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Evidence from Four Latin American Cities

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Abstract

We study inequality in monitoring and exposure to particulate matter air pollution in four metropolitan areas of Latin America, Bogota, Colombia, Mexico City, Mexico, Gran Santiago, Chile, and Sao Paulo, Brazil. We find that the population residing in close proximity to at least one monitoring station in Bogota, Mexico City, and Sao Paulo generally have higher educational attainment and income. In contrast, in Gran Santiago, education levels are generally higher further from monitoring stations. In Bogota, Mexico City, and Sao Paulo, the distance to the closest monitoring station declines and the number of monitoring stations within 3 km increases as the mean education level of the census geographic unit increases. Considering only census geographic units that contain a monitoring station, we find that areas where individuals with lower educational attainment reside tend to be exposed to higher pollution levels. While we find small and mostly insignificant disparities in mean annual concentrations of particulate matter, we find that lower education quintiles experience significantly more hours of extreme pollution relative to the highest education quintile. Non-linear effects of pollution imply that the small disparity in mean concentrations likely masks large disparities in the negative impacts of air pollution. Our findings indicate that in Bogota, Mexico City, and Sao Paulo, air pollution exposure is likely to be better monitored for those with higher educational attainment and income, and in all four cities, lower income and education groups have greater exposure to extreme levels of air pollution.[1]

JEL classifications: Q53; D63

Keywords: Inequality; Air pollution; Particulate matter; Cities; Latin America

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1 Introduction

Air pollution is the greatest environmental risk to physical health (WHO, 2016) and also affects many other dimensions of well-being (Aguilar-Gomez et al., 2022), including mental health (Chen et al., 2024), labor supply and productivity (Hoffmann and Rud, 2024; Adhvaryu et al., 2022; Chang et al., 2016), education and cognition (Bedi et al., 2021; Ebenstein et al., 2016), and decision-making and crime (Herrnstadt et al., 2021; Burkhardt et al., 2019; Sager, 2019). The impacts of air pollution exposure on health, education, and labor market outcomes imply that inequality in air pollution exposure can have long-term implications for economic inequality and social mobility.

We study inequality in air pollution monitoring and exposure within metropolitan areas of Latin America, the most unequal region of the world. While air pollution concentrations in many of the largest urban areas of Latin America have decreased substantially from the notoriously high levels of the 1990's, air pollution levels still regularly exceed the WHO's Air Quality Guidelines. Differences in air pollution exposure across the income distribution could exacerbate existing economic inequalities or contribute to their persistence.

We study particulate matter air pollution monitoring and exposure in four cities of Latin America, Bogota, Colombia, Mexico City, Mexico, Santiago, Chile, and Sao Paulo, Brazil, focusing on the metropolitan area of each city.[2] We consider all individuals residing within the broader metropolitan area to better approximate the set of individuals participating in a local economy and labor market. For instance, this avoids excluding residents who may be pushed to the urban periphery by high costs of living in the center of the city from the analysis. We combine hourly coarse (PM10) and fine (PM2.5) particulate matter concentrations data for 2023 from the network of ground monitoring stations operated by the government in each of our four cities with socioeconomic characteristics from the most recent census data that includes disaggregated residential geographic identifiers. We focus on PM10 and PM2.5 because exposure to particulate matter leads to a wide range of severe health impacts. The census data of all four countries contains

[2]The amount of air pollution that an individual inhales in a location with a given air pollution concentration depends on many factors including age, activity, and avoidance behavior.

socio-demographic characteristics of all individuals, such as educational attainment, and in addition, the census data for Brazil and Mexico contains income information. We harmonize the education variables across all four countries.

We begin by exploring whether there is inequality in air pollution monitoring across socioeconomic groups. Regulatory-grade ground monitoring stations operated by the government provide highly accurate and precise measurement of air pollutants at their location. But, the accuracy of these measurements for measuring exposure generally decreases with distance from the station and may be most useful for understanding exposure within a small radius around the station. Because we will explore inequality in air pollution exposure among the population of each metropolitan area that lives in close proximity to a monitoring station, understanding how the population that resides in close proximity to a monitoring station compares to the population of the metropolitan area is critical for developing a complete picture of inequality in air pollution exposure.

We document how the characteristics of the population change with distance from an air pollution monitoring station. We find that the population residing in close proximity to at least one monitoring station in Bogota, Mexico City, and Sao Paulo generally have higher education and income levels. In contrast, in Gran Santiago, education levels are generally higher further from monitoring stations. We also explore how many stations are within a given radius of the census geographic unit's centroid and the distance from the centroid to the nearest monitoring station. Having multiple air pollution monitoring stations in the vicinity could improve the quality of air pollution monitoring because missing data from one monitoring station could be replaced by data from another, reducing gaps in monitoring, and when multiple stations are recording data, air pollution levels from multiple monitoring stations could be combined to improve accuracy for areas between monitoring stations. In Bogota, Mexico City, and Sao Paulo, the distance to the closest monitoring station declines as the mean education level of the geographic unit increases. Furthermore, in these three cities, the number of monitoring stations within 3 km increases with the mean education level of the geographic unit.

This suggests that, in Bogota, Mexico City, and Sao Paulo, air pollution exposure is likely to be better monitored for those with higher education and income levels. Because air quality monitoring is a public service, this finding is consistent with a large literature documenting that public goods and services are better provided in neighborhoods with high income (Asher et al., 2024; Harari, 2024; Tiznado-Aitken et al., 2021; Owens and Candipan, 2019; Feigenbaum and Hall, 2016; Conley and Dix, 2004; Câmara and Banister, 1993; Inman and Rubinfled, 1979). Inequalities in air quality monitoring have important policy implications because inequalities in monitoring could contribute to inequalities in exposure. For instance, if localized policies to improve air pollution are spatially targeted to areas with measured high levels of pollution, unmonitored areas would be unlikely to receive these policy interventions.

Next, we explore whether there is inequality in exposure to particulate matter by socioeconomic group. We explore inequalities in both annual mean concentrations and extremely high concentrations because both chronic long-term exposure to particulate matter and acute exposure to peaks in particulate matter can lead to severe negative health impacts. Furthermore, non-linear impacts of particulate matter (Hoffmann and Rud, 2024), imply that focusing on exposure to extreme levels of particulate matter is important to understanding unequal impacts of air pollution.

First, we examine the relationship between pollution exposure and socioeconomic level using station-level data. We start by exploring mean annual concentrations at stations. Although the correlation is weak for some pollutants in some of the cities, overall, we find that mean annual concentrations PM10 and PM2.5 are negatively correlated with the education level of the census geographic unit where the station is located. Then, we focus on the number of hours that pollutant concentrations exceed the WHO Interim Target 1 (IT1), the WHO's least ambitious target, for PM10 and PM2.5. Considering only census geographic areas that contain a monitoring station, we find that areas where individuals with lower levels of education reside tend to be exposed to higher pollution levels. This suggests that, on average and based on the place of residence, less-educated communities are disproportionately exposed to harmful air pollutants, underscoring significant environmental inequalities.

Second, we spatially aggregate the air pollution data to the individual level to explore disparities in air pollution exposure across socioeconomic groups among individuals that reside in close proximity to a monitoring station. We use inverse distance weighting to calculate air pollution concentrations at the census geographic unit level, which we use to proxy for each individual's air pollution exposure. To focus on differences across socioeconomic groups in a given city, we categorize the population of each metropolitan area into quintiles of educational attainment. Higher education quintiles are exposed to lower annual mean concentrations of PM10 and PM2.5 but the differences are small and typically not significant. To explore disparities in exposure to peaks in air pollution across education levels, we normalize the hours above the WHO IT1 and IT2 thresholds for PM10 and PM2.5 for each education quintile by the number of hours above the threshold for the highest education quintile. This normalization allows for a clearer comparison of pollutant exposure across groups. We find that lower education quintiles experience significantly more hours above these critical thresholds relative to the highest education quintile. This disparity is consistent across all four cities and highlights the unequal distribution of air pollution exposure within each metropolitan area. For Mexico City and Sao Paulo, we extend this analysis to income deciles. The findings reinforce the pattern observed with education: individuals in lower-income deciles are exposed to higher levels of particulate matter, reflecting a strong socioeconomic gradient in exposure. Overall, in the four metropolitan areas studied, communities with lower education and income levels face greater exposure to peaks in pollution, exacerbating existing social and health inequalities.

Our results provide two key policy implications. First, inequality should be explicitly considered in the design of air quality monitoring systems. Decisions of where to site monitoring stations should consider economic inequality and the spatial distribution of low-income residents. Siting monitoring stations based on population density or distance to the central business district could inadvertently lead to inequality in monitoring in cities where low-income residents are clustered in the periphery. If policies to improve air pollution are spatially targeted to areas with measured high levels of air pollution, inequality in monitoring could dispossess low-income residents of improvements in air pollution. Second, on average, differences in mean concentrations of particulate matter across the education or income distribution are small but there is greater disparity in exposure to extremely high concentrations of particulate matter across education or income levels. Therefore, policies focused on reducing peaks in particulate matter, as opposed to reducing persistent daily concentrations of particulate matter, are likely to lead to a greater reduction in inequality in air pollution exposure and it's consequences across education and income levels.

This paper contributes to the literature studying disparities in the provision of and access to public goods and services across neighborhoods (Asher et al., 2024; Harari, 2024; Tiznado-Aitken et al., 2021; Owens and Candipan, 2019; Feigenbaum and Hall, 2016; Conley and Dix, 2004; Câmara and Banister, 1993; Inman and Rubinfled, 1979). For instance, Asher et al. (2024) and Harari (2024) document worse provision of public infrastructure services in neighborhoods with marginalized and low-income residents in lower and middle-income countries. We extend this literature by documenting that air quality monitoring, another public service, tends to be better provided in neighborhoods where people with higher income and education attainment reside.

This paper also contributes to the literature studying disparities in air quality across income and socioeconomic groups. Numerous studies in high-income countries document that low-income individuals and racial and ethnic minorities experience greater exposure to air pollution (Jbaily et al., 2022; Liu et al., 2021; Tessum et al., 2021; Colmer et al., 2020; Mikati et al., 2018; Rosofsky et al., 2018; Bell and Ebisu, 2012; Miranda et al., 2011; Pearce et al., 2006).[3] A smaller set of studies have focused on disparities in exposure to particulate matter in low- and middle-income countries and the results have differed across contexts and scale (Aguilar-Gomez et al., 2025; Behrer and Heft-Neal, 2024; Chakraborti and Voorheis, 2024; Wang et al., 2022; Wu et al., 2022; Xu et al., 2019; Rooney et al., 2012; Dionisio et al., 2010).[4] Specifically in Latin America, the evidence indicates that disadvantaged groups face higher exposure to particulate matter. Chakraborti and Voorheis (2024) documents that areas that experienced a decline in socioeconomic status in Mexico experienced an increase in annual mean concentrations of fine particulate mat-

[3]Other studies focus on disparities in exposure to other air pollutants (Clark et al., 2017) or study a mix of air pollutants (Germani et al., 2014) in high-income countries.

[4]In addition, other studies in low- and middle-income countries focus on exposure to a mix of air pollutants. For instance, (Kopas et al., 2020) study exposure to pollution from coal-fired power generation, which is composed of numerous of air pollutants including particulate matter.

ter, and Aguilar-Gomez et al. (2025) documents that individuals with lighter skin tones in Colombia disproportionately benefited from improvements in annual mean concentrations of fine particulate matter. Two additional studies in Latin America focus on disparities within a city. Bonilla et al. (2023) document overlapping inequalities in Bogota with lowest air quality (measured by PM2.5), economic and social levels occurring in the same geographic area, and Rose-Pérez (2015) documents that areas with high poverty levels also experience higher concentrations of PM2.5 in Santiago.[5]

Few studies in low- and middle-income countries study disparities in particulate matter exposure within a city (Bonilla et al., 2023; Xu et al., 2019; Rooney et al., 2012; Dionisio et al., 2010), and data scarcity implies that they often document disparities across a small number of neighborhoods (Rooney et al., 2012; Dionisio et al., 2010). We contribute systematic evidence of disparities in exposure to particulate matter by educational attainment and income across four large metropolitan areas of Latin America using census data and data from government operated air pollution monitors. In particular, we illustrate that disparities in mean concentrations of particulate matter are small but there are significant disparities in exposure to extremely high concentrations of particulate matter. Non-linear impacts of particulate matter air pollution (Hoffmann and Rud, 2024), implies that disparities in mean concentrations of particulate matter may mask disparities in the negative impacts of air pollution across levels of income and educational attainment.

2 Context

2.1 Bogota

Bogota is the largest metropolitan area in Colombia with a population of nearly 8 million. Bogota is located in the center of Colombia on a high plateau surrounded by mountains (Molina and Molina, 2004). The high altitude reduces the efficiency of combustion processes increasing emissions (Ramírez et al., 2018). Meteorological conditions like precip-

[5]Other studies focus on other air pollutants. For instance, García-Burgos et al. (2022) finds that disadvantaged areas in the southern periphery of Mexico City are exposed to higher concentrations of ozone while wealthy areas in the center of the city are exposed to higher concentrations of nitrogen dioxide and carbon monoxide.

itation and wind patterns affect the dispersion and concentration of pollutants across the city, leading to significant spatial variability in PM2.5 concentrations (Rodriguez-Villamizar et al., 2024).

Mobile sources, particularly related to vehicle traffic, are the dominant contributors to several air pollutants in Bogotá (Rodriguez-Villamizar et al., 2024; Matos, 2017). For instance, the transport sector in Bogotá is responsible for 23.9% of PM2.5 emissions (Secretaría Distrital de Ambiente, 2019). Furthermore, re-suspended particulate matter, particularly from paved and unpaved roads, contributes 88% of total PM10 emissions and 57% of PM2.5 emissions (Secretaría Distrital de Ambiente, 2019). Bogotá's vehicular emissions show strong temporal patterns related to rush hours and heavy-duty vehicles are responsible for 38% of traffic-related emissions of PM10 (Secretaría Distrital de Ambiente, 2019). In contrast to vehicular-related emissions of PM2.5, which tend to be concentrated in the city center where traffic is most congested, industrial sources of particulate matter are concentrated in the center-west and south of the city in designated industrial zones (Cifuentes et al., 2021). Seasonal wildfires, which typically occur between January and April, also contribute significant PM2.5 emissions. Furthermore, regional biomass burning in the Orinoco basin and Magdalena Valley and occasional Saharan dust intrusion events can further impact air quality in the city (Rodriguez-Villamizar et al., 2022).

2.2 Mexico City

The metropolitan area of Mexico City is the most populous urban area in North America, containing over 21 million residents (Chaussard et al., 2021) or approximately 20% of Mexico's population (Molina et al., 2009). Mexico City is located in the Valley of Mexico, which is located in the high plateaus of south-central Mexico. Mexico City has a minimum altitude of 2,200 meters above sea level and is surrounded by mountains and volcanoes that reach 5,000 meters in elevation (Chaussard et al., 2021). The metropolitan area typically has light winds that limit ventilation (Molina et al., 2009; Streit and Guzman, 1996). Thermal inversions, which trap pollutant emissions close to the ground, are more frequent during the cool, dry winter season from November to February leading to high concentrations of primary pollutants and particulate matter (Guzmán-Torres et al., 2009; Molina et al., 2009; Bravo-Alvarez and Torres-Jardón, 2002).

The main sources of PM2.5 and PM10 emissions in the metropolitan area of Mexico City are from vehicles powered by fossil fuels, re-suspension of particles from paved and unpaved roads, construction, residential combustion of fuel (such as, liquefied petroleum gas), the industrial sector, primarily industrial processes related to chemicals, minerals and cement, and the power sector (Mugica et al., 2009; Molina et al., 2010; Mancera et al., 2014). In addition, air pollution levels in the metropolitan area are affected by wildfires (Rios et al., 2023; Yokelson et al., 2007).

2.3 Santiago

Gran Santiago is the largest metropolitan area of Chile. The population of Gran Santiago is nearly 6 million and it comprises approximately 40 percent of the Chilean population. Santiago is located in central Chile in the flat basin of the Maipo and Mapocho rivers and it is surrounded by high mountain ranges that hinder the free movement of polluting particles (Mazzeo et al., 2018; Toro et al., 2019). This effect is more pronounced in winter, when the wind system is weaker (Mazzeo et al., 2018). Thermal inversions, which are more frequent during periods of low temperature, also reduce the dispersion of air pollution (Toro et al., 2019).

Levels of particulate matter are generally higher in the winter than in the summer because residential heating, including from wood-burning, emits fine particulate matter (Gramsch et al., 2006). In the summer, atmospheric conditions can disperse pollutants more effectively (Gramsch et al., 2006), but summer PM levels can occasionally match or surpass winter concentrations during periods of extensive forest fires in the region (de la Barrera et al., 2018).

2.4 Sao Paulo

Sao Paulo is the largest metropolitan area in Brazil with a population of nearly 20 million residents. Sao Paulo is located 60 km from the ocean at an elevation of approximately

800 meters above sea level (Atlas, 2019; de Lima and Rueda, 2018). Winds from the ocean can bring clean air, but weak winds fail to disperse pollutants effectively (Freitas et al., 2007). Mountains to the north and northwest reach 1,100 meters in height and often trap pollutants during thermal inversions (de Lima and Rueda, 2018; Vara-Vela et al., 2016). The city also experiences a significant urban heat island effect that creates conditions that can trap pollutants near the surface (Vara-Vela et al., 2016; Freitas et al., 2007). These geographical and meteorological conditions are especially likely to lead to high levels of air pollution during winter months when thermal inversions are more frequent and atmospheric conditions can lead to the accumulation of pollutants (Nogueira et al., 2017; Vara-Vela et al., 2016; Ribeiro and de Assuncao, 2001).

PM2.5 formation in Sao Paulo is heavily influenced by secondary processes. In particular, vehicular emissions lead to the formation of secondary particles accounting for 20-30% of PM2.5 concentrations in downtown Sao Paulo (Vara-Vela et al., 2016). Industrial activities are responsible for a large share of PM10 (Vara-Vela et al., 2016) and dust and sea salt aerosols also contribute 40-50% of total PM10 (Vara-Vela et al., 2016).

3 Data

We study exposure to air pollution in four cities of Latin America, Bogota, Colombia, Mexico City, Mexico, Santiago, Chile, and Sao Paulo, Brazil, focusing on the broader metropolitan area of each city. We consider all individuals residing within the broader metropolitan area in order to better approximate the set of individuals participating in a local economy and labor market. This avoids, for instance, excluding residents who may be pushed to the urban periphery by high costs of living in the center of the city from the analysis. We combine air pollution data for 2023 from the network of ground monitoring stations in each of our four cities with census data that provides residential geographic information and socio-demographic characteristics of all individuals.

3.1 Census Data

We use the census data that contains information on all individuals residing in each of our four metropolitan areas. We use the most recent census data in each country that contains disaggregated geographic identifiers in the individual level data. The census data of all four countries contains education information and the census data for Brazil and Mexico contain income information. We harmonize the education variables across all four countries. Specifically, our approach to harmonizing the education data assigns 12 years of education to high school completion, 17 years to a Bachelor's degree, 19 years to a Master's degree, and 23 years to a PhD degree.[6] The income variables for Mexico City and São Paulo measure total monthly labor income.

The census data also contains residential geographic identifiers that we use to merge individuals to air pollution data. Unfortunately, the census does not contain individuals' exact residential location and the size of the geographic unit at which we can identify residential locations in the census differs substantially across cities (see Table 1). While we conduct our analysis at the individual level, we match individuals to air pollution data at the geographic level provided by the census. There are 633 weighting areas in the metropolitan area of Sao Paulo and on average each weighting area contains 31,096 individuals. In the metropolitan area of Gran Santiago, there are 384 census tracts with an average population of 15,585 individuals per census tract. The geographic identifiers in Mexico City and Bogota are substantially larger. In the metropolitan area of Mexico City, there are 76 municipalities with an average population of 285,754 individuals per municipality. In the metropolitan area of Bogota, there are 42 localities and municipalities that contain 188,160 individuals on average. Because a common definition of localities is not available for the areas surrounding Bogotá's capital city, which are part of the metropolitan area, we use municipalities for these areas and localities for the capital city itself.

Inferring the relationship between air pollution and characteristics at the individual level from correlations between air pollution and characteristics estimated using group-level aggregated data raises concerns related to the ecological fallacy. The ecological fal-

[6] Tables C.9, C.10, C.11, and C.12 show the census education variables used for each city and the new categories for the harmonized years of education variable.

lacy cautions that the relationship estimated using aggregated data is equal to the relationship at the individual level only if there are no group-level effects correlated with air pollution (Banzhaf et al., 2019; Piantadosi et al., 1988). Depending on the correlation of the group-level effects and air pollution, the relationship estimated using the aggregated data could overestimate or underestimate the inequitable exposure (Banzhaf et al., 2019). Baden et al. (2007) assess the impact of the unit of analysis on the results of over 100 environmental justice studies and find stronger evidence of racial, ethnic, and income inequities when using smaller units of analysis. Therefore, we use the smallest geographic unit available in the census in our analysis.

Table 1: Census geographic units and Population of Metropolitan Areas

City	Year	Total population	Census geographic level	Number of census geographic units	Average population per census geographic unit
Bogota	2005	7,902,707	Locality/Municipality	42	188,160
Mexico	2020	21,717,324	Municipality	76	285,754
Gran Santiago	2017	5,984,604	Census tract	384	15,585
Sao Paulo	2010	19,683,975	Weighting area	633	31,096

Notes: This table summarizes the census data for each metropolitan area, including the census geographic unit. Data is sourced from the latest census with a geographical unit for disaggregation in each city.

3.1.1 Bogota

The census data for Bogotá is collected by the *National Administrative Department of Statistics (DANE)*. The census used in this analysis was conducted in 2005. The metropolitan area of Bogotá consists of the capital city and 22 surrounding municipalities that form the metropolitan area (Secretaría Distrital de Planeacion, 2022). Census data is available at the locality level for the capital city, while municipalities are used for the surrounding areas because a unified definition of localities does not exist for these regions.

The census does not provide direct income data for individuals. Instead, proxies such as education levels are used to infer socioeconomic status. The education variable was harmonized across cities to ensure comparability, as described at the beginning of the data section and detailed in the Data Appendix (Section 3.3).

3.1.2 Mexico City

The census data for Mexico City is collected by the *National Institute of Statistics and Geography (INEGI)*. The data used in this analysis comes from the 2020 census. The metropolitan area of Mexico City includes 76 municipalities that form the broader metropolitan region (Government of Mexico, 2012). Census data is provided at the municipality level, which is consistent across the metropolitan area.

Income data is available in the census and measures total monthly labor income. The education variables were harmonized across cities to ensure comparability, as described at the beginning of the data section and detailed in the Data Appendix (Section 3.4).

3.1.3 Santiago

The census data for Santiago is collected by the *National Institute of Statistics (INE)* of Chile. The data used in this study comes from the 2017 census. The metropolitan area of Gran Santiago consists of 384 census tracts and 35 comunas (CEPAL, 2001). Census tracts are consistently defined across the region and serve as the geographic units used for the analysis of the metropolitan area of Gran Santiago.

The census does not provide direct income data but includes proxies such as years of schooling to infer socioeconomic status. The education variable was harmonized across cities to ensure comparability, as described at the beginning of the data section and detailed in the Data Appendix (Section 3.5).

3.1.4 Sao Paulo

The census data for São Paulo is collected by the *Brazilian Institute of Geography and Statistics (IBGE)*. The census used in this analysis was conducted in 2010. The metropolitan area of São Paulo is defined by 633 weighting areas, which serve as the geographic units for this analysis (EMPLASA, 2019). The weighting areas are consistently defined across the metropolitan region.

The census provides income data, which measures total monthly labor income. The education variable was harmonized across cities to ensure comparability, as outlined at the beginning of the data section and detailed in the Data Appendix (Section 3.6).

3.2 Air Pollution Data

We focus on particulate matter air pollution. Particulate matter is not a single pollutant, but a mixture of solid particles and liquid droplets of different shapes, sizes, and chemical compositions. Particulate matter originates from natural sources, such as dust storms and wildfires, and human activities, such as industrial processes and vehicle emissions.

Exposure to ambient particulate matter is causally linked to morbidity and mortality (WHO, 2021; Wei et al., 2020; Schwartz et al., 2018; Baccini et al., 2017; Brook et al., 2010; EPA, 2009). Long-term exposure to ambient particulate matter leads to cardiovascular and respiratory disease and mortality (Anderson et al., 2011; Cesaroni et al., 2014; Crouse et al., 2015). Short-term exposure to high levels of ambient particulate matter leads to negative health impacts, including acute bronchitis, asthma attacks, increased susceptibility to respiratory infections, and worsened heart conditions, on the day of exposure and the following days (New York State Department of Health, 2021; EPA, 2010; Lin et al., 2002; Tertre et al., 2002). Exposure to particulate matter also negatively impacts a wide range of non-health outcomes, including labor productivity (Adhvaryu et al., 2022; Chang et al., 2016), labor supply (Hoffmann and Rud, 2024; Aragón et al., 2017), test scores (Bedi et al., 2021; Ebenstein et al., 2016), and decision-making and crime (Herrnstadt et al., 2021; Burkhardt et al., 2019; Sager, 2019).

Particulate matter is typically regulated, and therefore monitored, according to the size of the particles. PM10 and PM2.5 are two of the most commonly monitored types of particulate matter. PM10 refers to inhalable particulate matter with a diameter of less than 10 μm, and PM2.5, a subset of PM10, refers to fine particulate matter with a diameter of less than 2.5 μm. PM10 was the first type of ambient particulate matter to be monitored in many cities (Southerland et al., 2022; Riojas-Rodriguez et al., 2016) and PM2.5 is likely the most widely studied type of particulate matter (see for example, Aguilar-Gomez et al. (2022); Sharma et al. (2020); Yuan et al. (2019)). Relative to PM10, PM2.5 has stronger and broader health impacts (Bell et al., 2004; Pope and Dockery, 2006) and is more difficult to avoid because it permeates buildings more easily (Tracy and Layton, 1995; Vette et al., 2001; Pope and Dockery, 2006; CARB, 2021).[7]

Particulate matter is an important air pollutant in urban areas of Latin America. City-wide averages indicate that all four metropolitan areas in our study exceeded the WHO annual Air Quality Guideline (AQG) for PM10 and PM2.5 in 2023. Specifically, annual average PM10 levels ranged between 2 and 4 times the WHO guideline across the cities, while PM2.5 levels ranged between 3 and 5 times the guideline.[8]

We use air pollution data from each city's network of ground monitoring stations maintained by the government. This data is available at the station-hour level. Regulatory-grade ground monitoring stations record accurate and precise high-frequency measurements of air pollutants at their locations. This allows us to capture peaks in air pollution levels that could be masked by spatial or temporal averaging. However, there is sparse coverage of monitoring stations in some areas. Appendix Table A.1 shows the number of stations reporting data for PM2.5 and PM10 in 2023 by city. In general, Santiago has the fewest monitoring stations and São Paulo has the most. A detailed description of the air quality data for each city can be found in Appendix Sections 3.3, 3.4, 3.5, and 3.6.

