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Air pollution in an urban world: A global view on density, cities and emissions

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ABSTRACT

In this paper, we take a global view at air pollution looking at cities and countries worldwide. We pay special attention at the spatial distribution of population and its relationship with the evolution of emissions. To do so, we build i) a unique and large dataset for more than 1200 (big) cities around the world, combining data on emissions of CO2 and PM2.5 with satellite data on built-up areas, population and light intensity at night at the grid-cell level for the last two decades, and ii) a large dataset for more than 190 countries with data from 1960 to 2010. At the city level, we find that denser cities show lower emissions per capita. We also find evidence for the importance of the spatial structure of the city, with polycentricity being associated with lower emissions in the largest urban areas, while monocentricity being more beneficial for smaller cities. In sum, our results suggest that the size and structure of urban areas matters when studying the density-emissions relationship. This is reinforced by results using our country-level data where we find that higher density in urban areas is associated with lower emissions per capita. All our main findings are robust to several controls and different specifications and estimation techniques, as well as different identification strategies.

1. Introduction

Population growth and global warming are two of the most pressing challenges that humanity faces in the 21st century. Increasing populations and ongoing urbanization lead to larger and, in many cases, denser cities. One important side effect of urban life is air pollution.[1] Pollution is an important determinant of housing prices (Chay and Greenstone, 2005) and location choice (Banzhaf and Walsh, 2008; Bayer et al., 2009), with exposure to pollution known to significantly affect health, human capital and productivity (see for instance Graff Zivin and Neidell, 2013; Brauer et al., 2015; Anderson, 2019). According to the World Health Organization, more than 4 million deaths every year worldwide are estimated to be directly related to outdoor air pollution (WHO, 2018). Pollution has also been shown to be associated with higher spread and mortality of contagious diseases, including COVID-19.[2]

A larger population, other things equal, is expected to increase the emission of air pollutants. However, as populations grow their geographical distribution changes, generally with more people living in urban areas and cities of growing size. These changes in the spatial distribution of population and economic activity are likely to play a

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[1] We refer to air pollution in its broad sense, as “the presence in or introduction into the air of a substance which has harmful or poisonous effects” (as currently defined by most environmental institutions nowadays). This includes particles but also gases. As stated by many national and international agencies, including the US Environmental Protection Agency and the International Panel for Climate Change, potentially hazardous gases, like CO2, can be classified as *pollutants*, giving its excessively high levels and human-originated sources.

[2] High air pollution not only reduces the capacity of the immune system to fight pathogens, but also increases their contagion. Recent studies suggest that around 15% of global deaths due to COVID-19 were associated with high air pollution levels (see Pozzer et al., 2020).

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relevant role in how emissions per capita evolve. Nevertheless, this relationship is far from trivial, and global evidence and in particular on the role of population density in continuously growing cities, is limited and inconclusive (Ahlfeldt and Pietrostefani, 2019).[3]

In this paper, we take a global view at air pollution looking at cities and countries worldwide. We focus on emissions of carbon dioxide (CO2), in line with related papers (e.g. Cole and Neumayer, 2004; Martínez-Zarzoso et al., 2007). Exposure to high concentrations of CO2 is associated with a myriad of health problems, lower life expectancy and increased infant mortality (see e.g. Tol, 2005; Shindell et al., 2018; Alberini et al., 2018). Moreover, CO2 emissions, are the major responsible of current anthropogenic climate change (see IPCC, 2013).[4] We also look at particulate matter with aerodynamic diameters of less than 2.5 μm (PM2.5), as another important local pollutant whose adverse health effects have been shown in numerous studies (see e.g. Kopas et al., 2020; Zhu et al., 2019). To study the role of density and the spatial distribution of population on emissions, we build i) a large and unique dataset for more than 1200 (big) cities around the world with data for the last two decades, and ii) a large dataset for more than 190 countries with data from 1960 to 2010. We combine data from several sources, including data from air quality stations around the world, national and international statistics, and satellite imagery. In particular, we use city-level data from the European Commission's Global Human Settlement Layers (GHSL) from the Urban Centre Database (Florczyk et al., 2019) and different measures for the urban form for our 1234 cities based on satellite data on night-time lights (Bluhm and Krause, 2018). In our city-level analysis, we investigate how the relationship between population density and emissions per capita is shaped by various characteristics of cities, including their size, average income and spatial structure. We link and complement the insights obtained in our city-level analysis with a subsequent investigation at the country level, and paying special attention to a factor omitted in the literature to date, namely, *density in urban areas*. Population density in a country – the variable which usually considered in country-level studies - may vary substantially from density in urban areas.[5] The distinction is of vital importance, as the potential emissions-reducing effect of density usually depends on the economies of scale that come with proximity, something than mainly occurs in urban areas. Total population density and urban rates, as traditionally considered in the literature, cannot properly capture these economies of scale.[6]

