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In Most Low- and Middle-Income Countries Pollution Levels Are Higher in Wealthier Areas

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Abstract

Air pollution is a major threat to health, and the dangers are particularly acute in low- and middle-income countries. However, little is known about how the burden of pollution is spread across the wealth distribution in these countries. This paper uses new data providing high-resolution wealth estimates for more than 100 low- and middle-income countries, combined with equally high-resolution estimates of air pollution, to estimate how wealth is correlated with ambient air pollution around the world. The findings show that on average air pollution is positively correlated with wealth, but the relationship is highly heterogeneous across countries. The fact that air pollution and wealth are both disproportionately high in urban areas, where economic activity is largely concentrated, appears to drive this relationship. When the analysis is limited to anthropogenic sources of pollution, the relationship becomes less heterogeneous and more systematically positive. The paper also examines the relationship between pollution exposure and wealth within large cities around the world. Again, the findings show substantial heterogeneity across cities. The paper explores several hypotheses for this heterogeneity but does not find a single explanation. Economic concentration within cities appears to explain some of the relationship. Cities with more concentrated economic opportunity tend to have more positive correlations between pollution and wealth.

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In most low- and middle-income countries pollution levels are higher in wealthier areas

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1 Introduction

Air quality poses a significant threat to health in most parts of the world. At current levels air pollution is responsible for approximately 10 million premature deaths each year.[1] While the number of deaths associated with indoor air pollution has declined in recent years, increases in deaths due to ambient pollution have offset this improvement and led to an overall increase in total air pollution deaths. More than half of the world's population now lives in areas where ambient air pollution levels are increasing. The majority of those facing increasing levels of air pollution live in low- and middle-income countries (LMICs)[2] where more than 90% of air pollution-related deaths occur.[3]

The health burden of air pollution is also unequally shared *within* countries. With a few exceptions, low income populations in Europe are exposed to higher pollution levels than wealthy populations in the same country.[4] In the United States low income populations[5–8] and racial and ethnic minority populations[8–13] tend to be more exposed to ambient particulate pollution. These differences across groups have persisted over the past several decades despite universal reductions in pollution levels.[14,15]

While the within-country relationship between income or wealth and air pollution has been well documented in Europe and the US, evidence from LMICs is scarce.[16] This scarcity of evidence in the parts of the world with the largest populations, the highest levels of ambient pollution, and where pollution levels are increasing fastest limits our understanding of the present and future patterns of vulnerability. Lack of evidence may hinder effective policy-making to reduce the harms of this exposure. Furthermore, with the exception of recent studies in Eastern Europe[4] and China,[17] examinations of income and ambient air pollution outside of high-income countries have been limited to urban areas.[18–23] These city-level studies have documented pollution exposures declining with income[18–21,23] or non-linear relationships with pollution highest at wealth extremes.[22]

Population-scale estimates of the relationship between wealth and pollution in LMICs that include observations from both rural and urban areas are needed. Conclusions about the distribution of pollution exposures across wealth levels in Europe and the United States may not apply where settlement patterns differ.[17] Urban centers tend to be economic drivers that generate substantially higher incomes than are typically found in rural areas.[24,25] While this gradient exists in most countries it can be especially pronounced in LMICs. Higher levels of economic activity can simultaneously lead to higher levels of pollution[26–28] and wealth. If urban residents are on average wealthier and experience more ambient pollution than rural residents, then wealth could be positively correlated with ambient pollution exposure across the full population. This is true even in settings where within urban pollution is negatively correlated with neighborhood wealth. For these reasons the most comprehensive population-scale study[17] outside the U.S. and Europe, a population-scale study in China, finds a strong *positive* relationship between pollution and income. More broadly, for countries where anthropogenic sources of pollution dominate, there is a long recognized potential trade-off between urban-based development and environmental quality.

A primary reason that the few existing studies in LMICs have been mostly limited to urban areas is that data on air pollution and income or wealth are disproportionately available for cities. To overcome this challenge across a broad geographic scale we leverage recently released spatially resolved estimates of wealth for 103 LMICs.[25] These relative wealth indices (RWI) represent the most comprehensive micro-level wealth estimates to-date. They were derived from machine learning models trained on survey based measures of wealth. We combine these relative wealth estimates with global monthly spatially resolved estimates of ambient $PM_{2.5}$ for 2015-2020 that are derived from a combination of satellite observations and modeled output.[29] Together, the data allow us to estimate the correlation between relative wealth and average ambient $PM_{2.5}$ levels across grid cells in more than 100 LMICs at increasingly fine scales: across the full sample, separately within each country, and within cities.

For the pooled sample we regress average $PM_{2.5}$ on relative wealth at the grid-cell-level and include separate intercepts for each country (Equation 1). The intercepts (fixed effects) account for baseline differences in wealth and pollution across countries and for the fact that wealth measures are normalized at the country level. The estimated coefficient on relative wealth in this specification provides a measure of average within-country correlation between wealth and pollution. Next, we estimate separate regressions for each country again regressing cell-level average $PM_{2.5}$ on cell-level relative wealth (Methods). This exercise provides us with country-level estimates for the within-country correlation between wealth and pollution and allows us to assess which factors contribute to pollution being progressive or regressive in different settings. We next restrict our sample to large urban areas and estimate city-specific regressions in order to assess how pollution varies with wealth across neighborhoods within cities. Finally, we explore potential drivers of heterogeneity in both country- and city- level relationships.

2 Results

While wealthier LMICs tend to have lower pollution on average (Section SI-1.1), we find that the average within-country correlation between wealth and ambient pollution is positive. This relationship is seen both in the raw data and in our regression results. Areas with the lowest average $PM_{2.5}$ concentrations have the lowest average RWI levels while areas with the highest $PM_{2.5}$ concentrations have the highest average RWI (Figure 1a). Results from our preferred regression specification, weighting grid-cells jointly by country population and the inverse of the error on our wealth measure, indicate that a 1 standard deviation increase in the wealth index is associated with a 0.04 standard deviation increase in ambient $PM_{2.5}$. This result is robust to a variety of alternative weighting schemes (Table SI-1) and the relationship is further strengthened by trimming our wealth data at the 5^{th} and 95^{th} percentile (Table SI-2).

This positive correlation appears to be driven by urban-rural differences in both income and pollution. The shading in Figure 1b-c highlights that both grid-cells with the highest pollution levels and grid cells with the highest wealth levels are the most urban in our sample. More generally, being in or near larger urban areas is associated with higher levels of wealth (Figure SI-2). Wealth increases with urbanization both within and across categories (urban, peri-urban, rural) and the differences are stark enough that on average the wealthiest rural areas are poorer than the poorest urban areas. Exposure to ambient air pollution follows similar patterns albeit less dramatically (Figure 1c). Nonetheless, average pollution in urban areas is 12% (*t-stat:*47.7) higher than in peri-urban areas and 50% (*t-stat:*>100) higher than in rural areas.

Our pooled estimate hides substantial heterogeneity across countries. Country specific estimates indicate that ambient pollution increases with wealth in the majority of LMICs. However, a substantial minority of countries demonstrate the opposite relationship. While wealthier individuals live in more polluted locations in countries like Nepal, pollution decreases strongly with wealth in other countries like Nigeria (Figure 2a). When we map the country level relationship (Figure 2b-c) one immediate pattern becomes clear: countries with strong negative correlations between ambient pollution and wealth are highly concentrated in West or Central Africa. In most of the rest of the world, particularly Asia, wealthier areas have higher ambient pollution.

One reason the wealth-pollution relationship may differ in West and Central Africa is that a substantial portion of the ambient particulate pollution in these regions is driven by dust storms off the Sahel and Sahara.[30,31] Pollution from these sources does not generate the same correlation with urbanization (and hence wealth) as anthropogenic sources and is more severe in rural locations which are often in closer proximity to the dust sources (Figure 3). Across the sample dust and sea salt makeup 3.5% of $PM_{2.5}$ concentrations in urban areas but more than 30% of $PM_{2.5}$ in rural areas (Methods). Panels **A** and **B** of Figure 3 show the different spatial distributions of total $PM_{2.5}$ and $PM_{2.5}$ with dust and sea salt removed (an imperfect proxy for anthropogenic emissions) in West Africa. Total $PM_{2.5}$ is concentrated inland, near the Sahel in particular, while anthropogenic $PM_{2.5}$ is heavily concentrated along the coast, where urbanization and wealth are highest (Panels **C** and **D**). When we recalculate the correlation between wealth and pollution using $PM_{2.5}$ measures that remove dust and sea salt most of the correlations between wealth and total ambient pollution that were negative become positive suggesting that even in these settings anthropogenic emissions increase with wealth (Figure 2c,d inset). Examining correlations based on the primary source of anthropogenic pollution does not generate similar changes in the patterns of correlation (see Section SI-1.2).

Leveraging the fine spatial scale of the data, we estimate city-specific correlations across grid cells that lie within contiguous areas determined to be highly urban (see Methods). Estimating these correlations separately by city we find the relationship is again heterogeneous across locations (Figure 4a) and ranges from strongly negative to strongly positive. Re-estimating within-city correlations using the dust and sea salt removed pollution measures leads to more positive correlations on average across our cities but does not completely eliminate the presence of negative correlations and substantial heterogeneity remains. Figure 4b shows within-city correlations for three of the largest population centers in our sample (Rio de Janeiro, Delhi, and Lagos) and highlights the observed heterogeneity. Lagos's location on the coast in West Africa mean that dust and sea salt contribute relatively more to total $PM_{2.5}$ levels and thus the estimated correlation changes depending on whether we compare wealth with total or anthropogenic $PM_{2.5}$ (Figure 4a).

One factor that appears to be important in many cities is how populations sort across different terrains. We find that on average in cities where the wealthy tend to live at higher elevations they also tend to live in lower pollution areas and vice versa (Figure SI-5). This relationship does not explain all of the variation in the estimated correlation between wealth and pollution across cities but we find a standard deviation increase in the correlation between wealth and elevation is associated with a 0.2 standard deviation more negative correlation between wealth and pollution [t-stat: 3.03].

Comparing the pollution-wealth and pollution-elevation gradients in Lagos, Delhi, and Rio de Janeiro emphasizes both the potential importance of elevation and its varying influence. In Rio de Janeiro the poorest households live in higher-elevation neighborhoods further removed from primary emissions sources that are located near the center of town. As a result, wealthier neighborhoods in Rio de Janeiro on average have higher pollution. The opposite relationship exists in Lagos where the wealthiest live at the highest elevations in the city further removed from emissions sources. Delhi illustrates the limits of elevation as an explanatory variable as we observe a stronger gradient between wealth and pollution than in Rio de Janeiro yet we see a relatively weak gradient between wealth and elevation due at least in part to the limited elevation changes within the city.

We see similar patterns in other cities including Kathmandu, Dhaka, and Islamabad (Figure 3f). In both Islamabad and Kathmandu, cities in or near the mountains, higher wealth areas are more polluted. In Dhaka, where there is little elevation change, wealthier areas have less pollution. Comparing the joint distribution of wealth and pollution across all of South Asia (Panel **E**, Figure 3) emphasizes both the importance of terrain, highlighted by the large band of high pollution through the Indo-Gangetic plains into the Himalayan foothills, and that urban areas throughout the region are hotspots of both pollution and wealth. This is particularly notable in South India where wealth is relatively high and pollution relatively low, yet urban centers are still hotspots of high pollution. In contrast, we observe much weaker relationships between pollution and wealth when we look at within-city correlations in the US (Figure SI-10).

We consider several other factors that could influence neighborhood sorting patterns in Section SI-1.3. We find that economic concentration may explain some variation across cities, but find little difference in the pattern of heterogeneity based on countries' history of European colonization (Figures SI-11 & SI-12), location in equatorial regions, whether they were part of the Soviet Union or primary source of particulate pollution within the city (Figure SI-13).