To ensure data quality, we implement a cleaning procedure. Appendix Section 3.1 provides a detailed description. For each pollutant and station, we flag hourly observations as potentially unreasonable if they exceed the 99th percentile of the station-month distribution. We determine which of the flagged observations to replace with missing by comparing the flagged observations to the hourly observations before and after the flagged observation at the same station and to observations at neighboring stations. After cleaning, we spatially aggregate the data using inverse-distance weighting to create pollution concentrations for each census geographic unit. Specifically, for each pollutant, hourly measurements from monitoring stations within a given radius are weighted by the inverse of their distance to the centroid of each geographic unit. This approach ensures that closer stations contribute more heavily to the exposure estimates, effectively captur-

[7] https://ww2.arb.ca.gov/resources/inhalable-particulate-matter-and-health

[8] The WHO annual AQG for PM10 is 15 $\mu g/m^3$ and for PM2.5 is 5 $\mu g/m^3$. Our calculated exceedances are as follows: Bogotá (PM10: 2.1x, PM2.5: 3.0x); Mexico City (PM10: 2.7x, PM2.5: 3.9x); Santiago (PM10: 4.3x, PM2.5: 4.7x); and São Paulo (PM10: 1.9x, PM2.5: 2.9x). The exceedance factors are calculated as the ratio of the city-wide annual average concentration to the WHO AQG for each pollutant.

ing spatial variations in air pollution. A detailed description of the spatial aggregation procedure can be found in Appendix Section 3.2.

We study both longer-term and short-term measures of air pollution to understand chronic exposure and acute exposure across the education and income distributions. To capture chronic exposure, we calculate annual mean concentrations of each pollutant. To capture acute exposure, our short-term measures focus on capturing peaks in air pollution, which is important due to non-linearities in the impacts of air pollution (Hoffmann and Rud, 2024). Specifically, for each pollutant, we code the daily number of hours in which the hourly concentration of the pollutant is above the WHO Interim Targets 1 and 2 (IT1 and IT2) for 24-hour concentrations of the pollutant (WHO, 2021). Table A.2 presents the WHO IT1 and IT2 thresholds for PM10 and PM2.5. The interim targets are designed to be used as intermediate goals in high-pollution areas while progressing toward air pollution levels below the Air Quality Guidelines. IT1 is the highest and IT2 is the second highest of the four Interim Targets.

Figure 1 displays the kernel density distributions of hourly PM10 and PM2.5 in 2023 at all stations for each of the four metropolitan areas and the WHO Interim Threshold (IT1) and Interim Threshold (IT2). The WHO air quality guidelines and interim thresholds for PM10 and PM2.5 are in $\mu g/m^3$ units.[9] In Bogota, Santiago, and Sao Paulo the unit of measurement for PM10 is $\mu g/m^3 N$ and in Mexico City the unit of measurement for PM10 is $\mu g/m^3$. In Bogota and Sao Paulo the unit of measurement for PM2.5 is $\mu g/m^3 N$, and the unit of measurement of PM2.5 in Mexico City and Santiago is $\mu g/m^3$. Differences in measurement methods across cities implies that the concentrations of particulate matter may not be directly comparable across cities. Furthermore, while we use the WHO thresholds to identify peaks in air pollution in all four metropolitan areas, the concentrations recorded may not be directly comparable to the WHO guidelines or thresholds without adjustment of the air quality standards.[10] However, these differences in measurement methods across cities do not impact the comparison of particulate matter concentrations

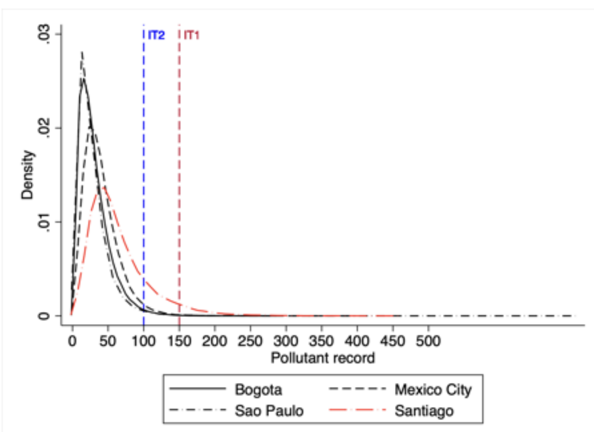
[9] The unit of measurement $\mu g/m^3$ indicates the concentration of particulate matter measured in local ambient conditions, and the unit of measurement $\mu g/m^3 N$ indicates the concentration of particulate matter under normalized conditions (specifically temperature of 25C and atmospheric pressure of 1 atm).

[10] For instance, see (Alvarez et al., 2013) for a discussion of adjustment of air quality standards in high altitude cities.

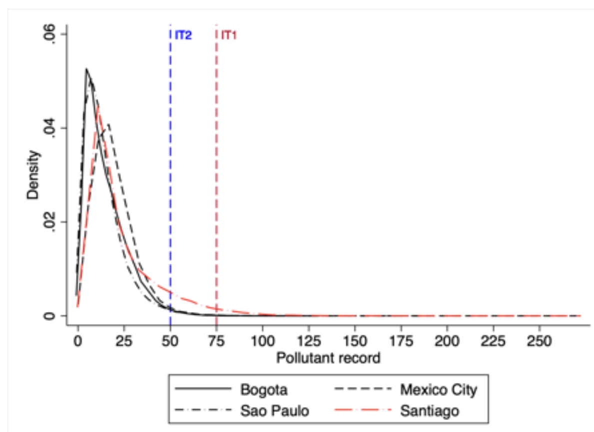
within cities, which is the focus of our analysis.

Panel A shows the PM10 distributions for each metropolitan area. Santiago (red line) frequently exceeds the WHO interim targets (IT1 at 150 $\mu g/m^3$ and IT2 at 100 $\mu g/m^3$). Mexico City exhibits a broader distribution below the thresholds, while Bogotá and São Paulo have the highest densities at low levels, indicating better air quality. Panel B depicts the PM2.5 distributions. Santiago frequently surpasses the WHO interim targets (IT1 at 75 $\mu g/m^3$ and IT2 at 50 $\mu g/m^3$) and experiences worse PM2.5 pollution than the other metropolitan areas. Mexico City presents a broader distribution, occasionally exceeding the WHO interim targets, while São Paulo and Bogotá remain largely below the IT2 threshold. Appendix figure B.1 shows the distributions of hourly PM10 and PM2.5 at the city-level in each of the four metropolitan areas in 2019 and 2022 and confirms the distributions are similar to those in 2023.

Figure 1: Distribution of PM10 and PM2.5 Concentrations in Each Metropolitan Area



(a) PM_{10} Distribution



(b) $PM_{2.5}$ Distribution

Notes: The figure illustrates the distribution of PM10 and PM2.5 concentrations in the metropolitan areas of Bogotá, Mexico City, São Paulo, and Santiago. The x-axis shows pollutant concentrations, while the y-axis shows density. The dashed vertical lines in Panel (a) indicate the WHO Interim Target 1 (IT1, red) and Interim Target 2 (IT2, blue) thresholds for PM10 levels, set at 150 $\mu g/m^3$ and 100 $\mu g/m^3$, respectively. PM10 units of measurements are $\mu g/m^3 N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City. Similarly, the vertical lines in Panel (b) represent the corresponding thresholds for PM2.5, set at 75 $\mu g/m^3$ and 50 $\mu g/m^3$. PM2.5 units of measurements are $\mu g/m^3 N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

Next, we focus on the right tail of the PM2.5 distributions to understand differences in peaks of PM2.5 across cities. Appendix table A.3 shows the number of days in 2023 with at least 1 hour or at least 2 hours above the IT1 and IT2 thresholds in each city. In panel A, the data is averaged across all stations in the metropolitan area to create a time series at the hourly level for each metropolitan area. At the city-level, Bogota, Mexico City, and Sao Paulo did not experience any days in 2023 with at least two hours above the IT1 threshold for PM10. Similarly, for PM2.5, these cities experienced at most 2 days with at least 2 hours above the IT1 threshold at the city-level. In contrast, Santiago recorded 45 days with at least 2 hours above the IT1 threshold for PM10 and 22 days with at least 2 hours above the IT1 threshold for PM2.5. Panel B displays the number of days in 2023 in which at least 1 station in the city exceeded the IT1 and IT2 thresholds for at least 1 hour or 2 hours. For both PM10 and PM2.5, Santiago experienced about triple the number of days with at least one station recording two or more hours above IT1 then the other three cities. Appendix table A.4 shows the average number of hours per day above IT1 and IT2 for each pollutant conditional on exceeding the threshold. Santiago experienced substantially longer high pollution spells than the other cities, which is especially clear in the station-hour panel (panel B). Furthermore, Appendix figure B.3 shows the distribution of consecutive hours with PM2.5 above IT2 for each city. Bogota experiences only two short episodes above the IT2 threshold. Given that PM2.5 crosses the IT2 threshold, there are more consecutive hours above IT2 in Santiago than in Mexico City or Sao Paulo. For instance, some of the peaks in PM2.5 persist for over 24 hours in Santiago. To visualize pollution concentrations across the day, Appendix figure B.2 displays the ridgeline distributions of hourly PM2.5 using the hourly time series for each city. While the distributions look similar across metropolitan areas, Santiago experiences many more hours of PM2.5 above the IT2 and IT2 thresholds, with peaks in pollution occurring across all hours of the day. In contrast, the other metropolitan areas do not experience peaks across all hours of the day.

3.2.1 Bogotá

We collected hourly data on PM10 and PM2.5 from Bogota's air quality monitoring network known as the *Red de Monitoreo de Calidad del Aire de Bogotá*. The air quality network is maintained by the *Secretaría Distrital de Ambiente* (SDA), Bogotá's environmental agency. In 2023, the Metropolitan Area of Bogotá had 19 real-time stations recording hourly concentrations (in $\mu g/m^3N$) of PM10 and PM2.5 (see Appendix Table A.1).[11] Figure 2 shows the location of these monitoring stations in the Metropolitan Area of Bogotá.

3.2.2 Mexico City

We collected hourly data on PM10 and PM2.5 from Mexico City's automatic air quality monitoring system (RAMA for *Red Automática de Monitoreo Atmosférico*) that is maintained by the *Secretaría del Medio Ambiente* (SEDEMA), the city's environmental agency.[12] In 2023, the Metropolitan Area of Mexico City had 23 real-time stations that recorded hourly concentrations (in $\mu g/m^3$) of PM10 and 19 real-time stations that recorded PM2.5 (in $\mu g/m^3$) (see Appendix Table A.1). Figure 2 illustrates the location of these monitoring stations in the Metropolitan Area of Mexico City.

3.2.3 Santiago

We collected hourly data on PM10 and PM2.5 from Santiago's air quality monitoring system (SINCA) that is operated by the *Ministerio del Medio ambiente* (MMA). In 2023, the Metropolitan Area of Gran Santiago had 10 real-time monitoring stations that recorded hourly concentrations (in $\mu g/m^3$) of PM10 (in $\mu g/m^3N$) and PM2.5 (in $\mu g/m^3$) (see Appendix Table A.1). Figure 2 plots the location of these monitoring stations in the Metropolitan Area of Gran Santiago.[13]

3.2.4 Sao Paulo

We collected hourly data on PM10 and PM2.5 from São Paulo's air pollutants monitoring system (CETESB QUALAR System for *Companhia Ambiental do Estado de São Paulo Qualidade do Ar*). The Metropolitan Area of São Paulo has 29 real-time stations that record hourly concentrations (in $\mu g/m^3N$) of PM10 (see Appendix Table A.1). Twenty-five stations in the network record hourly concentrations (in $\mu g/m^3N$) of PM2.5. Figure 2 plots

[11] The unit of measurement $\mu g/m^3$ indicates the concentration of particulate matter in local ambient conditions. $\mu g/m^3N$ indicates the concentration of particulate matter under normalized conditions (specifically temperature of 25C and atmospheric pressure fo 1 atm).

[12] Because the webpage was under maintenance, this data was obtained on August 27, 2024 by emailing the Dirección General de Calidad del Aire at calidadairesimat@gmail.com.

[13] One additional station, "Independencia" did not record any data in 2023.

the location of these monitoring stations in the Metropolitan Area of São Paulo. We restrict monitoring stations to those within 20 km of the metropolitan area, as there are additional monitoring stations located further away in the state of São Paulo.

4 Is There Inequality in Air Pollution Monitoring?

The first step in assessing inequality in air pollution exposure is to assess inequality in monitoring of air pollution by the network of in-situ monitoring stations operated by the government. When well-maintained, in-situ regulatory-grade ground monitoring stations provide highly accurate and precise measurement of air pollutants at their location. However, the accuracy of this data for measuring exposure to air pollutants generally declines with distance from the location of the monitoring station.[14] Therefore, we explore the implications of the siting of fixed location air pollution monitors for the coverage of air pollution measurement. We consider the monitoring stations in the network that measure and record data on PM10 or PM2.5 in 2023.

Figure 2 shows maps of each metropolitan area with the census geographic units, air pollution monitoring stations, and 3 km radii around each monitoring station. The color of the geographic unit represents the quintile of the distribution of years of schooling with darker colors representing higher education levels. To create population-weighted quintiles, we rank the geographic units by their average years of schooling and calculate each unit's share of the total population. Quintiles are then defined to ensure that each quintile represents an equal share of the total population (20%).

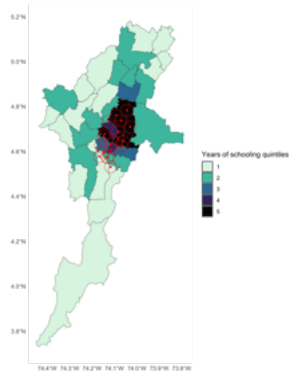
In Bogota, Mexico City, and Sao Paulo, the monitoring stations appear more likely to be located in geographic units in the top quintiles of the distribution of years of schooling. In Gran Santiago, there are many monitoring stations located in areas with geographic units in the bottom quintiles of the distribution of years of schooling and there are large areas with geographic units in the top two quintiles of the distribution of years of schooling with sparse or no coverage of monitoring stations.

[14] The specific functional form of the decline with distance from the monitor could differ by pollutant, location, weather, or other factors. For instance, Ito et al. (2001) show substantially different declines in monitor-to-monitor correlations with distance for different pollutants.

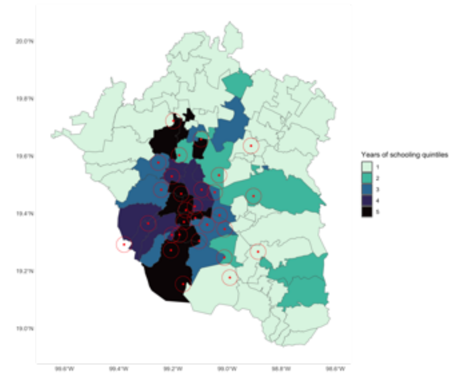
Appendix figure B.4 shows that the network of monitoring stations in each metropolitan area is concentrated in areas with high population density. In Bogota, Mexico City, and Sao Paulo, lower density areas in the periphery of the metropolitan areas also tend to have lower education levels (see figures 2 and B.4). The metropolitan area of Gran Santiago displays a different pattern. For instance, the northeast section of Gran Santiago contains geographic units in high education quintiles and has a very low population density, due to forests in these areas. Because low-income residents are often pushed to the periphery of metropolitan areas by the high costs of living in the central areas of cities, siting in-situ monitors based on population density and proximity to central districts of cities could result in inequality in monitoring of air pollution.

Figure 2: Years of Schooling Quintiles Across Geographic Units and 3km Buffers for Monitoring Stations (Population-Weighted Quintiles)

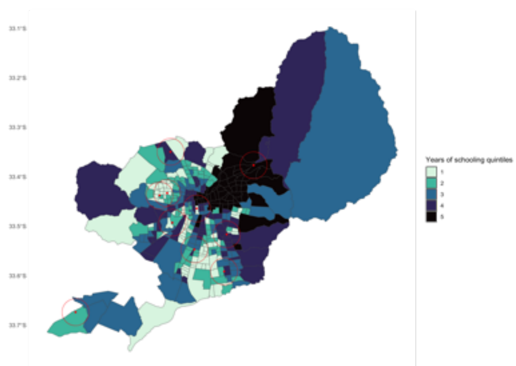
Metropolitan Area of Bogota



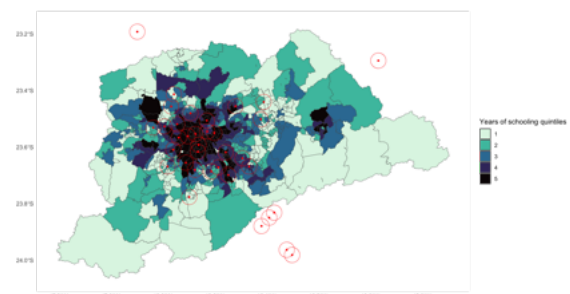
Metropolitan Area of Mexico City



Metropolitan Area of Gran Santiago



Metropolitan Area of Sao Paulo



Notes: The figure shows maps with population-weighted quintiles of years of schooling for geographic units in each metropolitan area, overlaid with active air quality monitoring stations in 2023 and their 3 km buffers. An active air quality monitoring station is a station that recorded at least one pollutant (PM10 or PM2.5) in 2023. Air quality monitoring stations are shown as red points, with the 3 km buffers represented by hollow red circles. For the metropolitan area of Bogotá, the geographic units consist of the localities of Bogotá's capital city and the municipalities from the surrounding areas that form the metropolitan area. The municipalities are used because a common definition of localities for these other areas could not be identified. For the metropolitan area of Mexico City, the geographic units are municipalities encompassing the entire metropolitan area. For Santiago the geographic units correspond to census tracts, and for São Paulo weighting areas. For detailed characteristics of these geographic units, see Table 1. Finally, for the metropolitan area of São Paulo, we restrict monitoring stations to those within 20 km of the metropolitan area, as there are additional monitoring stations located further away in the state of São Paulo.

We document how the characteristics of the population change with distance from an air pollution monitoring station. Tables 2 and 3 display the results. The first column presents the characteristics of the full population of the metropolitan area. The following columns present the characteristics of the population that resides in geographic units with a centroid within a specific radius of a monitoring station. The radius increases from 1 km in the second column to 20 km in the last column.

Table 2: Descriptive Statistics by Distance from Centroid to Air Pollution Monitoring Station

Variable	All	Within 1 km	Within 3 km	Within 5 km	Within 10 km	Within 20 km
Panel A. Bogota						
Number of localities	42	3	11	17	23	31
Population	7,902,707 (100%)	729,612 (9.23%)	3,636,460 (46.02%)	5,495,511 (69.54%)	7,077,862 (89.56%)	7,586,826 (96%)
Share of adults	0.546	0.576	0.57	0.568	0.552	0.548
Mean age	29.42	30.732	30.493	30.426	29.692	29.502
Share of women	0.521	0.526	0.526	0.526	0.523	0.522
Share of HH women	0.089	0.095	0.097	0.095	0.091	0.09
Share of black	0.014	0.011	0.012	0.014	0.014	0.014
Share of employed	0.607	0.621	0.599	0.603	0.605	0.607
Mean years of schooling	8.262	9.07	9.014	8.93	8.463	8.331
Share with no education	0.098	0.083	0.086	0.088	0.095	0.097
Share with graduate education	0.006	0.005	0.009	0.008	0.007	0.006
Range years of schooling	[5.013, 12.655]	[7.804, 9.666]	[7.34, 12.655]	[6.773, 12.655]	[6.388, 12.655]	[6.341, 12.655]
Total Population Density (pop/km²)	1870.844	12015.83	12538.388	10632.224	6197.142	3324.564
Average Population Density (pop/km²)	6108.156	45730.822	275406.502	466145.495	465080.845	388103.198
Panel B. Mexico City						
Number of municipalities	76	1	9	22	47	63
Population	21,717,324 (100%)	165,584 (0.76%)	5,373,332 (24.74%)	12,490,062 (57.51%)	18,851,758 (86.81%)	21,149,219 (97.38%)
Share of adults	0.63	0.578	0.673	0.654	0.639	0.632
Mean age	34.332	31.328	36.523	35.647	34.825	34.431
Share of women	0.518	0.506	0.522	0.52	0.519	0.518
Share of HH women	0.102	0.082	0.122	0.11	0.105	0.102
Share of indigenous	0.097	0.066	0.085	0.084	0.094	0.096
Share of employed	0.538	0.491	0.555	0.542	0.541	0.539
Mean years of schooling	9.329	8.47	10.122	9.703	9.471	9.367
Mean income	21391.568	9428.711	19719.884	21624.795	21684.03	21732.358
Share with no education	0.084	0.091	0.073	0.077	0.082	0.083
Share with graduate education	0.019	0.005	0.031	0.022	0.021	0.02
Range years of schooling	[6.954, 12.89]	[8.47, 8.47]	[8.47, 12.89]	[8.33, 12.89]	[7.648, 12.89]	[7.548, 12.89]
Total Population Density (pop/km²)	2752.642	1899.663	10788.847	9351.113	4950.426	3495.876
Average Population Density (pop/km²)	4167.896	1899.663	131261.032	327928.921	573122.484	632182.483

Notes: This table presents descriptive statistics categorized by the distance from the centroid of each geographic unit to the nearest air pollution monitoring station. Distances are measured in kilometers. These descriptive statistics capture the socioeconomic characteristics of areas as the radius from air pollution monitoring stations increases. The variable *Range years of schooling* represents the minimum and maximum average years of schooling of census geographic units.

Bogotá (Panel A of Table 2) has very few geographic units with a centroid within 1 km or 3 km of a monitoring station. As the radius around the monitoring stations increases, the mean education level decreases and the share of the population with no education increases. Similarly, Mexico City (Panel B of Table 2) has very few geographic units with a centroid within 1 km or 3 km of a monitoring station. Although the mean education level is relatively low and the share with no education level is relatively high within a 1 km radius of the stations, the mean education level consistently decreases and the share of the population with no education consistently increases as the radius increases from 3 km to 20 km. In contrast, income does not show a consistent decrease. In contrast, in Santiago (Panel A of Table 3), there is little change in the share of the population with no education across different radii, and the mean education level and the share of the population with graduate level education generally increases with the radius around monitoring stations. Among the four cities, Sao Paulo (Panel B of Table 3) has smallest geographic units and the greatest number of geographic units. Mean education levels and income decline as the radius around the monitoring stations increases. Overall, Tables 2 and 3 document that the population residing in close proximity to at least one monitoring station in Bogotá, Mexico City, and São Paulo generally have higher education or income levels.

Table 3: Descriptive Statistics by Distance from Centroid to Air Pollution Monitoring Stations

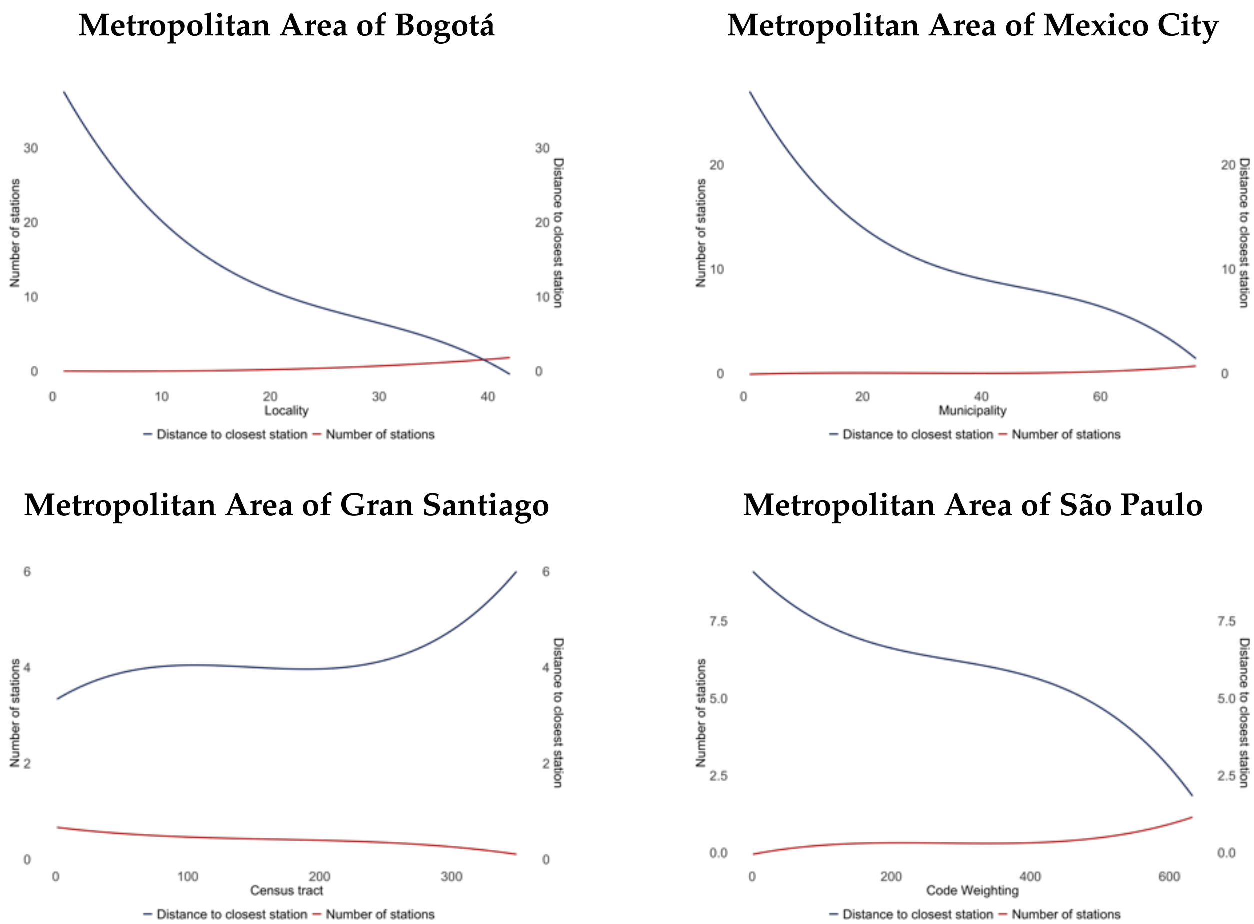
Variable	All	Within 1 km	Within 3 km	Within 5 km	Within 10 km	Within 20 km
Panel A. Santiago						
Number of census tracts	384	21	124	245	341	348
Population	6,194,221 (100%)	378,533 (6.11%)	2,024,901 (32.69%)	4,127,252 (66.63%)	6,045,580 (97.6%)	6,170,837 (99.62%)
Share of adults	0.658	0.645	0.663	0.66	0.659	0.658
Mean age	35.839	35.271	35.954	35.9	35.887	35.827
Share of women	0.515	0.5	0.511	0.513	0.516	0.516
Share of HH women	0.139	0.126	0.14	0.14	0.14	0.139
Share of Indigenous	0.103	0.114	0.111	0.11	0.103	0.102
Share of employed	0.612	0.594	0.612	0.612	0.612	0.612
Mean years of schooling	10.095	9.479	9.92	9.864	10.102	10.093
Share with no education	0.103	0.101	0.1	0.102	0.102	0.103
Share with graduate education	0.024	0.006	0.014	0.016	0.024	0.024
Range years of schooling	[7.026, 14.441]	[8.423, 11.685]	[7.246, 13.672]	[7.246, 14.379]	[7.246, 14.441]	[7.246, 14.441]
Total Population Density (pop/km²)	2582.487	10069.313	8207.991	7510.936	5047.891	3476.8
Average Population Density (pop/km²)	10635.401	353017.633	1824697.712	3507923.133	4698103.999	4702346.528
Panel B. Sao Paulo						
Number of weighting areas	633	31	214	396	545	602
Population	19,683,975 (100%)	1,002,772 (5.09%)	6,996,175 (35.54%)	13,317,895 (67.66%)	17,714,598 (90%)	19,128,746 (97.18%)
Share of adults	0.612	0.646	0.643	0.627	0.618	0.613
Mean age	32.463	34.214	34.036	33.183	32.71	32.488
Share of women	0.479	0.473	0.473	0.476	0.477	0.479
Share of whites	0.587	0.649	0.634	0.606	0.592	0.586
Share of blacks	0.393	0.331	0.341	0.372	0.388	0.395
Mean income	1868.308	2401.36	2431.746	2111.888	1933.136	1881.421
Share of formal employees	0.255	0.271	0.272	0.264	0.259	0.256
Share of informal employees	0.135	0.139	0.142	0.138	0.136	0.135
Mean years of schooling	9.418	10.208	10.257	9.782	9.535	9.434
Range years of schooling	[6.281, 15.475]	[7.589, 15.475]	[6.917, 15.475]	[6.379, 15.475]	[6.281, 15.475]	[6.281, 15.475]
Total Population Density (pop/km²)	2471.55	8822.36	10914.945	8815.516	6705.558	3602.895
Average Population Density (pop/km²)	11041.201	407873.265	3524810.484	5988964.68	7470133.563	7601263.297

Notes: This table presents descriptive statistics categorized by the distance from the centroid of each geographic unit to the nearest air pollution monitoring station. Distances are measured in kilometers. These descriptive statistics capture the socioeconomic characteristics of areas as the radius from air pollution monitoring stations increases. The variable *Range years of schooling* represents the minimum and maximum average years of schooling of census geographic units.