Our paper expands the literature on the link between population dynamics and pollution. Previous studies have usually focused on population and density at the country level (Erlich et al., 1971; Dietz and Rosa, 1997; Shi, 2003; Cole and Neumayer, 2004; Martínez-Zarzoso et al., 2007; Poumanyvong and Kaneko, 2010). Results in these papers are mixed and do not explore in much depth the role of cities. Moreover, none of these papers consider density in urban areas. Papers in the literature which investigate the relationship between population dynamics and pollution at the city level have typically looked at a single country and/or relied on a limited sample size (Glaeser and Kahn, 2010; Zheng et al., 2011; Cirilli and Veneri, 2014; Hilber and Palmer, 2014; Borck and Schrauth, 2019; Carozzi and Roth, 2020). A global analysis of the relationship between the spatial distribution of population, within countries as well as within cities, and air pollution is missing in the literature. With this paper, we aim to fill this gap.

We provide two main contribution to the literature. First, we provide a global analysis of emission at the city level relying on a unique dataset including detailed information on city-level population, density, income and spatial structure. Second, we enrich the literature on air pollution at the country level by studying the role of density in urban areas, a variable previously omitted by the literature and which helps us reconcile results at the city- and country-level. Our results show that denser cities exhibit lower emissions per capita. We also find new evidence of an Environmental Kuznets Curve (EKC) between economic development and pollution at the city level, and that a polycentric city structure leads to lower emissions per capita in the largest cities, while monocentricity is more beneficial for smaller cities. At the country level, we find that total higher population density is associated with higher emissions per capita. While this might look like a contradiction to the city-level results, considering *density in urban areas* reconciles these two findings: higher density in urban areas is associated with lower emissions per capita.

The rest of this paper is structured as follows: Section 2 relates our work to other theoretical and empirical papers in the literature. In Section 3, we perform our empirical analysis: first deriving an empirical specification (in section 3.1) to then study the density-emissions relationship at the city level (in section 3.2) and at the country level (in section 3.3). Finally, Section 4 discusses and concludes. The Appendix contains supplementary material.

2. Population, density and pollution: literature review

Air pollution is today a main challenge worldwide. As populations worldwide grow, total pollution emitted is expected to increase. However, the relation between growing populations and emissions per capita is not straightforward. The evolution of emissions per capita, and the population density-emissions relationship, is likely to depend on several factors, including affluence levels, productive technologies and demand patterns. The literature studying emissions has in fact relied on what is called the IPAT model, according to which environmental Impact (I) is a (positive) function of population size (P), affluence (A) and environmentally damaging technology (T). Relying on the IPAT model, several papers have explored the role of demographic factors on air pollution at the country level (see for instance Erlich et al., 1971; Dietz and Rosa, 1997; Cole and Neumayer, 2004; Martínez-Zarzoso et al., 2007). Conceptually, one can distinguish the Malthuasian (1967) from the Boserup (1981) view: according to the first theory, population growth overexploits resources and its increased demand for power, industry and transportation raises emissions per capita (Birdsall, 1992). Holdren (1991) notes that settlement changes induced by population growth may result in "more transport – per person- in resources, goods and people" (p.247). By contrast, arguing along the lines of Boserup, increases in population – and in particular in population densities – are helpful for fostering innovation, for example in agricultural technology and for saving energy (see for instance Simon, 1981). For high population densities, especially in urban areas, agglomeration economies and lower transport costs per person are expected (Ahlfeldt and Pietrostefani, 2019).

