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Summary

This study addresses the presence of an environmental justice issue along the dimensions of income and ethnicity in the urban context of Bologna, Italy. Among other Italian cities, Bologna has historically had a left-leaning political tendency and has made considerable substantial efforts to address social issues extensively. This makes it a useful cross-section dataset links gridded PM2.5 concentration data at 0.01°x0.01° resolution with census demographic characteristics and income per capita information for the year 2011. This study presents two main findings. i) it confirms the existence of an environmental justice gap, which affects vulnerable segments of the population along both income and ethnicity dimensions. A 1% increase in income per capita is associated with a 0.09% decrease in PM2.5 levels (a rise of 1 standard deviation of income per capita in the census corresponds to a reduction of -0.53 mg/m^3 in PM2.5); whereas a 1% increase in the share of non-white individuals living in the census tract leads to a 0.13% increase in PM2.5 levels (+3.92 mg/m^3 increase associated with a rise of 1 standard deviation in the proportion of non-whites in the census). ii) There is currently no evidence to suggest that exposure disparities for non-white individuals are changing depending on income level, whether it is lower or higher. Residence in lower/higher income areas of the city does not significantly exacerbate/alleviate these disparities for non-white communities. Overall, these results highlight the widespread occurrence of environmental injustice across various geographical and political settings, including those that have historically prioritized social concerns.

Keywords: Environmental inequality; Environmental justice; Air pollution; Racial disparities; Socioeconomic status.

JEL classification: Q53, Q56, I14, C21

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Breathing Inequality? Income, Ethnicity and PM2.5 Exposure in Bologna, Italy.

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Abstract

This study addresses the presence of an environmental justice issue along the dimensions of income and ethnicity in the urban context of Bologna, Italy. Among other Italian cities, Bologna has historically had a left-leaning political tendency and has made considerable substantial efforts to address social issues extensively. This makes it a useful reference point for studies on urban environmental justice in Italy and Europe. The used cross-section dataset links gridded PM2.5 concentration data at 0.01°x0.01° resolution with census demographic characteristics and income per capita information for the year 2011. This study presents two main findings.
i) it confirms the existence of an environmental justice gap, which affects vulnerable segments of the population along both income and ethnicity dimensions. A 1% increase in income per capita is associated with a 0.09% decrease in PM2.5 levels (a rise of 1 standard deviation of income per capita in the census corresponds to a reduction of -0.53 mg/m^3 in PM2.5); whereas a 1% increase in the share of non-white individuals living in the census tract leads to a 0.13% increase in PM2.5 levels (+3.92 mg/m^3 increase associated with a rise of 1 standard deviation in the proportion of non-whites in the census).
ii) There is currently no evidence to suggest that exposure disparities for non-white individuals are changing depending on income level, whether it is lower or higher. Residence in lower/higher income areas of the city does not significantly exacerbate/alleviate these disparities for non-white communities.
Overall, these results highlight the widespread occurrence of environmental injustice across various geographical and political settings, including those that have historically prioritized social concerns.

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1. Introduction

The adverse impacts of air pollution on human health, (WHO Europe, 2016; Landrigan et al., 2018), cognitive functioning (Zhang et al., 2018), and productivity (Zivin and Neidell, 2012) are extensively documented in academic literature. In light of these environmental threats, the European Union's Seventh Environment Action Programme (7th EAP) (EC, 2013) has identified the safeguarding of EU citizens from such hazards as one of its primary objectives. Identifying vulnerable populations exposed to pollution underscores the importance of examining pollution distribution through an environmental justice lens, which advocates for equitable protection from environmental impacts irrespective of social or economic status (Mohai et al., 2009). American studies have predominantly identified demographics and socioeconomic factors as potential sources of vulnerability, revealing persistent inequalities in PM2.5 exposure over time primarily associated with belonging to a lower income class and/or a racial minority (Colmer et al., 2020; Jbaily et al., 2022; Tessum et al., 2021; Gillingham and Huang, 2021; Currie et al., 2023; Cain et al. 2024), while in Europe results are less clear.

Despite the growing attention to this subject, the overall volume of research in Europe remains limited in comparison to the US. Significant obstacles for empirical studies derive from the broader challenge of data availability and its disaggregation level (Glatter-Gotz et al., 2019; Jünger, 2022). Among the European studies, some have used proxies for potential exposure such as distance of residential areas to a polluting facility (Glatter-Gotz et al., 2019; Raddatz et a 2013), or gridded demographic information matched to the location of polluting industrial facilities (Rüttenauer, 2018; Neier, 2021), which as extensively discussed by Currie et al. (2023), is an imperfect substitute for ambient air pollution exposure. In fact, while they provide clear evidence about the punctual emission from the facility, it is less clear how this translate into inequalities in measured exposures, due to missing information about air transport factors and mobile sources of pollution. Consequently, although those studies provide insights into racial composition of residents in proximity to toxic facilities and hazardous waste sites, the exact extent to which this translates into differences in measured exposures remains uncertain.

This study primary examines the presence of an environmental justice issue concerning income and ethnicity in the city of Bologna. It overcomes the data issues providing a dataset that exploits annual mean of Surface PM2.5 mg/m^3 gridded data at 0.01° × 0.01° [0.9 km by 1.11 km], keeping into account elements like winds, humidity and rainfall, therefore being more accurate in describing concentrations across areas. Gridded PM2.5 data are linked to the demographic's information provided by the census tracts for the year 2011 for the city of Bologna. This city provides an appealing urban reference point due to the gradual integration of ethnic minorities and its leftist political history. I adopt a multivariate linear regression with lagged explanatory variables to examine the association between PM2.5 levels, income pc and share of non-white minority, adding a vector of other socioeconomic controls.

To check if being part of a non-white minority is associated with higher PM2.5 exposure in lower income areas of the city, I add an interaction term between the share of non-white residents and a dummy variable that identifies the census where lower than median per capita income of the city. The findings indicate an environmental justice gap in the city along the income and the ethnicity dimensions. However, there is no evidence to suggest that ethnic exposure disparities are changing when interacted with income levels. Residence in lower/higher-income areas of the city does not significantly exacerbate/alleviate these disparities for non-white communities. Overall, identifying an environmental justice gap within one of Italy's most left-leaning mid-size urban environments has significant implications, revealing the widespread nature of environmental injustice concerns in diverse geographic locations and political contexts.