Next, we explore the number of stations within a given radius of the geographic unit's centroid and the distance from the centroid to the nearest monitoring station. Having multiple air pollution monitoring stations in the vicinity could improve the quality of air pollution monitoring because missing data from one monitoring station could be replaced with data from another, reducing gaps in monitoring, and when multiple stations are recording data, air pollution levels from multiple monitoring stations could be combined to improve accuracy for areas between monitoring stations.

Figure 3 displays the number of stations within 3 km of the geographic unit's centroid on the left vertical axis and the distance to the monitoring station nearest to the geographic unit's centroid on the right vertical axis. Geographic units are ordered on the horizontal axis from lowest mean education level on the left hand side to highest mean education level on the right hand side. In Bogotá, Mexico City, and São Paulo, the distance to the closest monitoring station declines as the mean education level of the geographic unit increases. In contrast, the number of monitoring stations within 3 km increases with the mean education level of the geographic unit. In these three cities the decrease in distance occurs over the full range of geographic units. However, the increase in the number of monitoring stations is most pronounced among geographic units with mean education levels greater than the median. In contrast, in Santiago, the distance to the nearest monitoring station trends upwards with the mean education level of the geographic unit and the number of monitoring stations within 3 km generally trends downwards as the mean education level of the geographic unit increases. Appendix Figures B.5, B.6, B.7 and B.8 show that these results are consistent when considering alternate radii around the centroid of the geographic units.

Figure 3: Number of Stations within a 3 km Radius and Distance to Nearest Station



Notes: The figure illustrates the number of monitoring stations within a 3 km radius and the distance to the nearest station for each metropolitan area. The data were processed by importing a distance matrix between geographic units and air quality monitoring stations that report PM10 levels, converting distances to kilometers, and identifying geographic unit centroids with stations within 3 km. To analyze trends, geographic units were sorted from lowest to highest status based on their mean years of schooling. The plots depict these trends using smooth lines fitted with a third-degree polynomial regression. Distance to the nearest station is displayed on the secondary y-axis.

Finally, we explore whether, among geographic areas in close proximity to an air quality monitor, geographic areas with higher education levels have higher quality air pollution monitoring. If resources for maintenance of air pollution monitors were disproportionately allocated to geographic areas with higher education levels, then we would expect to see a higher share of non-missing observations in areas with higher education levels.

To investigate differences in the quality of air pollution monitoring provided by stations, we calculate the share of non-missing observations by education quintile. For each city, we compute the share of non-missing pollutant observations for each station and use these shares to calculate weighted averages for each census geographic unit using an inverse distance weighted average of the pollutant data series from all active monitoring stations within a 3 km radius of the centroid of each geographic unit. We merge this data with the individual-level census data by proxying for each individual's monitoring quality with the quality of monitoring for their census geographic unit of residence. Using the individual-level panel of the share of non-missing PM2.5 and PM10 observations, we create education quintiles within each of the four cities and we average across the individuals within each quintile (or decile in the case of income) to obtain a share of missing observations by quintile.

For each pollutant, Table 4 displays the share of non-missing observations by education quintile. Overall, there is no evidence that geographic areas with lower education levels have more missing observations. This indicates that, where stations exist, there does not seems to be unequal quality of air pollution monitoring across socioeconomic groups within these cities.

Table 4: Share of Non-Missing Pollution Observations in 2023 by Quintiles of Years of Schooling

Pollutant	City	Q1	Q2	Q3	Q4	Q5
PM_{10}	Bogota	0.876	0.872	0.879	0.872	0.876
	Mexico City	0.708	0.712	0.710	0.660	0.671
	Santiago	0.947	0.949	0.949	0.956	0.967
	Sao Paulo	0.791	0.795	0.792	0.787	0.780
$PM_{2.5}$	Bogota	0.907	0.904	0.910	0.905	0.908
	Mexico City	0.771	0.775	0.758	0.733	0.742
	Santiago	0.936	0.937	0.938	0.944	0.954
	Sao Paulo	0.678	0.683	0.679	0.687	0.680

Notes: The table shows the share of hourly air pollution monitoring observations (PM_{10} and PM_{25} pollutants) in 2023 that are non-missing by quintiles of years of schooling in the metropolitan areas of Bogotá, Mexico City, Santiago, and São Paulo. The shares are calculated as the ratio of non-missing observations to total observations for each pollutant and are weighted by the number of observations in each quintile. Quintiles of years of schooling are defined separately for each city based on its census data. The stations used for calculating each share were the ones reporting the respective pollutant.

Together, our results suggests that, in Bogota, Mexico City, and Sao Paulo, air pollution exposure is likely to be better monitored for those with higher education and income levels. We find that geographic areas with higher education and income levels are more likely to be in close proximity to an air pollution monitor and are in close proximity to a greater number of air pollution monitors. However, conditional on being in close proximity to an air pollution monitor, the quality of air pollution monitoring in terms of the share of missing observations does not vary systematically across socioeconomic groups.

Air pollution monitoring by regulatory-grade monitors operated by the government is a public service. Therefore, this finding broadens the literature documenting that local public goods and services tend to be better provided in neighborhoods with higher incomes and fewer socially marginalized residents (Asher et al., 2024; Harari, 2024; Tiznado-Aitken et al., 2021; Owens and Candipan, 2019; Feigenbaum and Hall, 2016; Conley and Dix, 2004; Câmara and Banister, 1993; Inman and Rubinfled, 1979). With the exception of Grainger and Schreiber (2019), which studies the role of race and income in the siting of air pollution monitors in the United States, this finding is novel.

These results imply that the design of air quality monitoring networks should take into account the spatial distribution of residents with low education and income levels to reduce disparities in air pollution monitoring. Inequalities in monitoring of air pollutants could lead to or further exacerbate inequalities in exposure. For instance, if localized policies to improve air pollution are spatially targeted to areas with measured high-levels of pollution, unmonitored areas would be unlikely to receive these policy interventions. Because the location of monitoring stations is correlated with education and income levels, this could further exacerbate inequalities in air pollution exposure across education and income levels.

5 Pollution Exposure and Socioeconomic Status

This section examines disparities in air pollution exposure across socioeconomic groups. Using socioeconomic indicators from census data and air pollution monitoring data, we document how exposure to PM10 and PM2.5 varies by education and income level. We explore whether there are inequalities in annual mean concentrations and in exposure to extreme levels of pollution across socioeconomic groups because both chronic long-term exposure and acute exposure to particulate matter can lead to negative health and economic impacts. Furthermore, non-linear impacts of particulate matter imply that exposure to extreme levels of air pollutants is an important driver of unequal impacts of air pollution (Hoffmann and Rud, 2024). Specifically, we focus on the number of hours that hourly pollutant concentrations exceed the WHO Interim Target 1 (IT1) and Interim Target 2 (IT2) thresholds for PM10 and PM2.5 (see Appendix Table A.2):

- **PM10 Thresholds (24-hour mean):** IT1 150 μg/m³ and IT2 100 μg/m³
- **PM2.5 Thresholds (24-hour mean):** IT1 75 μg/m³ and IT2 50 μg/m³

We consider both IT1 and IT2 to provide a more detailed description of inequality in exposure to high concentrations of particulate matter across the relevant range of particulate matter for each metropolitan area (see Figure 1). For instance, while Santiago experiences many hours with particulate matter concentrations above IT1, Bogota experiences very few hours with particulate matter concentrations above IT1.

We begin by using station-level air pollution data to explore the relationship between the pollution levels recorded by monitoring stations and the average education and income level in the census geographic unit in which the station is located.[15] Figures B.9 and B.10 show the correlation between the mean annual concentration of particulate matter reported by a station and the average education level of the census geographic unit where the station is located. These scatterplots, therefore, reflect the relationship between station-level pollution measurements, prior to any aggregation procedure, and the education level of the census geographic unit in which the station is situated. To facilitate the interpretation, we include simple MCO linear fits for each scatterplot.

Figure B.9 shows that, across all four cities, there is a negative correlation between the annual mean PM10 concentration recorded by stations and the average education level of the census geographic unit where the station is located. The relationship is strongest

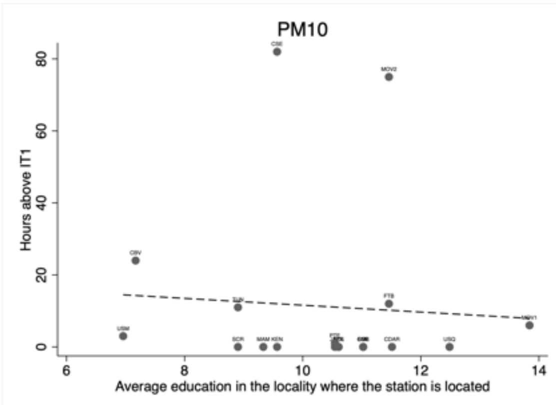
[15]The average level of education of each geographic unit is calculated as the average years of schooling reported in the census across individuals who reside in the geographic unit where the station is located.

in Mexico City, Gran Santiago and Sao Paulo. Figure B.10 shows a negative correlation between the annual mean concentration of PM2.5 recorded by stations in Gran Santiago and the average education level of the census geographic unit where it is located. This negative correlation appears to be largely driven by one monitoring station that records the lowest annual mean concentration of PM2.5 among all the stations in Gran Santiago and is located in a geographic unit with a high education level. The relationship is weak in Bogota and Mexico City, and there appears to be no relationship between the mean annual concentration of PM2.5 that a station records and the average education level of the census geographic unit where it is located in Sao Paulo.

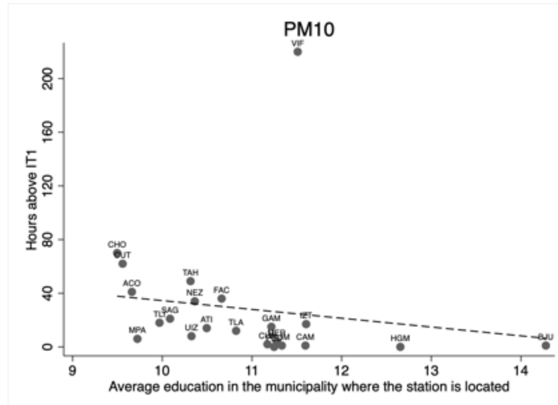
We also explore the relationship between the number of hours with extremely high concentrations of particulate matter that a station records and the average education or income level of the census geographic unit where the station is located. For each monitoring station, we calculate the total number of hours in 2023 in which PM2.5 and PM10 surpass the WHO IT1 threshold.

Figure 4: Hours Above PM10 IT1 in 2023 vs. Average Education

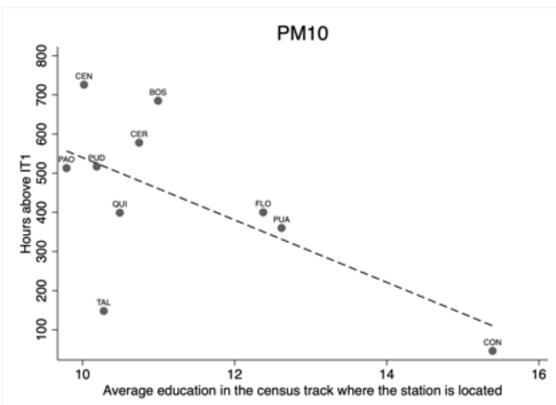
Metropolitan Area of Bogotá



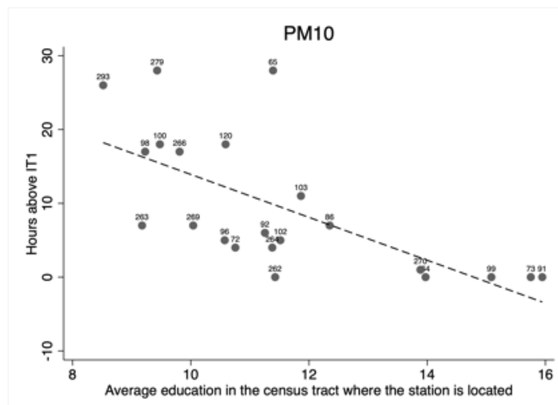
Metropolitan Area of Mexico City



Metropolitan Area of Gran Santiago



Metropolitan Area of São Paulo

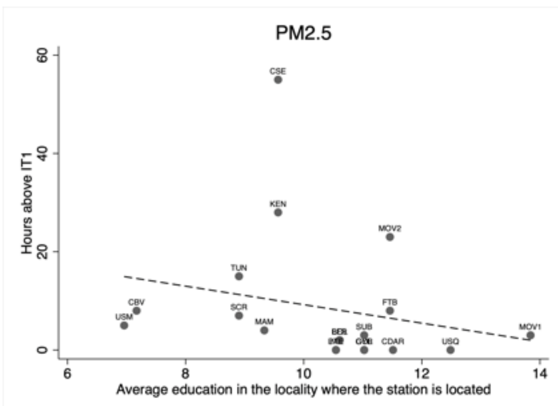


Notes: The figure shows the relationship, for each metropolitan area, between the number of hours in 2023 in which the PM10 concentration exceeded the 24-hour IT1 (Interim Target 1) threshold (IT1 = 150 $\mu g/m^3$) and the average education level in the geographic unit where the air pollution monitoring station is located. PM10 units of measurements are $\mu g/m^3N$ in Bogota, Gran Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City.

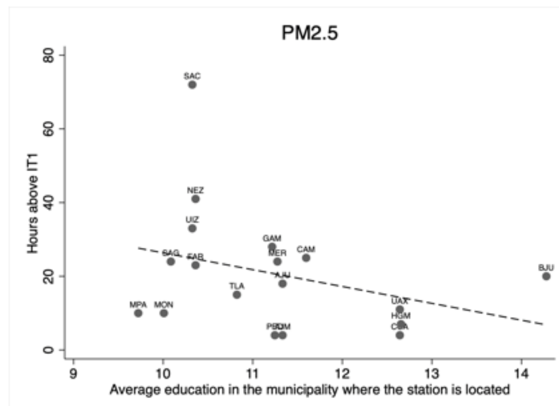
Overall, figures 4 and 5 highlight a negative relationship: areas with lower average education levels tend to experience greater exposure to particulate matter exceeding the IT1 thresholds. Comparing across cities, figure 4 shows that with the exception of two stations, Bogota has the fewest hours of PM10 above IT1, and Gran Santiago experiences substantially more hours of PM10 above the IT1 threshold than the other cities (see figure 4). In Bogota, the relationship between PM10 and education is flatter than the other three cities, implying that there are smaller differences in exposure to peaks in PM10 across education levels. In Gran Santiago, the relationship is largely driven by one station that reports a relatively low number of hours above the PM10 IT1 threshold and is located in a census geographic unit with a very high education level. In contrast, Mexico City and Sao Paulo show strong negative relationships between the number of hours above the PM10 IT1 threshold and the education level of the census geographic unit across the full range of education levels.

Figure 5: Hours Above PM2.5 IT1 in 2023 vs. Average Education

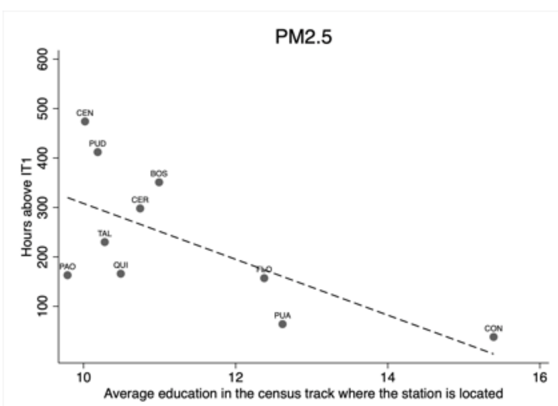
Metropolitan Area of Bogotá



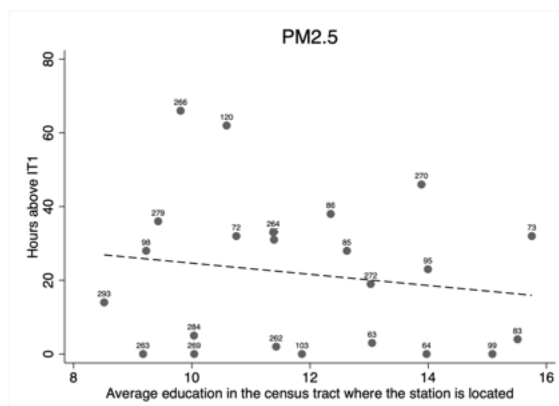
Metropolitan Area of Mexico City



Metropolitan Area of Gran Santiago



Metropolitan Area of São Paulo



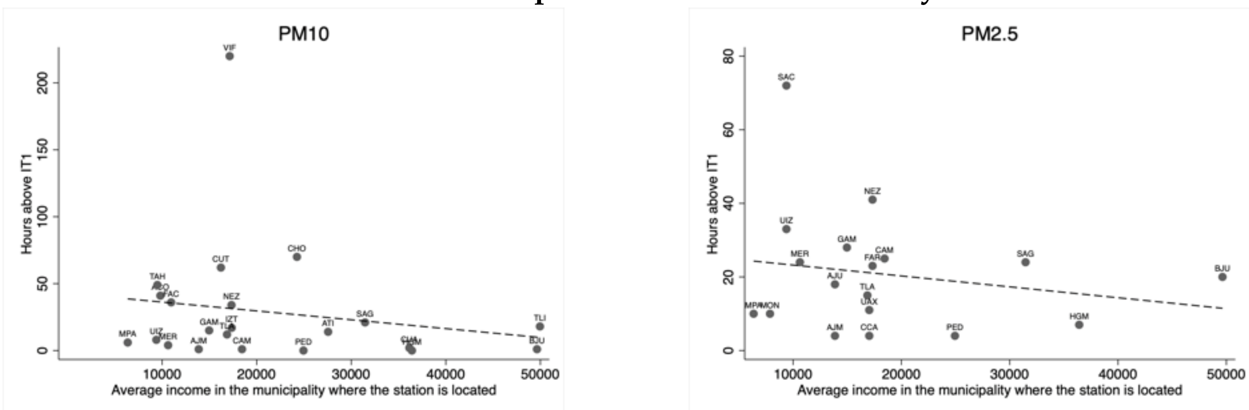
Notes: The figure shows the relationship, for each metropolitan area, between the number of hours in 2023 in which the PM2.5 concentration exceeded the 24-hour IT1 (Interim Target 1) threshold (IT1 = 75 $\mu g/m^3$) and the average education level in the geographic unit where the air pollution monitoring station is located. PM2.5 units of measurements are $\mu g/m^3 N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

Figure 5 shows that the relationship between the number of hours with PM2.5 above the IT1 threshold and the education of the census geographic unit where the station is located is similar to that of PM10. Bogota displays a slightly stronger relationship, while Mexico City and Sao Paulo display a slightly flatter relationship. In Santiago, while the negative relationship between hours of peak pollution and education looks very similar to that for PM10, the negative relationship between the number of hours of extreme levels of PM2.5 and education is apparent across the entire range of education levels. Appendix Figures B.11 and B.12 show that the relationship between the number of hours with PM10 and PM2.5 above the WHO's IT2 threshold and the average education level of the census geographic unit where the station is located is generally consistent with that for the IT1 threshold.

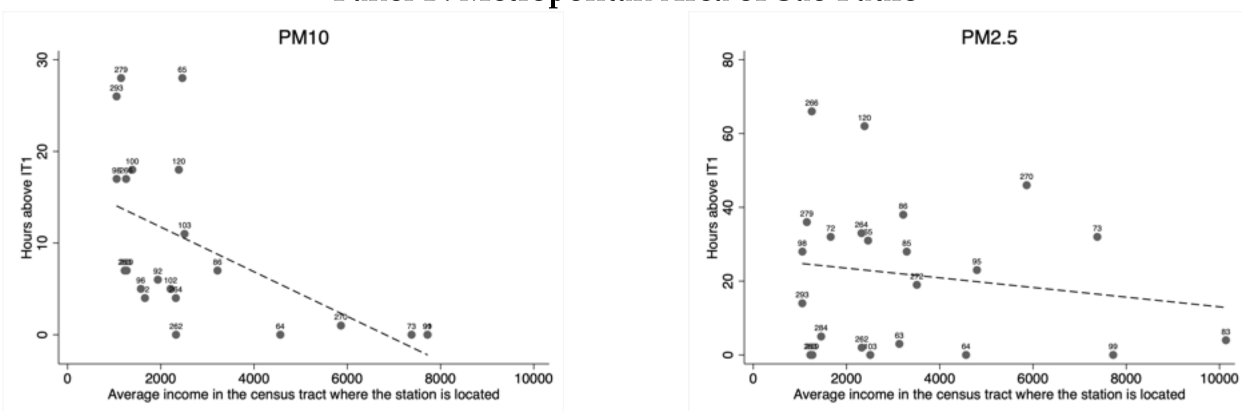
Figure 6 displays the relationship between the number of hours with PM2.5 and PM10 above the IT1 threshold and the average income of the census geographic unit where the monitoring station is located. Consistent with the results using education, the relationship between hours above IT1 and income is stronger for PM2.5 than PM10 in Mexico City and stronger for PM10 than PM2.5 in Sao Paulo.

Figure 6: Hours Above Pollutant's IT1 in 2023 vs. Average Income

Panel A: Metropolitan Area of Mexico City



Panel B: Metropolitan Area of São Paulo



Notes: Panel 1 displays scatter plots for the Metropolitan Area of Mexico City, and Panel 2 displays scatter plots for the Metropolitan Area of São Paulo. Each panel contains the relationship between the number of hours in 2023 in which the PM10 or PM2.5 concentration exceeded the IT1 threshold and the average income in the geographic unit where the air pollution monitoring station is located. The IT1 thresholds are based on the World Health Organization guidelines for air quality (in $\mu g/m^3$). PM10 and PM2.5 units of measurements are $\mu g/m^3$ in Mexico City and $\mu g/m^3 N$ in Sao Paulo.

Altogether, the results suggests that, on average, among the geographic units that contain a monitoring station, less-educated and lower-income communities are disproportionately exposed to higher mean levels of particulate matter and a greater number of hours of extreme concentrations of particulate matter at their place of residence, underscoring significant environmental inequalities.

Next, we spatially aggregate the air pollution data to the individual level to explore disparities in air pollution exposure across socioeconomic groups among individuals that reside in close proximity to a monitoring station. For each city, we build a panel of PM2.5

and PM10 concentrations at the individual-hour level. We proxy each individual's pollution exposure with the pollutant concentrations of their census geographic unit of residence. To calculate the pollutant concentrations for each census geographic unit, we use an inverse distance weighted average of the pollutant data series from all active monitoring stations within a 3 km radius of the centroid of each geographic unit.[16] We use the individual-hour panel to calculate each individual's annual mean exposure and exposure to hours above IT1 and IT2 thresholds for each pollutant. We use the individual-level census data to create education quintiles using the population of each city and income deciles within Mexico City and Sao Paulo. We merge the education quintiles (income deciles) and the individual level pollution data and we average across the individuals within each quintile or decile to obtain exposure measures by quintile and decile. Therefore, the education quintiles (and income deciles) are determined in the full population of the metropolitan area but the sample of individuals includes those who reside in census geographic units with a centroid within 3 km of a monitoring station.