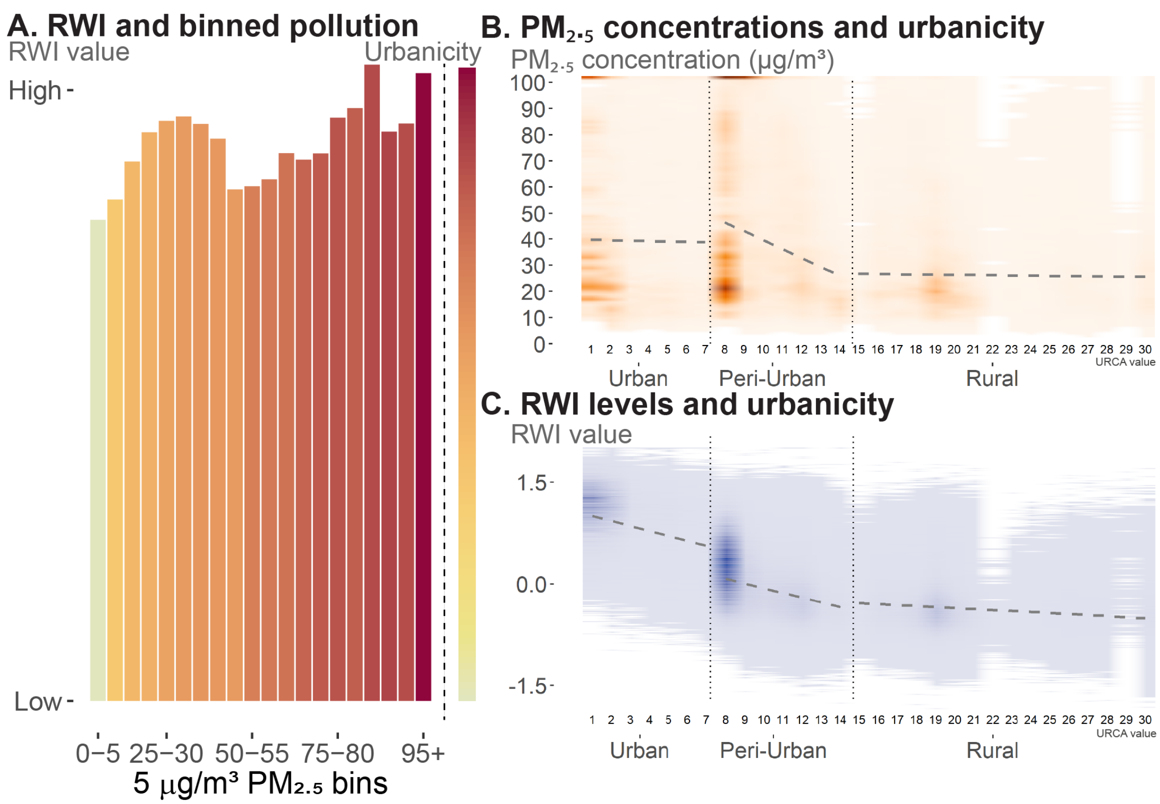

Figure 1: Pollution is higher in wealthier areas–Panel a plots the average wealth of 5 $\mu g/m^3$ PM$_{2.5}$ bins based on the RWI grid-cells in each bin. We top-code grid points in our sample at $100\mu g/m^3$ of PM$_{2.5}$ so that the 20^{th} bin represents the grid points that have an average level of PM$_{2.5}$ of at least $100\mu g/m^3$. The upward slope in the height of the bars indicates that more polluted areas are, on average, wealthier. The shading indicates the average level of urbanicity across grid-cells in the bins as defined by the URCA data. Darker bars are more urban. In **Panel b** we calculate the average PM$_{2.5}$ across grid-cells in each level of urbanicity. We shade to indicate the share of grid-cells within each PM$_{2.5}$-URCA score bin. The dashed lines indicate the best fit line for PM$_{2.5}$ across the URCA categories "Urban","Peri-urban", and "Rural" delineated by the vertical dashed lines. We top-code at 100 $\mu g/m^3$ for the figure but include all values in the calculation of the best fit lines. In **Panel c** we do the same but for wealth rather than average PM$_{2.5}$. We omit wealth scores above 2 from the figure for parsimony but include them in the calculation of the best fit line. In both **b** and **c** URCA scores below 7 indicate a city or town larger than 20,000. Scores between 8 and 14 indicate a city or town of at least 20,000 is less than 2 hours away. Scores above 15 indicate a town is more than 2 hours away. In all cases lower scores indicate greater urbanicity.

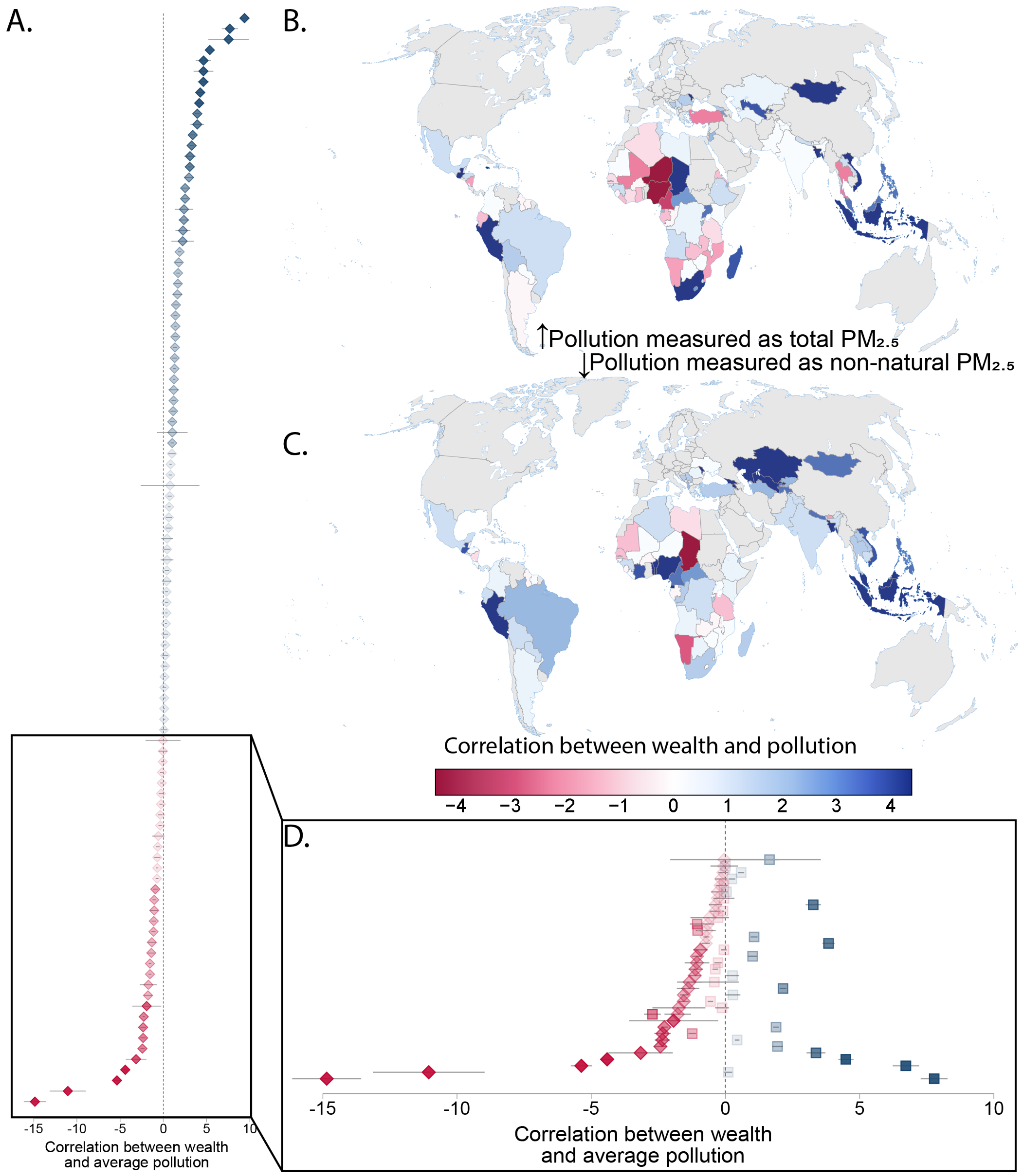

Figure 2: Variation in correlation between wealth and pollution across countries– Panel a plots the coefficients from country-level regressions of pollution measured as the average over the sample estimated against RWI. The unit of observation is a grid-cell within a country. grid-cells are weighted by the inverse of the reported error in the RWI data. Grey spikes indicate the 99% CI. The inset (**Panel d**) shows how the coefficients change when using the raw $PM_{2.5}$ data (diamonds) versus the $PM_{2.5}$ data with dust and sea salt removed (squares). **Panel b** maps the coefficients from the same regression using raw $PM_{2.5}$ data and **Panel c** maps the same using data from the dust and sea salt removed $PM_{2.5}$ data. The general pattern is robust to defining pollution based on median and highest monthly exposure. In the maps the coefficients are bottom and top coded to -4, 4 respectively.

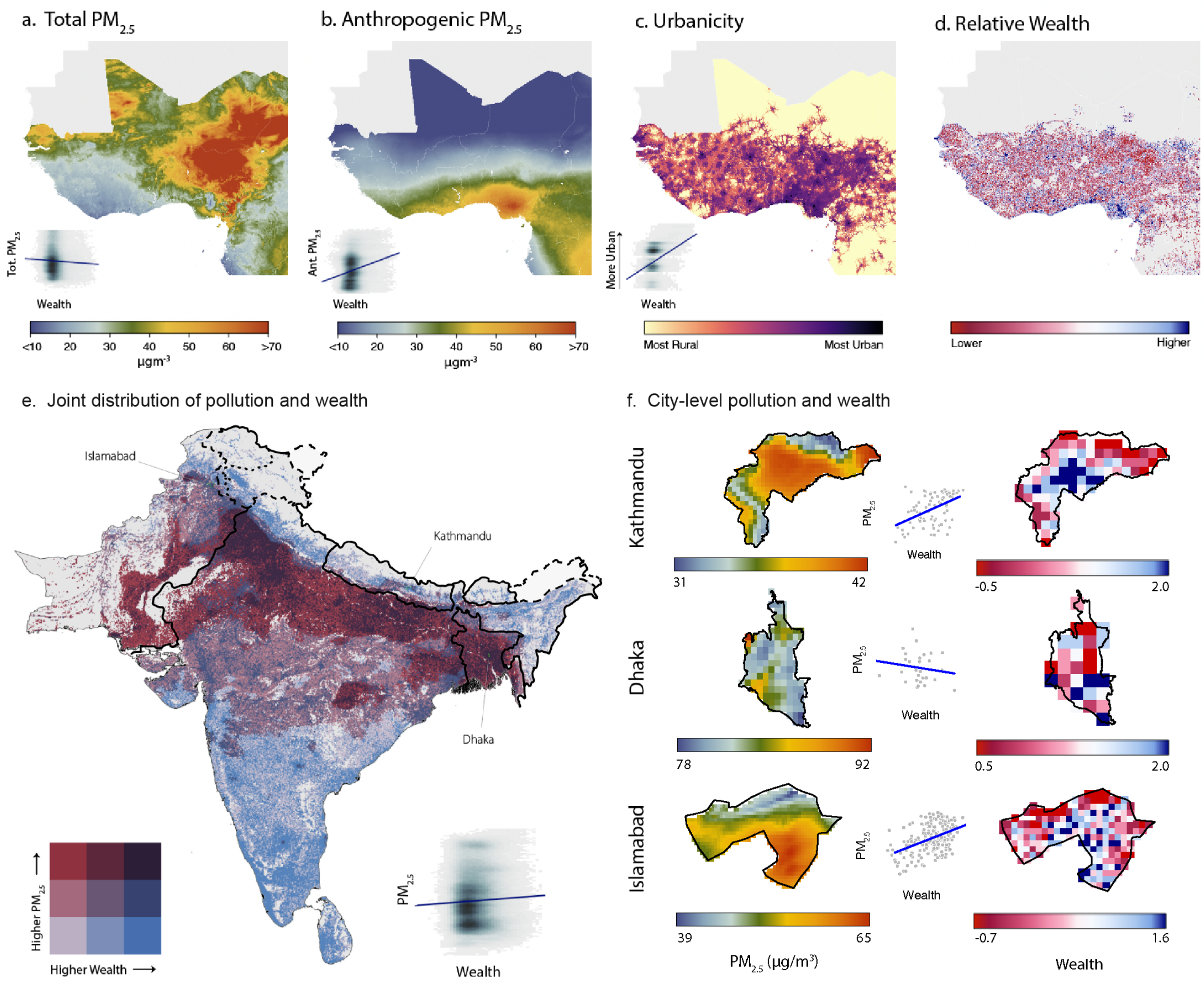

Figure 3: Pollution, Wealth, and Urbanicity Patterns in West Africa and South Asia– Average spatial distributions are shown for total $PM_{2.5}$ (**a**) anthropogenic $PM_{2.5}$ (i.e., $PM_{2.5}$ with dust and sea salt removed) (**b**), urbanicity (**c**), and relative wealth (**d**). Inset scatters in **Panels a-c** show the density of observations across different levels of relative wealth with lines of best fit plotted. While wealth decreases with total $PM_{2.5}$ in this region (**a**), it increases with anthropogenic $PM_{2.5}$ (**b**). Urban areas are wealthier than rural areas on average (**c**) as wealth tends to be largely concentrated in cities (**d**). **Panel e** shows the joint distribution of pollution and wealth across Bangladesh, Bhutan, India, Nepal, Pakistan, and Sri Lanka. **Panel f** shows the within-city relationships for Dhaka, Kathmandu, and Islamabad. Scatters show the cell level observations and blue lines show the best fit for pollution-wealth correlations.

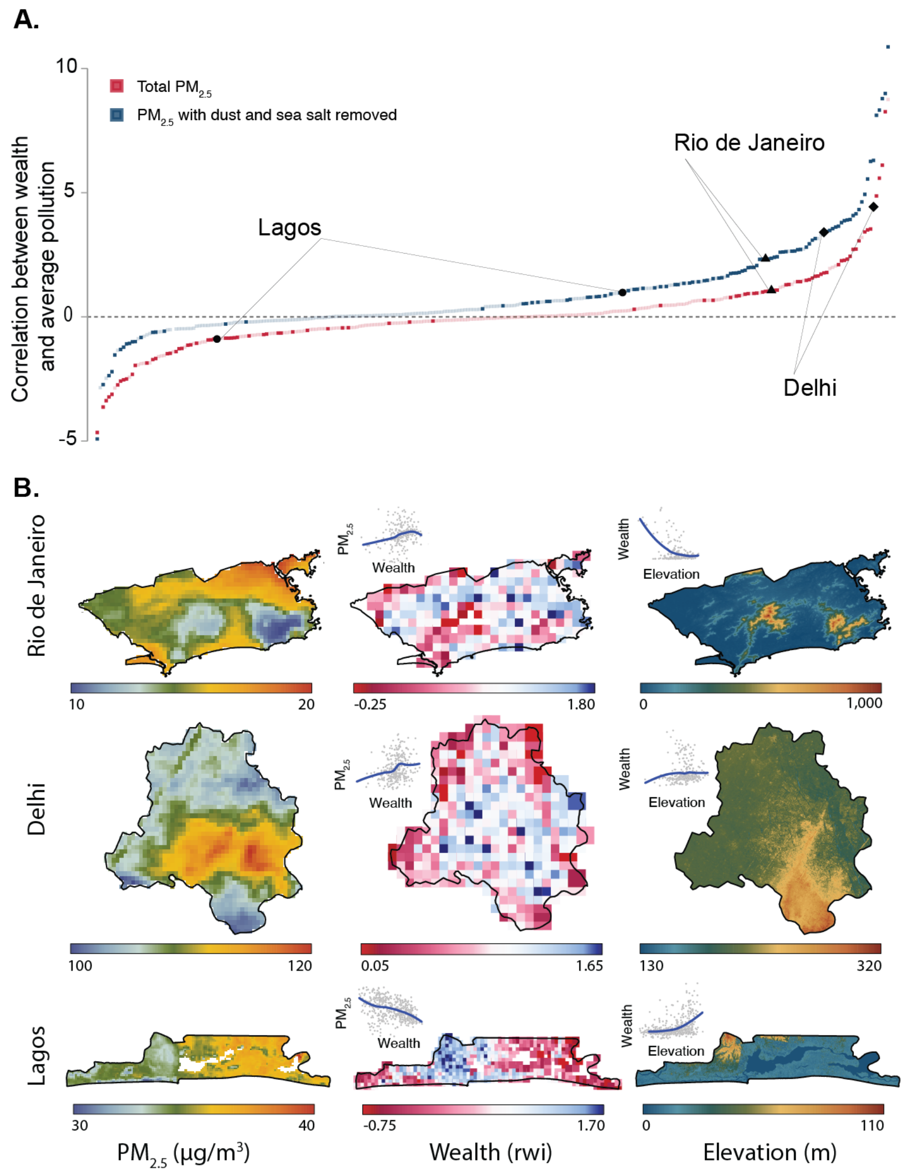

Figure 4: Heterogeneity within cities– Panel a reports the within city estimates for the cities within our sample. Cities are defined as contiguous urban areas with at least 50,000 individuals and that contain at least 30 RWI points. Darker shaded points indicate that the correlation is significant at 99%. Lighter shading indicates statistical insignificance. The red line shows the correlation using $PM_{2.5}$ measured as total particulates while the blue line shows the same using $PM_{2.5}$ measured with dust and sea salt removed. Two countries whose cities is less than -5 are omitted. **Panel b** details the relationship between wealth, pollution, and elevation in three of the largest cities in three of the most populous countries in our sample.