2. Conceptual Framework

Findings of the empirical studies of environmental justice in the United States suggest that non-white minorities and low-income individuals experience disproportionately higher levels of pollution (see Banzhaf et al., 2019; and Mohai et al., 2009; Hsiang et al., 2019; Colmer et al., 2020). However, there is a debate as to whether the observed associations between pollution and race are actually dependent on the presence of a deeper and more complex issue of income inequality (Banzhaf et al., 2019).
Polluting firms that evaluate sites may be drawn to the same cost-saving opportunities that initially attracted low-income individuals, ultimately ending up closer to disadvantaged neighborhoods and resulting in higher levels of pollution being faced by those communities (Wolverton et al. 2009). Environmental injustice could also arise from the residential decisions of individuals. Lower-income individuals will be less willing to pay higher prices for housing in exchange for higher environmental quality, due to income constraints, therefore moving closer to polluted areas (Banzhaf et al., 2019). The correlation between income, ethnicity and pollution exposure could result from either or both of the "siting versus move-in" paths, but overall, the socioeconomic factors underlying environmental inequality appear to be dependent on income disparities, rather than on pure racial or ethnic discrimination (Wolverton et al. 2009).
The main argument connecting ethnicity/race and unequal pollution exposure posits that for ethnic groups/racial minorities the capacity to advocate against polluters or regulators, as well as to initiate collective action, may be restricted due to language barriers or a lack of familiarity with/representation in local political processes (Hamilton, 1993; Cole et al. 2013). In addition, disparities in power related to race and ethnicity can exacerbate the disadvantage of economic vulnerability in bargaining for environmental outcomes. As a result, any inequalities in exposure based on race or ethnicity may lessen/intensify as incomes rise/decrease, and the impact of pollution exposure might probably be most pronounced in low-income non-white neighborhoods. Individuals who belong to both a marginalized ethnic group and a low-income bracket may experience compounded disadvantages compared to those who face only one form of disadvantage. This hypothesis can be tested by examining the interaction between race or ethnicity and income in empirical analyses (Apelberg et al. 2005; Zwickl et al. 2014).

3. Data

The cross-sections dataset counts 2072 census tracts. Annual average mean PM2.5 concentration data measured in micrograms per cubic meter mg/m^3 with a spatial resolution of $0.01° \times 0.01°$ (approximately 0.9 km by 1.11 km) are matched with census tracts information. This pollution data allows for consideration of both air transport factors and mobile sources of pollution, making it possible to overcome relying solely on datasets from punctual emissions of registered industrial facilities.

3.1. Pullution Data

Gridded yearly PM2.5 concentration data for the year 2013 are calculated utilizing a thorough methodology (Staffoggia et al. 2019) that integrates monitored PM data, aerosol optical depth (AOD) data, meteorological factors (daily mean air temperature, sea-level barometric pressure, and wind speed), and spatial predictors (geo-climatic zones, resident population, and land cover data). The use of this comprehensive approach is to offer precise predictions of PM concentrations ensuring dependable exposure estimates for environmental justice investigations.

3.2. Demographic and Socio-Economic data

Census socio-demographic and education variables are provided by ISTAT. Income values were obtained from Comune di Bologna Open Data at the statistical area level, an aggregation of census tracts. The raw income data represents the sum of the annual total declared income [1] from the individuals residing in the area. Using statistical areas population to calculate income per capita (pc), it was assumed that the income pc in a particular census section is equal to the income pc of the statistical area in which it is located. Census data and statistical area income data were made available for the year 2011 (see Appendix for further details).

4. Descriptive Statistics

Bologna has a population of 371,174 individuals, with 57.27% (212,592 individuals) residing in areas with a per capita income below the city's median per capita income of 18,000 euros. Non-white minorities constitute 6.18% (22,923 individuals) of the population, with 69.5% belonging to the Asian community and the remainder to the African community. 70% of non-white residents reside in lower-income neighborhoods.
Variations of PM2.5, income, and non-whites among census tracts and neighborhoods are shown in Appendix. The descriptive statistics for the variables utilized are displayed in Table 1. The variable 'Low education' refers to individuals who have completed elementary school, are currently in the process of completing elementary school, or lack the ability to read and write. The annual average pollution level in Bologna is 19.034 mg/m^3. This value exceeds the recommended threshold of 5 mg/m^3 set by the World Health Organization.

Table 1: Descriptive Statistics

Census tracts – Units	Obs	Mean	Std. Dev.	Min	Max
Annual average PM2.5 [ug/m3]	2072	19.034	.836	13.889	20.743
Total population	2072	179.138	158.987	1	1072
Non-whites	2072	11.063	16.048	0	124
Graduates	2072	40.132	40.841	0	286
High school	2072	52.87	48.341	0	271
Low education*	2072	38.841	41.318	0	259
Unemployed	2072	4.815	5.302	0	47
Children	2072	7.191	7.336	0	61
Elders	2072	26.203	26.581	0	226
Total buildings	2072	13.873	12.863	0	116
Income pc	2072	19840.46	5642.16	8473.261	44710.48
Census tracts – shares on total population					
share Non-whites	2072	.059	.093	0	1
share Graduates	2072	.231	.142	0	1
share High School	2072	.3	.105	0	1
share low education	2072	.21	.119	0	1
share Unemployed	2072	.026	.032	0	.667
share Children	2072	.04	.036	0	.5
share Elders	2072	.142	.1	0	1

* People that completed elementary school and people who lack the ability to write and/or read.

[1] The data refers to what in Italy is labeled as "reddito imponibile ai fini irpef".

4.1. The city of Bologna as benchmark for environmental justice studies

Bologna is a mid-size city with a relatively smaller and close-knit population. This has fostered stronger community ties across decades of migration influx, facilitating meaningful engagement with local residents, community organizations, and stakeholders. The most significant wave of economic migrants occurred in the 80s and 90s when North Africans, migrated to the surrounding of the city attracted by the availability of jobs in engineering and chemical sectors (Caponio, 2005). With the surge in demand for accommodation, the Bologna Municipality, led by the Communist Party, took a proactive step in 1989 by allocating substantial funding to provide first-accommodation services. This issue became increasingly relevant, and as a response, in 1990, the first foreign co-operative in Italy named "Metoikos" was founded in Bologna (Caponio, 2005). This evolution was bolstered by the left-wing local administration, which actively promoted a multicultural integration policy during that period (Caponio, 2005). Bologna is recognized for its notable left-wing history of administration, positioning it as one of the most leftist cities in the country (Giannini and Pirone, 2019), characterized by a more uniform left-wing tradition in local government until early 2000s (Caponio, 2005). Fabbri and Gaspari (2021) examine building energy performance's role in Bologna's energy poverty. They find no income-building performance correlation, crediting Bologna's social mix for this anomaly. Therefore, compared to other Italian cities, Bologna potentially might display a narrower environmental equity gap.

4.2. Mapping patterns

Figure 1 displays the city of Bologna, highlighting the main roads in red. The city can be divided into three main areas. Starting from the southern part, there is a hilly green area with a lower visible building density. Moving northward, the inhabited area becomes more concentrated, as the distribution of houses and buildings increases. This central part extends in an east-west direction, forming a striped shape that encompasses the historical city center. The historical center is recognizable as a rounded core located in the very center of the map. The third area is the northern region, located above the main road (in thicker red), characterized by a flatter morphology and a sparser presence of buildings.

The majority of the inhabited census tracts are concentrated in the central striped-shaped inhabited area, mainly in the immediate suburbs outside the historical center (Fig 2). This trend may be attributed to several factors, including the smaller dimensions of the census tracts in the historical center, the concentration of institutional and cultural buildings in this area. Also, the expansion of residential housing in Bologna can be traced back to the Italian economic boom of the 1960s and 1970s, when there was a considerable need for residential properties (Fabbri and Gaspari, 2021). As a result, many districts and suburbs in the surrounding areas were built to meet the high demand for housing.

Figure 3 illustrates the annual variability in average PM2.5 concentrations across the city. The results indicate a discernible pattern of increasing concentration from south to north, with the air quality being comparatively better in the hilly and greener southern areas and deteriorating progressively as one moves towards the northern part. The most polluted census tracts are those in proximity to the central station. Looking at the income distribution across the study area (Figure 4), it reveals that areas with higher income per capita are primarily situated in the central-south and southern parts. Notably, these areas also report lower annual levels of PM2.5 concentrations. Residents with higher incomes who live closer to the city center also experience higher levels of pollution, although they represent a smaller proportion of the population.