From an empirical perspective, results on the population-emissions per capita relationship at the country-level, have so far been inconclusive. Cole and Neumayer (2004) and Poumanyvong and Kaneko (2010) find that population increases are matched by proportional increases in CO2 emissions. However, Martínez-Zarzoso et al. (2007) find that for old, more developed EU member states, population increases in the 1975–1999 period are associated with decreases in emissions per capita; while for newer, less developed EU member states, the opposite

[3] As highlighted by Glaeser (2014), the challenge mega-cities in the developing world is that poverty and weak governance reduce the ability to address the negative externalities that come with density. Moreover, the problem is reinforced by the fact that climate change itself is already a strong force behind urbanization and city growth worldwide (see Castells-Quintana et al., 2021).

[4] Two reasons further justify the focus on CO2. First, as already emphasized, CO2 is responsible for innumerable health and environmental damages. Second, given our focus on density, and the fact that CO2 emissions can vary significantly with density and the spatial distribution of population, and thus mobility. On-road vehicles, in particular, are responsible for 59% of all CO2 emissions (according to the United States Environmental Protection Agency, https://www.epa.gov/co-pollution).

[5] For example, Egypt has a comparatively low population density, but a very high density in urban areas, driven by a high density in its main cities such as Cairo.

[6] Countries can have more cities and more people living in urban areas, but whether the actual density in urban areas increases or not is unclear unless you directly measure it as we do.

happens: a higher population is associated with higher emissions per capita. In a similar vein, Shi (2003) finds that the impact of population change on emissions is much more pronounced in developing than in developed countries.

Focusing on the affluence-emissions relationship, several papers have explored the role of economic growth and development (see for instance Grossman and Krueger, 1993, 1995). A key intuition in this literature is the Environmental Kuznets Curve (EKC), according to which the income-emissions relationship follows an inverted-U pattern, with emissions per capita going up at early stages of development, but then declining as development proceeds. Empirical evidence on the EKC at the national level has been provided, for example, by Schmalensee et al. (1998), Panayotou et al. (1999), and Andreoni and Levinson (2001). Using night-time lights rather than GDP data, Kacprzyk and Kuchta (2020) have recently found an EKC with an even lower turning point, although the main results still hold.

Beyond the IPAT model, at the national level emissions per capita may also depend on the spatial concentration of population, including not only density, but also urbanization rates. A higher urban rate can be expected to lead to higher emissions due to the typically more polluting-intensive behavioral patterns of those in urban areas; Ponce de León and Marshall (2014) show that a 1% increase in urbanization correlates with a 0.95% increase in total emissions. Cole and Neumayer (2004), as well as Poumanyvong and Kaneko (2010), also find evidence of this emissions-increasing role of urbanization, especially in middle-income countries. But Martínez-Zarzoso and Maruotti (2011) find that the urbanization-emissions relationship actually follows an inverted-U pattern, with emissions per capita falling back with further increases in urbanization, probably suggesting differentiated patterns in the urban process at different stages of development. Nevertheless, none of these papers empirically considers the actual density and form of urban areas.

The study of the determinants of air pollution has recently been complemented by papers analyzing emissions in cities. At the city level, the determinants of emissions per capita may be similar to that at the country level, with affluence and technology playing an important role. But emission per capita may also depend on the size, density and spatial structure of the city (see Kahn, 2006). However, the empirical literature to date studying the density-emissions per capita relationship at the city level is still limited and inconclusive (Ahlfeldt and Pietrostefani, 2019). Papers to date have focused either on specific countries or limited samples. Glaeser and Kahn (2010), relying on carbon dioxide emissions in 66 U.S. cities in the year 2000, show that emissions per capita fall with density. Zheng et al. (2011) reach similar findings using data for 74 Chinese cities in 2006. Hilber and Palmer (2014) also suggest an emissions-reducing role of density relying on panel data for 75 global cities from 2005 to 2011. This emissions-reducing role of density is usually explained by the fact that high density allows cities to exploit economies of scale for urban infrastructure, reduce car usage and commuting distances - the “compact city theory” (see for instance Newman and Kenworthy, 1989; Burton, 2000; Liddle, 2004 and Chen et al., 2008). However, it has also been argued that increasing urban density may cause more congestion, overcrowding and greater air pollution (Breheny, 2001; Rudlin and Falk, 1999).