3 Discussion

Using large-scale spatially resolved wealth and pollution data we find that ambient air pollution is, on average, positively correlated with wealth in LMICs around the world. This appears to be driven by urbanization, which is highly positively correlated with both wealth and ambient air pollution in most LMICs. However, there is substantial heterogeneity in this result which appears driven partly by the the weaker correlation between urbanization and ambient air pollution in countries where the primary source of ambient air pollution is non-anthropogenic.

Within cities the theoretically anticipated relationship between pollution and wealth is ambiguous. It will be driven by patterns of residential sorting that are likely influenced by cultural, geographic, and historic differences. As a result, one would expect city-level results to vary widely across different cities in different countries. We find this to be the case. Sorting across different terrains, particularly elevation, appears to be important in places where cities are built on varied geographies. Concentration of economic activity also appears to explain some of the relationship between wealth and pollution levels. Cities with more economic concentration have a stronger and more positive relationships between wealth and pollution. This may be due to the relatively wealthy wishing to live closer to areas of concentrated economic opportunity – which may also be the most polluted areas. This is analogous to the mechanism that appears to drive the correlations between pollution and wealth at a country level – living in close proximity to economic opportunity can come at the cost of living closer to emissions sources.

There are several limitations to our results. First, we do not account for indoor air pollution, which is negatively correlated with urbanization[32] because rural households are more likely to cook with pollution-generating fuels. Relatively higher concentrations of indoor air pollution in rural areas suggests that the total burden of air pollution may be less positively correlated with wealth than the ambient concentrations examined here. In the extreme case, sufficiently high levels of indoor concentrations in rural areas could completely offset the positive correlation of ambient concentrations with wealth and lead to a regressive total burden of air pollution.

A second limitation is that we do not observe how ambient pollution levels translate to personal exposures and impacts. Personal exposures are mediated through the built environment,[33] patterns of commuting, and workplace conditions. Individuals living in neighborhoods with the same ambient pollution levels may not be personally exposed to the same amount of pollution because of differences in these conditions. For example, less wealthy neighborhoods may have lower quality housing and may therefore experience higher levels of infiltration than urban areas.[32] Greater wealth may also allow individuals to better insulate themselves from negative impacts for a given level of personal exposure[34] if, for example, wealth is correlated with better health care access. Therefore, even in countries where ambient pollution is higher in wealthier areas, the least wealthy members of society may still be most vulnerable to the negative impacts of air pollution.

We rely on spatially resolved estimates of wealth and $PM_{2.5}$ that are constructed by model predictions from observed inputs, particularly from satellite imagery. While both sets of predictions are trained using data collected on the ground for areas in which that data exists, they are useful precisely because data does not exist everywhere. In areas without ground collected data their accuracy cannot be verified. We confirm that our results are robust to using alternative measures of wealth and pollution (see Section SI-1.4) for the areas in which that data exists but these are also the areas where the algorithms would be expected to be most accurate. It is by construction uncertain how accurate the wealth and $PM_{2.5}$ predictions are in areas for which we have no ground data. If, for example, wealth is systematically underestimated in less polluted areas, or pollution levels are overestimated in wealthy areas, then our approach would overestimate the degree of progressivity in the pollution-wealth relationship. Conversely, if the wealth data systematically underestimates wealth in polluted areas or pollution is underestimated in poorer areas then our approach will underestimate the progressivity.

Understanding the distribution of ambient air pollution concentrations across wealth levels in LMICs is important for policymakers. The common perception that the least wealthy members of society typically live in the most polluted areas is not consistent with the empirical evidence presented here. Our results indicate the relationship around the world differs from that found in high income countries and varies across countries. The substantial heterogeneity we document highlights that the benefits of reducing ambient air pollution will accrue to different populations in different settings. Finally, our results emphasize that ambient air pollution is a problem in precisely the places that are engines of economic growth in most countries.[24] Failure to address the challenges of ambient air pollution in these settings is likely holding back economic growth.[35]

This work leaves open several important questions. In particular, more research is needed to understand if there is a consistent driver of the relationship between wealth and pollution across cities or whether these relationships are explained by idiosyncratic conditions. The answers will inform our understanding of the pollution burden around the world and how cities can be designed to maximize the economic opportunities they offer while minimizing the negative consequences of the pollution they generate.

4 Materials and Methods

4.1 Data

Wealth data–Our wealth data comes from recently published estimates of relative wealth on a 2.4×2.4 km grid for populated areas in 103 countries around the world.[25] These data use machine learning algorithms to combine satellite data, mobile phone data, and data from Facebook users to estimate relative wealth (RWI) within countries. The algorithms are trained on Demographic and Health Survey (DHS) collected measurements of wealth. The gridded wealth data provide estimates for each grid-cell of how wealthy that grid-cell is relative to others in the same country as well as an estimated error for that estimate. The relative wealth indicator ranges from -2.5 to 2.5 over the full data in our sample, with smaller ranges within individual countries.

As a robustness check we also re-estimate our model with the Demographic and Health Survey (DHS) derived wealth indices that the gridded wealth estimates were trained on.[36]

Pollution data–We use estimated pollution concentrations from the global dataset produced by the Van Donkelaar research group[29]. This provides monthly average pollution estimates on a 0.01×0.01 decimal degree covering the entire planet. We use the average of estimates spanning 2015 to 2020 and for each wealth grid cell assign it the value of the nearest $PM_{2.5}$ grid-cell. To calculate the average we collapse the monthly pollution estimates in three different ways. In our primary analysis we calculate the average across all years and months from 2015 to 2020. Secondly, we calculate the median across all months and years. Finally, we use the maximum monthly average level of particulates for each grid-cell for the month-of-year that had the highest average pollution from 2015 through 2020. For example, Delhi is assigned the average December $PM_{2.5}$ concentration because that is the month-of-year in which average particulate values are highest. In the analysis of the correlation between wealth and particulate pollution from non-dust and sea salt sources we use the dust and sea salt removed estimates produced by the Van Donkelaar group at the annual level and match to RWI points in the same way.

As a robustness check we also re-estimate our models with available ground monitor measurements of $PM_{2.5}$. All ground measurements come from the OpenAQ network (`https://openaq.org`).

Elevation data– We use data from NASA's ASTER project that provides a global digital elevation model (DEM) that provides elevation at 30m resolution comprehensively around the world.

Pollution source data–We use data from the EU EDGAR database that provides information on contribution of different economic sectors to particulate pollution for each point on a grid covering the whole planet. We aggregate these sectoral figures into broad categories (e.g. power generation) and calculate the total contribution of each broad category within each country based on the sum of the contributions of that broad category at each grid-cell within the country.

Urbanization data– We use data measuring urban and rural catchment areas from ref.[37] This data provides a pixel level estimate of the travel time to the nearest urban area (URCA). Pixels within an urban areas are assigned values that indicate they are within an urban area of various sizes. These values range from 1, indicating the pixel is in a city of at least 5 million people, to 30, indicating the pixel is in a rural hinterland. Values in between 1 and 30 indicate the pixel is in an urban area of increasingly smaller sizes (e.g. 20,000-50,000 people) or is less than 1 hours travel, 1-2 hours travel, or more than 2 hours travel time from a city of various sizes (e.g. 1 hour from a city of 20,000-50,000 people). We define pixels that fall within urban areas of any size as urban, those that are less than 1 hours travel from a city of any size as peri-urban, and those that are more than an hour's travel from a city as rural. These classifications are only for explanatory purposes, in all analysis we use the assigned score from 1-30. To classify RWI pixels we assign it the URCA value of the nearest URCA pixel. The plurality of grid-cells in our sample are in the peri-urban category (Figure SI-6).

Economic concentration– We use data from the Global Human Settlement Layer (GHSL) data product BUILT-V that measures the built-up volume of a pixel as the number of cubic meters of built volume in that pixel. We use a pixel size of 100m. We collected data on the NRES version of the BUILT-V product that only include non-residential built up area in the calculation of the built volume. For each city in our data we calculate the standard deviation in the BUILT-V-NRES value across the BUILT-V-NRES cells within that city. We normalize this value by dividing by the sum of the BUILT-V-NRES values within the city.

Country-level income– We use data from the World Bank World Development indicators to measure country level GDP per capita (constant 2015 US$) when we examine the correlation between pollution averaged across the entire country and income averaged across the entire country. We also use the Urban population (% of total population) at the country level in the same analysis. Data available here: `https://data.worldbank.org/`.

Data for additional heterogeneity analyses– In our analysis of heterogeneity by primary source of pollution we use data from the EU EDGAR database on the amount of $PM_{2.5}$ emitted from various different sources on a global grid. We assign grid points to countries (or cities) and calculate the total $PM_{2.5}$ emissions from each category of source in the EDGAR data (e.g. air transportation). We then aggregate into broad categories (e.g. transportation, industry, etc.). We then determine the primary source of emissions by summing all the categories and choosing the category that accounts for the largest share of the total. Data available here: `https://edgar.jrc.ec.europa.eu/`. For heterogeneity by history of colonization and equatorial location we assemble indicators for each country based on a review of the country's history of colonization (or status as a post-Soviet state) from various sources.

Income and pollution in the United Stats– To assess the correlation between income and ambient pollution in the United States we utilize census tract level median income from the American Community Survey 5-year estimate 2016-2020. Ambient pollution comes from the same $PM_{2.5}$ data used in the global analysis but averaged to the census tract level.

4.2 Methods

To measure correlation between wealth and ambient concentrations of pollution we estimate fixed effects regressions of the form:

$$PM_g = \beta RWI_g + \psi_c \tag{1}$$

where PM_g is the measure of pollution at RWI grid-cell g aggregated over our time period in one of the three ways described in the Data section. RWI_g is the RWI value at that grid-cell. ψ_c is a country fixed effect that we include in the pooled regressions (these are omitted in the country specific regressions). We employ various weighting schemes, weighting by: grid-cell population, the inverse of the reported RWI estimation error, the grid-cell population multiplied by the inverse of the error, the population of the country containing the grid-cell, and the inverse of the error times the population of the country containing the error.

In a separate analysis we compare the share of pollution in urban and rural areas coming from dust and sea salt to the share coming from other sources. To do this we first measure the average levels of exposure in rural and urban areas using the total $PM_{2.5}$ pollution data. We then repeat this calculation using the dust and sea salt removed measures of $PM_{2.5}$. We attribute the difference in these averages to dust and sea salt.

To assess heterogeneity we use several different approaches. To examine heterogeneity based on primary emissions sources, level of per capita income, or colonization history we simply stratify the sample by the relevant measure of heterogeneity and re-estimate equation 1 (omitting the fixed effects) within each country (or city) within each strata.

To assess the role that elevation plays in driving heterogeneity across cities we calculate the correlation between wealth and elevation separately within each city and the correlation between wealth and pollution within each city. We then run a simple OLS regression at the city level with the correlation between wealth and pollution as the dependent variable and the correlation between wealth and elevation as the independent variable. Our estimation, where i denotes cities, takes the form:

$$\text{Corr}(\text{Wealth/Pollution})_i = \beta \text{Corr}(\text{Wealth/Elevation})_i + \epsilon \tag{2}$$

We estimate a similar equation to assess how much of the variation in the correlation between wealth and pollution can be explained by economic concentration. In that specification we replace the *Corr(Wealth/Elevation)* term on the right hand side of equation 2 with the standard deviation of the volume of non-residential built up area in city i normalized by the total volume of non-residential built up area in city i from the Global Human Settlement layer.

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6 Data Availability

All data used in the study is publicly available. Links to the original data sources are provided in the methods section.

7 Code Availability

Code to replicate the results will be made available on the authors' websites.

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Supplementary Information

SI-1 Supplementary text

SI-1.1 Country level correlations

To provide context for the relationship between wealth and pollution globally we draw on data from the World Bank to estimate the country-level correlation across the entire world

The general intuition that pollution is higher in lower income countries is borne out by the country-level data. Two results stand out: first, as has been well documented, country-level average pollution is lower on average in higher income countries (Figure SI-1a). Only two countries with a per capita income above \$50,000 have average pollution levels above 20 $\mu g/m^3$ (Macau and Qatar). Countries with low levels of per capita income (less than \$15,000) span the full range of pollution levels but the majority have pollution concentrations above 25 $\mu g/m^3$. Simple cross-country regression confirms this correlation, every \$10,000 increase in per capita income, is associated with a decline in pollution of 1.8 $\mu g/m^3$ (*t-stat*: 4.3).