Figure 5 displays the proportion of non-white individuals in each census tract as a percentage

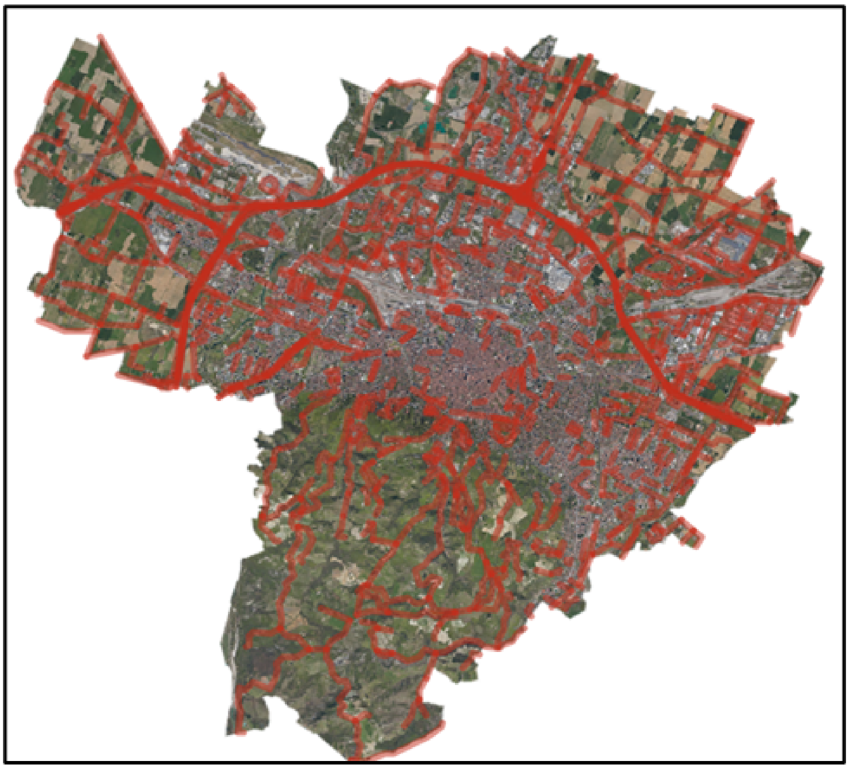

Figure 1: Map of Bologna. Main streets in red.

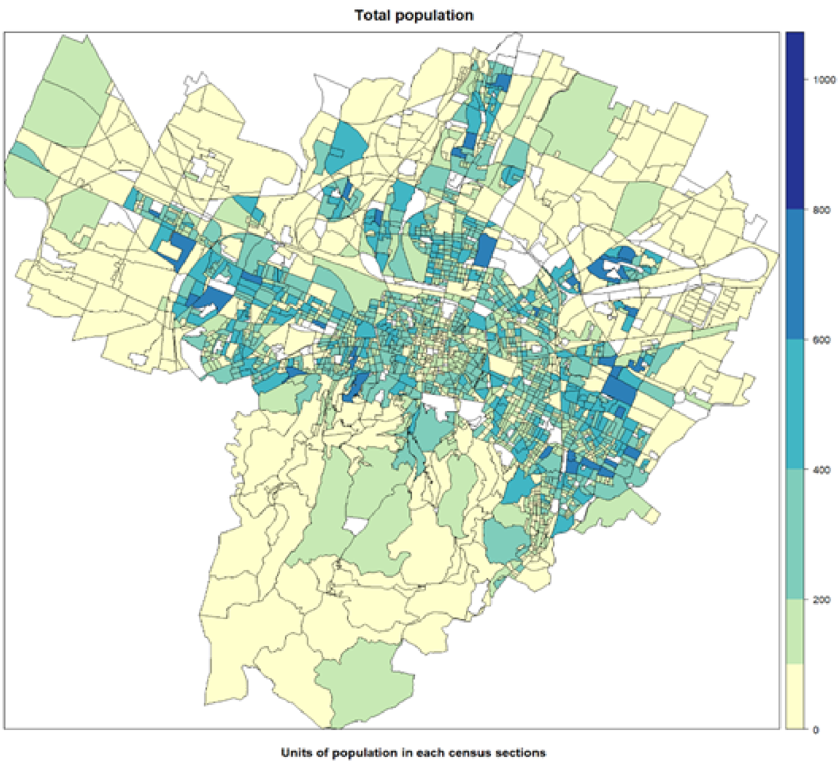

Figure 2: Population distribution in Bologna.

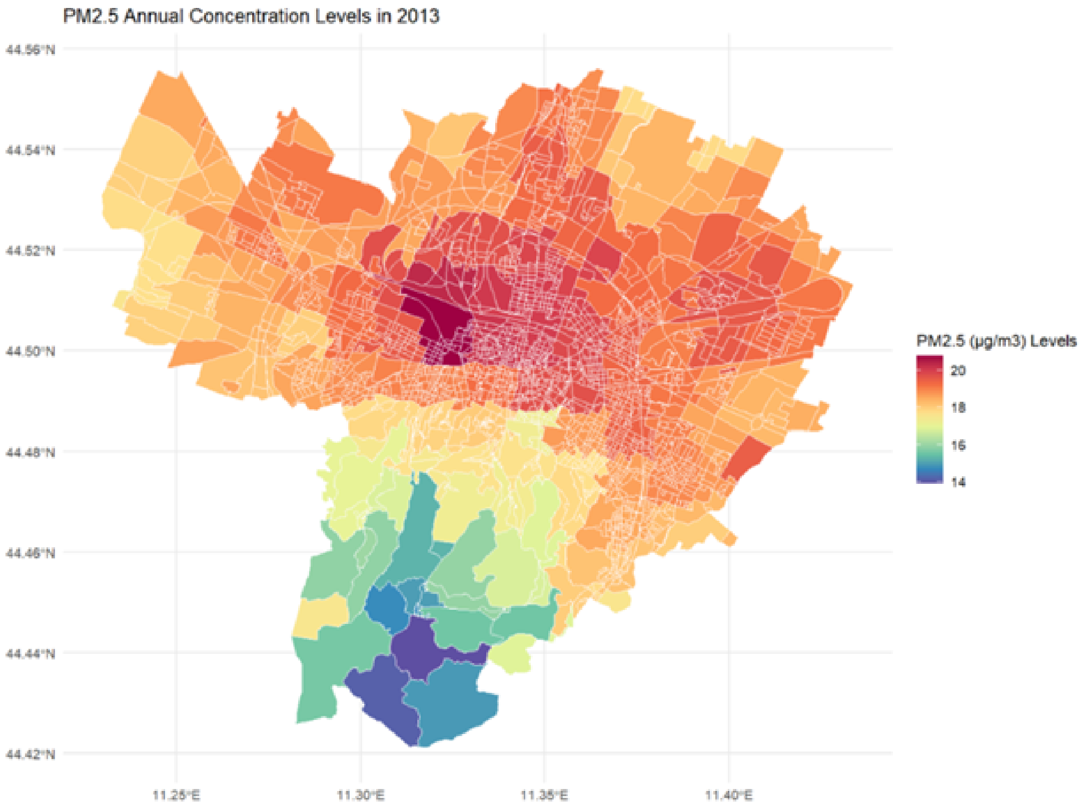

Figure 3: Distribution of PM2.5 in Bologna.