The literature has also analyzed the relation between the spatial structure of cities and pollution. Theoretical insights tend to consider general equilibrium effects of location choices, in terms of transport efficiency, congestion and housing prices. An important prediction from these theoretical papers is that, as cities grow, more polycentric urban structures can lead to lower emissions per capita. The main reason behind this is that the average distance from residence to workplace is expected to be lower in denser and polycentric urban areas than in sparse, monocentric ones (see for instance Gaigné et al., 2012, Denant et al., 2018). Evidence on the reduction of commuting as density increase has been shown by Duranton and Turner (2018) and Blaudin de Thé et al. (2018) for American and French cities, respectively. But empirical evidence on the role of the spatial structure of cities on emissions is very scarce, usually focusing on cities within a single country (Cirilli and Veneri, 2014, for Italy) or limited samples (Hilber and Palmer, 2014, for 74 global cities).

A global analysis of the relationship between density and emissions per capita using a large data set for countries and cities is still missing in the literature. Our study aims to fill this gap and consequently also combine the two strands of the empirical literature at the country and city level. Using different scales allows us to better understand and detail the role of the spatial distribution of population and economic activity on the evolution of emission per capita.

3. Density and pollution: empirical analysis

3.1. Deriving an empirical specification

To derive an empirical specification for our empirical analysis, first at the country and then at the city level, we rely on the IPAT model, as given by Eq. (1) and as commonly used in the literature[7]:

$$I = P^{\theta} A^{\varphi} T, \tag{1}$$

In logarithms, the stochastic version of Eq. (1) defines pollution as a linear function of Population, Affluence and Technology, suitable for regression analysis (the so-called STIRPAT model):

$$log(I_{it}) = \alpha + \theta \log(P_{it}) + \varphi \log(A_{it}) + \beta \log(T_{it}) + \epsilon_{it} \tag{2}$$

where sub-index *i* refers to the unit of observation, either countries or cities at time period *t* . and ϵ_{it} is an idiosyncratic shock. For I_{it} we consider emissions. For P_{it}we use total population or population density, while $A_{it}$and T_{it} are proxied for by income per capita and the share of industry in GDP, respectively. In our estimations, we also include time fixed effects, to control for global shocks, and country or city fixed effects, to control for idiosyncratic time-invariant characteristics, like geographical location. This means that our estimates are based on within country or city variation over time. Also, the coefficients in our log-log specification, give us the elasticities we are looking for. Coefficients for φ will capture the affluence-emissions relationship (and a potential Kuznets curve if we include the square of income per capita), while coefficients for θ represent the emissions elasticity with respect to population (or population density).

3.2. Density and pollution at city level

3.2.1. A global panel of cities: data and stylized facts

To study the relationship between population density and air pollution at the city level, we build a unique dataset including information for more than 1200 cities in more than 146 countries worldwide. An analysis of city size, density, structure and pollution has never been carried out in such a large global panel. Our dataset includes information on several variables at the city level from various sources. For pollution, population and physical extent of cities, we use the GHSL Urban Centre Database. The GHSL data identifies the urban extent based on the build-up area for more than 10,000 urban settlements around the world in 1975, 1990, 2000 and 2015, providing information on physical area and population for cities worldwide. The dataset also includes additional measures from other sources, such as urban greenness (Corbane et al., 2018), CO2 emissions, and PM2.5 emissions and concentration (Crippa et al., 2018). Given our focus on population density and spatial structure, and the available data from other data sources, we focus on world cities which had more than

[7] Beyond the literature on the IPAT model, this specification is found in many theoretical papers, with a few variations, explained by different levels of analysis: emissions at the household, firm, or aggregated city level (see for instance Calmette and Péchoux, 2007; Larson et al., 2012; Borck and Tabuchi, 2018; and Denant et al., 2018).