Appendix figures B.13 to B.16 show the distribution of individual-hour PM10 and PM2.5 concentrations by education quintile for each metropolitan area. These distributions have non-normal shapes because they take into account the spatial distribution of the population of the metropolitan area. We show the distributions using both a 3 km radius and a 20 km radius to aggregate pollution observations from monitoring stations to census geographic units i.e. individuals. Using a 3 km radius implies that the analysis is restricted to the small share of the metropolitan areas' residents who reside in close proximity to a monitoring station but that the stations' measurements more accurately reflect the ambient pollution concentrations at individuals' residences. In contrast, using a 20 km radius implies that the analysis includes nearly all residents of the metropolitan areas but that the interpolated ambient pollution concentrations at individuals' location of residence may be less accurate. For each city, the highest education quintile has greater mass at lower ambient concentrations and has less mass at the highest ambient concentrations. The results are often most clear in the figures using a 20 km radius where there is greater

[16] We also examine whether our results are sensitive to using other magnitudes of the radius (e.g from 1 km to 20 km).

spatial variation in pollution since many more census geographic units are included in the analysis.

To quantify disparities in pollution exposure, we first explore differences in the annual mean concentration of pollutants across socioeconomic groups within each city. Appendix Table A.5 displays the mean annual exposure of each education quintile. The first row of each panel shows that the annual mean exposure to PM10 generally decreases with education levels for each city, although the trend is only monotonic across all education quintiles in Gran Santiago. Similarly, the third row of each panel shows that the annual mean exposure to PM2.5 is generally decreasing with education levels in all four cities, although the decrease is only monotonic in Mexico City and Gran Santiago. In particular, the highest education quintile in all four cities has the lowest annual mean exposure to PM10 and PM2.5, except in Sao Paulo in which the lowest education quintile has the lowest annual mean exposure to PM2.5. Despite clear trends in which higher education quintiles experience lower mean annual exposure to particulate matter, for both PM10 and PM2.5, the differences in exposure across education quintiles are very small. For instance, in Santiago, which has the highest annual mean PM10 and PM2.5 concentrations among the four cities, the annual mean exposure of the lowest education quintile is 2.6% and 6.0% higher than the highest education quintile for PM10 and for PM2.5, respectively. Furthermore, the difference in mean annual concentrations between the lowest education quintile and the highest education quintile are only statistically significant for PM10 and PM2.5 in Santiago and for PM10 in Sao Paulo. Appendix figure B.17 presents the mean annual exposure to PM10 and PM2.5 across education quintiles. Appendix Table A.5 also shows median annual concentrations of PM10 and PM2.5 for each quintile of education, which typically show similar patterns across education quintiles but tend to display less variation across quintiles.

Appendix Table A.6 shows mean annual concentrations by income decile in Mexico City and Sao Paulo. Similar to the findings for education quintiles, we find small differences in mean annual exposure to PM10 and PM2.5 across income levels. In Mexico City, the mean annual exposure of the first, nineth, and tenth income deciles to PM 10 and PM2.5 are lower than the mean annual exposures of income deciles two to seven.

The lowest income decile's lower exposure to particulate matter may reflect a different mechanism than the lower exposure of high income deciles. Individuals with low incomes may often live on the periphery of the city where there is less economic activity and traffic leading to lower mean annual exposure to particulate matter. In Sao Paulo, the highest two income deciles experience lower mean annual exposure to PM10 and income deciles three to four have the lowest mean annual exposure to PM2.5, but the differences are very small. For instance, in Sao Paulo, the income decile with the highest mean annual exposure to PM2.5 is only 2.6% higher than the mean annual exposure of the income decile with the lowest exposure.

Next, we explore inequality in exposure to high concentrations of particulate matter across socioeconomic groups among individuals residing in census geographic units with their centroid within 3 kilometers of a monitoring station. We focus on the annual number of hours above the WHO IT1 and IT2 thresholds for PM10 and PM2.5 in 2023. Appendix table A.7 displays the average number of hours with PM2.5 and PM10 above IT1 and IT2 for each education quintile. While there is variation across cities, pollutants, and thresholds, there is a general trend in which higher education quiniles experience fewer hours of high pollution.

To create a clearer comparison across groups, we normalize the mean number of hours above the threshold for the highest education quintile or income decile to 0 for each pollutant and WHO threshold. Specifically, for each pollutant and threshold, we use the individual-level data for each metropolitan area to calculate the mean number of hours above the WHO threshold for the highest education quintile or income decile. Then, we normalize the number of hours above the WHO threshold for each individual by dividing each individual's exposure by the mean for the highest education quintile (or income decile). Next, because every individual in a census geographic unit has the same pollution exposure in our data, we collapse the data to the census geographic unit-education quintile level and create weights for each observation that are equal to the number of people that both reside in the census geographic unit and are in that education quintile divided by the total population of that education quintile. Finally, we use the data at the census geographic unit-quintile level to regress the number of hours of pollution above the WHO threshold on indicators for quintiles 1 to 4 (or income deciles 1 to 9) weighting each observation by that census geographic unit's share of the respective quintile's population. In this way, the regression coefficients represent the mean exposure of each education quintile relative to the highest education quintile, with the highest quintile included in the visualization as the reference quintile (coefficient = 0). The normalization allows us to interpret these coefficients as the percent increase or decrease in the number of hours above the WHO threshold experienced by a given quintile relative to the highest education quintile or income decile. The figures also plot 95% confidence intervals for the regression coefficients. A confidence interval that lies above the horizontal axis indicates that, on average, the education quintile experiences significantly more hours of that pollutant above the WHO threshold than the highest education quintile based on location of residence.

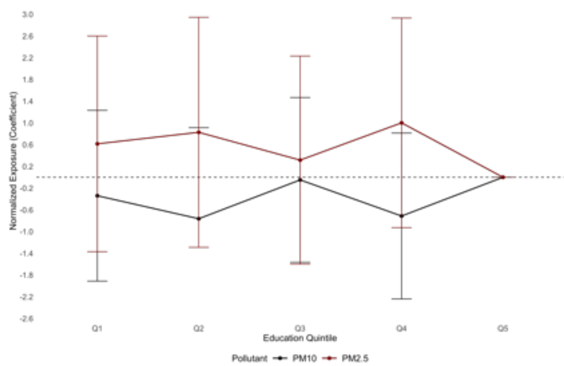
Figure 7 displays the results for hours with PM10 and PM2.5 above the IT1 threshold and Figure 8 displays the results for hours with PM10 and PM2.5 above the IT2 threshold. These figures show that lower education quintiles experience more hours above these critical thresholds, although the disparity is only significant in Gran Santiago and Sao Paulo. With the exception of the number of hours above the IT1 threshold for PM10 in Bogota, this disparity in PM10 and PM2.5 is consistent across all four cities for both the IT1 and IT2 thresholds. Furthermore, the magnitude of the disparity in exposure to peak levels of pollution is substantial. For instance, the lowest education quintile experiences approximately 20% more hours of PM2.5 above the IT1 threshold than the highest education quintile in Sao Paulo. This disparity in PM2.5 is approximately 40% in Mexico City, and in Bogota and Gran Santiago, this disparity is approximately 60%. This disparity for PM10 is smaller in Bogota and Gran Santiago, but it reaches 70% in Mexico City and 130% in Sao Paulo. Although the disparities in exposure to peaks in pollution is substantial, in Bogota and Sao Paulo, the number of hours above the IT1 threshold is very low for the highest education quintile, implying that the large relative disparities do not translate into large differences in the number of hours exposured to peaks in pollution above IT1.[17] Overall, figures 7 and 8 highlight the unequal distribution of air pollution

[17] Appendix table A.7 shows the average number of hours above IT1 and IT2 thresholds by education

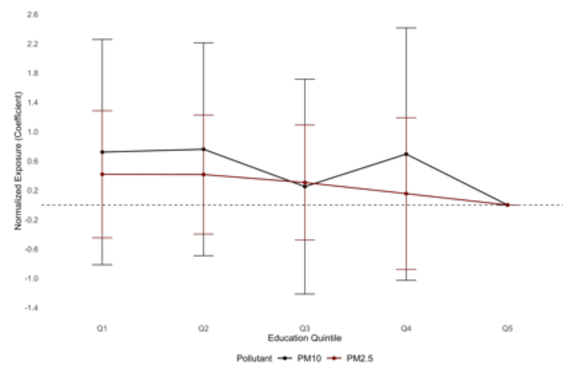
exposure within each city.

Figure 7: Normalized Hours Above IT1 by Education Quintile in 2023

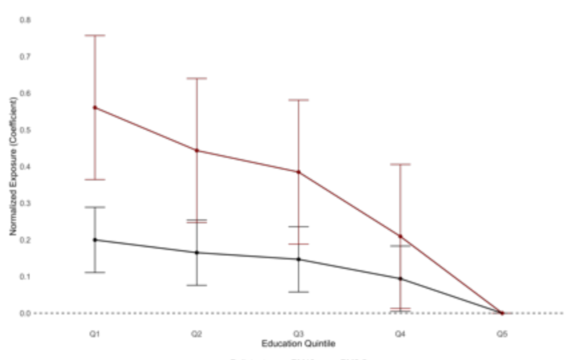
Metropolitan Area of Bogota



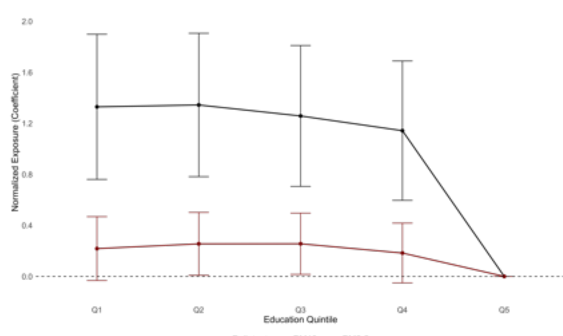
Metropolitan Area of Mexico City



Metropolitan Area of Gran Santiago



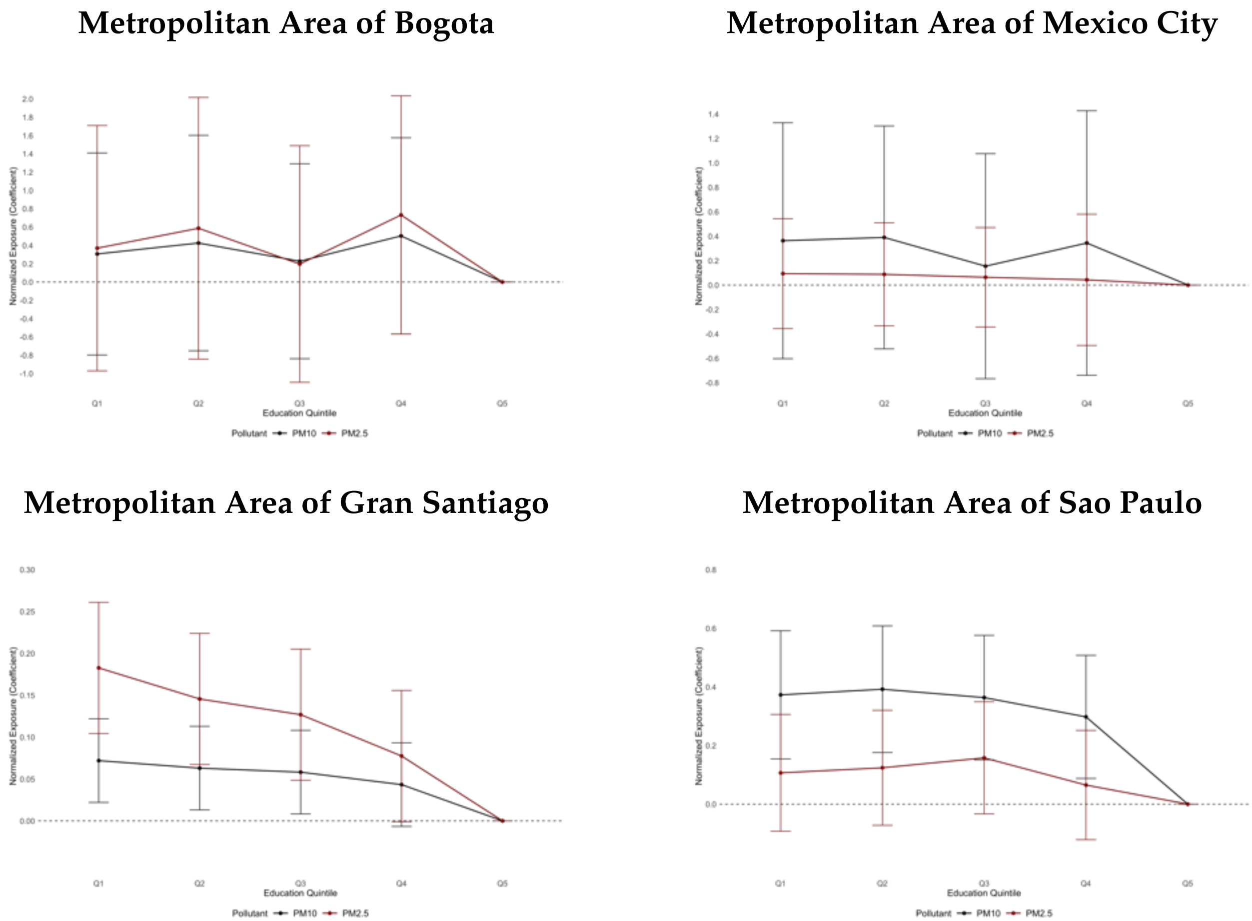
Metropolitan Area of Sao Paulo



Notes: The figure shows, by metropolitan area, the normalized average number of hours in 2023 in which the pollutant concentration exceeded the WHO 24-hour IT1 (Interim Target 1) threshold, categorized by quintiles of education. The pollutants considered are PM_{10} and $PM_{2.5}$. The WHO 24-hour IT1 thresholds for $PM_1$0 and $PM_{2.5}$ are 150 $\mu g/m^3$ and 75 $\mu g/m^3$, respectively. The hours are normalized such that the value for quintile 5 is set to 0. A dashed horizontal line at 0 indicates the reference level for quintile 5. The line types differentiate the pollutants. The x-axis represents quintiles of education, ranging from 1 (lowest education) to 5 (highest education). PM10 units of measurements are $\mu g/m^3 N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City. PM2.5 units of measurements are $\mu g/m^3 N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

quintiles.

Figure 8: Normalized Hours Above IT2 by Education Quintile in 2023

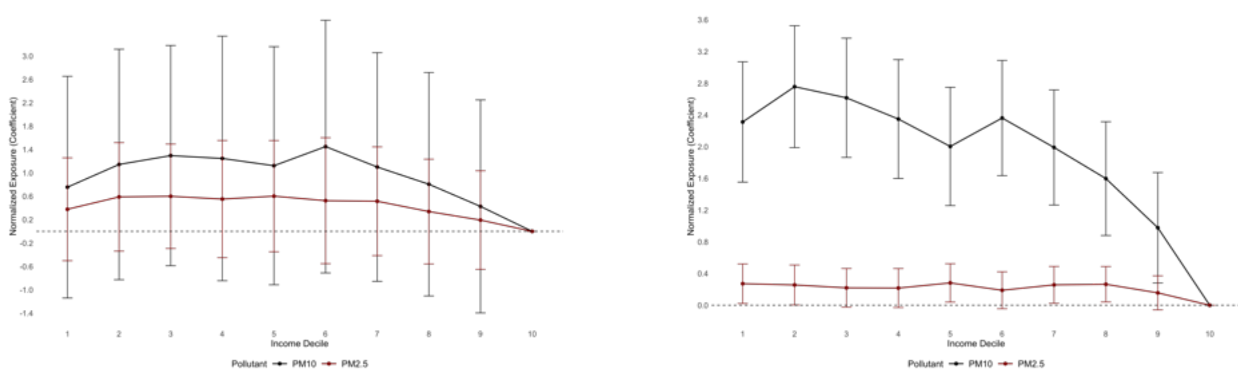


Notes: The figure shows, by metropolitan area, the normalized average number of hours in 2023 in which the pollutant concentration exceeded the WHO 24-hour IT2 (Interim Target 2) threshold, categorized by quintiles of education. The pollutants considered are $PM_1 0$ and $PM_{2.5}$. The WHO 24-hour IT2 thresholds for PM_{10} and $PM_{2.5}$ are 100 $\mu g/m^3$and 50 $\mu g/m^3$, respectively. The hours are normalized such that the value for quintile 5 is set to 0. A dashed horizontal line at 0 indicates the reference level for quintile 5. The line types differentiate the pollutants. The x-axis represents quintiles of education, ranging from 1 (lowest education) to 5 (highest education). PM10 units of measurements are $\mu g/m^3 N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City. PM2.5 units of measurements are $\mu g/m^3 N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

For Mexico City and São Paulo, we extend this analysis to income deciles (Figure 9). The findings reinforce the pattern observed with education: individuals in lower-income deciles are exposed to higher levels of air pollution. While the figures display a socioeconomic gradient in exposure, the disparities in exposure are only significant in Sao Paulo. In Mexico City, while middle deciles of the income distribution have the highest exposure to peaks in PM2.5 and PM10, the lowest income decile still experiences approximately 40% more hours of PM2.5 and nearly 80% more hours of PM10 above the IT1 thresholds than the highest income deciles. In São Paulo, exposure to peaks in PM10 and PM2.5 is decreasing steadily across income deciles. The lowest income decile experienced nearly 30% more hours of PM2.5 and over 200% more hours of PM10 above the IT1 threshold than the highest income decile. Similar to the case of education quintiles, the low number of hours above IT1 in Sao Paulo implies that the substantial disparities in exposure across income deciles does not lead to large differences in the absolute number of hours of expsoure to peaks in pollution.[18]

Figure 9: Normalized Hours Above IT1 by Income Decile in 2023

Metropolitan Area of Mexico City **Metropolitan Area of Sao Paulo**



Notes: The figure shows the normalized average number of hours in 2023 in which the pollutant concentration exceeded the WHO 24-hour IT1 (Interim Target 1) threshold, categorized by quintiles of income. The pollutants considered are PM_{10} and $PM_{2.5}$. The WHO 24-hour IT1 thresholds for PM_{10} and $PM_{2.5}$ are 150 $\mu g/m^3$ and 75 $\mu g/m^3$, respectively. The hours are normalized such that the value for income quintile 5 is set to 0. A dashed horizontal line at 0 indicates the reference level for quintile 5. The line types differentiate the pollutants. The x-axis represents quintiles of income, ranging from 1 (lowest income status) to 5 (highest income status). PM10 and PM2.5 units of measurements are $\mu g/m^3 N$ in Sao Paulo and are $\mu g/m^3$ in Mexico City.

Air pollution data often suffer from missing observations due to technical issues, station maintenance, or data collection inconsistencies. In section 4, we found that there were not substantial disparities in the share of missing observations across stations located in higher or lower education areas. However, missing observations could drive the inequality in pollution exposure that we document if missing observations in areas with

[18] Appendix table A.8 shows the average number of hours above IT1 and IT2 by income decile in Mexico City and Sao Paulo.

low education levels systematically occur during hours with low concentrations of pollution and missing observations in areas with high education areas systematically occur during hours with high concentrations.

To explore the role of missing data in the exposure disparities that we document, we take advantage of the rich panel data at the station-hour level to impute missing observations using observations from other stations at the same time. To generate predictions for missing observations, we estimate the following regression model at the station-hour level:

$$p_{st} = \omega_{s \times t} + \sum_{m \neq s} \beta_m p_{mt} + \sum_{m \neq s} \gamma_m \mathbb{1}[p_{mt} = missing] + \epsilon_{st} \tag{1}$$

where p_{st} is the pollutant level of station s at time t, p_{mt} is the pollutant level of all other stations m different from station s at time t, and $\omega_{s \times t}$ includes a set of station s and time fixed effects. In other words, our approach uses a fixed effects model that includes controls for station, month, day of the week, and hour. It also incorporates interactions between these fixed effects. In addition, as key explanatory variables, we include pollution levels from other stations. When data from other stations is missing, we replace these missing values with zero and add indicator variables to indicate when this replacement occurs. We use the coefficients from this regression equation to impute values for missing station-hour observations.

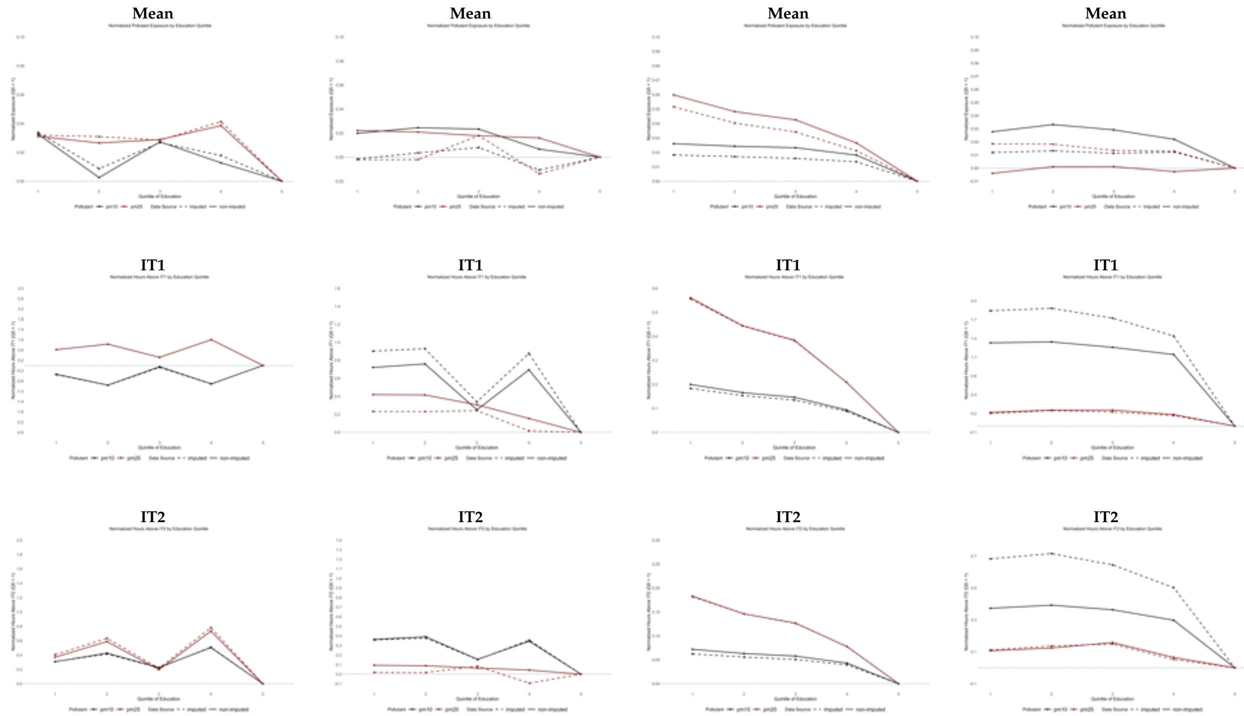
To assess this simple linear prediction model, figures B.18, B.19, B.20 and B.21 show the linear predictions for PM10 and PM2.5 using the prediction model and the actual hourly data series for each station. The predictions from our linear prediction model vary less than the actual data but capture general movements.

Next, we use our predicted values for missing observations to assess whether missing observations are likely to be systematically higher or lower than non-missing observations. Appendix figure B.22 shows the ratio of the average predicted pollution concentration of missing observations to the average pollution concentration of non-missing observations by station for each pollutant. Stations are ordered within each metropolitan area by the average education level reported in the census geographic area in which the station is located from lowest education (1) to highest education. A value of 1 indicates that the mean of the predicted values for the missing observations for that station is equal to the mean of the non-missing observations at that station. Values higher than 1 indicate that, on average, the missing observations are predicted to be higher than the station's average pollution concentration. Across all metropolitan areas, there are both stations with missing observations predicted to be on average higher than non-missing observations and stations with missing observations predicted to be on average lower than non-missing observations. In all four metropolitan areas, there is no clear pattern in which stations located in census geographic areas with low education levels have systematically lower predicted concentrations for missing observations than for non-missing observations or in which stations located in census geographic areas with high education levels have systematically higher predicted concentrations for missing observations than for non-missing observations. This implies that systematically missing observations are not likely to be increasing the distribution of non-missing observations for stations in low education areas and systematically missing observations are not likely to be decreasing the distribution of non-missing observations for stations in high education areas.

Finally, to determine whether systematically missing observations are likely to be driving disparities in pollution exposure, we use panel data composed of both actual data and imputed values from our prediction model for missing observations to estimate exposure to each pollutant across education quintiles. Figure 10 illustrates the results. The results are qualitatively similar to those using only the actual pollution data and the relative pollution disparities across education quintiles are consistent with those using only the actual pollution data, indicating that systematically missing observations are unlikely to be driving the disparities in exposure to peaks of pollution that we document.

Figure 10: Normalized Plots with Missing Imputation for PM_{10} and $PM_{2.5}$ by Metropolitan Area

(a) **Bogotá** (b) **Mexico City** (c) **Santiago** (d) **Sao Paulo**



Notes: This figure illustrates our baseline specification for estimating exposure to each pollutant across education quintiles using the *"combined data"* that includes both actual data and imputed data for missing values by metropolitan area: Bogotá (Panel a), Mexico City (Panel b), Santiago (Panel c), and Sao Paulo (Panel d). The *"combined data"* refers to the time series composed of the actual observed data combined with imputed pollutant concentrations for missing observations, where the imputed values for the missing observations are derived from our baseline specification described in equation 1. PM10 units of measurements are $\mu g/m^3N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City. PM2.5 units of measurements are $\mu g/m^3N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

Overall, our results indicate that, while mean annual concentrations of air pollutants experienced by different socioeconomic groups are similar, less educated and lower-income individuals experience a greater number of hours with extremely high concentrations of particulate matter. These results suggest that policies focused on reducing peaks in particulate matter, as opposed to reducing typically daily concentrations of particulate matter, are likely to lead to a greater reduction in the disparity of air pollution exposure and it's consequences across education and income levels.

The inequality in air pollution exposure that we document is consistent with evidence that willingness to pay for air quality, is increasing in income and education (Maarraoui et al., 2023; Sun et al., 2016). More specifically, this finding is consistent with empirical evidence of residential sorting of higher income households to neighborhoods with better local public goods, specifically better air quality (Depro et al., 2015; Banzhaf and Walsh, 2008; Zheng and Kahn, 2008). While we do not explore separate sorting versus siting mechanisms behind the inequality in particulate matter exposure that we document, our results are consistent with Aguilar-Gomez et al. (2025) that finds evidence suggesting sorting of socially marginalized individuals to neighborhoods with lower air pollution and siting of pollution sources in neighborhoods with more socially marginalized individuals in Colombia.

