et al. 2007).

The study has some obvious limitations. First, the study is descriptive and cannot infer a causal relationship between SES and PM2.5 or be generalized to other country contexts. Secondly, 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 permit to analyse a more fine-grained geographical unit. On the other hand, attention on schools' limits 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. For example, air pollution has been linked with increased school absences and lower test scores (Amazandeh et al. 2020; Currie et al., 2009). Moreover, other SES measures could be used to observe differing associations with air pollution (Hajat et al., 2015). Similarly, air pollutants such as PM10, Ozone, Nitrogen Dioxide or Lead could have enlarged the analysis on other environmental risks. Nonetheless, real estate value has shown to be a good proxy of a neighbourhood SES (Ware, 2019) and PM2.5 is often cited as the most harmful air pollutant (Colmer et al., 2020).

In conclusion, the article has two main take-home messages. First, despite a constant improvement in air quality, air pollution continues to pose a threat for Italian students as the level of PM2.5 exceeds in most schools the WHO guidelines of 10 μg/m3, particularly in the Po Valley. Secondly, exposing the quadratic relationship between SES and air pollution in Italy, we highlight how middle SES schools are the most exposed to high levels of pollution in Italy

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