300,000 inhabitants in 1990 and create a panel of these cities for the years 1975, 1990, 2000 and 2015.

We combine the GHSL data with satellite data on night-time lights. Satellite data of night-time lights have become established as a proxy for local economic activity in recent years (see Henderson et al., 2012; Donaldson and Storeygard, 2016). The 'stable night light images' are collected by the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS), operated by the National Oceanic Administration Agency (NOAA). The values are published at the pixel level (30 arc *sec*, corresponding to less than 1 km^2 at the equator) as a yearly panel from 1992 to 2013. The light values are measured by a Digital Number (DN) ranging from 0 (dark) to 63 (fully illuminated). While this data has been extensively used in development and regional economics in recent years, the 'stable light' data suffer from top-coding and fail to appropriately capture the brightness of the largest cities. With cities forming the focus of our analysis, we therefore use the top-coding corrected data by Bluhm and Krause (2018). Based on this data, we calculate, for each city, several variables: (i) Light per capita, obtained as the sum of lights divided by the population, as a proxy of local economic activity, (ii) inequality in light, calculated as the Gini coefficient of light, giving us an indication of the spatial distribution of population and economic activity within the city, and iii) Moran's (1950) I index, as a measure of spatial autocorrelation indicating how monocentric or polycentric the city is (with a low value indicating polycentricity, or fragmentation, and a high value indicating monocentricity, see Tsai, 2005).[8] Table A.1 in Appendix A gives definitions and sources for the variables used in our city-level analysis.

Table 1 presents descriptive statistics of the main variables for our sample of 1244 cities in our data set, for 1990, the beginning of the lights-based data, and 2015, the end of the sample to show the variation across both countries and time. Some clear trends emerge. First, the average of emissions per capita across our sample of cities has increased. And the variability in emissions per capita across cities is higher than if we look at variability across countries, justifying the relevance of a city-level analysis. CO2 emissions per capita are still considerably larger in cities in developed countries, but they show a decrease from 7.73 m tons to 6.12 m tones since 1990 – while their counterparts in developing countries show an increase from 1.3 to 2.3 m tons. Second, total population and population density in the average city of our sample have increased considerably, particularly for cities in developing countries.[9] Third, despite the increase in lights per capita, stark differences in luminosity still exist between cities around the world, which correlate strongly with income levels at the country level. The mean of light per capita is 40.59 DN, but it goes from nearly zero in some smaller African cities, with hardly any observed light, to 664 DN in Manama, Bahrain. Within cities, inequality in light has fallen in the developing world, potentially reflecting more electrification (Bluhm and Krause, 2018). Finally, looking at the spatial structure of cities (using our lights-based measures), we find that cities in developed countries have, on average, a higher Moran's I, suggesting more monocentric structures and less fragmentation. Moreover, larger cities are more monocentric in general, making cities below 1 m inhabitants in developing countries the least monocentric and most fragmented. Fig. A.1 in Appendix A complements these statistics by illustrating the spatial structure of four different cities.

Fig. 1 provides a geographical illustration for CO2 emissions. We map, for 2015, both the cross-country variability in emissions per capita as well as that of cities with more than 1 million inhabitants. Most polluting cities (in per capita terms) are located in rich regions but also in some countries in the Middle East and other regions in Asia, especially in China. In fact, 6 of the 10 most polluting cities in per capita terms are Chinese.

Fig. 2 presents some scatter plots between our main variables at the city level.[10] We see a clear association between lights per capita and emissions per capita; richer cities pollute more. We also see that, on average, denser cities have lower CO2 emissions per capita. However, denser cities are, on average, poorer. Regarding the spatial structure of cities, we see a clear positive association between monocentricity and emissions per capita.[11]

Finally, Fig. A.2 in Appendix A shows the evolution over time of emissions in the average city by sector, while Table A.4 shows correlations among sectors. All sectors show an increasing trend in emissions from 1975 to 2015. The industrial sector is typically responsible for most emissions, although in 2015 the energy sector has become the leading emitter of CO2. Transport contributes a small but growing share of CO2 emissions. We see high correlations across the different sectors (with agriculture being the exception); cities that emit a lot of CO2 seem to do so across all sectors.