6 Conclusion

We study exposure to air pollution in four large metropolitan areas of Latin America: Bogotá, Colombia, Mexico City, Mexico, Santiago, Chile, and São Paulo, Brazil, using socioeconomic data from each country's census and hourly data on air pollutants from the governments' networks of ground monitoring stations. Our findings provide evidence of inequality in air pollution monitoring across socioeconomic groups in Bogotá, Mexico City, and São Paulo. Neighborhoods with better air pollution monitoring have disproportionately high education and income levels. In addition, among areas in close proximity to air quality monitoring stations, where air pollution levels recorded by ground monitoring stations are likely to be a more accurate measure of exposure, our findings provide robust evidence of inequality in air pollution exposure across the metropolitan areas of Bogotá, Mexico City, Gran Santiago, and São Paulo. We find small disparities in annual mean concentrations but substantial and significant disparities in exposure to peaks in particulate matter, which are likely to contribute to economic and health disparities. Together, these finding suggest important inequalities in air pollution monitoring and exposure within these metropolitan areas.

Our results provide two key policy implications. First, the design of air quality monitoring systems should consider economic inequality and the spatial distribution of lower-income residents. Siting monitoring stations based on population density or distance to the central business district could inadvertently lead to inequality in monitoring in cities where low-income residents are clustered in the periphery. Inequalities in monitoring of air pollutants could further exacerbate the inequalities in exposure if localized policies to improve air pollution are spatially targeted to areas in which air pollution levels are measured. Second, because disparities in exposure are driven by peaks in air pollution, policies focused on reducing peaks in particulate matter, as opposed to reducing typical daily concentrations of particulate matter, are likely to lead to a greater reduction in inequality in air pollution exposure and it's consequences across education and income levels.

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A Tables

Table A.1: Number of Monitoring Stations Reporting Data for each Pollutant in 2023 by Metropolitan Area

City	PM_{10}	$PM_{2.5}$
Santiago	10	10
Bogotá	19	19
Mexico City	23	19
São Paulo	29	25

Notes: This table shows the number of air quality monitoring stations reporting data for each pollutant in 2023, across four metropolitan areas: Santiago, Bogotá, Mexico City, and São Paulo. The pollutants included in the sample are PM_{10} and $PM_{2.5}$.

Table A.2: WHO Interim Targets (IT1 and IT2) for Air Pollutants

Pollutant	**Averaging Time**	**IT1 ($\mu g/m^3$)**	**IT2 ($\mu g/m^3$)**
$PM_{2.5}$	Annual	35	25
	24-hour	75	50
PM_{10}	Annual	70	50
	24-hour	150	100

Notes: This table shows the WHO Interim Targets (IT1 and IT2) for $PM_{2.5}$ and PM_{10} pollutants. These thresholds are based on WHO (2021).

Table A.3: Number of Days with at Least One/Two Hour(s) Above IT1/IT2

	At least 1 hour		At least 2 hours		At least 1 hour		At least 2 hours	
City	IT1 PM10	IT2 PM10	IT1 PM10	IT2 PM10	IT1 PM2.5	IT2 PM2.5	IT1 PM2.5	IT2 PM2.5
Panel a. City-hour series								
Bogota	0	1	0	0	0	3	0	2
Santiago	60	163	45	137	27	87	22	79
Mexico City	1	13	0	6	5	24	2	17
Sao Paulo	0	8	0	4	1	15	1	11
Panel b. Station-hour series								
Bogota	63	230	34	183	45	209	18	143
Santiago	182	295	140	257	103	173	87	155
Mexico City	23	118	9	79	15	123	5	72
Sao Paulo	31	130	16	75	58	173	30	114

Notes: This table shows the number of days with at least one or two hour(s) above the IT1 and IT2 thresholds for PM_{10} and $PM_{2.5}$. Panel (a) reports the count of days by first aggregating the pollution data at the city-hour level. Then, we count the days above a threshold in the city-level hourly time series. Panel (b) provides the count of days using the station-hour series. This means that a day is counted as exceeding a threshold if at least one station reports an exceedance. PM10 units of measurements are $\mu g/m^3N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City. PM2.5 units of measurements are $\mu g/m^3N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

Table A.4: Average Hours Per Day Above IT1/IT2 Conditional on Exceedance

	Average hours above:			
City	IT1 PM10	IT2 PM10	IT1 PM2.5	IT2 PM2.5
Panel a. City-hour series				
Bogota	NA	1.00	NA	1.67
Santiago	4.05	7.56	3.74	8.54
Mexico City	1.00	2.15	3.00	3.62
Sao Paulo	NA	2.75	7.00	4.07
Panel b. Station-hour series				
Bogota	1.76	3.10	1.54	2.70
Santiago	4.42	7.04	4.49	7.96
Mexico City	1.66	2.47	2.94	2.85
Sao Paulo	1.94	2.72	2.32	3.36

Notes: This table reports the average number of hours per day in which pollutant concentrations (PM_{10} and $PM_{2.5}$) exceed IT1 or IT2 thresholds, conditional on a day having exceeded the threshold. Panel (a) provides the average number of hours by first aggregating the pollution data at the city-hour level. Then, conditional on a day exceeding the threshold, we report the average number of hours that exceed the threshold. NA values indicate that no exceedances were recorded. Panel (b) provides the average number of hours using the station-hour series. This means that, conditional on a station having exceeded the threshold on a given day (at least one hour above the threshold), we calculate the average number of hours above the threshold across stations that exceeded the threshold. PM10 units of measurements are $\mu g/m^3N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City. PM2.5 units of measurements are $\mu g/m^3N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

Table A.5: Annual Mean and Median Pollutant Concentrations by Education Quintile

Years of education quintile	1	2	3	4	5
Panel A. Bogota					
PM_{10} Mean	32.27	32.24	31.74	32.87	30.68
PM_{10} Median	27.74	27.57	27.74	27.61	27.61
$PM_{2.5}$ Mean	16.12	16.44	15.85	16.75	15.33
$PM_{2.5}$ Median	14.33	14.73	14.20	14.73	13.69
P-value (t-test Q1 vs. Q5 for PM_{10})	0.71				
P-value (t-test Q1 vs. Q5 for $PM_{2.5}$)	0.70				
Panel B. Mexico City					
PM_{10} Mean	39.22	39.32	39.37	38.44	38.40
PM_{10} Median	39.14	39.14	39.14	37.49	37.49
$PM_{2.5}$ Mean	20.27	20.25	20.16	20.06	19.74
$PM_{2.5}$ Median	20.46	20.46	20.46	20.46	20.31
P-value (t-test Q1 vs. Q5 for PM_{10})	0.62				
P-value (t-test Q1 vs. Q5 for $PM_{2.5}$)	0.60				
Panel C. Santiago					
PM_{10} Mean	68.43	68.32	68.25	67.90	66.70
PM_{10} Median	69.52	69.52	69.52	69.52	69.73
$PM_{2.5}$ Mean	24.41	24.14	24.01	23.64	23.03
$PM_{2.5}$ Median	24.71	24.29	24.29	22.74	22.74
P-value (t-test Q1 vs. Q5 for PM_{10})	0.02				
P-value (t-test of Q1 vs. Q5 for $PM_{2.5}$)	0.00				
Panel D. Sao Paulo					
PM_{10} Mean	26.34	26.48	26.38	26.19	25.63
PM_{10} Median	26.53	26.53	26.53	26.40	26.13
$PM_{2.5}$ Mean	14.05	14.12	14.12	14.07	14.10
$PM_{2.5}$ Median	14.26	14.41	14.41	14.41	14.22
P-value (t-test Q1 vs. Q5 for PM_{10})	0.02				
P-value (t-test of Q1 vs. Q5 for $PM_{2.5}$)	0.55				

Notes: This table presents the mean and median pollutant concentrations for PM_{10} and $PM_{2.5}$ categorized by education quintiles across four metropolitan areas: Bogotá, Mexico City, Santiago, and São Paulo. Each panel corresponds to a different metropolitan area. Education quintiles range from 1 (lowest education levels) to 5 (highest education levels). PM10 units of measurements are $\mu g/m^3N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City. PM2.5 units of measurements are $\mu g/m^3N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago. The table also shows the p-value from a weighted t-test comparing PM_{10} exposure levels between the first (quintile 1) and fifth (quintile 5) education quintiles. The procedure involves aggregating PM_{10} exposure data at the census district level, calculating the mean PM_{10} exposure for each district, and using population size as a weight in the analysis. The weighted t-test compares the district-level mean exposure values between the two quintiles, accounting for differences in district population sizes. The resulting p-value indicates the statistical significance of the observed difference in PM_{10} exposure between the lowest and highest education quintiles.

Table A.6: Annual Mean and Median Pollutant Concentrations by Income Decile

Income deciles	1	2	3	4	5	6	7	8	9	10
Panel A. Mexico City										
PM_{10} Mean	39.12	39.33	39.89	38.23	39.36	39.37	37.76	38.68	38.59	38.19
PM_{10} Median	39.14	39.14	40.43	37.49	39.14	39.14	34.79	37.49	37.49	37.33
$PM_{2.5}$ Mean	20.16	20.44	20.22	20.35	20.22	20.15	20.41	20.04	19.77	19.71
$PM_{2.5}$ Median	20.46	20.51	20.46	20.51	20.46	20.46	20.46	20.31	20.31	19.92
P-value (t-test D1 vs. D10 for PM_{10})	0.58									
P-value (t-test D1 vs. D10 for $PM_{2.5}$)	0.69									
Panel B. Sao Paulo										
PM_{10} Mean	26.29	26.33	26.56	26.32	26.14	26.51	26.26	26.21	25.89	25.45
PM_{10} Median	26.53	26.53	26.53	26.53	26.40	26.53	26.40	26.40	26.13	25.68
$PM_{2.5}$ Mean	13.99	13.96	13.91	13.91	14.11	13.95	14.09	14.27	14.10	14.12
$PM_{2.5}$ Median	14.22	14.26	14.22	14.22	14.41	14.22	14.41	14.41	14.41	14.41
P-value (t-test D1 vs. D10 for PM_{10})	0.01									
P-value (t-test D1 vs. D10 for $PM_{2.5}$)	0.25									

Notes: This table presents the mean and median pollutant concentrations for PM_{10} and $PM_{2.5}$ categorized by income deciles across the metropolitan areas of Mexico City and São Paulo. PM10 and PM 2.5 units of measurements are $\mu g/m^3 N$ Sao Paulo and $\mu g/m^3$ in Mexico City. Each panel corresponds to a different metropolitan area. Education quintiles range from 1 (lowest income levels) to 10 (highest income levels). The table also shows the p-value from a weighted t-test comparing PM_{10} exposure levels between the first (decile 1) and tenth (decile 10) income deciles. The procedure involves aggregating PM_{10} exposure data at the census district level, calculating the mean PM_{10} exposure for each district, and using population size as a weight in the analysis. The weighted t-test compares the district-level mean exposure values between the two quintiles, accounting for differences in district population sizes. The resulting p-value indicates the statistical significance of the observed difference in PM_{10} exposure between the lowest and highest income deciles.

Table A.7: Average Hours Above IT1 and IT2 WHO Thresholds by Education Quintiles

Education quintile	Average hours $\geq$ IT1		Average hours $\geq$ IT2	
	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$
Panel A. Bogota				
1	0.84	5.50	48.63	99.43
2	0.30	6.23	53.07	115.23
3	1.21	4.48	45.68	86.85
4	0.36	6.82	55.97	125.75
5	1.27	3.41	37.22	72.59
Panel B. Mexico city				
1	6.10	22.72	68.60	130.16
2	6.23	22.67	69.95	129.47
3	4.43	20.91	58.10	126.62
4	6.00	18.49	67.65	124.14
5	3.54	16.01	50.31	119.00
Panel C. Santiago				
1	495.82	262.89	1568.89	928.24
2	481.51	243.22	1555.88	898.74
3	474.33	233.59	1549.10	885.11
4	452.20	203.67	1527.12	845.54
5	413.25	168.45	1463.37	784.73
Panel D. Sao Paulo				
1	5.18	16.80	68.89	132.24
2	5.21	17.32	69.86	134.30
3	5.02	17.33	68.43	138.35
4	4.76	16.32	65.12	127.26
5	2.22	13.80	50.17	119.47

Notes: The table shows the average number of hours in 2023 in which the pollutant concentration exceeded the WHO IT1 (Interim Target 1) and IT2 (Interim Target 2) thresholds categorized by education quintiles. The pollutants considered are PM_{10} and $PM_{2.5}$. IT1 and IT2 thresholds for each pollutant are defined by WHO air quality guidelines in $\mu g/m^3$ units. Education quintiles range from 1 (lowest education) to 5 (highest education). Each panel displays the results for a metropolitan area: Bogotá, Mexico City, Santiago, and São Paulo. PM10 units of measurements are $\mu g/m^3N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City. PM2.5 units of measurements are $\mu g/m^3N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

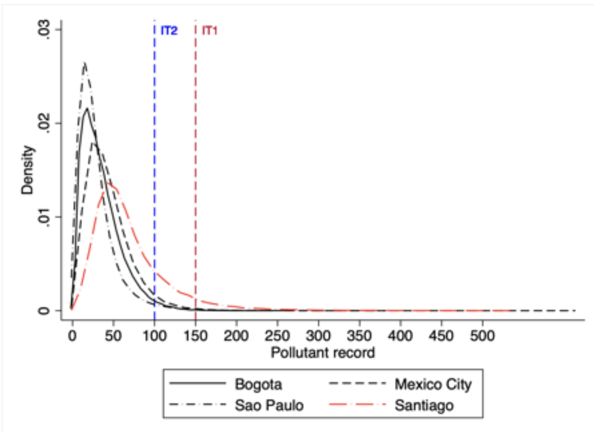
Table A.8: Average Hours Above IT1 and IT2 WHO Thresholds by Income Decile

Income decile	Average hours $\geq$ IT1		Average hours $\geq$ IT2	
	PM10	PM2.5	PM10	PM2.5
Panel A. Mexico city				
1	4.61	19.44	59.84	125.85
2	5.64	22.43	65.43	127.75
3	6.03	22.57	68.02	128.81
4	5.91	21.90	67.75	126.76
5	5.58	22.61	66.05	128.23
6	6.44	21.51	71.01	128.95
7	5.52	21.38	65.07	127.71
8	4.75	18.89	59.70	122.66
9	3.75	16.83	52.26	120.91
10	2.63	14.11	41.59	120.36
Panel B. Sao Paulo				
1	5.02	16.66	68.30	130.12
2	5.70	16.45	69.06	127.98
3	5.48	15.97	71.43	120.51
4	5.08	15.94	66.95	124.44
5	4.55	16.79	64.47	136.37
6	5.10	15.57	70.18	120.28
7	4.54	16.47	65.22	131.95
8	3.94	16.57	63.02	135.42
9	3.00	15.15	56.22	127.50
10	1.52	13.10	44.14	119.10

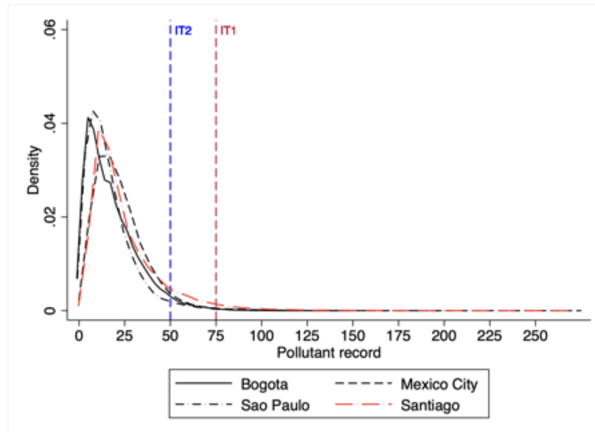
Notes: The table shows the average hours in 2023 in which pollutant levels exceeded the WHO IT1 (Interim Target 1) and IT2 (Interim Target 2) thresholds. The pollutants included are PM_{10} and $PM_{2.5}$. PM10 and PM2.5 units of measurements are $\mu g/m^3N$ in Sao Paulo and $\mu g/m^3$ in Mexico City. Data are categorized by income deciles, ranging from 1 (lowest income) to 10 (highest income). Panels represent Mexico City and São Paulo. IT1 and IT2 thresholds are defined by WHO air quality guidelines.

B Figures

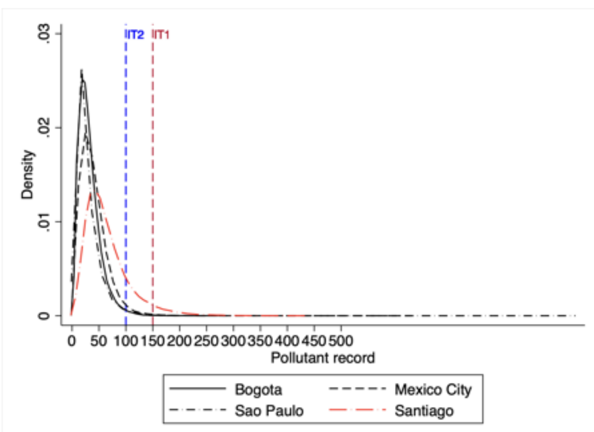
Figure B.1: Distribution of PM10 and PM2.5 Concentrations in Each Metropolitan Area (2019 and 2022)



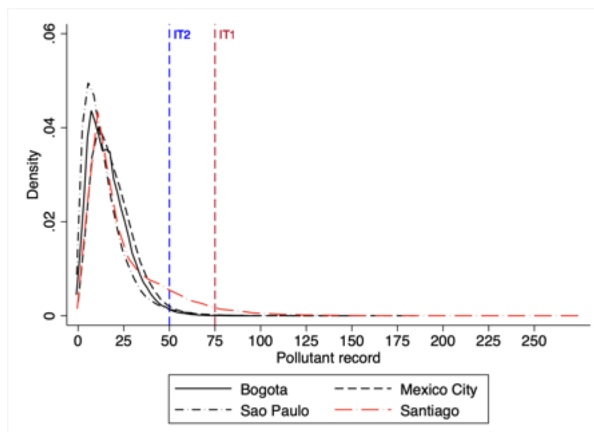
(a) 2019 PM10 Distribution



(b) 2019 PM2.5 Distribution



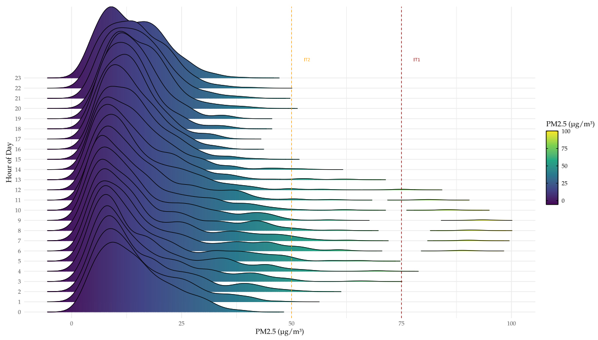
(c) 2022 PM10 Distribution



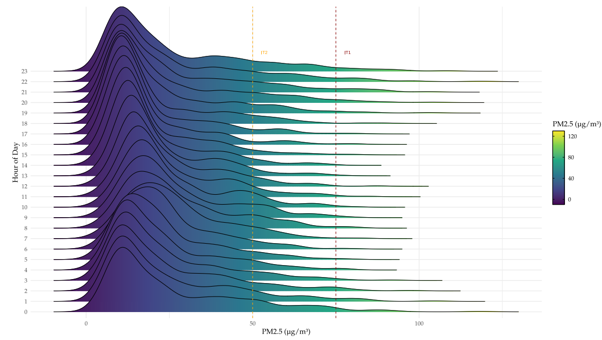
(d) 2022 PM2.5 Distribution

Notes: The figure illustrates the distribution of PM10 and PM2.5 concentrations across the metropolitan areas of Bogotá, Mexico City, São Paulo, and Santiago in 2019 and 2022. The x-axis shows pollutant levels, while the y-axis shows density. The dashed vertical lines in Panels (a) and (c) indicate the WHO Interim Target 1 (IT1, red) and Interim Target 2 (IT2, blue) thresholds for PM10 levels, set at 150 $\mu g/m^3$ and 100 $\mu g/m^3$, respectively. Similarly, the vertical lines in Panels (b) and (d) represent the corresponding thresholds for PM2.5, set at 75 $\mu g/m^3$ and 50 $\mu g/m^3$. PM10 units of measurements are $\mu g/m^3 N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City. PM2.5 units of measurements are $\mu g/m^3 N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

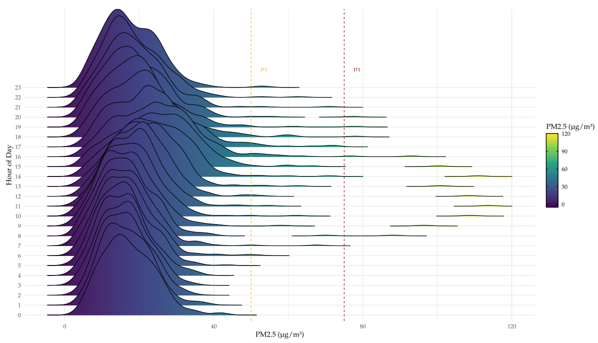
Figure B.2: Ridgeline Distributions of Hourly $PM_{2.5}$ Across Four Cities



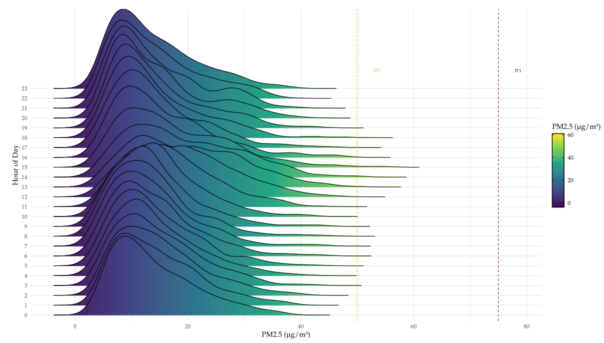
(a) São Paulo



(b) Santiago



(c) Mexico City



(d) Bogotá

Notes: Each panel shows a ridgeline plot of hourly $PM_{2.5}$ distributions by hour of day for the specified city (y-axis). The dashed vertical lines at 50 µg/m^3 (orange) and 75 µg/m^3 (dark red) represent WHO Interim Target 2 (IT2) and Interim Target 1 (IT1), respectively. Values are based on ground-station measurements for 2023. Areas under the ridgeline curves indicate the relative frequency of $PM_{2.5}$ concentrations at different hours. PM2.5 units of measurements are $\mu g/m^3N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

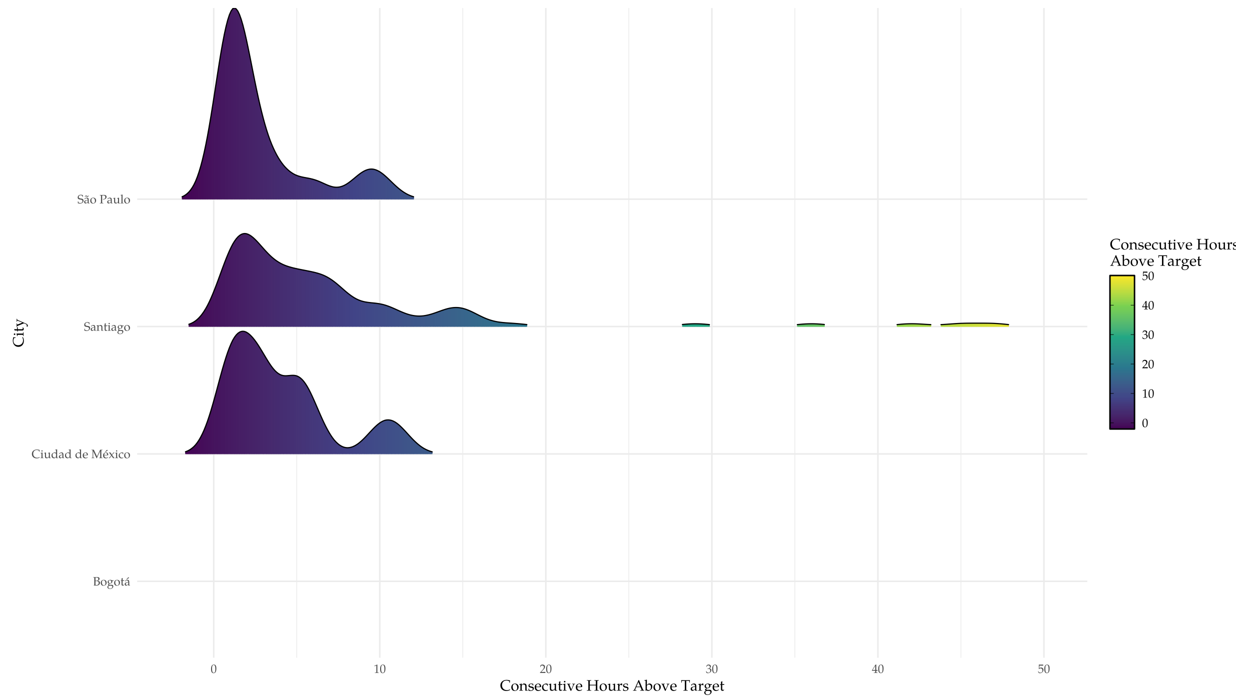
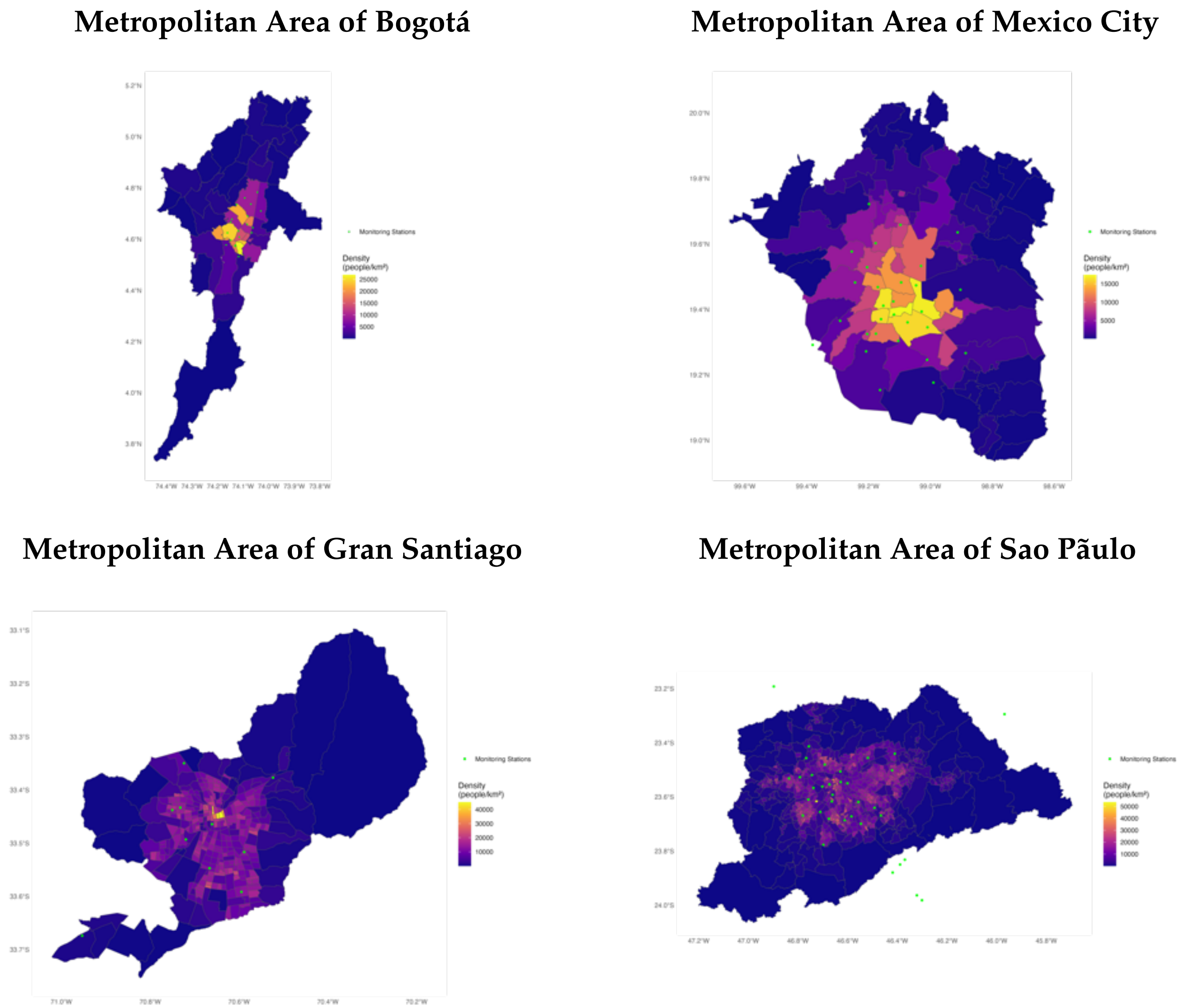