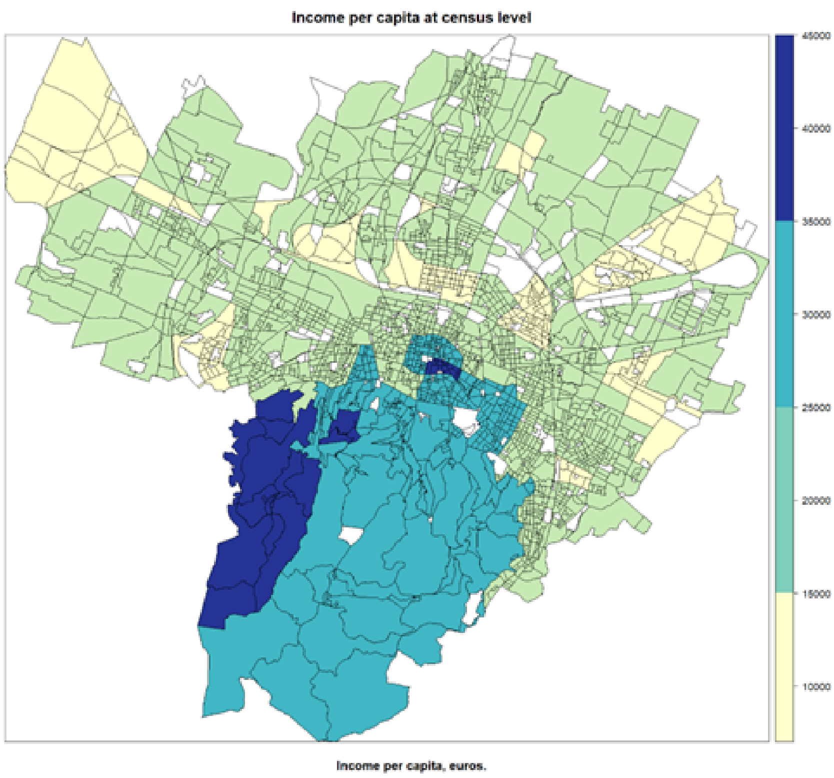

Figure 4: Income distribution in Bologna.

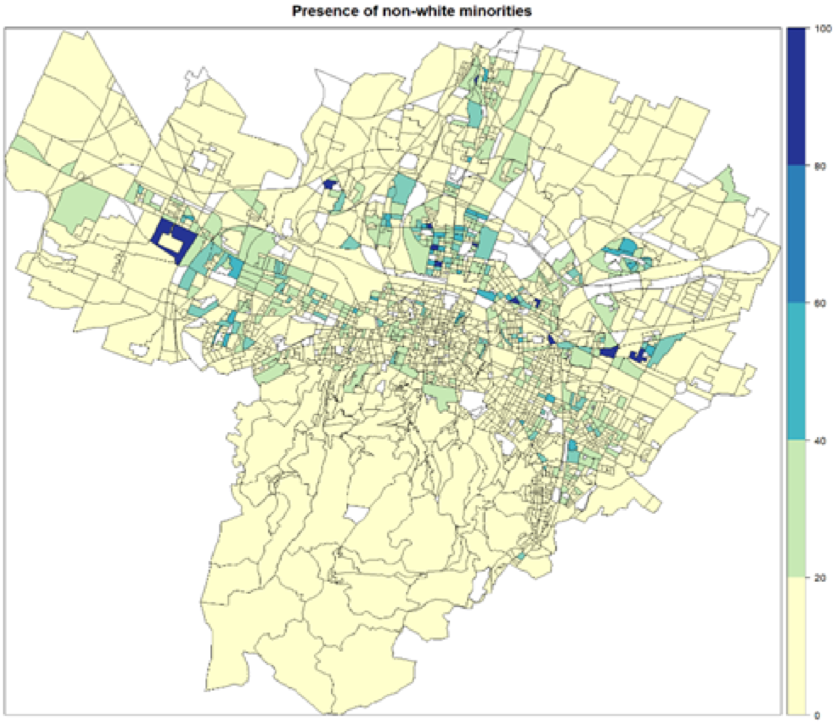

Figure 5: Distribution of PM2.5 in Bologna.

of the total population. The census tracts with the highest percentages of non-white individuals are primarily located in the further suburbs, particularly on the western-eastern border of the city, which overlaps with areas of above-average pollution.

5. Empirical Strategy

The multivariate regression model is specified as follows:

$$\ln(\mathrm{PM}_{2.5})_i = \beta_0 + \beta_1 \ln(\text{income\_pc})_i + \beta_2 \text{share\_NonWhites}_i + \gamma X_i + \varepsilon_s \tag{1}$$

where i indicates the census tracts. Since income is an aggregated regressor, errors are clustered accordingly. By clustering at this level, the analysis appropriately addresses the potential dependence introduced by the aggregated dimension of the income variable. In addition, clustering in this way allows to account for potential spatial dependence of the observations and for potential measurement errors encountered during the recording of PM2.5 levels across diverse census tracts. Share of non-whites indicates the presence of non-white minorities over total population of the census. The vector $\mathbf{X}_i$ includes a set of control variables such as the share of people according to their education levels, to their age class, share of unemployed and total buildings of the census tracts. To capture the associations of education on pollution exposure, variables reflecting the share of individuals possessing at least an undergraduate/bachelor's university degree, high school diploma, and the share of those who finished elementary school and those who are lacking reading and writing skills are added to the model. Buildings can serve as sources of PM2.5 emissions: combustion processes, such as heating and cooking, can release particulate matter into the indoor and outdoor environment (Martins and Carrilho da Graça, 2018). The dependent variable and per capita income are transformed into logarithms to smoothen the relative distribution. In the case of pc income, the beta coefficient is the elasticity of PM2.5 exposure levels with respect to income pc. Social categories and demographic variables are expressed as shares of the total population of the area of interest; therefore, the model is weighted according to census population. Regarding the shares, they follow the log-level interpretation.
To test the hypothesis that, within a lower-income areas, being part of a non-white minority is associated with higher PM2.5 exposure, I include an interaction in the model. In the spirit of Zwickl et al. (2014), I interact the share of residents being part of one of the non-white minorities with a dummy variable equal to 1 if the average per capita income of the census tract is lower than the median income per capita of the city. The interaction model is defined as follows:

$$\begin{aligned}\ln(\mathrm{PM}_{2.5,i}) = \beta_0 &+ \beta_1 \text{LOWERINCOME}_i + \beta_2 \text{share\_NonWhites}_i \\ &+ \beta_3 (\text{LOWERINCOME}_i \times \text{share\_NonWhites}_i) \\ &+ \beta_4 X_i + \varepsilon_s \end{aligned} \tag{2}$$

Where c indicates the census tracts dimensions, LOWERINCOME is the dummy variable that takes value = 1 if the census is located within a statistical area that register an income pc lower than the median one of the city and 0 otherwise. $\mathbf{X}_i$ is the vector of socio-demographic controls. The errors, ε_s, are clustered at the statistical area level. Environmental inequalities can arise from differences in the income levels of urban areas, leading to differences in pollution levels, or from the opposite phenomenon. The purpose of this study is to determine the current state of environmental inequities and not to investigate their formation. Therefore, delineating the causal influence of any of the variables of interest on pollution and its related mechanism is beyond the scope of this paper. However, regressing pollution levels on income still can introduce endogeneity problems (Germani et al. 2014). This approach accounts for the possibility that economic and socio-demographic conditions may take some time to exhibit their effects on air pollution levels. To avoid potential endogeneity issues, pollution at time t is regressed on explanatory variables lagged at time t-2. To estimate the association between pollution and income pc, I exploit the variation within the urban area of Bologna in the income pc levels and pollution concentration level at the census tract dimension. Having income pc as an aggregate regressor, I assume all the census tracts included in the census tract group to share the same level of income per capita. To estimate the associations between pollution and presence of ethnic minorities I exploit the variation of the presence of non-whites within the urban area at the census tract level.