3.2.2. *Econometric analysis at the city level*

We now econometrically explore the connection between population density and air pollution at the city level, relying on our global panel of 1244 cities. We rely on a STIRPAT specification where air pollution per capita is explained by measures of population, affluence and technology, as explained in Section 3.1. For air pollution, we focus on emissions of CO2 and PM2.5, as the most important and studied air pollutants. For population, we consider both total population and population density. The distinction is relevant for cities, contrary to countries, as there is variation over time not only in population but also in physical size. For affluence, we use lights per capita as a proxy for income. While there is no available information on the industry share to proxy for technology at the city level, we make sure that our results are robust to controlling for the industry share at the country level (at the expense of losing observations) as well as introducing country or city fixed effects.

Tables 2 and 3 present results of estimates using CO2 and PM2.5 emissions as the dependent variable, respectively. In columns 1 to 3 we consider total population, while in columns 4 to 6 we consider population density. In columns 1, 2, 4 and 5 we include time fixed effects, to control for global shocks, and country fixed effects, to control for country-specific time-invariant characteristics. In this way, estimates in these columns rely on variation across cities within countries. In columns 2 and 5, we further control for city random effects. In columns 3 and 6 we include city fixed effects, so in this case estimates rely on within-city variation over time. In columns 1 and 2 we find that larger cities in a given country tend to display significantly higher levels of emissions per capita. However, in column 3, we find that as cities grow in population, they display fewer emissions per capita. Similarly, in columns 4 to 6, we find that higher density is associated with significantly lower emissions (of both CO2 and PM2.5). Additionally, and as expected, we find that higher income and share of industry are significantly associated with more emissions per capita, in line with the STIRPAT model.

[8] As night-time lights-based variable are available from 1992 to 2013, while the GHSL data is given for the years 1975, 1990, 2000 and 2015, we assign the first year of the lights data, 1992, to 1990 as well as the last year, 2013, to 2015. This gives us a combined panel of three time periods, namely 1990, 2000, 2015, which allow us to capture within-city variation over 25 years.

[9] Density in cities has increased, while, as we will see later, density in urban areas (at the country level) has decreased. This is explained by two factors. First, the fact that our country-level data include all urban areas, for example lower-density towns and smaller cities, while for our city-level application, we focus on cities larger than 300.000 inhabitants. Second, the fact that, nationally, the share of population living in low density urban areas has increased (see OECD, 2018).

[10] Table A.2 in Appendix A shows a correlation table between the variables.

[11] We also see that richer cities (i.e., with higher values of lights per capita) tend to be more spatially concentrated (i.e., more monocentric) and more spatially unequal. This is in line with insights from the urban economics literature suggesting i) that agglomeration economies lead to high concentration of population and economic activity in core districts of the city (Ciccone and Hall, 1996; Rosenthal and Strange, 2004) and ii) that larger cities tend to be more unequal (see Castells-Quintana et al., 2020).

Results in Tables 2 and 3 suggest that denser cities, on a global average, tend to have lower emissions per capita. This result is in line with previous evidence for smaller samples (Glaeser and Kahn, 2010; Zheng et al., 2011; Hilber and Palmer, 2014). Our results suggest an elasticity between 0.22 and 0.54: a 1% increase in population density is associated with between 0.22 and 0.52% less emissions per capita.[12]

3.2.3. The Environmental Kuznets Curve and endogeneity concerns

As shown in Tables 2 and 3 our results are robust to controlling for country and city time-invariant characteristics as well as for several time-variant ones. The inclusion of city fixed effects also helps to alleviate measurement errors inherent to the construction of global data sets. In Tables A.4 and A.5 in Appendix A, we further test the robustness of our results. In Table A.4, we allow for a more flexible specification. In particular, we include our proxy for income – lights per capita - in linear and quadratic terms to control for potential non-linearities, as suggested by the EKC. We find a highly significant non-linear association yielding an inverted-U. This inverted U holds using CO2 or PM2.5 emissions, is robust across different specifications, and it suggests that as cities become richer, emissions per capita first increase and then decline. To the best of our knowledge, this is the first time that the EKC is reported using a global panel of cities.[13] In any case, even controlling for the EKC, our coefficient for density remains significant.[14]