Second, consistent with the negative relationship between income and pollution the most polluted countries in the world are concentrated in Central and West Africa, the Middle East, and South Asia (Figure SI-1b-c). With the exception of the Middle East, these are among the lowest income regions in the world. Of the four countries that are notable outliers with pollution levels higher than would be expected given their income levels (labeled in Figure SI-1a), three are highly urbanized city states (The United Arab Emirates, Macau, and Monaco). The fourth, Qatar, has a significant portion of air pollution coming from natural pollution sources like dust storms.

SI-1.2 Heterogeniety by per capita income and pollution source

The spatial pattern of ambient particulate pollution, and hence its correlation with wealth, may also vary depending on the primary sources of particulate pollution and on country-level income. For example, in places where transportation is the primary source of emissions, high pollution areas may be less spatially concentrated than in places where pollution is primarily generated by industrial activity which is more likely to be concentrated in a handful of cities. Because the nature of economic activity changes at different levels of development[1] these spatial patterns may also vary by country-level per capita income.

We do not find evidence that suggests either of these hypotheses can explain our country level results. We observe similar patterns of heterogeneity across countries when we group by average per capita GDP or by the primary source of particulate pollution in the country.

Dividing countries into five bins based on per capita GDP (from \$0-\$2,000 to >\$8,000, all USD2015) we find that within every bin the range of correlations spans strongly negative to strongly positive (Figure SI-3a) suggesting that income alone does not explain the observed patterns. When we group countries based on their primary sources of particulate emission we observe similar patterns. Heterogeneity persists whether the primary source of pollution is the power, transport, industrial, or agricultural sectors (Figure SI-3c). While re-estimating the correlation between wealth and ambient pollution using the measure of $PM_{2.5}$ that removes dust and sea salt substantially reduces the number of countries with a negative relationship across all categories, there still do not appear to be clear patterns in the relationship between wealth and anthropogenic pollution across GDP or primary pollution sources (Figure SI-3b & d).

SI-1.3 City level heterogeneity

In seeking to explain the observed heterogeneity across cities we first classify city heterogeneity separately by strength (proxied by statistical significance) and by sign (whether relationship is positive or negative). We do this to account for the possibility that the drivers of these two different measures of heterogeneity may not be the same. For example, cities in which the relationship is weak and positive may be more qualitatively similar to cities with a weak but negative relationship than to cities with a strong positive relationship.

To better understand these dimensions of heterogeneity we focus on understanding three components of cities - the degree of pollution inequality, the degree of wealth inequality, and the proximity of wealthy neighborhoods to high pollution areas. In some cities pollution and wealth vary dramatically across neighborhoods while in other cities both are more uniformly distributed. Among cities with large ranges of wealth and pollution levels, settlement patterns could have resulted in highly different proximities of wealthy neighborhoods to polluted areas. Ultimately, understanding city-level heterogeneity requires understanding why some cities have high levels of variation in pollution while others do not, why there is large variation in wealth levels in some cities and not others, and, in cities with large variation in both wealth and pollution, why settlement patterns have resulted in the wealthy living in relatively higher pollution neighborhoods in some cities and relatively lower pollution neighborhoods in other cities.

We explore several potential answers to these questions.

In the main text we highlight that elevation does appear to be an important determinant in some cities, especially those with substantial changes in elevation within the city limits. This is because pollution is consistently lower at higher elevations. How wealth sorts across the elevation gradient varies by city however. In some, like Santiago, Chile the wealthy live at higher elevations.[2] In others, like Tbilisi, Georgia, the opposite is true. As a result, sometimes cities with a large change in elevation exhibit a positive relationship between wealth and pollution while in others the relationship is negative.

Concentration of economic activity may also play an important role in determining how much variation exists in pollution levels across a city and may be related to the fact that pollution is lower at higher elevations. In our data elevation is correlated with terrain roughness. Increased terrain roughness may make it more expensive to build in high elevation areas and so these locations may have fewer local sources of pollution. We measure concentration of economic activity as the standard deviation of the volume of non-residential built up area normalized by the total volume from the Global Human Settlement layer. This provides an estimate of how much the volume of non-residential built area varies across 100m cells covering each city. We observe that within cities elevation and terrain roughness both have a significant negative correlation with the volume of non-residential built area.

We also find that cities that have more concentration in their economic activity have larger and more positive correlations between wealth and pollution levels. A standard deviation increase in our measure of concentration is associated with a 0.12 standard deviation change [t-stat: 1.71] in the correlation between wealth and pollution. This increases to 0.22 standard deviations [t-stat: 1.88] if we focus only on the cities with a correlation between wealth and pollution that is significant at 5%. This relationship persists when we control for correlation between elevation and wealth.

Historical conditions are another potential factor that could influence all three components of cities today. European colonization has had a persistent impact on settlement patterns in many LMICs around the world.[3,4] In particular, choices about where colonizing rulers chose to live may have led to different patterns in where the wealthy live today. These choices may have been driven in part by the presence of tropical diseases[3] which would imply different patterns in equatorial countries. In addition, patterns of urban settlement in the Soviet Union may have evolved differently than non-Soviet countries due to central planning of urban development[5,6] in part because the allocation of apartments based on employment in economically prioritized sectors may have resulted in less sorting by wealth than in non-Soviet locations that has persisted.[7]

We examine whether any of these factors explain the patterns of heterogeneity that we measure. We find that they do not. There is little difference in the pattern of heterogeneity with respect either to magnitude, significance or sign within city groups based on their containing country's history of European colonization (Figures SI-11 & SI-12), whether they are located in equatorial regions, or whether they were part of the Soviet Union. Like with the country level results there also do not appear to be differences based on the primary source of particulate pollution within the city (Figure SI-13).

As a contrast to our city level results in LMICs, in Figure SI-10 we examine these relationships in three of the largest cities in the United States (Los Angeles, Houston, and New York City).

In all three of these cases the relationships we observe are less stark than in the LMICs in our sample. This is consistent with differential patterns of residential sorting in the United States – in particular, greater suburbanization in the United States leading to lower pollution exposure[8] – driving a different relationship between pollution exposure and wealth. It is also consistent with a relatively weak relationship between income and ambient pollution exposure in the United States.[9]

SI-1.4 Robustness of Results

Our results are robust to a variety of alternative specification and data choices. Measuring pollution as the median across months and years, rather than the average, in our sample results in broadly similar results (Table SI-1). The choice of weighting scheme appears to matter more when pollution is measured as the median and the magnitude of the correlation is somewhat smaller. In particular, weighting by grid-cell population eliminates the correlation in the pooled sample when using the median. This suggests there are a few grid-cells with very high populations that do not exhibit any correlation between wealth and median pollution but do exhibit a correlation when pollution exposure is measured using the average level of pollution. We believe that using average pollution is a more appropriate measure than median pollution because the average is sensitive to extremely high values of pollution that may be particularly harmful (e.g. spikes in Delhi during the crop burning season).

Alternatively, we can calculate the average level of pollution by month for each grid-cell in our sample and assign the average value of the month with the highest average level of pollution to each grid-cell. This approach focuses heavily on the spikes that might occur as a result of seasonal crop burning or forest clearing or due to seasonal increases in dust storms. Using this approach yields results that are qualitatively similar to using the average across the full sample but the magnitudes of the correlation are larger in the maximum approach (Table SI-1).

Comparing the country specific estimates of the correlation between wealth and pollution exposure, Figure SI-4, indicates broad agreement in the estimated correlation when exposure is measured as median or average levels of pollution. Most countries fall on or near the 45° line.

There is less agreement between the maximum measure and the average measure however. At the extremes the qualitative patterns seem to persist - Nigeria for example has a negative correlation with both measures and has the strongest negative correlation in the sample. The notable exception is India and Pakistan (which are treated as a single unit in the RWI data, a choice we preserve), which has a substantially higher positive correlation using the maximum measure rather than the average measure. This is likely driven by very high levels of pollution in some North Indian cities during December. One possible explanation for these somewhat divergent results using the maximum measure rather than the average measure is that the maximum measure captures large, non- or semi-anthropogenic sources of pollution that may spike in certain months (e.g. seasonal forest burning).

We also examine whether our results are sensitive to alternative data on wealth, using data from DHS clusters, or pollution, using ground based monitor data. In both cases the sample we are able to analyze using the alternative datasets is smaller than our global sample because of a lack of comprehensive data covering all 103 countries in our sample.

When we estimate the country-specific correlation using DHS wealth data and our global pollution data set we find the same general pattern of correlation with roughly half the countries exhibiting a positive relationship between wealth and pollution (Figure SI-7). Nigeria and Nepal remain the countries with the most negative and most positive correlations respectively. There are some countries where the sign of the correlation flips when using the DHS data relative to RWI but in general there is broad agreement in sign and magnitude across the two data sets (Figure SI-8).

We also examine the trend in pollution within the seven countries for which we have pollution data from ground monitors that represent at least 10 distinct RWI grid-cells. Figure SI-9 shows that in most of these countries, including all of those for which we have the largest number of ground monitors, the relationship between pollution and wealth is qualitatively similar when calculated using satellite measures of pollution or ground monitors. In the same figure we highlight which ground monitors are in urban or rural settings to underline the point that restricting analysis to those places with ground monitors will often result in the omission of most rural locations and so will fail to capture the urban-rural gradient that appears to be at the heart of our primary results. In several of the countries included in this sample there is only data from one or two rural ground monitors for the entire country. There is also often substantial temporal gaps in ground monitor data, on average ground monitors only report measurements in 45% of the months over which we have satellite measures of pollution. This can also lead to substantial bias when using ground monitor data if the ground monitor data is missing observations during particular seasons when pollution spikes (or is only available in those seasons).

In our city level results the choice of city boundaries is an important determinant of the sign and magnitude of the within-city correlation. The overall pattern of heterogeneity remains regardless of which precise city boundary is chosen but estimates for individual cities do change. In contrast, the threshold for the minimum level of RWI points within a city does not change our results in the range from 10 to 50.

In Figure SI-14 we show how the point estimates change for three cities in our data for which we have both the URCA designated boundaries as well as administrative boundaries. In some cases (e.g. Delhi) the URCA and administrative boundaries align relatively closely but in others they differ sharply (e.g. Rio de Janeiro). In general the URCA designated boundaries we use align well with boundaries drawn using other gridded products (e.g. Global Human Settlement Layer and the World Settlement Layer). How these boundaries are defined is both somewhat arbitrary and, as the changing signs in the cases of Lagos and Rio de Janeiro show, important for the estimation of correlations. This is true, at least in part, because a more geographically expansive definition of a city's boundaries is more likely to capture differences in ambient pollution levels driven by the gradient in pollution and wealth between urban and peri-urban/rural that we highlight in our country level results.

SI-1.5 Kuznets curves discussion

Taking advantage of the granularity of our data we examine whether they provide evidence for the existence of Environmental Kuznets Curves (EKC) within the countries in our sample. We do not find compelling evidence that the relationship between pollution exposure and wealth fits the hypothesized inverted U pattern either across the full sample or within individual countries.

Figure SI-15 plots the average level of pollution for all grid-cells within various RWI bands across all the countries in our sample. In Figure SI-16 we plot the same for the ten most populous countries in our sample. Lighter grey point represent the relationship at the most dis-aggregated level of RWI while green and blue dots indicate results averaging within larger bandwidths of RWI. In all cases we fail to see strong evidence of an inverted U. The relationships that we do observe vary across countries, consistent with our previous results. This variation includes countries in which pollution levels are higher at higher wealth levels to those with flat to declining or declining pollution levels moving up the wealth distribution depending on the country.

SI-2 Supplementary Tables

Table SI-1: Correlation between RWI and $PM_{2.5}$

	Unweighted	Population weighted	Country population weight	Error weighted	Jointly weighted	Country jointly weighted
(A) $PM_{2.5}$ measured as average						
Wealth Index	0.748***	0.549***	1.851***	0.643***	0.467***	1.701***
	(0.018)	(0.098)	(0.060)	(0.019)	(0.094)	(0.058)
	[<0.00009]	[<0.00009]	[<0.00009]	[<0.00009]	[<0.00009]	[<0.00009]
N	2,672,997	2,672,372	2,672,997	2,672,997	2,672,372	2,672,997
(B) $PM_{2.5}$ measured as median						
Wealth Index	0.421***	0.047	0.412***	0.350***	-0.001	0.321***
	(0.016)	(0.081)	(0.050)	(0.016)	(0.077)	(0.050)
	[<0.00009]	[0.5574]	[<0.00009]	[<0.00009]	[0.9859]	[<0.00009]
N	2,672,997	2,672,372	2,672,997	2,672,997	2,672,372	2,672,997
(C) $PM_{2.5}$ measured as average during maximum month						
Wealth Index	2.269***	1.537***	8.496***	2.025***	1.534***	8.278***
	(0.032)	(0.208)	(0.119)	(0.031)	(0.194)	(0.113)
	[<0.00009]	[<0.00009]	[<0.00009]	[<0.00009]	[<0.00009]	[<0.00009]
N	2,679,731	2,678,430	2,679,731	2,679,731	2,678,430	2,679,731
Fixed Effects:						
Country	Y	Y	Y	Y	Y	Y

NOTES: Each column reports the results of a linear fixed effects regression of pollution against RWI at the grid-cell level across all countries in our sample. Each row is a seperate regression. RWI is a country specific wealth index that ranges across our full dataset from -2.022 to 2.456. We collapse pollution across all months and years in the sample by RWI grid-cell. In row **A** we collapse as the average across all months and years. In row **B** we collapse as the median. In row **C** we calculate the monthly average across all years and assign grid-cells the average in the month with the highest monthly average. Population weights by the population at the RWI grid-cells. Error weights by the inverse of the error reported by the creators of the RWI data for each RWI estimate. Joint weights by both population and the inverse of the error. Country population weights by the total population of the countries in which the grid-cell is located. Country jointly weights by the country population and the inverse of the error. p-values reported in brackets. (* p<.10 ** p<.05 *** p<.01).