6. Results

6.1. Environmental Justice Gap

Table 2 presents the findings of the multivariate linear regression model. The model was weighted by the census population (columns 5-8) to adjust for population density and potential bias in the use of shares, providing further robustness. Examining the association of income pc with PM2.5 levels, both regression models show a significant negative coefficient, even after accounting for and education, unemployment status, age groups and census characteristics. In the weighted model the magnitude of the coefficients is slightly larger (-0.098% in Table 2, column 8), remaining significant and showing a negative association. Keeping the most robust coefficient for income (Table 2, column 8): an increase of 1 standard deviation of income pc (5642.16 euros) across census tracts is associated with a decrease of -0.53 mg/m^3. The findings suggest that census with higher income pc in Bologna are associated with lower exposure to PM2.5.

This result is consistent with both previous studies conducted in the United States at the census level/zip code tabulation area level (Colmer et al., 2020; Jbaily et al. 2022) and with previous European studies that found air pollution concentration was higher in the most deprived areas (Morelli et al. 2016, Brunt et al. 2017). In the case of Bologna, per capita income and pollution show an inverse correlation, supporting the income-related hypothesis of environmental justice. The coefficients related to the association between the percentages of non-whites residents and pollution levels are positive in both models. Taking the most robust coefficient of the weighted model (Table 2, column 8), an increase of 1% in the share of non-whites in the census tracts to a +0.133% in PM2.5 The increase of 1 standard deviation in the share of non-whites within the census is associated with an increase of 3.92 mg/m^3 of PM2.5 levels.

This finding replicates the observations made in empirical American and European studies that used comparable disaggregated data concerning pollution and demographic variables. For the US, Colmer et al. (2020) identified a positive association between census tracts characterized by a lower proportion of white residents and higher PM2.5 rank points. Similarly, Jbaily et al. (2022) documented a 13.7% higher average PM2.5 concentration for the Black population compared to the white population at the conclusion of their study period. For Europe, T. Rüttenauer (2018) shows that the share of minorities within a census cell positively correlates with the exposure to industrial pollution across Germany. Neier (2021) shows that the presence of a foreign population consistently indicates a significant and positive association with the level of pollution across Austria, especially in urban areas, with the exception of the city of Wien.

Education levels exhibit significant associations with PM2.5 levels in both the models (Table 2, columns 4A and 4B). The association between the share of graduates and higher levels of pollution may seem counterintuitive, given the hypothesis that higher education is correlated with higher income and, therefore, greater resources to avoid pollution. In the case of Bologna, this trend could stem from a residential pattern where graduates tend to reside in the city center, in areas where pollution levels can be higher typically due to transportations. The added age categories of children are correlated with lower pollution exposure in both models, which might suggest the presence of some sort of efficient residential patterns that mitigate pollution exposure for this vulnerable group. The two regression models exhibit comparable explanatory power regarding the variation in pollution levels, higher for the weighted one, as indicated by the R-squared values (0.158 for the not weighted model A and 0.210 for the weighted model B), implying improvements in the accuracy of the coefficients' magnitude and significance in the weighted model. Robustness checks are shown in Appendix.

Table 2: Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln PM2.5	Model 1A	Model 2A	Model 3A	Model 4A	Model 1B	Model 2B	Model 3B	Model 4B
ln income pc	-0.0497*	-0.0846***	-0.0859***	-0.0859***	-0.0404**	-0.0975***	-0.100***	-0.0982***
	(0.0261)	(0.0307)	(0.0307)	(0.0307)	(0.0192)	(0.0202)	(0.0202)	(0.0199)
Share Non-whites	0.0361***	0.0409***	0.0496***	0.0493***	0.0883***	0.116***	0.132***	0.133***
	(0.0136)	(0.0113)	(0.0111)	(0.0110)	(0.0220)	(0.0222)	(0.0236)	(0.0238)
Share Graduates		0.0905***	0.0816***	0.0811***		0.165***	0.131***	0.136***
		(0.0258)	(0.0219)	(0.0220)		(0.0363)	(0.0299)	(0.0289)
Share High School		0.0218	0.0110	0.0111		0.0735*	0.0349	0.0444
		(0.0151)	(0.0138)	(0.0141)		(0.0390)	(0.0381)	(0.0368)
Share Low education		-0.0186	-0.0408*	-0.0410*		0.0301	-0.0525	-0.0482
		(0.0164)	(0.0238)	(0.0239)		(0.0302)	(0.0406)	(0.0391)
Share Unemployed		0.0648	0.0665	0.0658		0.150	0.156*	0.167*
		(0.0438)	(0.0455)	(0.0453)		(0.0929)	(0.0931)	(0.0924)
Share Children			-0.0874***	-0.0882***			-0.172***	-0.154***
			(0.0280)	(0.0285)			(0.0492)	(0.0484)
Share Elders			0.0199	0.0203			0.0599	0.0511
			(0.0242)	(0.0246)			(0.0391)	(0.0374)
ln Total Buildings				0.000497				-0.00413*
				(0.00208)				(0.00230)
Constant	3.433***	3.752***	3.775***	3.774***	3.343***	3.833***	3.893***	3.881***
	(0.255)	(0.297)	(0.298)	(0.297)	(0.188)	(0.194)	(0.196)	(0.194)
Observations	2,072	2,072	2,072	2,071	2,072	2,072	2,072	2,071
R-squared	0.091	0.152	0.158	0.158	0.092	0.188	0.202	0.210

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 1-4 show unweighted models; columns 5-8 show models weighted by census population. Errors are clustered at the statistical area level.

6.2. Belonging to an ethnic minority within lower income areas.

The aim of this analysis is to understand how the interaction between the two conditions of disadvantage (living in lower income areas and belonging to a non-white community) is associated with pollution levels. Table 3 displays the coefficients of the regression models, and table 6 displays the computation of the marginal effects to interpret the output of the interaction.