Figure B.3: Distribution of Consecutive Hours Above IT2

Notes: This figure displays the distribution of consecutive hours in which hourly $PM_{2.5}$ measurements remained at or above the WHO Interim Target 2 (50 µg/m^3). The underlying data combine hourly pollution values from ground monitoring stations in four cities (Bogotá, Santiago, Mexico City, and São Paulo) over the year 2023. For each city, we identified "episodes" where pollution levels were consistently above 50 µg/m^3 and recorded the number of consecutive hours in each episode. Bogotá shows no visible distribution here because it only had two short episodes—lasting 1 or 2 hours—above IT2. By contrast, Santiago exhibited multiple long episodes, including three instances exceeding 40 consecutive hours above the 50 µg/m^3 threshold. PM2.5 units of measurements are $\mu g/m^3N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

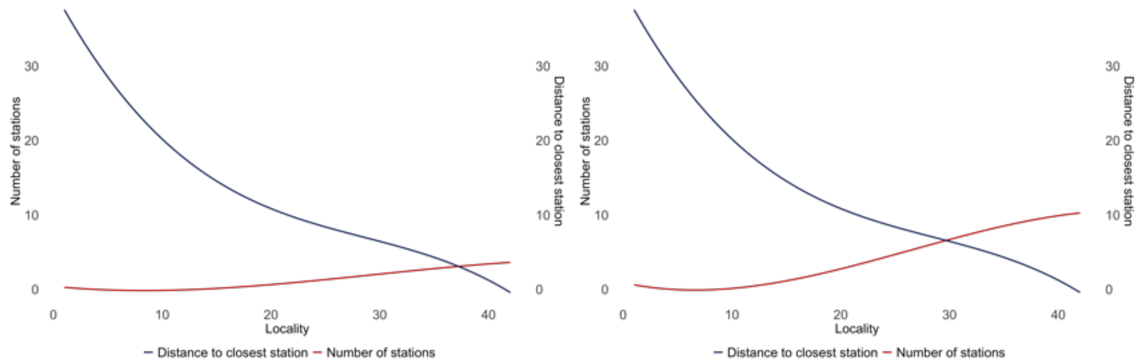
Figure B.4: Population Density of Each Metropolitan Area



Notes: The figure exhibits the population density of the metropolitan areas of Bogota, Mexico City, Gran Santiago, and São Paulo. The density is calculated as people per square kilometer. The green dots represent the location of the active air quality monitoring stations in 2023.

Figure B.5: Number of Stations within a 5 km/10 km Radius and Distance to Nearest Station, Metropolitan Area of Bogotá

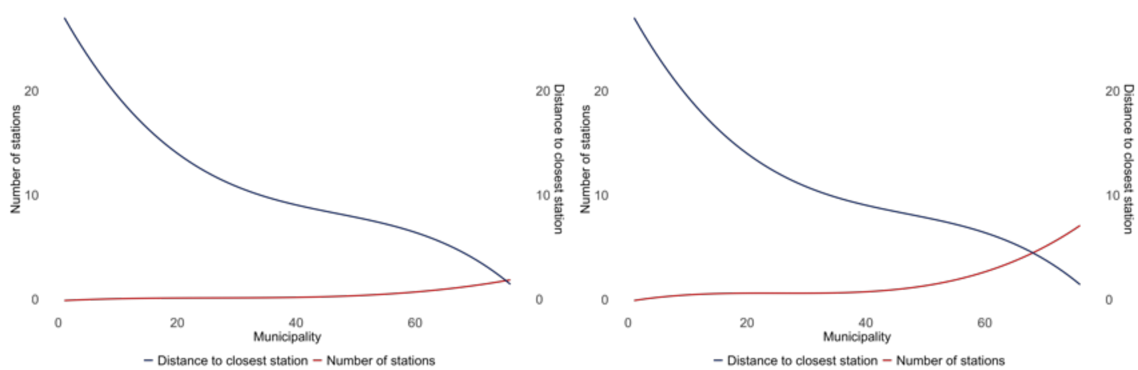
5 km **10 km**



Notes: The figure illustrates the number of monitoring stations within a 5 km and 10 km radius and the distance to the nearest station for the metropolitan area of Bogota. The data were processed by importing a distance matrix between geographic units and air quality monitoring stations that report PM10 levels, converting distances to kilometers, and identifying geographic unit centroids with stations within 3 km. To analyze trends, geographic units were sorted from lowest to highest status based on their mean years of schooling. The plots depict these trends using smooth lines fitted with a third-degree polynomial regression. Distance to the nearest station is displayed on the secondary y-axis.

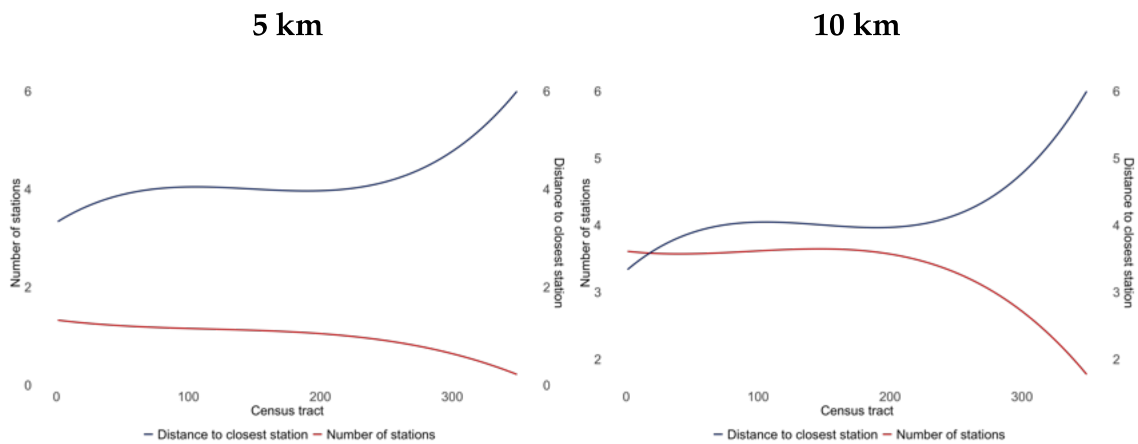
Figure B.6: Number of Stations within a 5 km/10 km Radius and Distance to Nearest Station, Metropolitan Area of Mexico City

5 km **10 km**



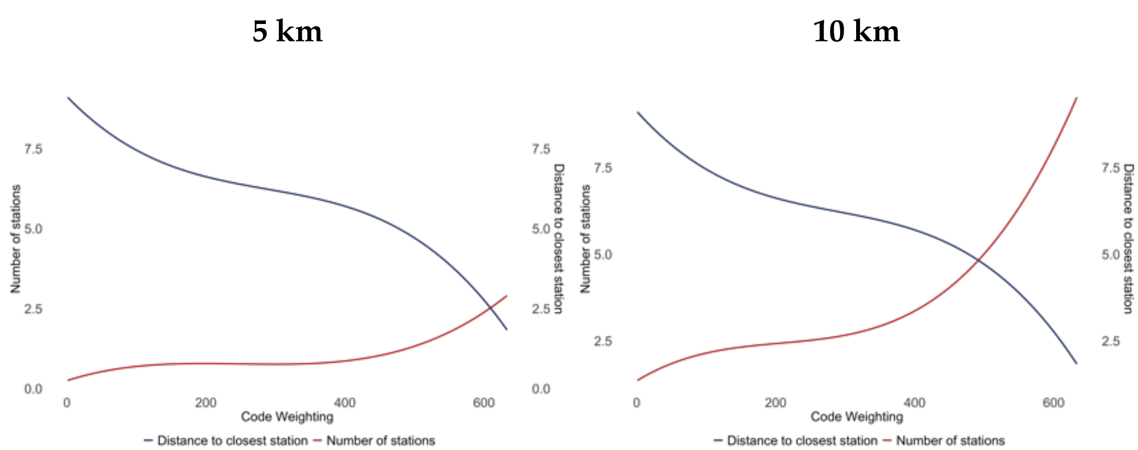
Notes: The figure illustrates the number of monitoring stations within a 5 km and 10 km radius and the distance to the nearest station for the metropolitan area of Mexico City. The data were processed by importing a distance matrix between geographic units and air quality monitoring stations that report PM10 levels, converting distances to kilometers, and identifying geographic unit centroids with stations within 3 km. To analyze trends, geographic units were sorted from lowest to highest status based on their mean years of schooling. The plots depict these trends using smooth lines fitted with a third-degree polynomial regression. Distance to the nearest station is displayed on the secondary y-axis.

Figure B.7: Number of Stations within a 5 km/10 km Radius and Distance to Nearest Station, Metropolitan Area of Santiago



Notes: The figure illustrates the number of monitoring stations within a 5 km and 10 km radius and the distance to the nearest station for the metropolitan area of Santiago. The data were processed by importing a distance matrix between geographic units and air quality monitoring stations that report PM10 levels, converting distances to kilometers, and identifying geographic unit centroids with stations within 3 km. To analyze trends, geographic units were sorted from lowest to highest status based on their mean years of schooling. The plots depict these trends using smooth lines fitted with a third-degree polynomial regression. Distance to the nearest station is displayed on the secondary y-axis.

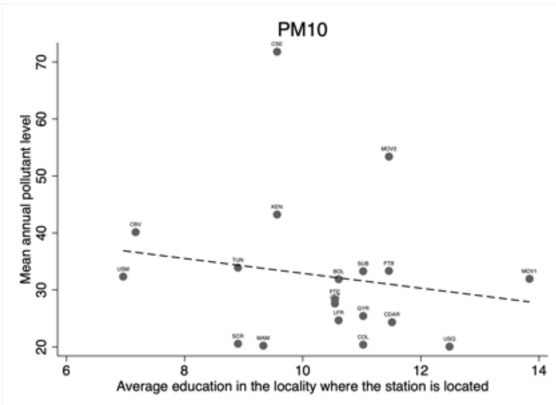
Figure B.8: Number of Stations within a 5 km/10 km Radius and Distance to Nearest Station, Metropolitan Area of Sao Pãulo



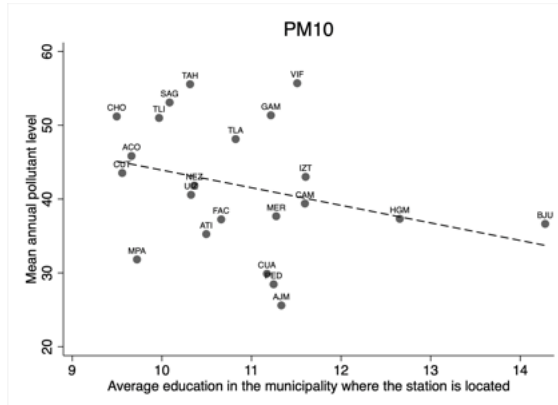
Notes: The figure illustrates the number of monitoring stations within a 5 km and 10 km radius and the distance to the nearest station for the metropolitan area of Sao Paulo. The data were processed by importing a distance matrix between geographic units and air quality monitoring stations that report PM10 levels, converting distances to kilometers, and identifying geographic unit centroids with stations within 3 km. To analyze trends, geographic units were sorted from lowest to highest status based on their mean years of schooling. The plots depict these trends using smooth lines fitted with a third-degree polynomial regression. Distance to the nearest station is displayed on the secondary y-axis.

Figure B.9: Mean Annual PM10 Concentration in 2023 vs. Average Education

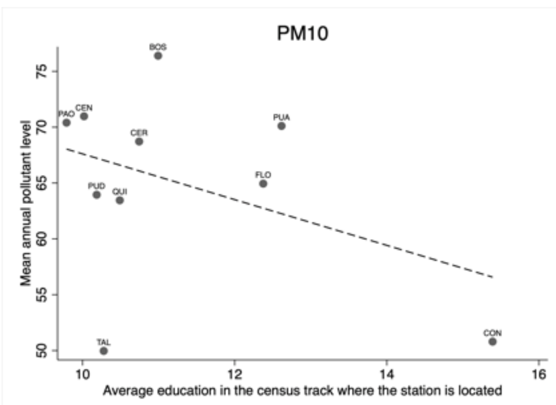
Metropolitan Area of Bogotá



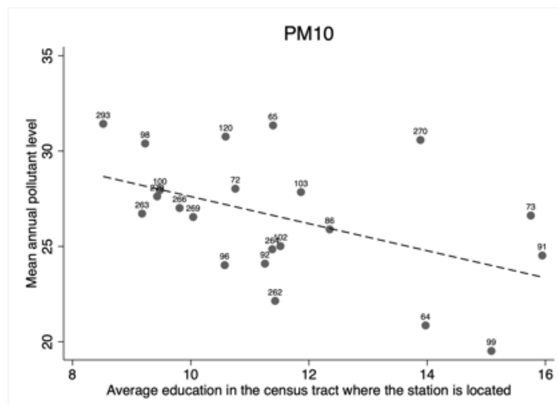
Metropolitan Area of Mexico City



Metropolitan Area of Gran Santiago



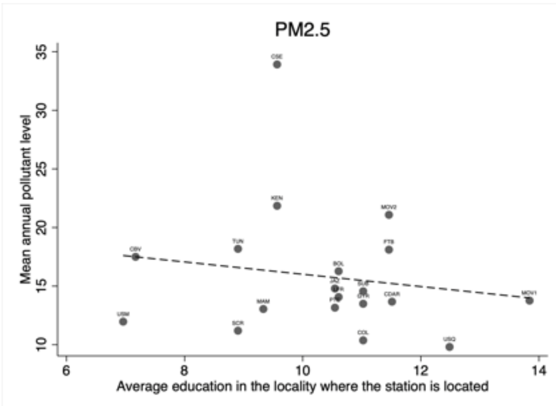
Metropolitan Area of São Paulo



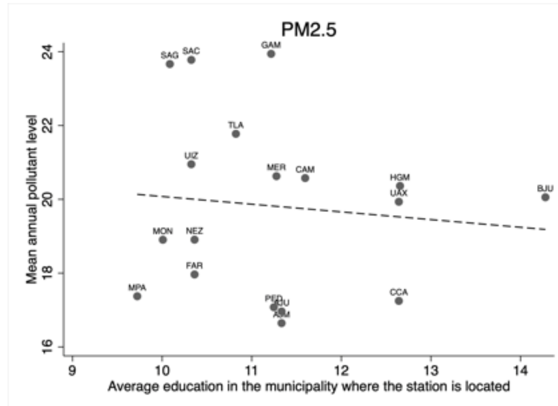
Notes: The figure shows the relationship, for each metropolitan area, between the mean annual PM10 concentration in 2023 and the average education level in the geographic unit where the air pollution monitoring station is located. PM10 units of measurements are $\mu g/m^3N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City.

Figure B.10: Mean Annual PM2.5 Concentration in 2023 vs. Average Education

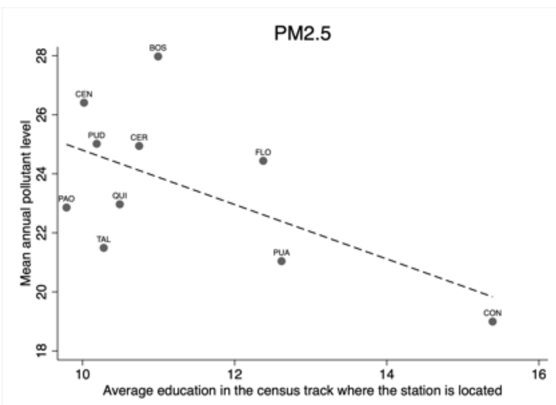
Metropolitan Area of Bogotá



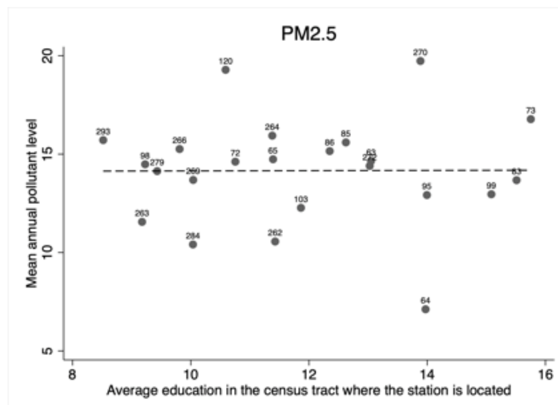
Metropolitan Area of Mexico City



Metropolitan Area of Gran Santiago

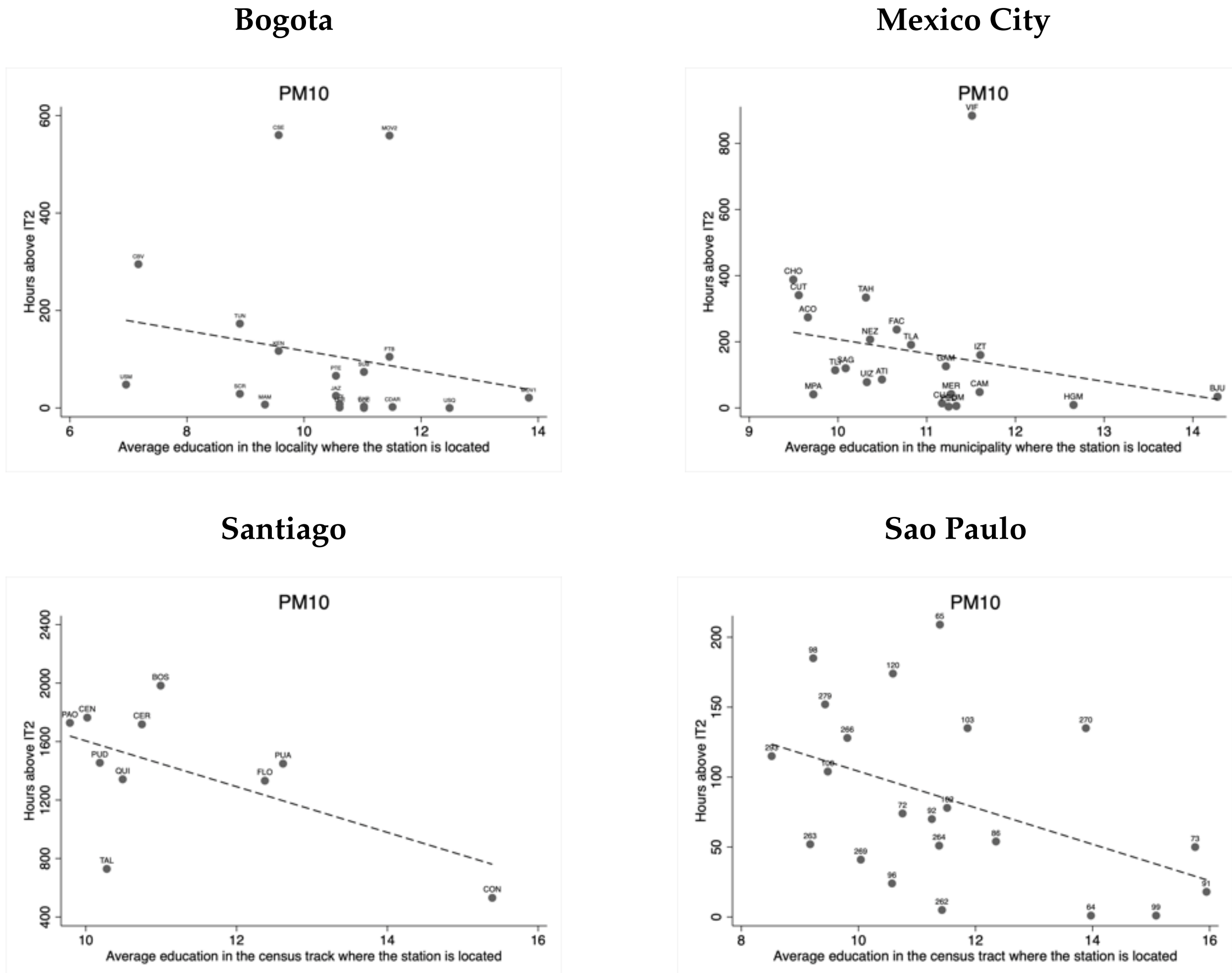


Metropolitan Area of São Paulo



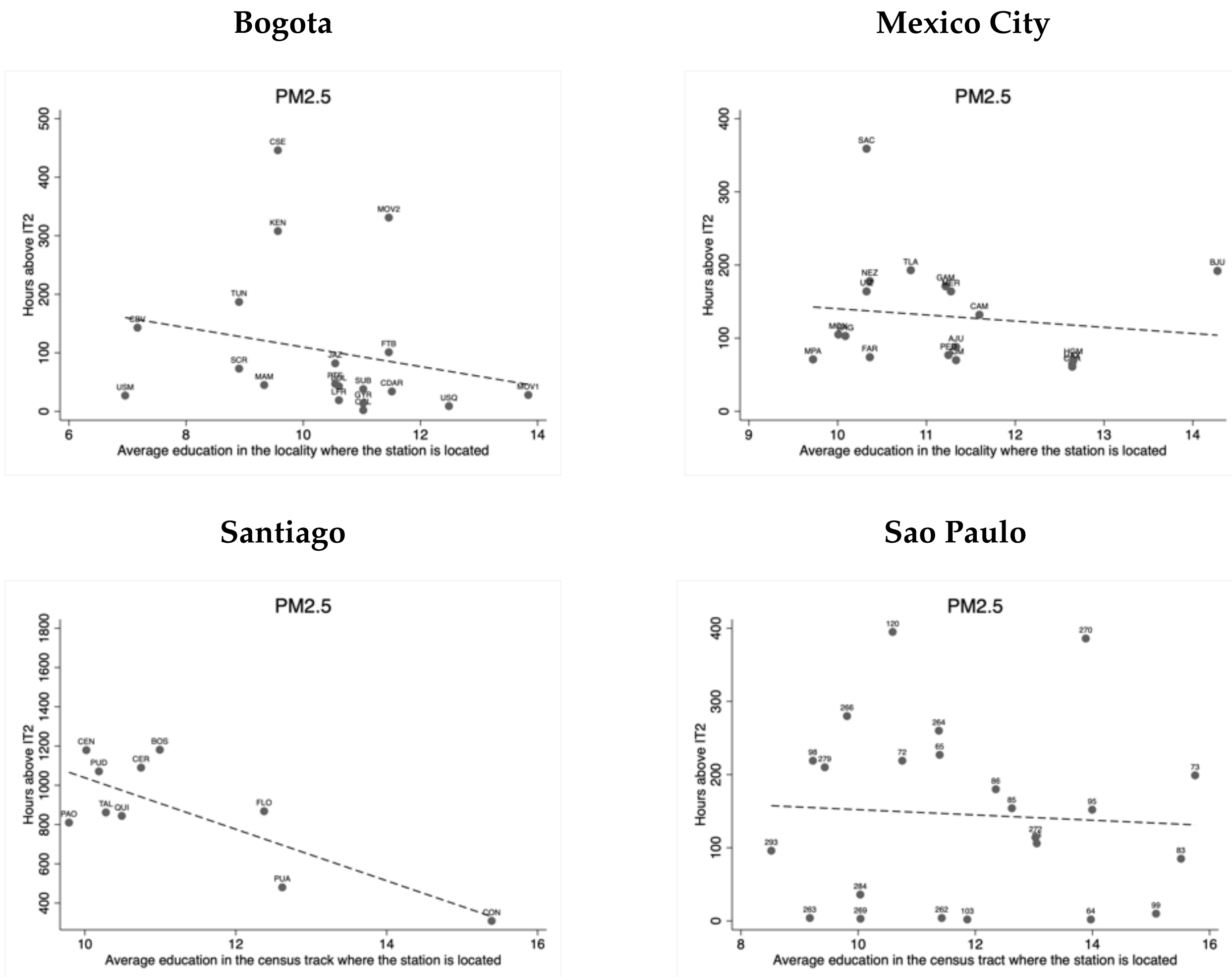
Notes: The figure shows the relationship, for each metropolitan area, between the mean annual PM2.5 concentration in 2023 and the average education level in the geographic unit where the air pollution monitoring station is located. PM2.5 units of measurements are $\mu g/m^3N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

Figure B.11: Hours Above PM10 IT2 in 2023 vs. Average Education



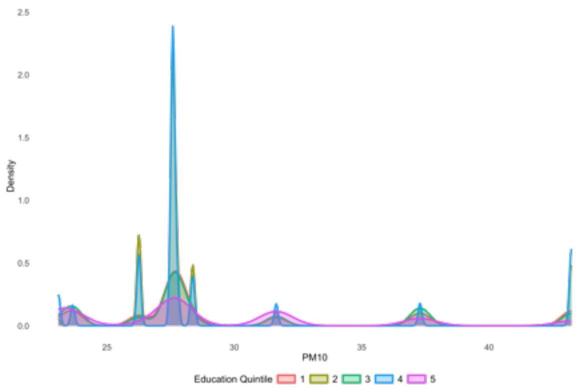
Notes: The figure shows the relationship, for each metropolitan area, between the number of hours in 2023 in which the PM10 concentration exceeded the 24-hour IT2 (Interim Target 2) threshold (IT2 = 100 $\mu g/m^3$) and the average education level in the geographic unit where the air pollution monitoring station is located. PM10 units of measurements are $\mu g/m^3 N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City.