Table SI-2: Correlation between RWI and $PM_{2.5}$, winsored

			Top & bottom 5% sample		
	Winsored across	Winsored within	Pooled	Bottom 5%	Top 5%
(A) $PM_{2.5}$ measured as average					
Wealth Index	2.098***	2.158***	-0.035	-6.721***	-2.383***
	(0.064)	(0.064)	(0.087)	(0.924)	(0.539)
	[<0.00009]	[<0.00009]	[0.6920]	[<0.00009]	[<0.00009]
N	2,672,997	2,672,997	268,145	134,482	133,663
(B) $PM_{2.5}$ measured as median					
Wealth Index	0.516***	0.573***	-0.955***	-6.727***	-2.523***
	(0.055)	(0.055)	(0.075)	(0.840)	(0.445)
	[<0.00009]	[<0.00009]	[<0.00009]	[<0.00009]	[<0.00009]
N	2,672,997	2,672,997	268,145	134,482	133,663
(C) $PM_{2.5}$ measured as average during maximum month					
Wealth Index	9.664***	9.705***	4.681***	0.599	-2.761***
	(0.124)	(0.124)	(0.164)	(1.628)	(1.045)
	[<0.00009]	[<0.00009]	[<0.00009]	[0.7129]	[0.0082]
N	2,679,731	2,679,731	268,842	134,646	134,196
Fixed Effects:					
Country	Y	Y	Y	Y	Y

NOTES: Each column reports the results of a linear fixed effects regression of pollution against RWI at the grid-cell level across all countries in our sample. Each row is a seperate regression. RWI is a country specific wealth index that ranges across our full dataset from -2.022 to 2.456. We collapse pollution across all months and years in the sample by RWI grid-cell. In row **A** we collapse as the average across all months and years. In row **B** we collapse as the median. In row **C** we calculate the monthly average across all years and assign grid-cells the average in the month with the highest monthly average. We winsorize at the fifth and ninety-fifth percentiles of the RWI distribution across the whole sample in the Winsored across column and at the same thresholds within countries in the Winsored within column. In columns 3-5 we calculate the top and bottom 5% of RWI points within each country and only include the points that fall into the categories indicated in the column headings. We weight all regressions by the inverse of the error reported in the RWI data multiplied by the population containing the grid point. p-values reported in brackets. (* p<.10 ** p<.05 *** p<.01).

Table SI-3: Colonization history and city correlations

	Base	Dust and SS removed	Base	Dust and SS removed	Base	Dust and SS removed
British	0.174	-0.092				
	(0.269)	(0.331)				
	[]0.5179	[]0.7809				
French	-0.039	-0.267				
	(0.418)	(0.515)				
	[]0.9253	[]0.6043				
Spanish/Portuguese	0.098	-0.592*				
	(0.287)	(0.353)				
	[]0.7333	[]0.0952				
Other	-0.242	1.176**				
	(0.372)	(0.458)				
	[]0.5161	[]0.0107				
Equitorial			0.350*	0.261		
			(0.208)	(0.263)		
			[]0.0934	[]0.3225		
Post-soviet					0.007	-0.239
					(0.271)	(0.343)
					[]0.9782	[]0.4853
N	273	273	273	273	273	273

NOTES: The unit of observation for all regressions is a city in our data. All columns regress the coefficient for the within-city correlation between RWI and average $PM_{2.5}$ as calculated with or without dust and sea salt (denoted in column headings) against a series of dummies indicating the colonization history of the country containing the city. In the first and second column the omitted category are countries that were never formally colonized by a European power prior to WWI. Equitorial countries are those between the Tropic of Capricorn and the Tropic of Cancer. Post-soviet countries are those that were formally part of the Soviet Union. *p*-values reported in brackets. (* p<.10 ** p<.05 *** p<.01).

SI-3 Supplementary Figures

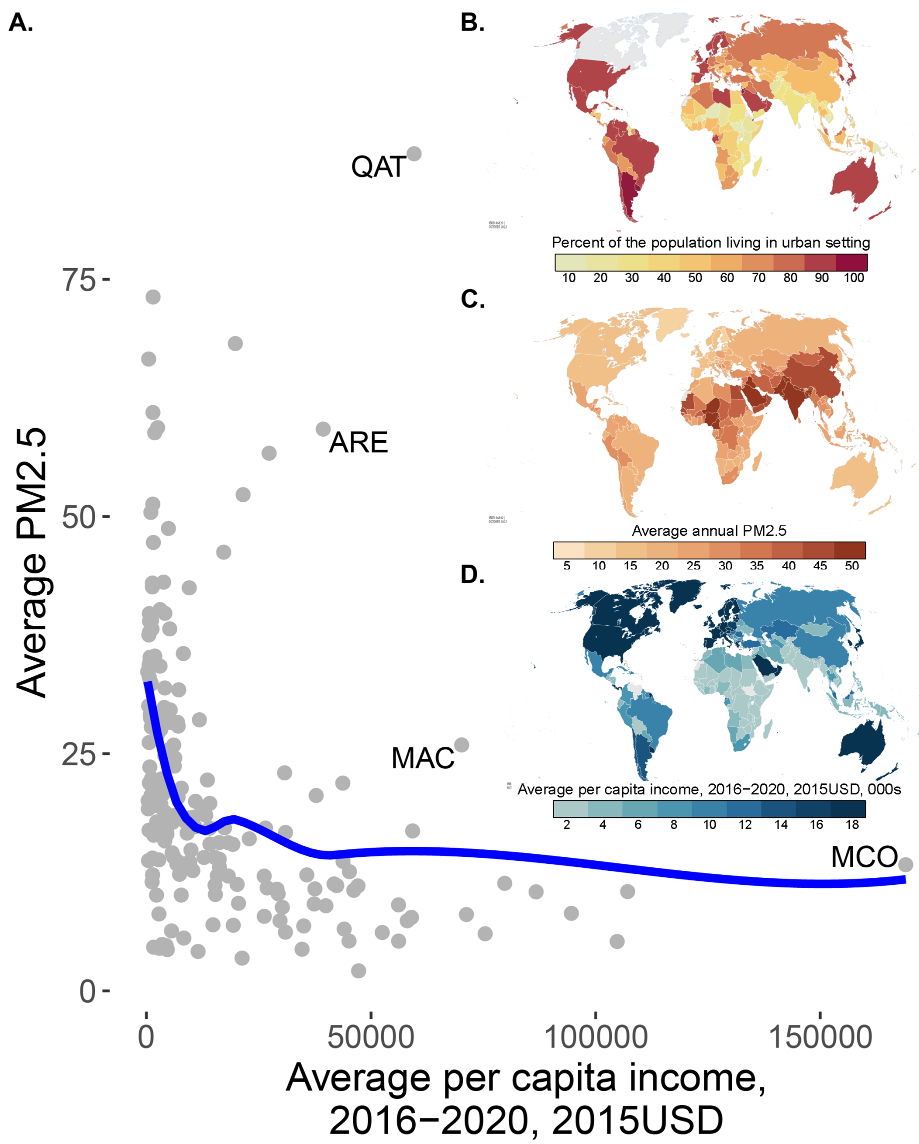


Figure SI-1: Global relationship between pollution, income, and urbanization– Across countries pollution tends to decline as average per capital income, measured by the World Bank Development Indicators, increases (**Panel a**). The labelled outliers are Qatar, the United Arab Emirates, Macao, and Monaco. Areas with higher shares of the population living in urban areas, as measured by the World Bank Development Indicators, (**Panel b**) tend to have lower levels of pollution (**Panel c**) and higher levels of income (**Panel d**).

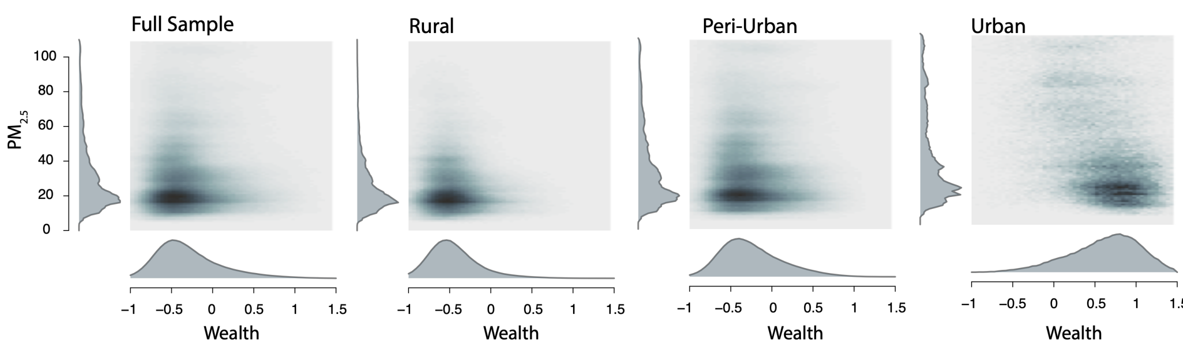


Figure SI-2: Joint distribution of wealth and $PM_{2.5}$ in urban, peri-urban, and rural areas– grid-cells are classified as urban (1-7), peri-urban (8-14), or rural (>14) based on their URCA score. The figure plots the density of grid-cells at a given RWI index - $PM_{2.5}$ concentration combination, within each category of urbanicity. Darker colors indicate more observations.

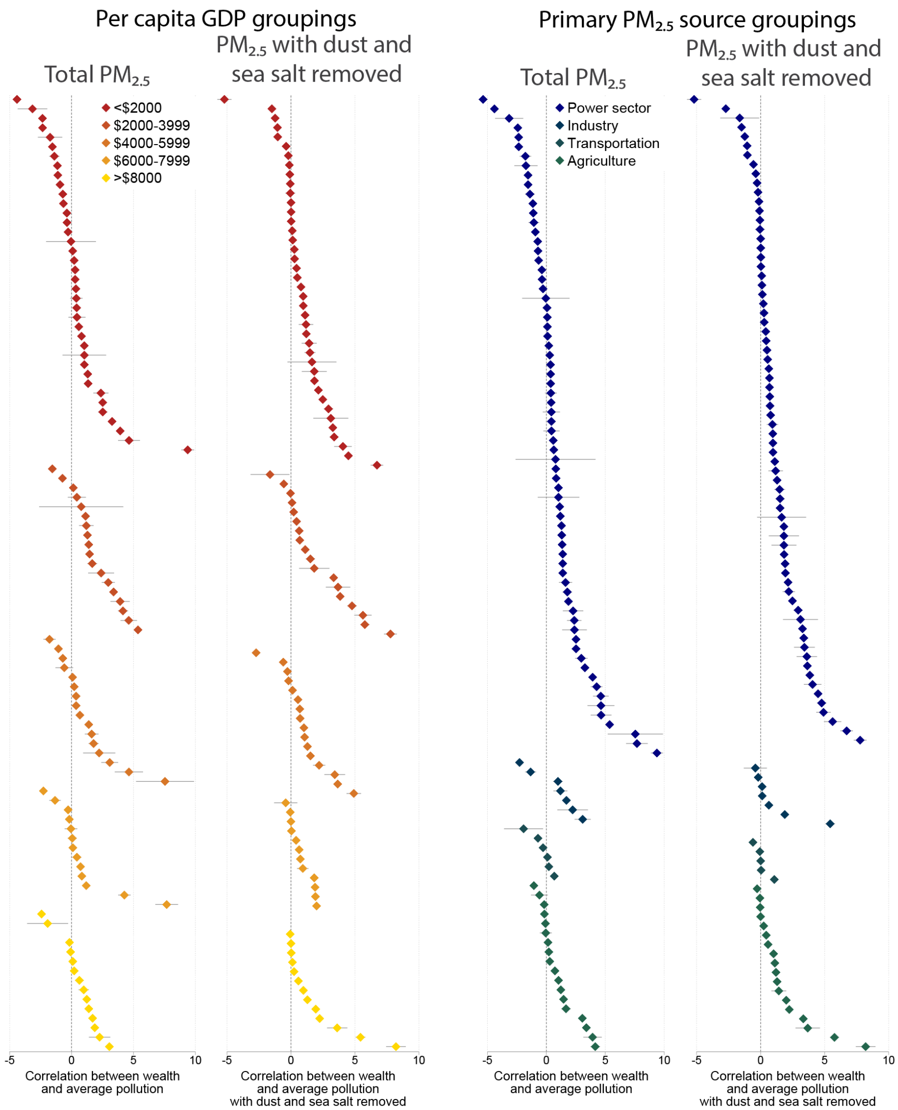
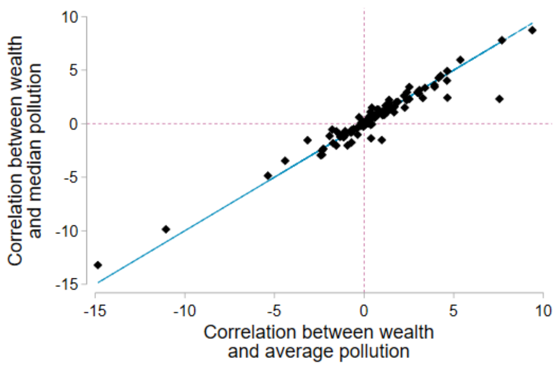
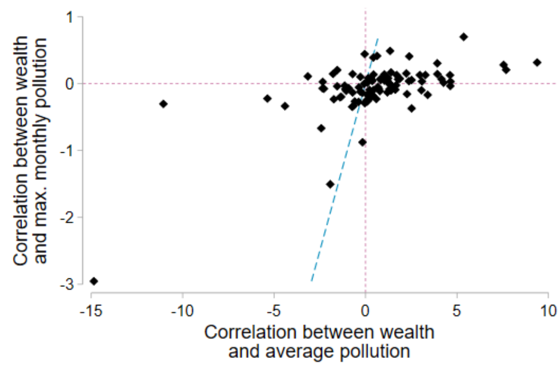


Figure SI-3: Correlation between wealth and pollution by income and primary $PM_{2.5}$ source–The plots on the left plot correlation between wealth and pollution estimated at the country-level (each dot is a country level coefficient) where countries are grouped by per capita GDP in 2019 from the World Bank's World Development Indicators data. The plots on the right show the same but countries are grouped by their primary source of $PM_{2.5}$ based on data from the EU EDGAR database. In both sets of plots the plot on the left shows the correlation estimated using total $PM_{2.5}$ data while the plot on the right show the correlation estimated using $PM_{2.5}$ data that has dust and sea salt removed.