In Table 3, the coefficient of the lower-income areas dummy variables exhibits statistical significance and a positive sign, indicating strong association between residing in lower income census tracts and higher levels of pollution exposure when the ethnicity component is absent, suggesting lower income areas are exposed to higher levels of pollution regardless of the ethnicity of the residents. To understand whether being part of a minority has a greater impact on exposure to pollution within lower-income areas, marginal effects are calculated for different values of the Lower Income dummy variable (0, 1). Table 4 displays the results of these calculations. When the Lower Income dummy is equal to 1, the share of non-whites shows a significant marginal effect. The marginal effect's coefficient of 0.127 of the interaction Lower Income-nonwhites means that non-whites minority living in areas with below-median income are 0.127% more exposed than non-whites living in areas with above-median income. Interestingly, when the

Lower Income dummy is equal to 0, the coefficient of the marginal effect is extremely similar, meaning that the difference between the two slopes is very small in magnitude. This finding suggests that individuals from non-white minority groups living in lower income areas are not exposed to higher levels of pollution compared to their higher incomes counterparts.
The study's findings differ from previous American empirical literature. Zwickl et al. (2014) discovered that minority status tends to have a stronger impact in lower-income neighborhoods, particularly in the Midwest and South-Central regions. In these areas, African Americans and Hispanics in the lower-income half of the city consistently exhibit higher estimated coefficients than those in the higher-income half. Apelberg et al. (2005) identified a significant interaction between race and income, indicating a stronger association between race and the risk of cancer from air pollutants among households with lower incomes in Maryland. However, this finding is specific to the urban/regional case study of Bologna and may differ from prior literature due to the strong internal validity of the study itself.
Overall, in the urban context of Bologna, individuals from non-white backgrounds in disadvantaged communities are not disproportionately exposed to pollution compared to their non-whites higher income counterparts. This finding suggests that pollution burdens are distributed more evenly across racial and ethnic groups when there is already an economic disadvantage present. On the other hand, this indicates that despite variations in income per capita levels, racial and ethnic disparities in pollution exposure remain relatively persistent.

Table 3: Multiple linear regression model with interaction, census level.

	(1)
ln PM2.5	Interaction Model
Lower Income	0.0308***
	(0.00264)
Share Nonwhites	0.127***
	(0.0280)
Lower Income * Share Nonwhite	0.000786
	(0.0317)
Share Graduates	0.0794***
	(0.0176)
Share High School	0.0674***
	(0.0232)
Share Low Education	-0.0550**
	(0.0271)
Share Children	-0.119***
	(0.0460)
Share Elders	0.0699***
	(0.0164)
Share Unemployed	0.243***
	(0.0515)
ln Total Buildings	-0.00594***
	(0.000942)
Constant	2.904***
	(0.0160)
Observations	2,071
R-squared	0.161

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The model is weighted by census population. SE clustered at the statistical area level.

Table 4: Marginal effects.

	dy/dx	Std. err.	t	P>|t|	[95% conf. interval]
Share Non-whites Lowerincome = 1	.1279498	.0280202	4.54	0.000	.0722132 .1821148
Share Non-whites Lowerincome = 0	.127164	.0280202	4.54	0.000	.0722132 .1821148

7. Discussion and Conclusions

This paper investigates the associations between socioeconomic and demographic attributes and exposure to PM2.5 pollution across the census tracts of Bologna, located in the Emilia-Romagna region of Italy. To achieve this goal, the study employes gridded PM2.5 concentration data at a resolution of 0.01°x0.01° [0.9km x 1.1km] and census tracts demographics.

The primary finding of this analysis reveals the presence of an environmental justice gap within the city, driven by income and ethnicity. Notably, there is an inverse correlation between pollution and income per capita, indicating that higher-income areas experience lower pollution exposure. Specifically, a 1% increase in income per capita within a census tract is associated with a 0.09% reduction in PM2.5 exposure. In other terms, a rise of 1 standard deviation of per capita income (5642.16 euros) in the census corresponds to a reduction of -0.53 mg/m^3 in PM2.5 This association remains robust when accounting for income proxies, neighborhoods dummies, and additional checks. Belonging to a non-white ethnic minority is also associated with changes in pollution levels. A 1% increase in the proportion of non-whites within the census population corresponds to a 0.13% increase in PM2.5 levels (+3.92 mg/m^3 increase is associated with a rise of 1 standard deviation in the share of non-whites in the census). The result is robust to the inclusion of socio-demographic controls, population weights, and fixed effects of neighborhoods.

The second result sheds light on whether in lower income areas the non-white minorities are disproportionately exposed to higher pollution levels compared to their higher-income counterpart. On one hand, low-income groups, regardless of ethnicity, are exposed to similar levels of pollution, indicating no environmental justice gaps along the racial dimension within lower income areas. On the other hand, nonwhite minorities still face higher levels of pollution despite living in higher-income areas, as their exposure does not significantly decrease as income of the census increases.

These findings carry several implications. Firstly, in a socio-political perspective, the identification of an environmental justice gap in Bologna, a mid-size city with a historical left-leaning political orientation, is the main novelty brought by this works. Given the socio-political context of the city, a small, if any, urban environmental justice gap would have seemed more probable. This would suggest that if environmental justice problems exist in Bologna, they are likely to be widespread in many other urban areas across the country. In addition, the fact that this issue is present in a city that is politically and socially distinct from the American context, where the first studies have been carried and in which similar findings have been reported, underscores the pervasiveness of environmental injustice across different geographies and political contexts.

Secondly, the persistent exposure of the lower income and non-white populations in certain census areas to higher levels of pollution, in conjunction with dangerously high average annual levels (the annual average pollution level in Bologna is 19.034 mg/m^3, above the safety threshold of WHO air quality standards, which sets the annual average limit for PM2.5 at 5 mg/m^3), could result in adverse health outcomes ranging from respiratory diseases to issues related to life expectancy and mortality. A body of literature reveals associations between prolonged exposure to pollution levels and health hazards (Morrison et al. 2014, Morelli et al. 2016, Brunt et al. 2017, Greenstone and Fan 2018). The results suggest that environmental inequality, if prolonged, may disproportionately affect the population segment with the fewest resources to mitigate its harmful effects.

In conclusion, documenting the exposure gap is a significant contribution to policy-making. It helps identify where to focus regulatory efforts to achieve equity-related objectives by highlighting within-urban differences in pollution levels across census segments. Therefore, policymakers must take into account the emerging trend that the population segment subjected to higher levels of pollution often has limited resources to mitigate its effects.

This study has some limitations. It does not investigate the causal mechanisms behind the formation of environmental inequality in the city. Additionally, it relies on the assumption that the income per capita of the census is the same as that of the statistical area to which the census belongs. This is because income data is aggregated at the census tract group level.

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A. Appendix

A.1. Income Data

Income details are provided for clusters of census tracts. This aggregation process combines the 2,072 census tracts into 90 statistical areas, each representing a distinct geographical unit. The statistical areas serve to present income data at a more general but still fairly disaggregated level suitable for intra-urban analysis. For the purpose of this study, it is assumed that the per capita income of each census tract is equal to the per capita income of the corresponding statistical area it belongs to. The figures below illustrate the relationship between the census and the statistical area dimensions. Panel A shows the geographical dimension of the statistical areas, panel B shows the geographical dimension of the census tracts, Panel C shows the distribution of income across census tracts based on data aggregated at the statistical area level.