Figure B.12: Hours Above PM2.5 IT2 in 2023 vs. Average Education

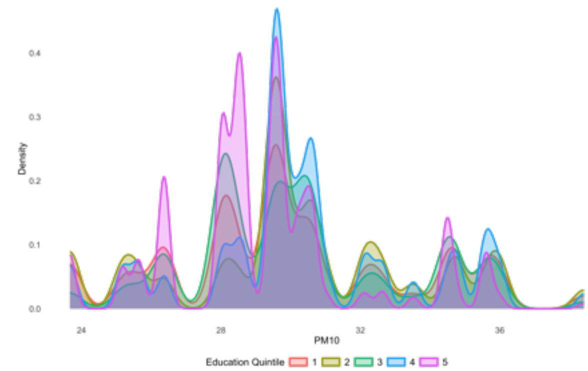


Notes: The figure shows the relationship, for each metropolitan area, between the number of hours in 2023 in which the PM2.5 concentration exceeded the 24-hour IT2 (Interim Target 2) threshold (IT2 = 50 $\mu g/m^3$) and the average education level in the geographic unit where the air pollution monitoring station is located. PM2.5 units of measurements are $\mu g/m^3 N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago.

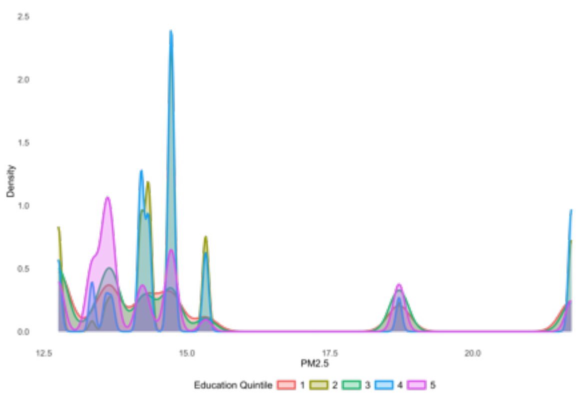
Figure B.13: Distributions of Individual-Hour PM_{10} and $PM_{2.5}$ by Quintile of Education, Metropolitan Area of Bogotá



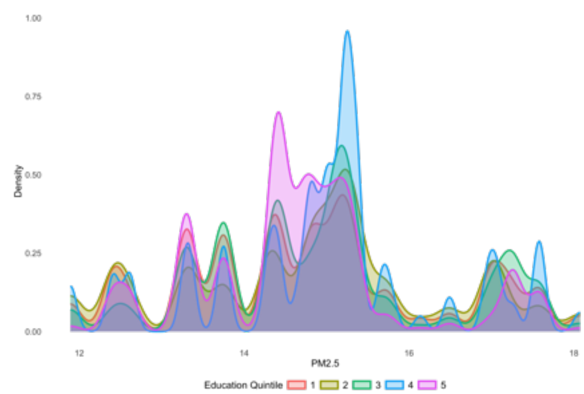
(a) Within 3 km PM_{10} stations



(b) Within 20 km PM_{10} stations



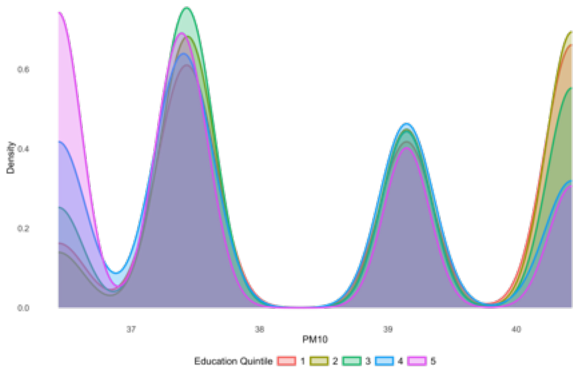
(c) Within 3 km $PM_{2.5}$ stations



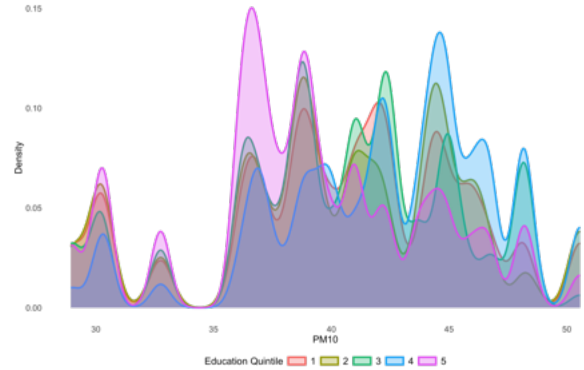
(d) Within 20 km $PM_{2.5}$ stations

Notes: The figure shows the distribution of PM_{10} ($\mu g/m^3N$) and $PM_{2.5}$ ($\mu g/m^3N$) pollutant concentrations for each education quintile in the Metropolitan Area of Bogotá using data from 2023. The plots are derived by considering stations within the specified radius (3 km or 20 km) of geographical units centroids. Panels (a) and (b) display the distribution of PM_{10} levels for stations within 3 km and 20 km, respectively. Panels (c) and (d) show the distribution of $PM_{2.5}$ levels for stations within 3 km and 20 km, respectively. The pollutant concentration are calculated as weighted averages for each geographical unit, using an inverse-distance weighting procedure across all stations within the specified radius. Education quintiles were created using census data for the entire population of the metropolitan area at the individual level. The x-axis shows pollutant levels, while the y-axis represents density.

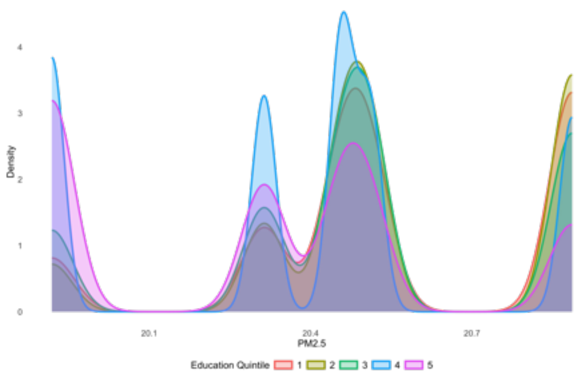
Figure B.14: Distributions of Individual-Hour PM_{10} and $PM_{2.5}$ by Quintile of Education, Metropolitan Area of Mexico City



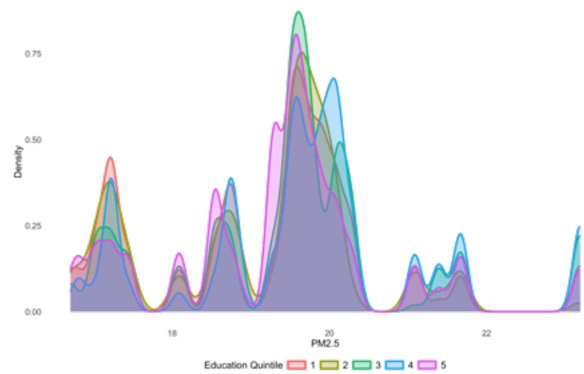
(a) Within 3 km PM_{10} stations



(b) Within 20 km PM_{10} stations



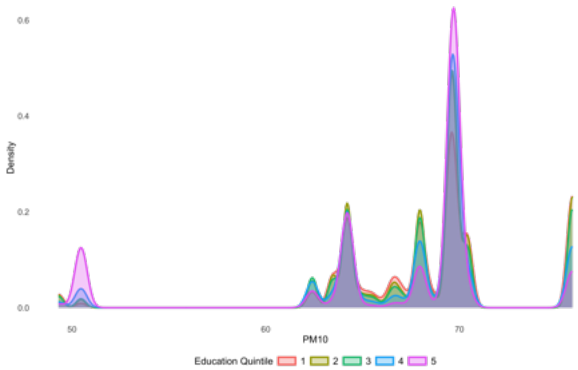
(c) Within 3 km $PM_{2.5}$ stations



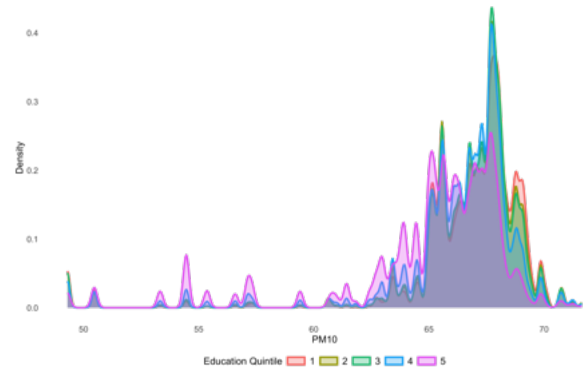
(d) Within 20 km $PM_{2.5}$ stations

Notes: The figure shows the distribution of PM_{10} ($\mu g/m^3$) and $PM_{2.5}$ ($\mu g/m^3$) pollutant concentrations for each education quintile in the Metropolitan Area of Mexico City using data from 2023. The plots are derived by considering stations within the specified radius (3 km or 20 km) of geographical units centroids. Panels (a) and (b) display the distribution of PM_{10} levels for stations within 3 km and 20 km, respectively. Panels (c) and (d) show the distribution of $PM_{2.5}$ levels for stations within 3 km and 20 km, respectively. The pollutant concentrations are calculated as weighted averages for each geographical unit, using an inverse-distance weighting procedure across all stations within the specified radius. Education quintiles were created using census data for the entire population of the metropolitan area at the individual level. The x-axis shows pollutant levels, while the y-axis represents density.

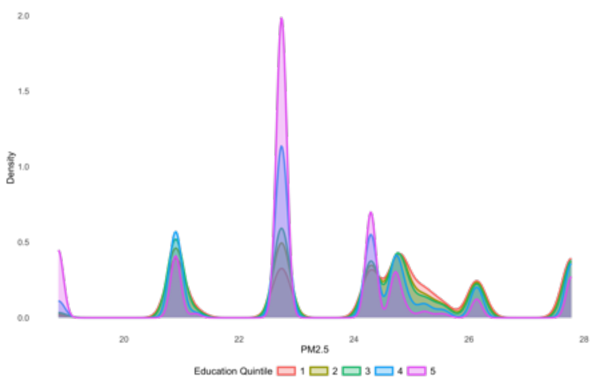
Figure B.15: Distributions of Individual-Hour PM_{10} and $PM_{2.5}$ by Quintile of Education, Metropolitan Area of Gran Santiago



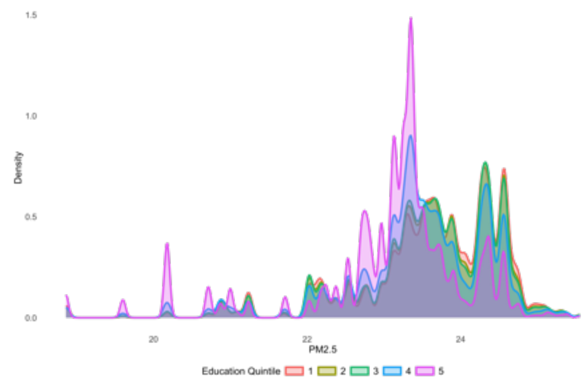
(a) Within 3 km PM_{10} stations



(b) Within 20 km PM_{10} stations



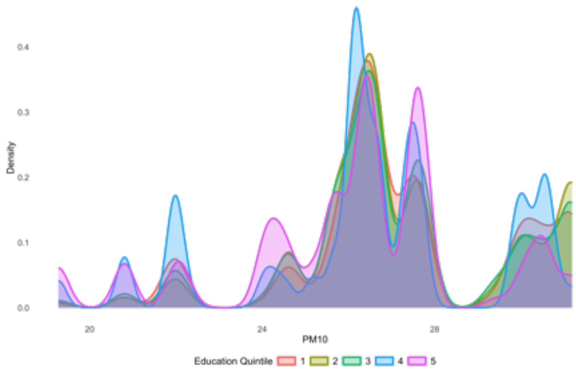
(c) Within 3 km $PM_{2.5}$ stations



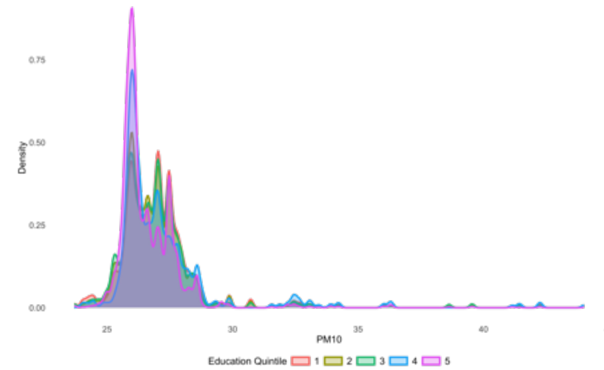
(d) Within 20 km $PM_{2.5}$ stations

Notes: The figure shows the distribution of PM_{10} ($\mu g/m^3N$) and $PM_{2.5}$ ($\mu g/m^3$) pollutant concentrations for each education quintile in the Metropolitan Area of Gran Santiago using data from 2023. The plots are derived by considering stations within the specified radius (3 km or 20 km) of geographical units centroids. Panels (a) and (b) display the distribution of PM_{10} levels for stations within 3 km and 20 km, respectively. Panels (c) and (d) show the distribution of $PM_{2.5}$ levels for stations within 3 km and 20 km, respectively. The pollutant concentrations are calculated as weighted averages for each geographical unit, using an inverse-distance weighting procedure across all stations within the specified radius. Education quintiles were created using census data for the entire population of the metropolitan area at the individual level. The x-axis shows pollutant levels, while the y-axis represents density.

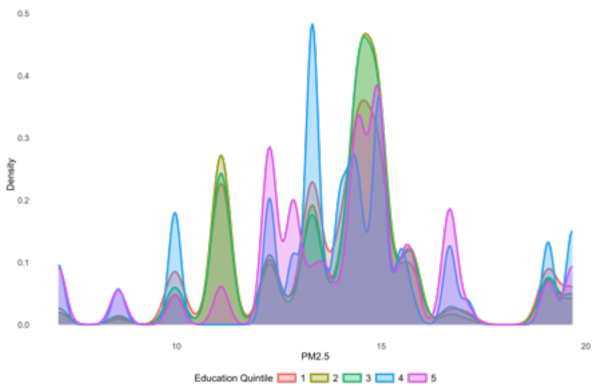
Figure B.16: Distributions of Individual-Hour PM_{10} and $PM_{2.5}$ by Quintile of Education, Metropolitan Area of Sao Pãulo



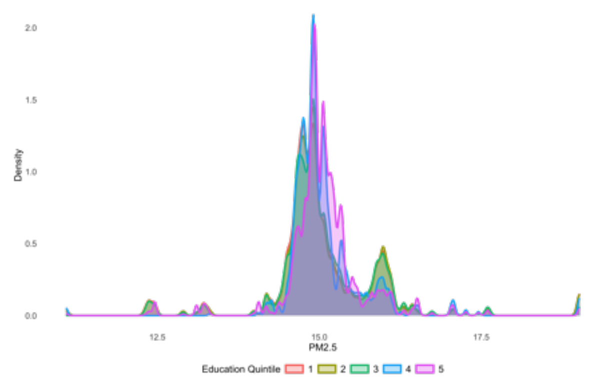
(a) Within 3 km PM_{10} stations



(b) Within 20 km PM_{10} stations



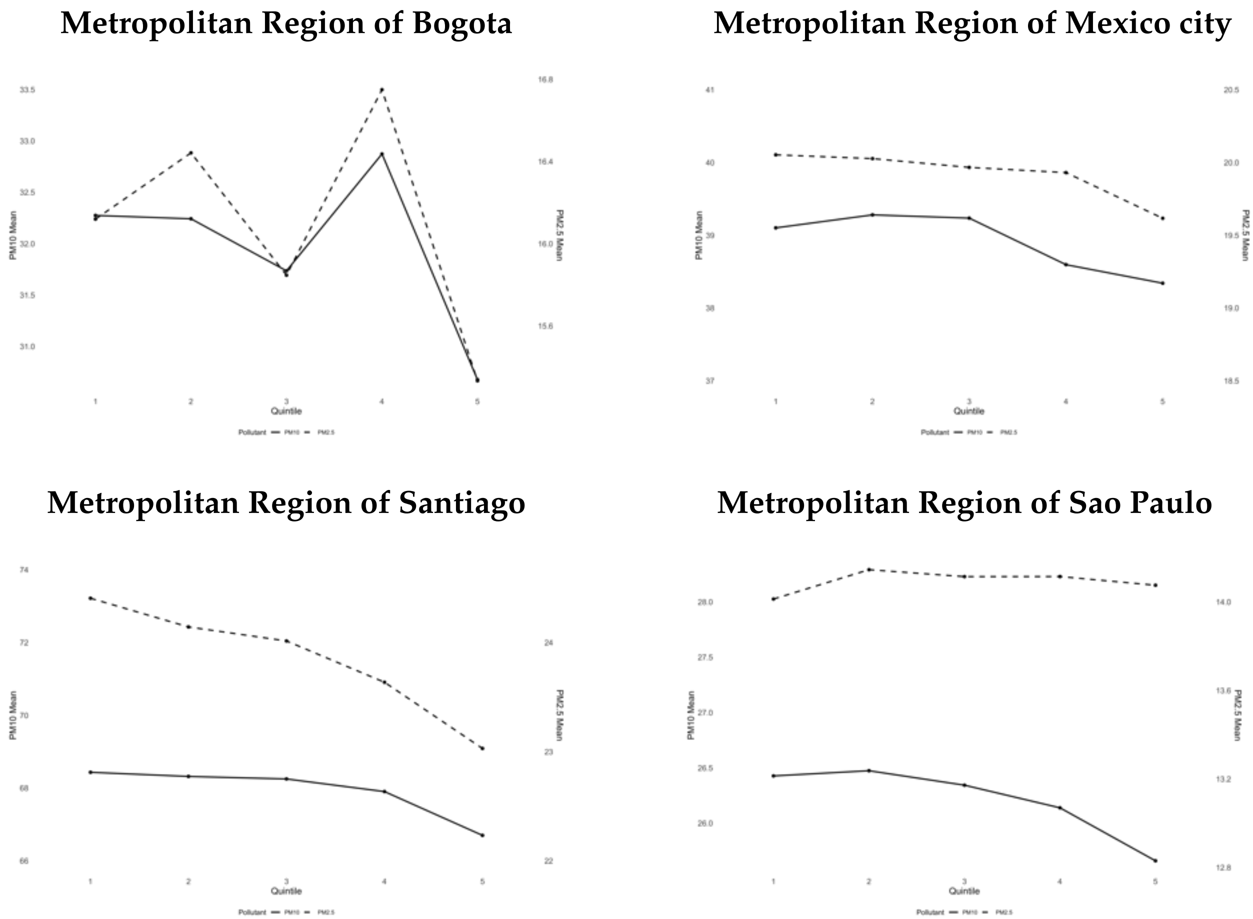
(c) Within 3 km $PM_{2.5}$ stations



(d) Within 20 km $PM_{2.5}$ stations

Notes: The figure shows the distribution of PM_{10} ($\mu g/m^3N$) and $PM_{2.5}$ ($\mu g/m^3N$) pollutant concentrations for each education quintile in the Metropolitan Area of Sao Pãulo using data from 2023. The plots are derived by considering stations within the specified radius (3 km or 20 km) of geographical units centroids. Panels (a) and (b) display the distribution of PM_{10} levels for stations within 3 km and 20 km, respectively. Panels (c) and (d) show the distribution of $PM_{2.5}$ levels for stations within 3 km and 20 km, respectively. The pollutant concentrations are calculated as weighted averages for each geographical unit, using an inverse-distance weighting procedure across all stations within the specified radius. Education quintiles were created using census data for the entire population of the metropolitan area at the individual level. The x-axis shows pollutant levels, while the y-axis represents density.

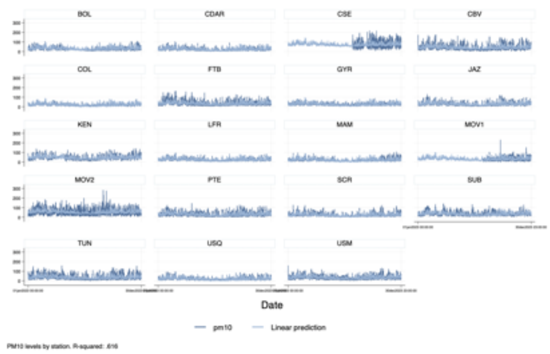
Figure B.17: Mean PM10 and PM2.5 Exposure by Education Quintiles in 2023



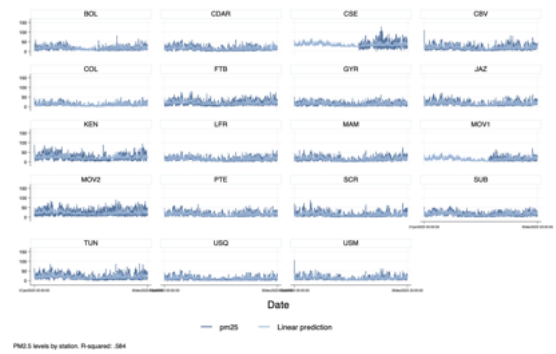
Notes: The figure shows, by metropolitan area, the mean PM10 and PM2.5 concentrations in 2023, categorized by quintiles of education. The line types differentiate the pollutants. PM10 units of measurements are $\mu g/m^3N$ in Bogota, Santiago, and Sao Paulo and $\mu g/m^3$ in Mexico City. PM2.5 units of measurements are $\mu g/m^3N$ in Bogota and Sao Paulo and $\mu g/m^3$ in Mexico City and Santiago. The x-axis represents quintiles of education, ranging from 1 (lowest education) to 5 (highest education).

Figure B.18: Bogotá: Linear Prediction of Hourly Observations by Stations

PM10



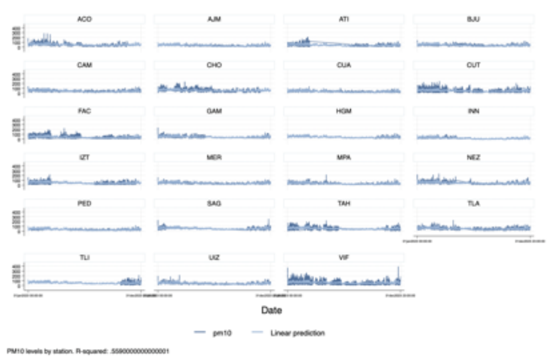
PM2.5



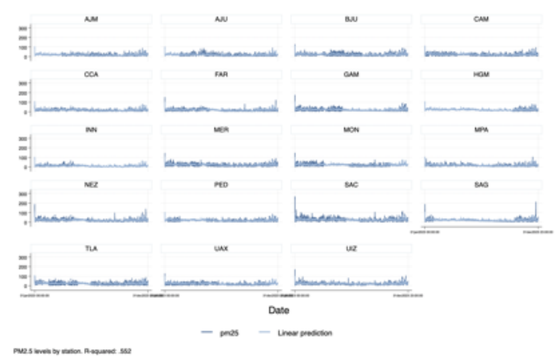
Notes: This figure shows the linear prediction (light blue) from our baseline specification described in equation 1, and the observed pollution levels for PM_{10} ($\mu g/m^3N$) and $PM_{2.5}$ ($\mu g/m^3N$).

Figure B.19: Mexico City: Linear Predictions of Hourly Observations by Station

PM10



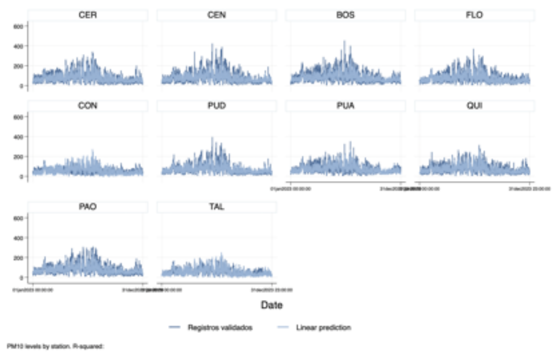
PM2.5



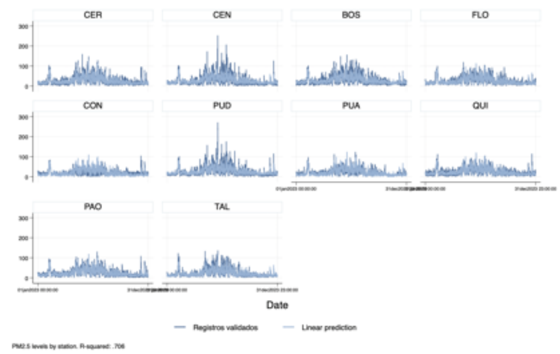
Notes: This figure shows the linear prediction (light blue) from our baseline specification described in equation 1, and the observed pollution levels for PM_{10} ($\mu g/m^3$) and $PM_{2.5}$ ($\mu g/m^3$).

Figure B.20: Santiago: Linear predictions of Hourly Observations by Station

PM10



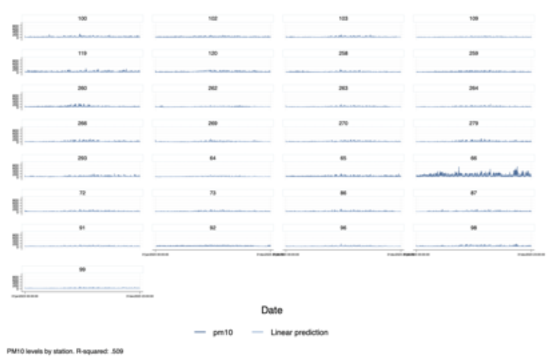
PM2.5



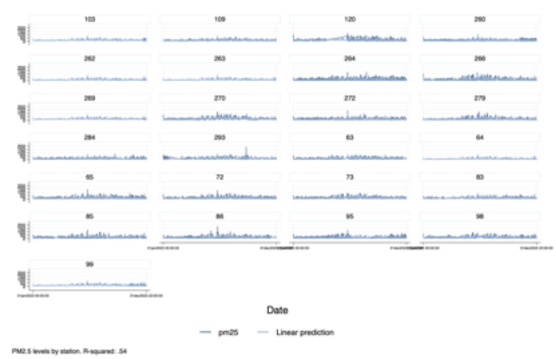
Notes: This figure shows the linear prediction (light blue) from our baseline specification described in equation 1, and the observed pollution levels for PM_{10} ($\mu g/m^3 N$) and $PM_{2.5}$ ($\mu g/m^3$).