Our results so far suggest associations that are novel, or to date in the literature not shown with such a large sample. These association are interesting in their own, and we have shown that they are robust to several controls, different specifications and fixed effects. We also provide a simple theoretical model that reinforces our empirical analysis (see Appendix B). However, we must be careful to interpret our estimates in Tables 2 and 3 as causal effects; results may be biased due to reverse causality (i.e., it could be that more pollution leads to less density), or due to relevant omitted variables. To further address endogeneity concerns, in Table A.5, we perform alternative estimation techniques.[15] In column 1, we present First Difference (FD) estimates of Eq (2). We find a negative and significant coefficient for density, very similar in magnitude to the one estimated with fixed effects. In static models, first differencing is almost equivalent to introducing fixed effect (see Wooldridge, 2010). However, a first-differences specification allows us to use lags of density to predict first-differences and perform Instrumental Variables (FD-IV) estimations, in the vein of Arellano and Bond (1991).[16] FD-IV estimates show that lagged levels of density are significantly relevant to predict first-differences, and yield a negative and significant coefficient for density in our regression for emissions per capita (see column 2). In column 3 we use a simple long-run difference, regressing the change in emissions per capita between 1990 and 2015 on the same 25-years change of the right-hand-side variables. In column 4, we run a 'deep' cross-section regressing emission per capita measured in 2015 on right-hand-side variables measured in 1990. These are alternative strategies to further reduce problems of reverse causality and consider a long-run association (25 years) between density and emissions per capita.[17] Results again yield a negative and highly significant coefficient for density. Finally, in columns 5 and 6, we rely on IV estimates using population data circa 1870, constructed with historical data from Mitchell (2013), but at the expense of losing observations.[18] Results show that historical data is relevant to predict population density in the last decades (either in 1990 or 2015). Our IV coefficients for density remain negative and significant, in line with our baseline results.[19]

3.2.4. The role of city structure

Our city-level results suggest that denser cities pollute less, in per capita terms. But cities do not have the same density in all its areas. While some cities show a highly dense core surrounded by less dense areas, other cities show a more polycentric structure. In this sub-section, we investigate the role of the spatial structure of cities on emissions per capita using our global panel of cities and relying on night lights-based measures of city structure.

In Appendix B, we provide a simple urban economics model, building on Borck and Tabuchi (2018). The original model predicts a standard result, namely, that equilibrium population at the city level is not necessarily optimal, and can therefore generate too much pollution per capita. This allows us to compare equilibrium and optimal city size and determines under which conditions a city is too populated or not. On this basis, we introduce an index of polycentricity in the model (see eq. B.10) to capture the role of spatial structure in the density-emissions relationship.[20] According to this simple extension of the model, in large cities, and everything else equal, a more polycentric structure should lead to lower emissions per capita. In Table 4, we test this prediction using our city-level data, with CO2 emissions as our dependent variable and Moran's I as our measure of spatial structure. In columns 1 and 3 we look at population size, while in columns 2 and 4 we look at population density. According to results in columns 1 and 2, there is a negative and significant association between concentration and emissions; more monocentric cities display lower emissions per capita. However, according to columns 3 and 4, the role of the spatial structure of cities seems to depend on city size (but not on overall density of the city). For a relatively small city size, monocentricity is associated with fewer emissions, but as cities grow, monocentricity is associated with more

[12] Our results for density, either using CO2 emissions or PM2.5 as dependent variable, are also robust to excluding cities in large countries, like China or the USA or, splitting cities by city size, for instance between those above and below one million inhabitants. The results are available upon request.

[13] Harbaugh et al. (2002) looked at particles, SO2 and smoke in 72 cities in 42 countries, and used national level income per capita. We look at particles and CO2 emissions in more than 1200 cities in 182 countries, with measure for income per capita both at the country *and* city level. Millimet et al. (2003) looked at US state level data. For more evidence on the EKC at country level see Schmalensee et al. (1998), Panayotou et al. (1999), Andreoni and Levinson (2001). Kacprzyk and Kuchta (2020) have recently used night-time lights, as we do, but still rely on cross-country comparisons and not on a *cross-city* panel as in our case.