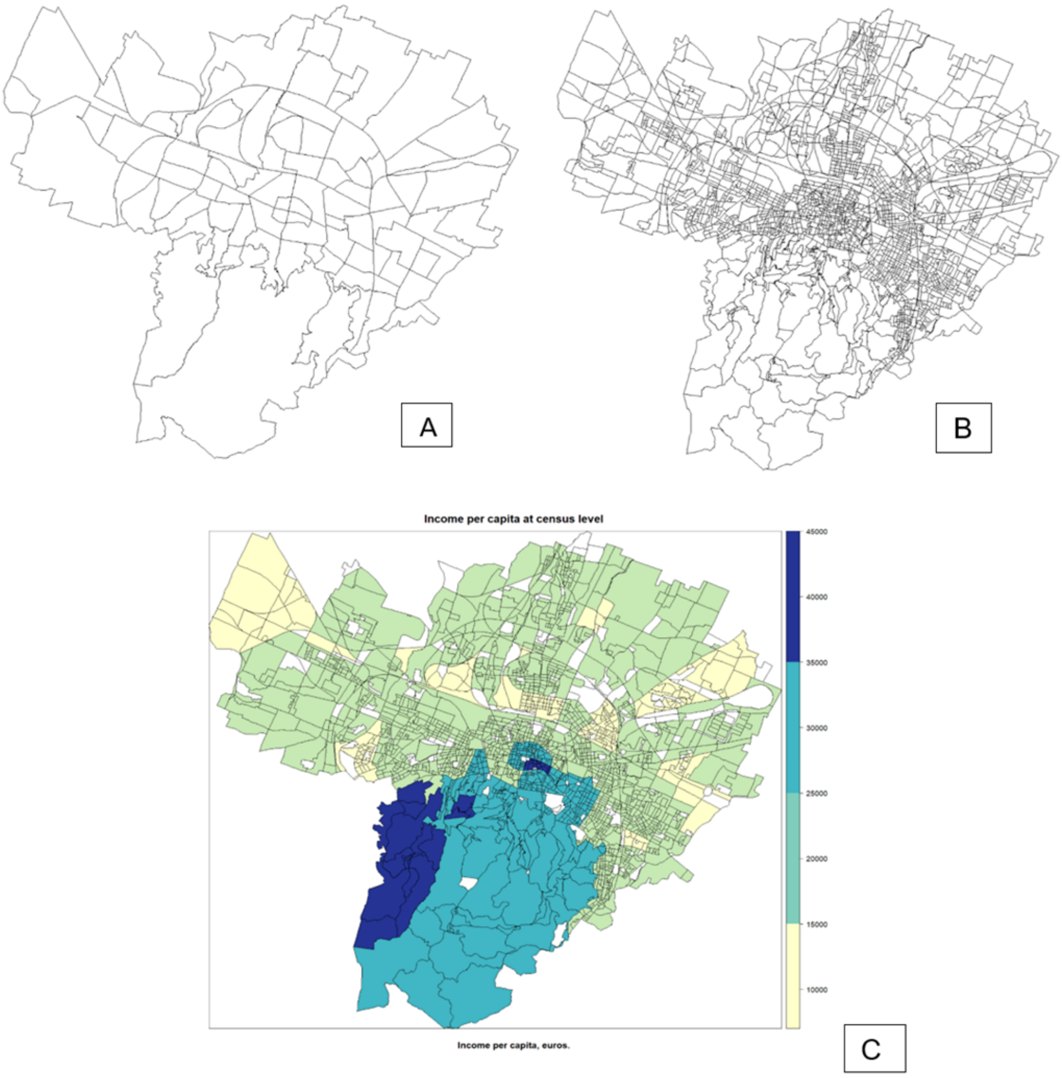

Figure 6: Map of statistical zones, census tracts and income pc distribution.

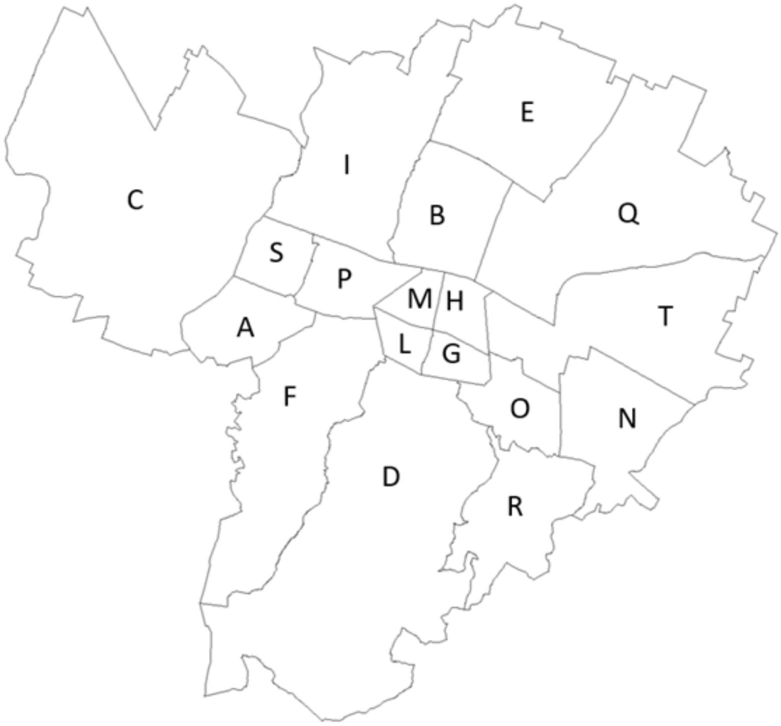

Figure 7: Map of statistical zones in Bologna.

Zone Code	Name	Perimeter (m)	Area (m2)
A	Barca	7987.736	3321911
B	Bolognina	8849.296	4943557
C	Borgo Panigale	27871.66	26166338
D	Colli	30542.73	24725142
E	Corticella	14652.45	9877294
F	Costa Saragozza	20386.15	11079668
G	Galvani	4375.401	1116791
H	Irnerio	5075.87	1375567
I	Lame	18332.5	11054352
L	Malpighi	4269.096	959600
M	Marconi	4426.128	1058290
N	Mazzini	13159.27	5747189
O	Murri	8534.222	2822504
P	Saffi	7571.745	2668886
Q	San Donato	22257.89	15464546
R	S. Ruffillo	15301.52	5712906
S	S. Viola	5561.49	1947286
T	S. Vitale	20385.86	10803918

A.2. Variation of PM2.5, income pc and non-white minorities.

Table 5: Variation of PM2.5 income pc and non-white minorities between and within neighborhoods.

Variable	Variation	Mean	Std. Dev.	Min	Max	Observations
PM2.5	overall	19.03457	0.8358603	13.8894	20.74351	2072
	between		0.4563879	18.12098	20.03811	18
	within		0.7295838	14.80299	20.7249	T = 115.1
Income pc	overall	19840.46	5642.16	8473.261	44710.48	2072
	between		3.784.745	12985.37	27406.94	18
	within		4.465.779	9.132.497	46247.9	T = 115.1
Non-whites	overall	11.06322	16.04828	0	124	2072
	between		5.68325	2.349398	27.80741	18
	within		15.16896	-16.74418	107.2558	T = 115.1

Table 6: Pearson's correlations, weighted by census population.