(a) Mean vs. Median



(b) Mean vs. Max

Figure SI-4: Correlation between average pollution and alternative aggregations–In all panels the dashed line is 45° and each regression is weighted by the inverse of the error multiplied by the population surrounding the grid-cell. In **Panel a** each dot is the country-level coefficient from a country-specific regression of pollution against RWI when pollution is measured as the average over the sample period vs. measuring it as the median over the period. **Panel b** plots the the coefficietns with pollution measured as the average over the period vs. measuring it as the average in the month with the highest monthly average over the period (e.g. the month with the highest monthly average in India is December and so we use each grid-cell's December monthly average over the sample as the measure for pollution exposure in that grid-cell).

Figure SI-5: Correlation between wealth and pollution vs. wealth and elevation– Each point is a city in our data. The correlation between wealth and elevation (x-axis) is the estimated coefficient from a regression of RWI and average elevation at the grid-cell level within each city. The correlation between wealth and average pollution (y-axis) is the estimated coefficient from a regression of RWI and average $PM_{2.5}$ at the grid-cell level within each city. Cities are defined as contiguous areas with URCA scores of less than 6 and with at least 30 RWI points.

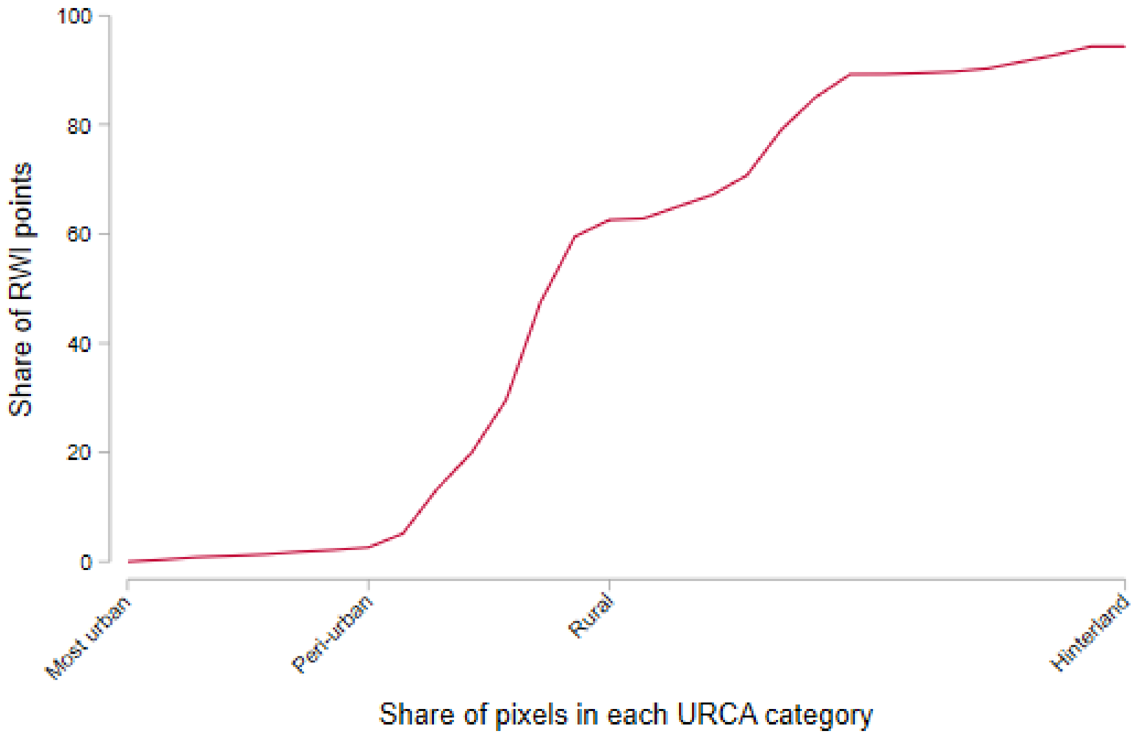


Figure SI-6: CDF of urban pixels–The red line indicates the cumulative share of RWI grid-cells that fall into each URCA category starting at 1 and increasing to 30. The "Peri-urban" label is placed at an URCA value of 8. The "Rural" label is placed at an URCA value of 15. The "Hinterland" is placed at an URCA value of 30. RWI grid-cells are assigned the urban score of the nearest pixel.

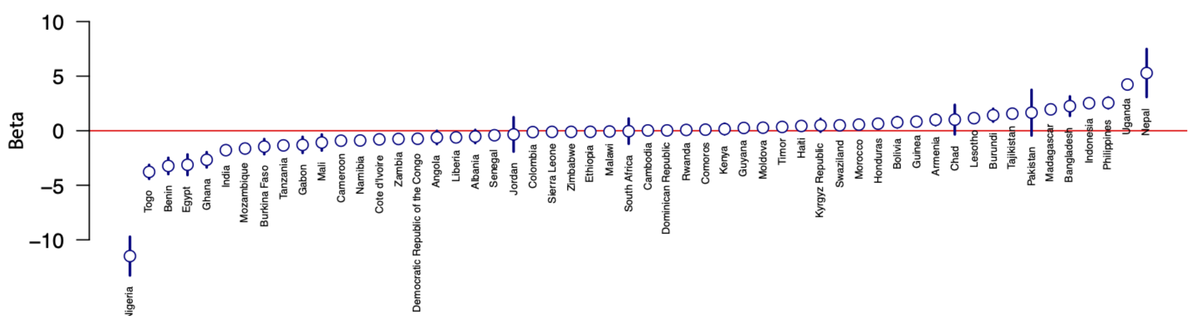


Figure SI-7: Correlation between average pollution and wealth using DHS data–Each point plots the country-level coefficient from a country-specific regression of average pollution on wealth. However, wealth is measured using DHS cluster data rather than RWI. As with the RWI data the outliers at the negative and positive ends (Nigeria and Nepal) are exactly the same.

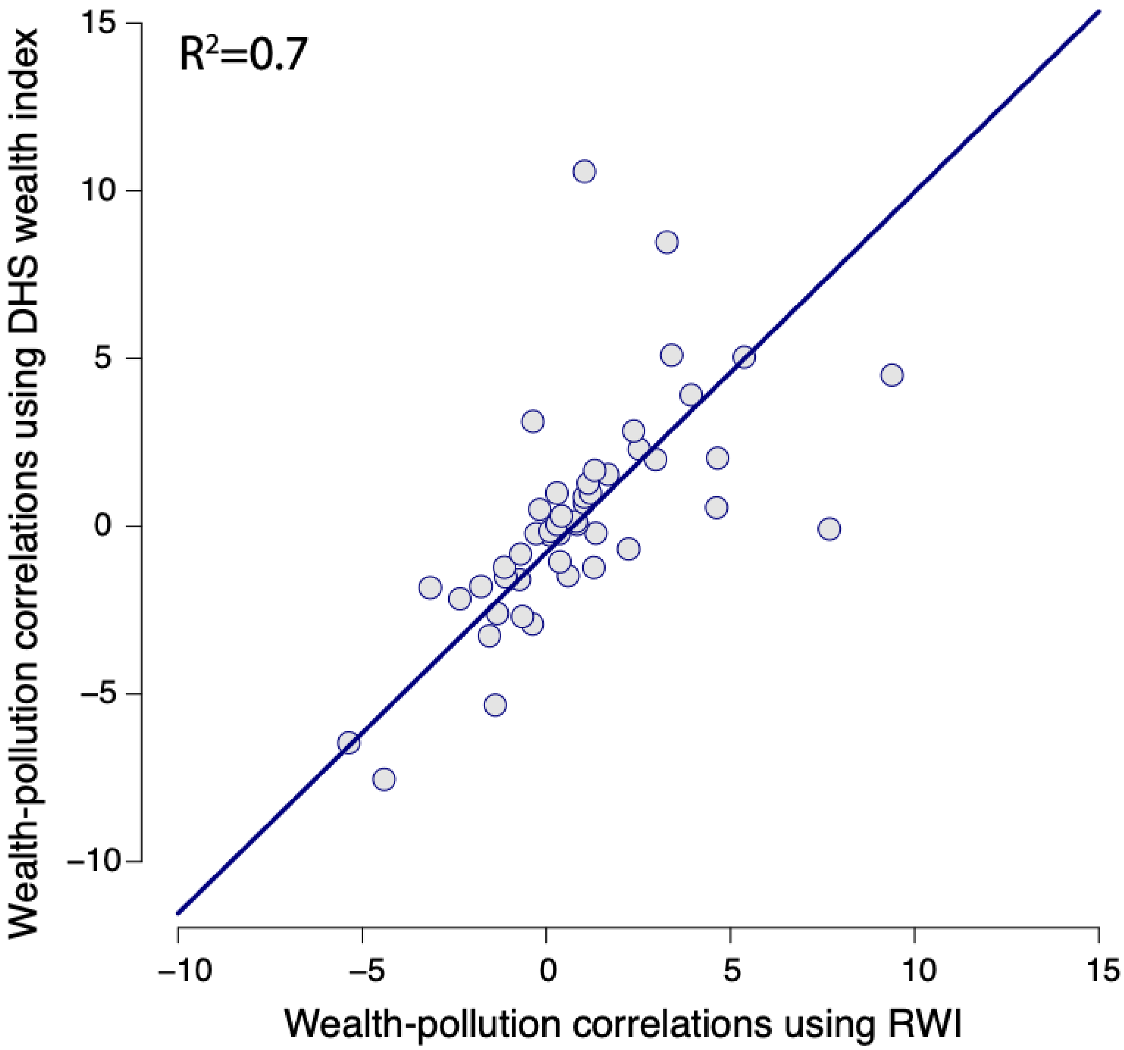


Figure SI-8: Estimating the pollution-wealth relationship across wealth datasets– Each point is a country. The y-axis indicates the correlation between average pollution and wealth estimated using DHS data to measure wealth. The x-axis reports the same correlation but using the RWI data used in our analysis[10] to measure wealth. Solid line indicates the best-fit and dotted line indicates the 45 degree line. The R^2 associated the best-fit line is 0.7.

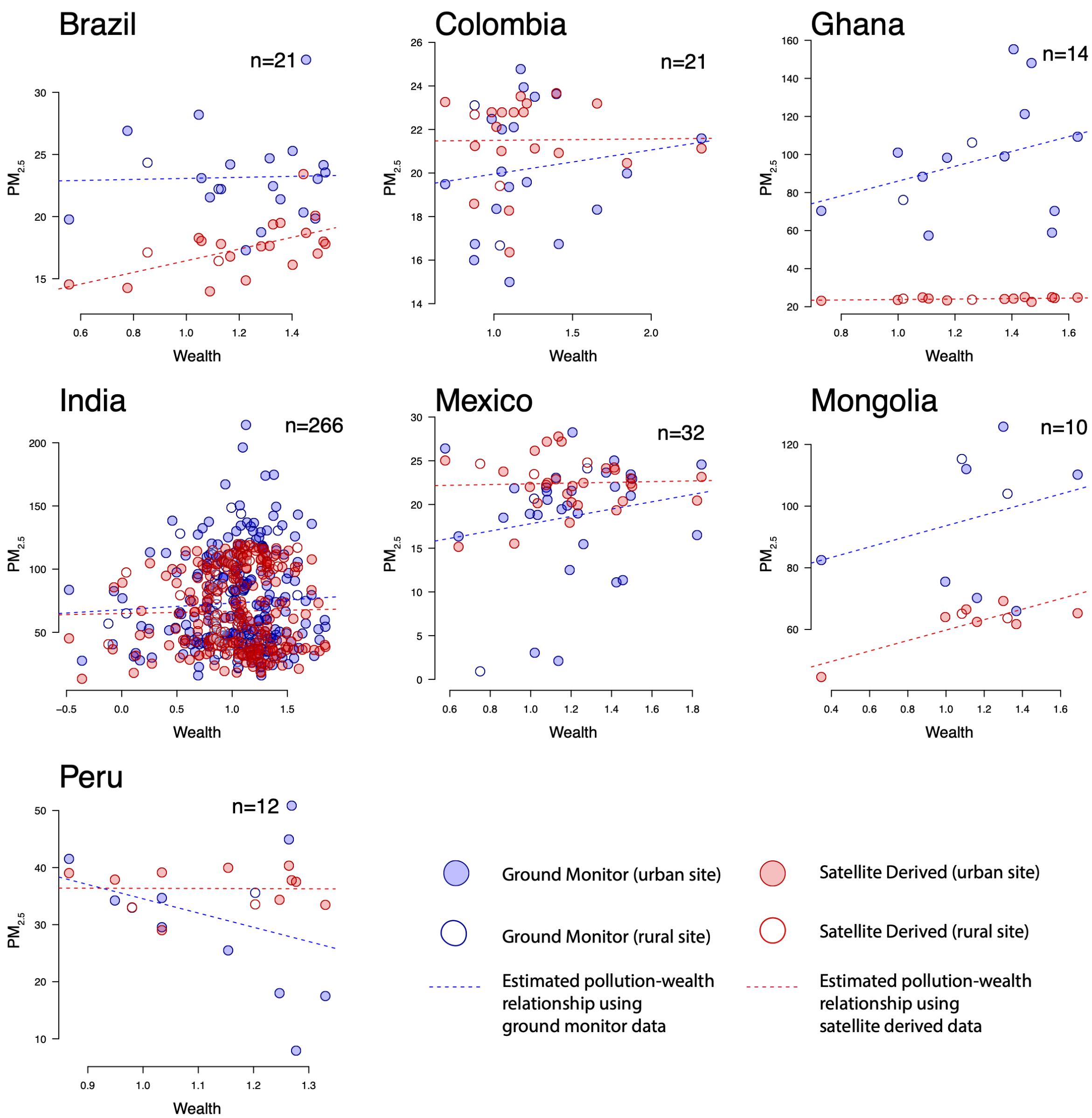


Figure SI-9: Estimating the pollution-wealth relationship across $PM_{2.5}$ datasets– Each panel shows a wealth-$PM_{2.5}$ scatter and best-fit line estimated using relative wealth data combined with either $PM_{2.5}$ measured by ground monitors (blue) or $PM_{2.5}$ from the satellite based estimates used in our main analysis (red). Each observation corresponds to the same ground monitor sites. For the comparison we replace the ground monitor measurements with the grid cell level satellite derived $PM_{2.5}$ estimates. Most ground monitors are sited in urban locations (filled in circles) with very few rural monitors. Comparison was limited to countries with wealth data that had at least 10 ground pollution monitors.