Figure B.21: Sao Paulo: Linear predictions of Hourly Observations by Station

PM10



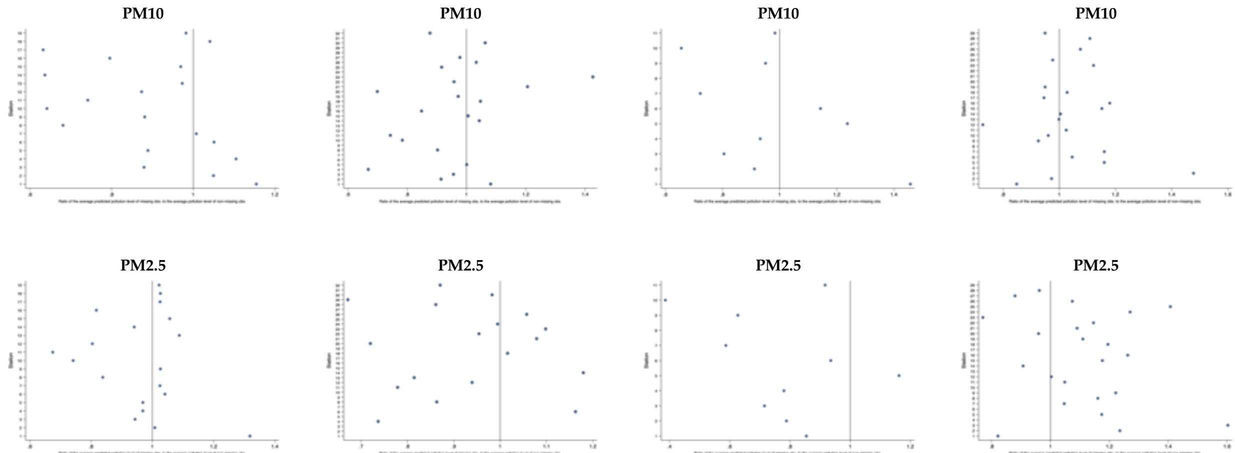
PM2.5



Notes: This figure shows the linear prediction (light blue) from our baseline specification described in equation 1, and the observed pollution levels for PM_{10} ($\mu g/m^3 N$) and $PM_{2.5}$ ($\mu g/m^3 N$).

Figure B.22: Ratio of the Average Predicted Pollution Concentration of Missing Observations to the Average Pollution Concentration of Non-Missing Observations by Metropolitan Area

(a) **Bogotá** (b) **Mexico City** (c) **Santiago** (d) **Sao Paulo**



Notes: This figure shows the ratio of the average predicted pollution concentrations for missing observations to the average observed pollution concentrations for non-missing observations disaggregated by station and pollutant in the metropolitan areas of Bogotá (Panel a), Mexico City (Panel b), Santiago (Panel c), and Sao Paulo (Panel d). The predicted pollution concentrations for missing observations result from predictions based on equation 1. Stations are order by the mean education level reported in the census geographic area where they are located from lowest education (1) to highest education.

C Data Appendix

3.1 Outlier Detection Procedure

To better detect outliers, we followed a structured process as detailed below. In summary, observations were classified as reasonable or unreasonable based on the distribution of the first difference at the station-month level. For unreasonable observations, further investigation involved analyzing the difference between values at neighboring stations during the same month. Observations were reclassified as reasonable when applicable.

Basic Notation

Let S denote the set of stations within the metropolitan areas. For each $s \in S$, we used the minimum straight distance to detect a neighboring station $n \in S \setminus \{s\}$. Let $p_{s,t}$ represent the pollutant measurement for station s at time t.

Generate Reference Variables

To detect outliers, we first generated reference variables. For each $s \in S$, the first difference of the pollutant value and its difference with respect to a neighboring station were calculated:

$$\Delta p_{s,t} := p_{s,t} - p_{s,t-1}$$

$$\Delta p_{s,n,t} := p_{s,t} - p_{n,t}$$

Benchmark Types

The differences defined above required benchmarks to classify observations as reasonable or unreasonable. We defined three benchmark types:

1. **Type 1:** For time t, the benchmark was the average of values at $t-1$ and $t+1$ for station s, provided both values were non-missing.

2. **Type 2:** If only one of $t-1$ or $t+1$ was non-missing, the benchmark used that value.

3. **No Benchmark:** If both $t-1$ and $t+1$ were missing, no benchmark was defined.

Let $\bar{p}_{s,t}$ denote the benchmark value. The difference between a pollutant value and its benchmark is defined as:

$$\Delta\bar{p}_{s,t} := p_{s,t} - \bar{p}_{s,t}$$

Identifying the Outliers

We flagged observations exceeding the 99th percentile of the pollutant distribution at the station-month level. For station s at time t, an observation was classified as reasonable if:

$$\Delta p_{s,t} - 2\sqrt{\mathrm{Var}(\Delta p_{s,t})} < \Delta\bar{p}_{s,t} < \Delta p_{s,t} + 2\sqrt{\mathrm{Var}(\Delta p_{s,t})}$$

If the difference between the pollutant value and its benchmark was too extreme, it was classified as unreasonable.

Adjusting the Classification

For observations classified as unreasonable, neighboring stations were investigated. If the pollutant value at station s was close enough to its neighbor's value, the observation was reclassified as reasonable:

$$\Delta p_{s,n,t} - 2\sqrt{\mathrm{Var}(\Delta p_{s,n,t})} < \Delta p_{s,t} < \Delta p_{s,n,t} + 2\sqrt{\mathrm{Var}(\Delta p_{s,n,t})}$$

3.2 Spatial Aggregation of Air Quality Data

To assign air pollution exposure values to geographic units for each city, we implement a spatial aggregation procedure using inverse-distance weighting. This method ensures that monitoring stations closer to a given geographic unit contribute more heavily to the exposure estimates. Below, we outline the steps used to perform spatial aggregation consistently across all cities:

1. **Identify active monitoring stations:** For each pollutant, we flag monitoring stations as active if they report at least one hourly measurement in the year of analysis.

2. **Filter by distance:** For each geographic unit (e.g., census tract or municipality), we include only monitoring stations within a specified radius (e.g., 3 km for our

baseline results) of the geographic unit's centroid. This ensures that the exposure calculations are not dominated by distant stations.

3. **Calculate inverse-distance weights:** For each pollutant, we calculate the inverse distance between the monitoring station and the centroid of the geographic unit. The inverse-distance weight is defined as:

$$w_{i,j} = \frac{1}{d_{i,j}}$$

   where $d_{i,j}$ is the distance between monitoring station i and geographic unit j.

4. **Normalize Weights:** The weights for each geographic unit are normalized so that they sum to one:

$$\tilde{w}_{i,j} = \frac{w_{i,j}}{\sum_i w_{i,j}}$$

5. **Final aggregation:** After obtaining hourly aggregated values for each geographic unit, we calculate annual averages and other summary statistics (e.g., the number of hours exceeding WHO thresholds) to assess exposure over time. This aggregation is conducted at quintile levels of years of schooling and income, using census data of each metropolitan area, allowing for an analysis of exposure disparities across different socioeconomic groups.

This spatial aggregation procedure is designed to account for spatial heterogeneity in monitoring station coverage while ensuring that geographic units with nearby stations are assigned more accurate pollution exposure values. This methodology was applied uniformly to all cities in the study to ensure comparability of results.

3.3 Metropolitan Area of Bogotá

Air quality data for Bogotá is sourced from the Bogotá Air Quality Monitoring Network (*Red de Monitoreo de Calidad del Aire de Bogotá*, RMCAB), managed by the *Secretaría Distrital de Ambiente* (SDA). The data can be accessed through the official RMCAB platform at `http://rmcab.ambientebogota.gov.co/Report/stationreport`. We accessed the air quality data in March 2024.

To replicate the dataset for Bogotá:

1. Access the RMCAB platform.
2. Navigate to the *Reportes de Estaciones* section to select the monitoring stations and the date range for the data. Air quality data is available at the hourly level for pollutants such as PM10, PM2.5, O3, CO, and NO2.
3. Download the data by station and date range.

Census data for the Metropolitan Area of Bogotá comes from the *Departamento Administrativo Nacional de Estadística* (DANE). The 2005 Census provides sociodemographic variables at the locality and municipality level. Because a common definition of localities is not available for the areas surrounding Bogotá's capital city, which are part of the metropolitan area, we use municipalities for these areas and localities for the capital city itself. We downloaded the census data in March 2024. The data is publicly available at `https://microdatos.dane.gov.co/index.php/catalog/421/get-microdata`. Our main comparison variable, the year of schooling variable, was harmonized such that:

- Completing high school represents 12 years of education [1-12]
- Completing a Bachelor's degree represents 17 years of education [13-17]
- Completing a Master's degree represents 19 years of education [18-19]
- Completing a PhD degree represents 23 years of education [20-23]

Table C.9 shows the census education variable for the Metropolitan Area of Bogotá and the new categories for the version of the harmonized years of schooling variable.

Table C.9: Education variable in census data: Metropolitan Area of Bogotá

City	Variable	Question	Range Categories	Category	Label	New Categories
Bogota	P44B3_NIVEL_ANOS	Nivel de Estudios y Años Aprobados en ese nivel	1-43, 98, 99	1	Prejardin	0
				2	Jardin	0
				3	Transición	0
				4	Básica primaria 1	1
				5	Básica primaria 2	2
				6	Básica primaria 3	3
				7	Básica primaria 4	4
				8	Básica primaria 5	5
				9	Básica secundaria 6	6
				10	Básica secundaria 7	7
				11	Básica secundaria 8	8
				12	Básica secundaria 9	9
				13	Media academica clasica 10	10
				14	Media academica clasica 11	12
				15	Media tecnica 10	10
				16	Media tecnica 11	12
				17	Normalista 10	10
				18	Normalista 11	12
				19	Normalista 12	13
				20	Normalista 13	14
				21	Técnica profesional 1	13
				22	Técnica profesional 2	14
				23	Tecnológica 1	13
				24	Tecnológica 2	14
				25	Tecnológica 3	15
				26	Profesional 1	13
				27	Profesional 2	14
				28	Profesional 3	15
				29	Profesional 4	16
				30	Profesional 5	17
				31	Profesional 6	17
				32	Especialización 1	17
				33	Especialización 2	17
				34	Maestria 1	18
				35	Maestria 2	19
				36	Maestria 3	19
				37	Doctorado 1	20
				38	Doctorado 2	21
				39	Doctorado 3	22
				40	Doctorado 4	23
				41	Doctorado 5	23
				42	Doctorado 6	23
				43	Ninguno	0
				98	Año Inválido	.
				99	No Informa	.

Notes: This table presents the education variable from the census data for the Metropolitan Area of Bogotá, detailing the original variable (P44B3_NIVEL_ANOS) and its corresponding categories and labels. The "Range Categories" column indicates the original numeric ranges, and the "Category Label" provides the descriptive labels for each level of education. The "New Categories" column shows the harmonized years of schooling used in this study to ensure comparability across all cities included in the analysis. Special values, such as "No informa" (99) and "Año inválido" (98), are excluded from the harmonized variable.

3.4 Metropolitan Area of Mexico City

Air quality data for Mexico City is sourced from the *Sistema de Monitoreo Atmosférico* (SIMAT), managed by the *Secretaría del Medio Ambiente* (SEDEMA). The data is available on the SIMAT platform at http://www.aire.cdmx.gob.mx/estadisticas-consultas/concentraciones/index.php and the *Sistema Nacional de Información de la Calidad del Aire* (SINAICA) at https://sinaica.inecc.gob.mx/scica/. Because the webpage was under maintenance, this data was obtained on August 2024 by emailing the Dirección General de Calidad del Aire at calidadairesimat@gmail.com. To replicate the dataset for Mexico City:

1. Access the SIMAT platform.
2. Navigate to the *Consultas* section to select pollutants and the period of interest.
3. Data is available at an hourly level for pollutants such as PM10, PM2.5, O3, CO, and NO2.
4. Download the data by pollutant and date range.

Census data for Mexico City is sourced from the 2020 Census conducted by the *Instituto Nacional de Estadística y Geografía* (INEGI). The census includes education and income variables at the municipality level. Our main comparison variable, the year of schooling variable, was harmonized such that:

- Completing high school represents 12 years of education [1-12]
- Completing a Bachelor's degree represents 17 years of education [13-17]
- Completing a Master's degree represents 19 years of education [18-19]
- Completing a PhD degree represents 23 years of education [20-23]

Table C.10 presents the census education variable for the Metropolitan Area of Mexico City and the new categories for the harmonized years of schooling variable. Additionally, the income variable used in our analysis measures total labor income.

Table C.10: Education variable in census data: Metropolitan Area of Mexico City

City	Variable	Question	Range categories	Category	Label	New categories	Notes
Mexico city	escoacum	Escolaridad	0-24, 99	0	- Sin escolaridad	0	- Sin escolaridad
					- Algún grado aprobado en preescolar		- Algún grado aprobado en preescolar
				1	- 1 grado aprobado de primaria	1	- 1 grado aprobado de primaria
				2	- 2 grados aprobados de primaria	2	- 2 grados aprobados de primaria
				3	- 3 grados aprobados de primaria	3	- 3 grados aprobados de primaria
				4	- 4 grados aprobados de primaria	4	- 4 grados aprobados de primaria
				5	- 5 grados aprobados de primaria	5	- 5 grados aprobados de primaria
				6	- 6 grados aprobados de primaria	6	- 6 grados aprobados de primaria
				7	- 1 grado aprobado de secundaria	7	- 1 grado aprobado de secundaria
					- 1 grado aprobado de estudios técnicos/comerciales con primaria terminada		- 1 grado aprobado de estudios técnicos/comerciales con primaria terminada
				8	- 2 grados aprobados de secundaria	8	- 2 grados aprobados de secundaria
					- 2 grados aprobados de estudios técnicos/comerciales con primaria terminada		- 2 grados aprobados de estudios técnicos/comerciales con primaria terminada
				9	- 3 grados aprobados de secundaria	9	- 3 grados aprobados de secundaria
					- 3 grados aprobados de estudios técnicos/comerciales con primaria terminada		- 3 grados aprobados de estudios técnicos/comerciales con primaria terminada
				10	- 1 grado aprobados de preparatoria o bachillerato general	10	- 1 grado aprobados de preparatoria o bachillerato general
					- 1 grado aprobados de estudios técnicos/comerciales con secundaria terminada		- 1 grado aprobados de estudios técnicos/comerciales con secundaria terminada
					- 1 grado aprobado de normal con primaria o secundaria terminada		- 1 grado aprobado de normal con primaria o secundaria terminada
				11	- 2 grados aprobados de preparatoria o bachillerato general	11	- 2 grados aprobados de preparatoria o bachillerato general
					- 2 grados aprobados de estudios técnicos/comerciales con secundaria terminada		- 2 grados aprobados de estudios técnicos/comerciales con secundaria terminada
					- 2 grados aprobados de normal con primaria o secundaria terminada		- 2 grados aprobados de normal con primaria o secundaria terminada
				12	- 3 grados aprobados de preparatoria o bachillerato general	12	- 3 grados aprobados de preparatoria o bachillerato general
					- 3 grados aprobados de estudios técnicos/comerciales con secundaria terminada		- 3 - 4 grados aprobados de estudios técnicos/comerciales con secundaria terminada
					- 3 grados aprobados de normal con primaria o secundaria terminada		- 3 - 4 grados aprobados de normal con primaria o secundaria terminada
				13	- 4 grados aprobados de estudios técnicos/comerciales con secundaria terminada	13	- 1 grado aprobado de estudios técnicos/comerciales con preparatoria terminada
					- 1 grado aprobado de estudios técnicos/comerciales con preparatoria terminada		- 1 grado aprobado profesional
					- 4 grados aprobados de normal con primaria o secundaria terminada		
					- 1 grado aprobado profesional		
				14	- 2 grados aprobados de estudios técnicos/comerciales con preparatoria terminada	14	- 2 grados aprobados de estudios técnicos/comerciales con preparatoria terminada
					- 2 grados aprobados profesional		- 2 grados aprobados profesional
				15	- 3 grados aprobados de estudios técnicos/comerciales con preparatoria terminada	15	- 3 grados aprobados de estudios técnicos/comerciales con preparatoria terminada
					- 3 grados aprobados profesional		- 3 grados aprobados profesional
				16	- 4 grados aprobados profesional	16	- 4 grados aprobados profesional
				17	- 5 grados aprobados profesional	17	- 5 - 8 grados aprobados profesional
					-1 años aprobado de maestría		
				18	- 6 grados aprobados profesional	18	- 1 año aprobado de maestría
					- 2 años aprobados de maestría		
				19	- 7 grados aprobados profesional	19	- 2 o más años aprobados de maestría
					- 3 años aprobados de maestría		
					- 1 año aprobado de doctorado		
				20	- 8 grados aprobados profesional	20	- 1 año aprobado de doctorado
					- 4 años aprobados de maestría		
					- 2 años aprobados de doctorado		
				21	- 3 años aprobados de doctorado	21	- 2 años aprobados de doctorado
				22	- 4 años aprobados de doctorado	23	- 3 años aprobados de doctorado
				23	- 5 años aprobados de doctorado	23	- 4 años aprobados de doctorado
				24	- 6 años aprobados de doctorado	23	- 5 o más años aprobados de doctorado
				99	- No especificaron grados aprobados.	.	- No especificaron grados aprobados.
					- Nivel no especificado		- Nivel no especificado

Notes: This table presents the education variable from the census data for the Metropolitan Area of Mexico City. The original variable (`escacum`) represents accumulated years of schooling, ranging from 0 to 24 and 99 (not specified). The "Range Categories" column indicates the numeric values for years of schooling, while the "Category Label" provides detailed descriptions for each level of education. The "New Categories" column shows harmonized years of schooling used in this study to ensure comparability across all cities included in the analysis. The "Notes" column provides additional information for specific categories, including clarifications about technical, professional, and advanced degrees.

3.5 Metropolitan Area of Gran Santiago

Air quality data for Santiago is obtained from the *Sistema de Información Nacional de Calidad del Aire* (SINCA), maintained by the *Ministerio del Medio Ambiente* (MMA) of Chile. The data is available through the SINCA platform at `https://sinca.mma.gob.cl/index.php/region/index/id/M`. We accessed the air quality data in January 2020.
To replicate the dataset for Santiago:

1. Use the region-specific menu to filter monitoring stations in the Metropolitan Region.

2. Select pollutants such as PM10, PM2.5, O3, CO, and NO2, along with the desired date range.

3. Download the hourly data for each pollutant and station.

Census data for Mexico City is sourced from the 2020 Census conducted by the *Instituto Nacional de Estadística y Geografía* (INEGI). The census includes education and income variables at the municipality level. We downloaded the census data in March 2024. The data is publicly available at `https://www.inegi.org.mx/programas/ccpv/2020/#microdatos`. We downloaded the census data in July 2023. The census data is publicly available at `https://www.ine.gob.cl/estadisticas/sociales/censos-de-poblacion-y-vivienda/censo-de-poblacion-y-vivienda`. Our main comparison variable, the year of schooling variable, was harmonized such that:

- Completing high school represents 12 years of education [1-12]

- Completing a Bachelor's degree represents 17 years of education [13-17]

- Completing a Master's degree represents 19 years of education [18-19]

- Completing a PhD degree represents 23 years of education [20-23]

Table C.11 shows the census education variable from the Metropolitan Area of Gran Santiago and the new categories for the version of the harmonized years of schooling variable.

Table C.11: Education variable in census data: Metropolitan Area of Santiago

City	Variable	Question	Range categories	Category	Label	New categories
Santiago	ESCOLARIDAD	Años de escolaridad	0-21, 99	0	Sala cuna o jardín infantil	0
				0	Prekínder	0
				0	Kínder	0
				0	Especial o diferencial	0
				1	Educación básica 1	1
				2	Educación básica 2	2
				3	Educación básica 3	3
				4	Educación básica 4	4
				5	Educación básica 5	5
				6	Educación básica 6	6
				7	Educación básica 7	7
				8	Educación básica 8	8
				9	Científico-humanista 1	9
				10	Científico-humanista 2	10
				11	Científico-humanista 3	11
				12	Científico-humanista 4	12
				9	Técnica profesional 1	9
				10	Técnica profesional 2	10
				11	Técnica profesional 3	11
				12	Técnica profesional 4	12
				12	Técnica profesional 5	12
				7	Humanidades 1 (sistema antiguo)	7
				8	Humanidades 2 (sistema antiguo)	8
				9	Humanidades 3 (sistema antiguo)	9
				10	Humanidades 4 (sistema antiguo)	10
				11	Humanidades 5 (sistema antiguo)	11
				12	Humanidades 6 (sistema antiguo)	12
				7	Técnica comercial, industrial/normalista 1 (sistema antiguo)	7
				8	Técnica comercial, industrial/normalista 2 (sistema antiguo)	8
				9	Técnica comercial, industrial/normalista 3 (sistema antiguo)	9
				10	Técnica comercial, industrial/normalista 4 (sistema antiguo)	10
				11	Técnica comercial, industrial/normalista 5 (sistema antiguo)	11
				12	Técnica comercial, industrial/normalista 6 (sistema antiguo)	12
				12	Técnica comercial, industrial/normalista 7 (sistema antiguo)	12
				13	Técnico superior 1	13
				14	Técnico superior 2	14
				15	Técnico superior 3	15
				13	Profesional 1	13
				14	Profesional 2	14
				15	Profesional 3	15
				16	Profesional 4	16
				17	Profesional 5 o más	17
				18	Magíster 1	18
				19	Magíster 2	19
				20	Magíster 3	19
				20	Doctorado 1	20
				21	Doctorado 2	21
				21	Doctorado 3	22
				21	Doctorado 4	23
			.	No aplica	.	.
			.	Missing	.	.

Notes: This table presents the education variable from the census data for the Metropolitan Area of Santiago. The original variable (`ESCOLARIDAD`) represents years of schooling, ranging from 0 to 21, with 99 indicating missing or not applicable values. The "Range Categories" column shows the numeric ranges corresponding to levels of education, while the "Category Label" provides detailed descriptions for each educational level. The "New Categories" column contains harmonized years of schooling used in this study to ensure comparability across all cities analyzed.

3.6 Metropolitan Area of São Paulo data

Air quality data is available on the platform **QUALAR**. The version of the data we are using is from May 22, 2024. To fully replicate our dataset, please follow the steps below:

1. Create a user account on the platform above;
2. Access the tab *"Consultas"* and then navigate to *"Exportar dados avançado"*;
3. Generate a table with the following columns: monitoring station, parameter, initial date, final date, latitude, and longitude, using the information in the tab *"Consultas"*, in the menu *"Configuração das estações"*. This table will be used as a consulting file, since there are many queries to be done inside the QUALAR's system;
4. Download the data for each parameter. It is possible to download data for three parameters at a time for a specific monitoring station, for a period of one year.

Census data comes from the 2010 Brazilian Census. These data were retrieved using version 0.3.2 of the R package **censobr**. Education variables are only available for the survey component of the census, whose most granular geographic unit is the weighting area; they were obtained using the function **read_population**. The other variables are available in both the survey and the universe components, allowing them to be generated at the census tract level using the function **read_tracts**. Our main comparison variable, the year of schooling variable, was harmonized such that:

- Completing high school represents 12 years of education [1-12]
- Completing a Bachelor's degree represents 17 years of education [13-17]
- Completing a Master's degree represents 19 years of education [18-19]
- Completing a PhD degree represents 23 years of education [20-23]

Tables C.12 presents the census education variable for the Metropolitan Area of São Paulo and the new categories for the harmonized years of schooling variable. Additionally, the income variable used in our analysis measures total labor income.

Table C.12: Education variables in census data: Metropolitan Area of Sao Paulo

City	Variable	Question	Range categories	Category V0633	Category V0634	Label	New categories
Sao Paulo Metropolitan Area	V0633 and V0634	"Curso mais elevado que frequentou" (V0633) and "Conclusão deste curso (V0634)"	01-14, 1-2, em branco	01	All	Creche, pré-escolar (maternal e jardim de infância), classe de alfabetização - CA	0
				02	2	Alfabetização de jovens e adultos incompleta	0
				02	1	Alfabetização de jovens e adultos completa	2
				03	2	Antigo primário (elementar) incompleto	0
				03	1	Antigo primário (elementar) completo	5
				04	2	Antigo ginásio (médio 1º ciclo) incompleto	5
				04	1	Antigo ginásio (médio 1º ciclo) completo	9
				05	2	Ensino fundamental ou 1º grau (da 1ª a 3ª série/ do 1º ao 4º ano) incompleto	0
				05	1	Ensino fundamental ou 1º grau (da 1ª a 3ª série/ do 1º ao 4º ano) completo	4
				06	2	Ensino fundamental ou 1º grau (4ª série/ 5º ano) incompleto	4
				06	1	Ensino fundamental ou 1º grau (4ª série/ 5º ano) completo	5
				07	2	Ensino fundamental ou 1º grau (da 5ª a 8ª série/ 6º ao 9º ano) incompleto	5
				07	1	Ensino fundamental ou 1º grau (da 5ª a 8ª série/ 6º ao 9º ano) completo	9
				08	2	Supletivo do ensino fundamental ou do 1º grau incompleto	0
				08	1	Supletivo do ensino fundamental ou do 1º grau completo	9
				09	2	Antigo científico, clássico, etc..... (médio 2º ciclo) incompleto	9
				09	1	Antigo científico, clássico, etc..... (médio 2º ciclo) completo	12
				10	2	Regular ou supletivo do ensino médio ou do 2º grau incompleto	9
				10	1	Regular ou supletivo do ensino médio ou do 2º grau completo	12
				11	2	Superior de graduação incompleto	12
				11	1	Superior de graduação completo	17
				12	2	Especialização de nível superior (mínimo de 360 horas) incompleta	17
				12	1	Especialização de nível superior (mínimo de 360 horas) completa	19
				13	2	Mestrado incompleto	17
				13	1	Mestrado completo	19
				14	2	Doutorado incompleto	19
				14	1	Doutorado completo	23
				Em branco	All	Missing	NA

Notes: This table presents the education variables from the census data for the Metropolitan Area of São Paulo. The variables (`V0633` and `V0634`) represent the highest level of education attended and whether the course was completed. The "Range Categories" column shows the numeric ranges corresponding to educational levels, while "Category V0633" and "Category V0634" denote specific codes for attendance and completion status. The "Label" column describes the detailed educational level, and the "New Categories" column contains harmonized years of schooling used in this study.