Variables	1	2	3	4	5	6	7	8	9	10
pm25	1.00									
income pc	-0.275***	1.00								
Share of non-whites	0.205***	-0.256***	1.00							
Share Graduates	-0.023	0.746***	-0.293***	1.00						
Share High school	0.036*	0.072***	-0.218***	0.162***	1.00					
Share low-education	-0.017	-0.583***	0.223***	-0.828***	-0.523***	1.00				
Share Unemplyed	0.128***	-0.144***	0.307***	-0.147***	-0.151***	0.105***	1.00			
Share Children	-0.026	-0.069***	0.206***	-0.024	-0.059***	-0.112***	0.027	1.00		
Share Elders	-0.016	-0.128***	-0.131***	-0.248***	-0.264***	0.494***	-0.145***	-0.327***	1.00	
Total buildings	-0.175***	0.184***	-0.037*	0.169***	0.099***	-0.200***	0.011	0.092	-0.195***	1.00

* p<0.1, ** p<0.05, *** p<0.01

A.3. Robustness checks

The same multivariate regression model of Table 2 is performed with PM2.5 concentrations in levels instead of logs, producing coefficients that are consistently significant but slightly different in magnitude. The results are shown in table 7. To further investigate the robustness of the model, two additional variables related to house property were incorporated in place of income levels. The results are consistent with those presented in Table 2, they can be found in Table 8. Then, to further enhancing the robustness of the findings in table 2, a fixed-effect model is employed. The model includes a dummy variable for each of the 18 zones that delineate the city, comparable to neighborhoods. By including neighborhoods fixed effects, the analysis accounts for unobserved heterogeneity specific to each neighborhood, capturing the characteristics of each neighborhood that are constant over time but differ across neighborhoods (eg presence of roads and infrastructures, morphological features, cultural customs), that could potentially impact the dependent variable. Results can be found in Table 9 and are consistent with the ones showed in Table 2.

Table 7: OLS regression results, census level, PM2.5 in units.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM2.5 in units	Model 1A	Model 2A	Model 3A	Model 4A	Model 1B	Model 2B	Model 3B	Model 4B
ln income pc	-0.883*	-1.533***	-1.557***	-1.557***	-0.732**	-1.820***	-1.870***	-1.834***
	(0.469)	(0.543)	(0.542)	(0.542)	(0.360)	(0.373)	(0.372)	(0.367)
Share Non-whites	0.711***	0.799***	0.956***	0.953***	1.719***	2.233***	2.531***	2.558***
	(0.260)	(0.218)	(0.212)	(0.211)	(0.419)	(0.424)	(0.453)	(0.456)
Share Graduates		1.683***	1.523***	1.516***		3.135***	2.489***	2.586***
		(0.461)	(0.394)	(0.397)		(0.681)	(0.564)	(0.545)
Share High School		0.400	0.204	0.206		1.351*	0.631	0.812
		(0.282)	(0.257)	(0.265)		(0.733)	(0.721)	(0.694)
Share Low education		-0.349	-0.745*	-0.747*		0.538	-1.007	-0.924
		(0.304)	(0.422)	(0.425)		(0.568)	(0.772)	(0.744)
Share Unemployed		1.214	1.243	1.233		2.912*	3.034*	3.235*
		(0.816)	(0.845)	(0.843)		(1.735)	(1.741)	(1.729)
Share Children			-1.628***	-1.640***			-3.208***	-2.880***
			(0.512)	(0.519)			(0.920)	(0.903)
Share Elders			0.337	0.342			1.119	0.952
			(0.427)	(0.431)			(0.743)	(0.707)
ln Total Buildings				0.00734				-0.0785*
				(0.0387)				(0.0439)
Constant	27.70***	33.64***	34.06***	34.04***	26.24***	35.60***	36.73***	36.49***
	(4.586)	(5.252)	(5.272)	(5.248)	(3.526)	(3.590)	(3.619)	(3.574)
Observations	2,072	2,072	2,072	2,071	2,072	2,072	2,072	2,071
R-squared	0.086	0.148	0.155	0.155	0.089	0.187	0.200	0.208

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 8: OLS Regression with proxy of income

ln_pm2.5	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6
ln_entireproperty	-0.0137***	-0.0115***				
	(0.00439)	(0.00348)				
ln_house_property			-0.00788***	-0.00518**		
			(0.00253)	(0.00222)		
Share_Nonwhite	0.110***	0.0559**	0.122***	0.0644***	0.138***	0.0717***
	(0.0324)	(0.0252)	(0.0308)	(0.0181)	(0.0286)	(0.0179)
share_Graduates	-0.0275	-0.0271	0.0134	0.0309	0.0198	0.0321
	(0.0435)	(0.0381)	(0.0395)	(0.0370)	(0.0377)	(0.0350)
share_HighSchool	0.112*	0.0463	0.0956**	0.0657**	0.0800*	0.0546*
	(0.0570)	(0.0377)	(0.0457)	(0.0305)	(0.0433)	(0.0288)
share_low_education	0.0266	-0.00204	0.000283	0.0111	0.00254	0.0113
	(0.0506)	(0.0394)	(0.0365)	(0.0295)	(0.0329)	(0.0268)
share_Unemployed	0.238**	0.199**	0.184	0.128	0.210**	0.159*
	(0.107)	(0.0833)	(0.116)	(0.0972)	(0.103)	(0.0872)
log_TotalBuildings					-0.00599**	-0.00371**
					(0.00257)	(0.00163)
Neighboorhoods fe	no	yes	no	yes	no	yes
Constant	2.876***	2.895***	2.904***	2.898***	2.925***	2.913***
	(0.0377)	(0.0298)	(0.0270)	(0.0242)	(0.0252)	(0.0234)
Observations	1,089	1,089	1,969	1,969	2,071	2,071
R-squared	0.125	0.307	0.069	0.311	0.071	0.311

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

All weighted by census population. All errors are clustered at the statistical areas levels.
House property refers to the number of households who live in a property house.
Entire property refers to the number of households who live in a one-story building designed for residential purposes.

Table 9: OLS regression results with neighborhood's fixed effects, census level.

ln pm2.5	(1) Model 1FE	(2) Model 2FE	(3) Model 3FE	(4) Model 4FE
ln income pc	-0.0273	-0.0696***	-0.0729***	-0.0720***
	(0.0188)	(0.0197)	(0.0196)	(0.0194)
Share Non-whites	0.0482***	0.0756***	0.0886***	0.0884***
	(0.0156)	(0.0167)	(0.0182)	(0.0184)
Share Graduates		0.127***	0.103***	0.107***
		(0.0285)	(0.0256)	(0.0248)
Share High School		0.0567**	0.0297	0.0362
		(0.0271)	(0.0270)	(0.0267)
Share Low education		0.0319	-0.0331	-0.0308
		(0.0256)	(0.0346)	(0.0343)
Share Unemployed		0.126	0.138	0.148*
		(0.0847)	(0.0856)	(0.0851)
Share Children			-0.119**	-0.109**
			(0.0457)	(0.0448)
Share Elders			0.0537*	0.0501
			(0.0304)	(0.0308)
ln Total Buildings				-0.00281*
				(0.00163)
Neighborhoods FE	yes	yes	yes	yes
Constant	3.190***	3.551***	3.610***	3.608***
	(0.181)	(0.188)	(0.188)	(0.186)
Observations	2,072	2,072	2,072	2,071
R-squared	0.314	0.356	0.365	0.368

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
The model is weighted by census population. SE clustered at the statistical area level.

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