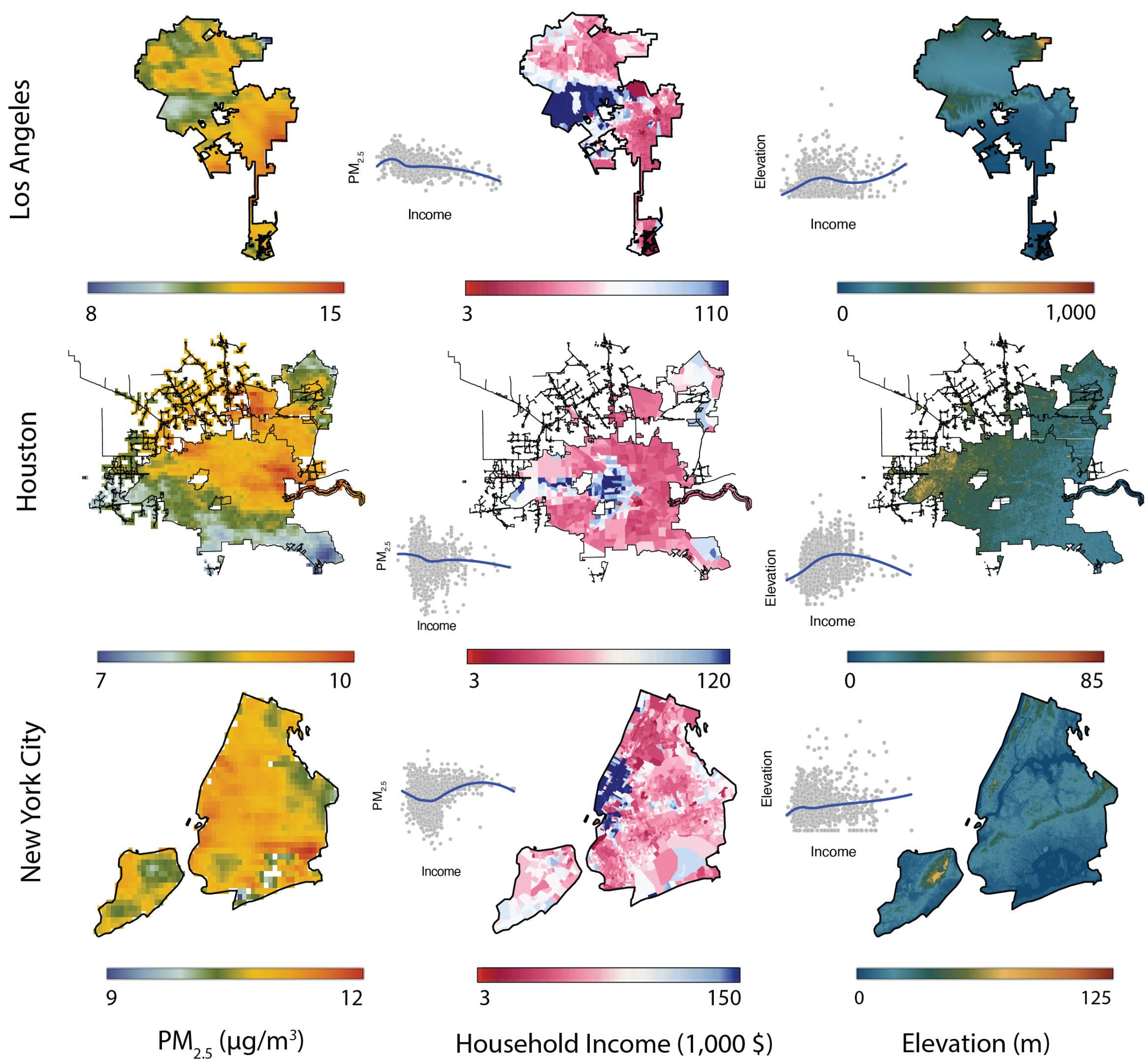
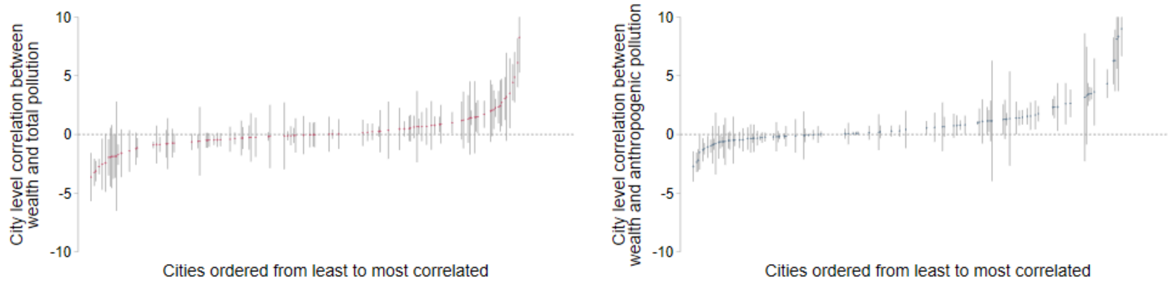
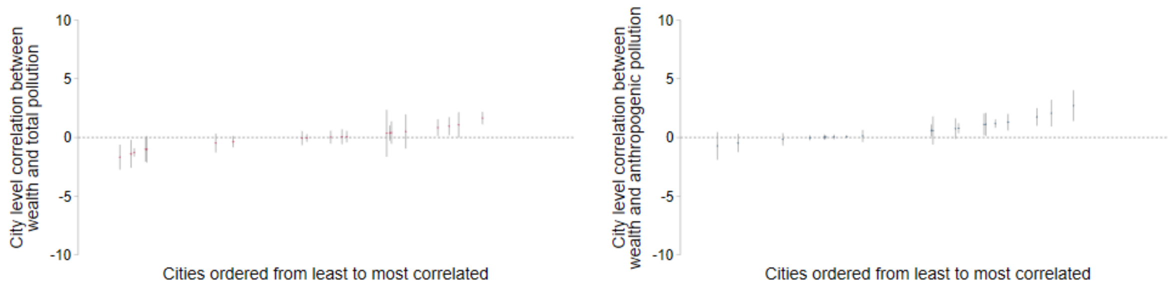


Figure SI-10: Within urban variation in pollution, wealth, and elevation for select U.S. cities– Average $PM_{2.5}$, average census-tract household income, and elevation for three of the largest US cities. Scatter plots show cell level values and and best fit lines. To illustrate within-city changes the color scales are tailored to each city. Colors are therefore only comparable across cities in relative, not absolute, terms.

British



French



Spanish/Portuguese

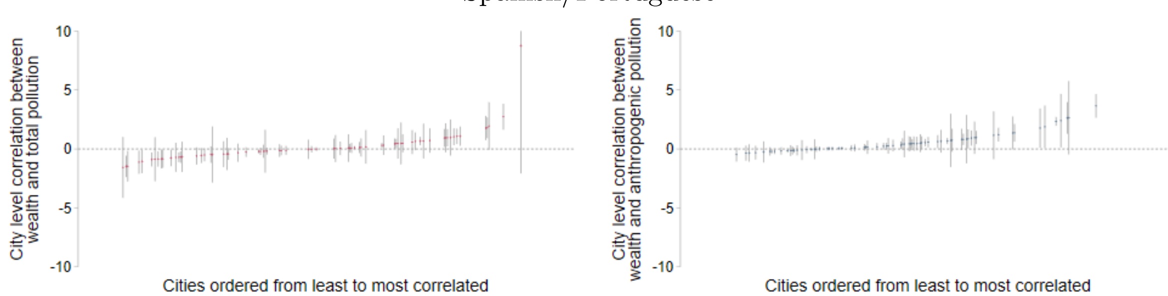


Figure SI-11: City level heterogeneity by colonization history–Each panel graphs the correlations plotted in Figure SI-3a separately based on the containing country's history of colonization by European countries. "Other" refers to colonization primarily by Germany, Italy, Belgium, or the Netherlands. "Never" refers to countries that were never formally colonized (e.g. Ethiopia) prior to World War I. Assignment of European countries is based on the dominant colonial power prior to World War I. "Equatorial" indicates that the containing country lies between the Tropic of Cancer or Capricorn. "Post-Soviet" indicates that the containing country was once part of the Soviet Union. Red curves (left column) indicate estimates based on total particulate pollution and blue curves (right column) indicate estimates based on particulate pollution with dust and sea salt removed. The grey spikes indicate 99% confidence intervals. Two countries whose correlation is less than -5 are omitted.

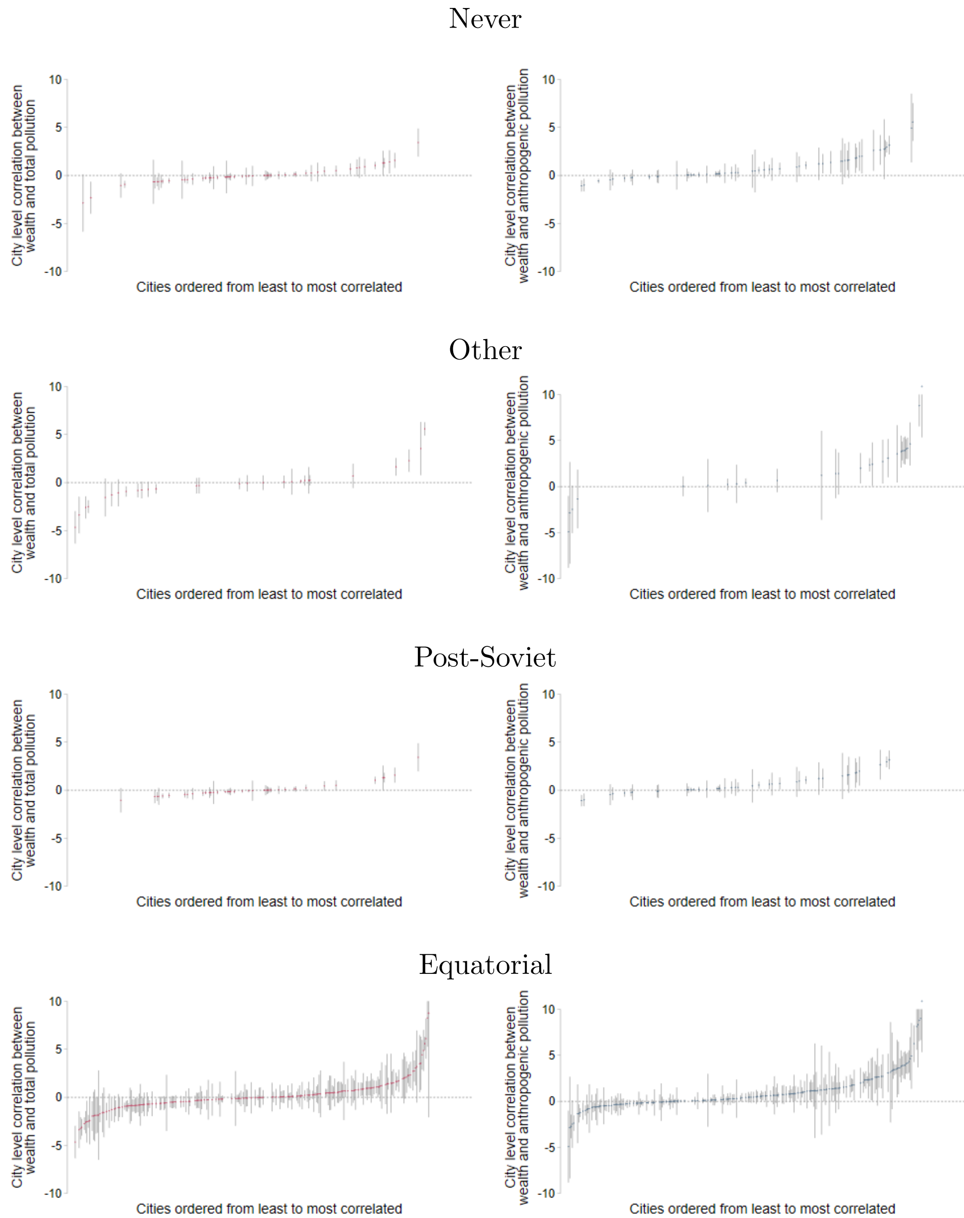


Figure SI-12: City level heterogeneity by colonization history (con't)–Each panel graphs the correlations plotted in Figure SI-3a separately based on the containing country's history of colonization by European countries. "Other" refers to colonization primarily by Germany, Italy, Belgium, or the Netherlands. "Never" refers to countries that were never formally colonized (e.g. Ethiopia) prior to World War I. Assignment of European countries is based on the dominant colonial power prior to World War I. "Equatorial" indicates that the containing country lies between the Tropic of Cancer or Capricorn. "Post-Soviet" indicates that the containing country was once part of the Soviet Union. Red curves (left column) indicate estimates based on total particulate pollution and blue curves (right column) indicate estimates based on particulate pollution with dust and sea salt removed. The grey spikes indicate 99% confidence intervals. Two countries whose correlation is less than -5 are omitted.

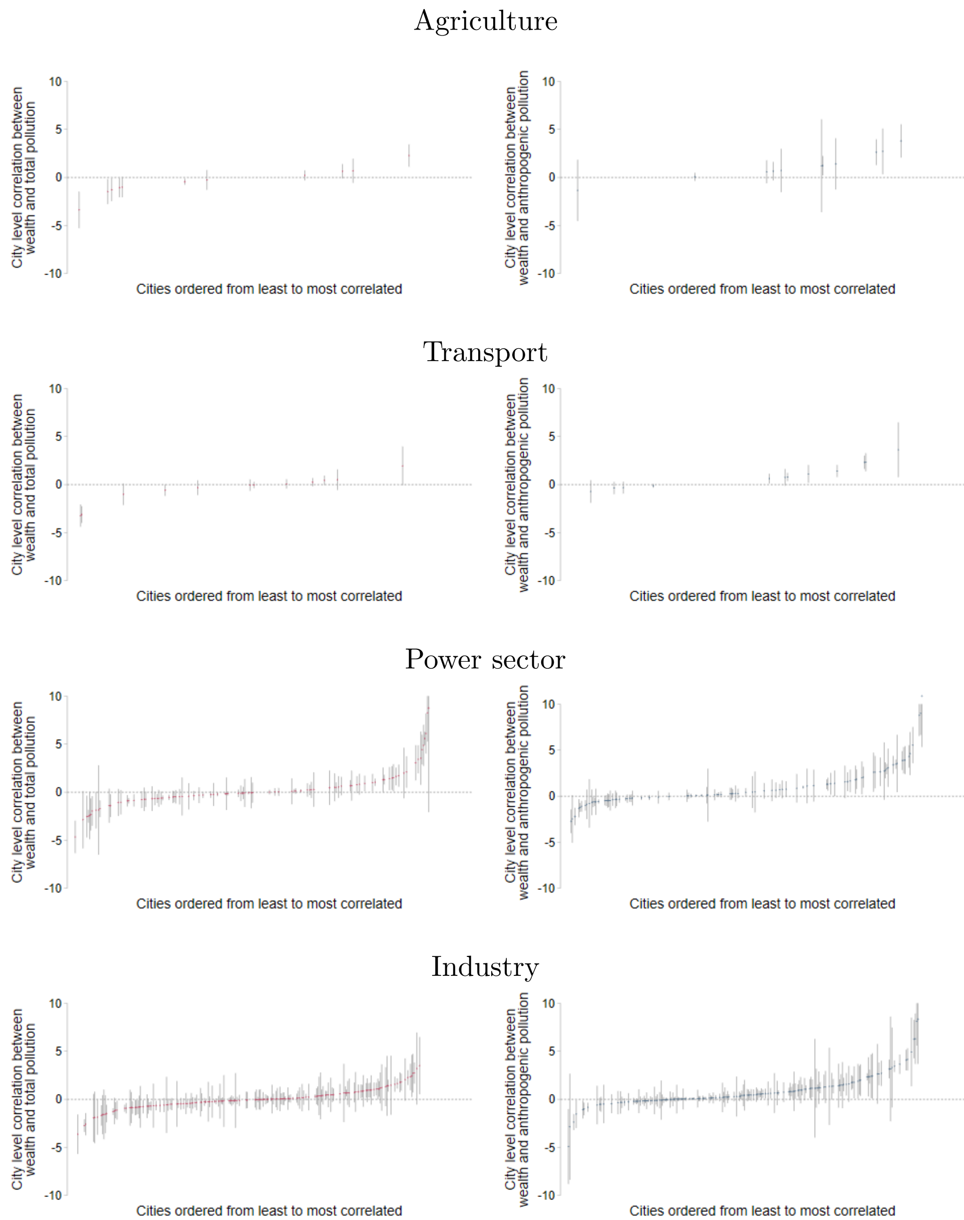


Figure SI-13: City level heterogeneity by pollution source–Each panel graphs the correlations plotted in Figure SI-3a separately based on the primary source of particulate pollution in a given city. Data on sources comes from the EU EDGAR database. The primary source is determined by summing across all sources and all grid-cells within a city and choosing the sector with the largest total. Red curves (left column) indicate estimates based on total particulate pollution and blue curves (right column) indicate estimates based on particulate pollution with dust and sea salt removed. The grey spikes indicate 99% confidence intervals. Two countries whose correlation is less than -5 are omitted.

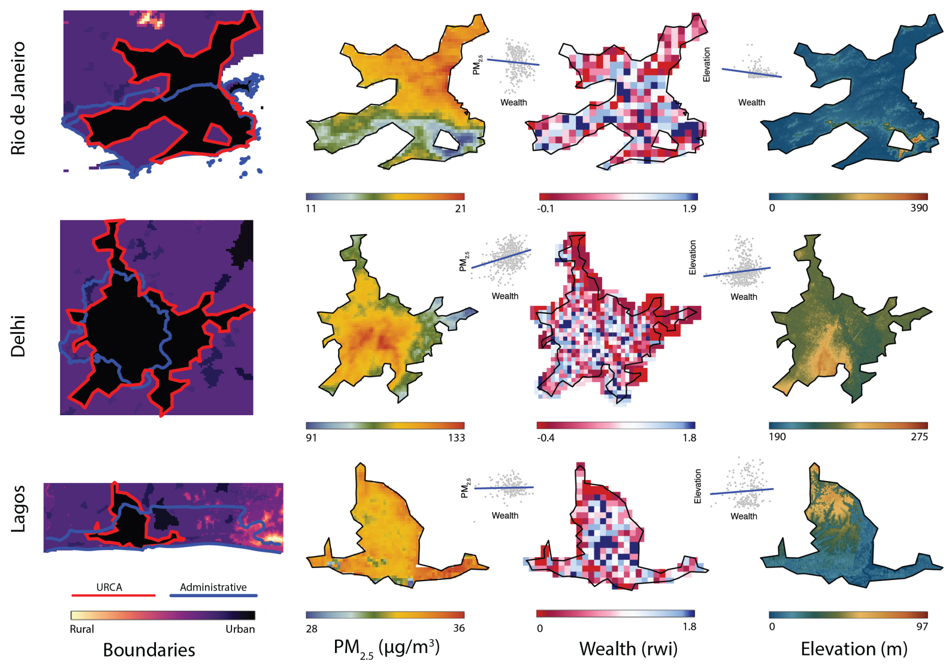


Figure SI-14: Importance of city boundary choice–Column 1 shows the outlines of each city based on the URCA designation and the official administrative boundaries. Columns 2-4 show the levels of pollution, wealth, and elevation using the URCA boundaries.

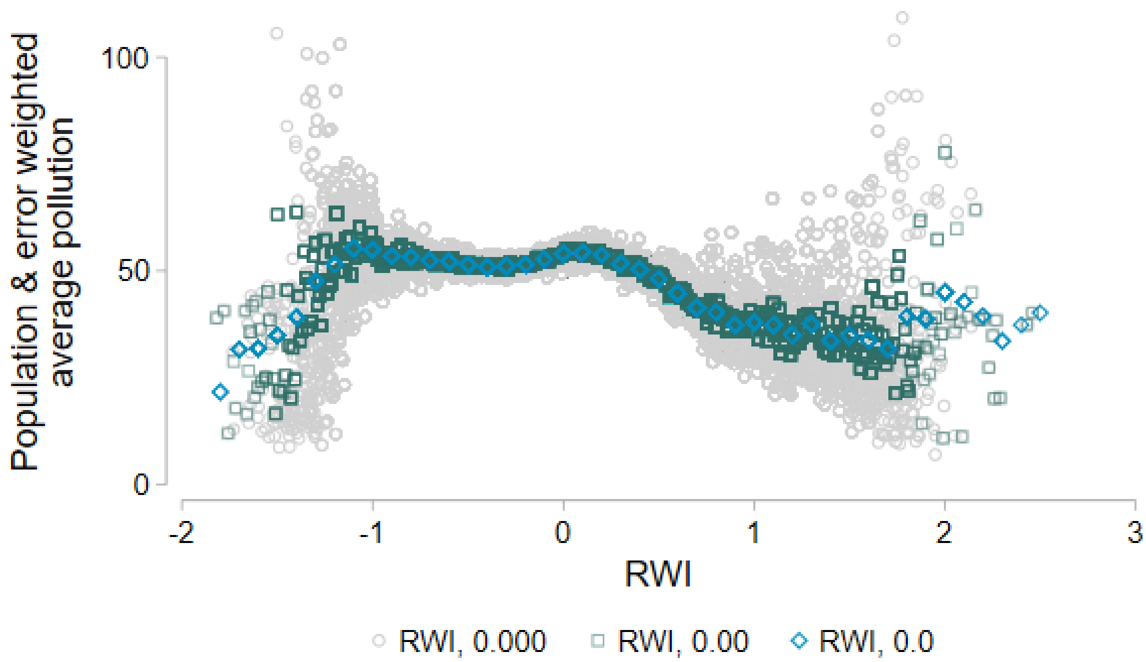
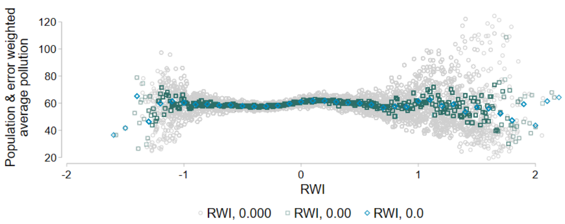
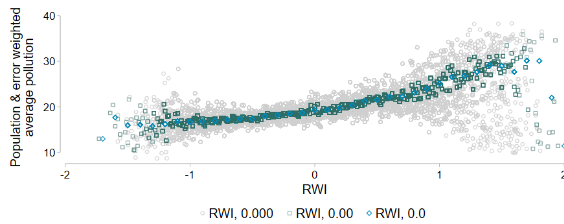


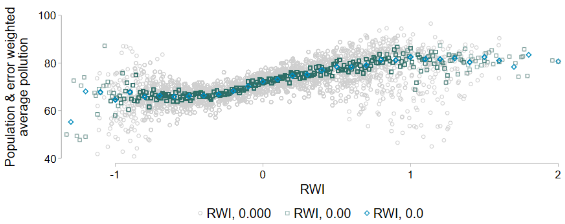
Figure SI-15: Kuznets relationship across all countries–Each dot indicates the average pollution levels weighted by the inverse of the error and the population around grid-cells with a given RWI level, averaging across all the countries in our sample. Colors indicate different bandwidths of RWI value. Grey dots are based on the raw RWI data. Green squares indicate RWI values rounded to hundredths and blue diamonds indicate RWI scores rounded to tenths.



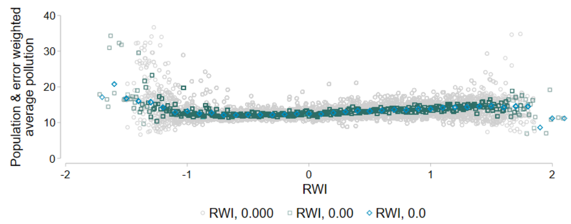
(a) India/Pakistan



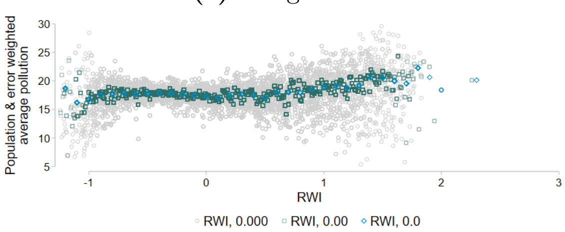
(b) Indonesia



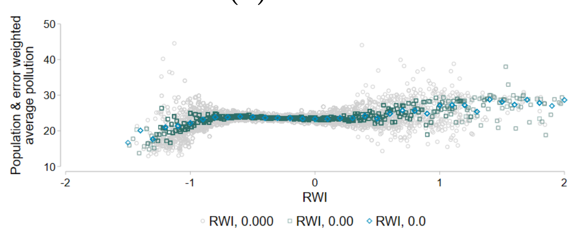
(c) Bangladesh



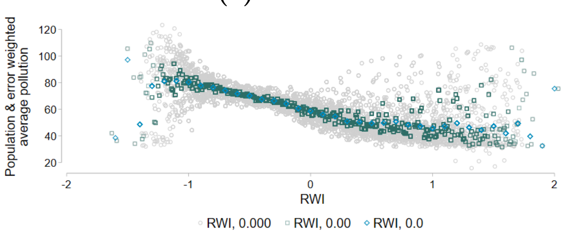
(d) Brazil



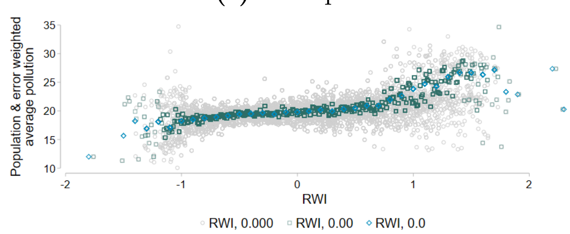
(e) Mexico



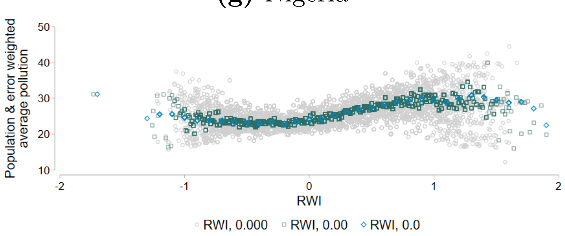
(f) Ethiopia



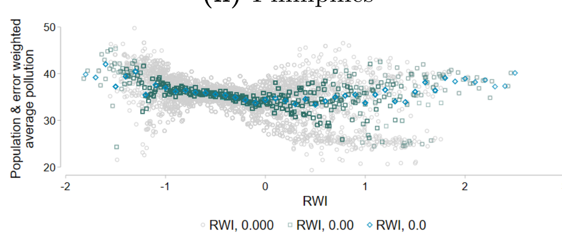
(g) Nigeria



(h) Phillipines



(i) Vietnam



(j) Democratic Republic of the Congo

Figure SI-16: Kuznets relationship in the 10 largest countries countries–Each dot indicates the average pollution levels weighted by the inverse of the error and the population around grid-cells with a given RWI level, averaging within the named countries. These ten countries are the largest by population in our data. Colors indicate different bandwidths of RWI value. Grey dots are based on the raw RWI data. Green squares indicate RWI values rounded to hundredths and blue diamonds indicate RWI scores rounded to tenths.

SI-4 Supplementary References

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