[14] Our results for density, either using CO2 emissions or PM2.5 as dependent variable, are also robust to excluding cities in large countries, like China or the USA or, splitting cities by city size, for instance between those above and below one million inhabitants. The results are available upon request.

[15] In Table A.5, we present results using CO2 emissions as dependent variable. Results are similar using PM2.5. results available upon request.

[16] Gonzalez-Navarro and Turner (2018) and Castells-Quintana (2018) also work with panel data on city-level population across the world, and use a similar identification strategy, building on Olley and Pakes (1991) and Arellano and Bond (1991).

[17] Panel FE, or panel FD, estimates consider variation within countries over time, so results relate to the association between *changes* in density and *changes* in emissions per capita. Our cross section setting considers variation between countries, so results relate to the association between *levels* in density in the past (1990) and *levels* in emissions per capita today (2015).

[18] Recent papers have used historical data to instrument for current population (see Duranton (2015) and Castells-Quintana, 2018). We construct agglomeration size circa 1870 using total population of major cities around in 1870 (or the earliest year available), and combining cities that are today part of the same urban agglomeration.

[19] To test for the exclusion restriction, we estimate residuals from the first and second stage and then run residuals of the second stage on those from the first stage. Results are not significant, indicating that the two residuals are not correlated, and providing evidence to support the exclusion restriction.

[20] Our model, based on Borck and Tabuchi (2018), is a multi-region framework, in which each city is characterized by a Central Business District (CBD) and a city border. Individuals commute towards the CBD – and these commuting flows will be considered as the main source of pollution. As population increases, utility increases due to agglomeration forces while it decreases because of longer commuting distances and competing for land.

Table 1
Summary Statistics at city level (1244 cities in 146 countries).

	1990			2015		
	World	Dev'd	Dev'ing	World	Dev'd	Dev'ing
CO2 pc	2.7051	7.7338	1.3111	3.1431	6.1232	2.3170
	(5.8636)	(9.7407)	(2.9544)	(6.0044)	(9.6455)	(4.1459
PM2.5 pc	0.0025	0.0029	0.0024	0.0021	0.0015	0.0022
	(0.0053)	(0.0032)	(0.0057)	(0.0032)	(0.0037)	(0.0030)
Pop	1.0988	1.3007	1.0428	1.6179	1.5501	1.6367
	(2.1035)	(2.4675)	(1.9887)	(3.2020)	(2.9526)	(3.2690)
Density	4373.21	2862.66	4791.94	6284.77	3129.59	7159.40
	(2354.19)	(1458.21)	(2384.03)	(3514.40)	(1432.24)	(3418.03)
Lights pc	37.17	101.74	19.26	40.59	103.13	23.24
	(74.87)	(123.54)	(38.20)	(54.96)	(69.88)	(33.48)
Gini in	0.3327	0.2740	0.3491	0.2663	0.2937	0.2587
Lights	(0.1142)	(0.0975)	(0.1131)	(0.0956)	(0.0857)	(0.0969)
Moran's I	0.7645	0.8160	0.7501	0.7514	0.8258	0.7307
	(0.1035)	(0.0756)	(0.1057)	(0.1186)	(0.0670)	(0.1215)
Moran's I	0.8582	0.8849	0.8488	0.8396	0.8812	0.8280
if pop >1 m	(0.0605)	(0.0405)	(0.0635)	(0.0716)	(0.0406)	(0.0741)
Moran's I	0.7343	0.7875	0.7206	0.7044	0.7962	0.6789
if pop <1 m	(0.0962)	(0.0680)	(0.0976)	(0.1117)	(0.0591)	(0.1094)
# Cities	1244	270	974	1244	270	974

Note: The summary statistics are CO2 per capita (non-short cycle CO2 emissions from all sectors, measured in tones), PM2.5 emissions per capita, population in million inhabitants, density in people per sq. km, lights per capita (in Digital Number units), the Gini coefficient of spatial inequality in lights, Moran's I as a measure of monocentricity vs fragmentation. Standard deviation in parentheses.

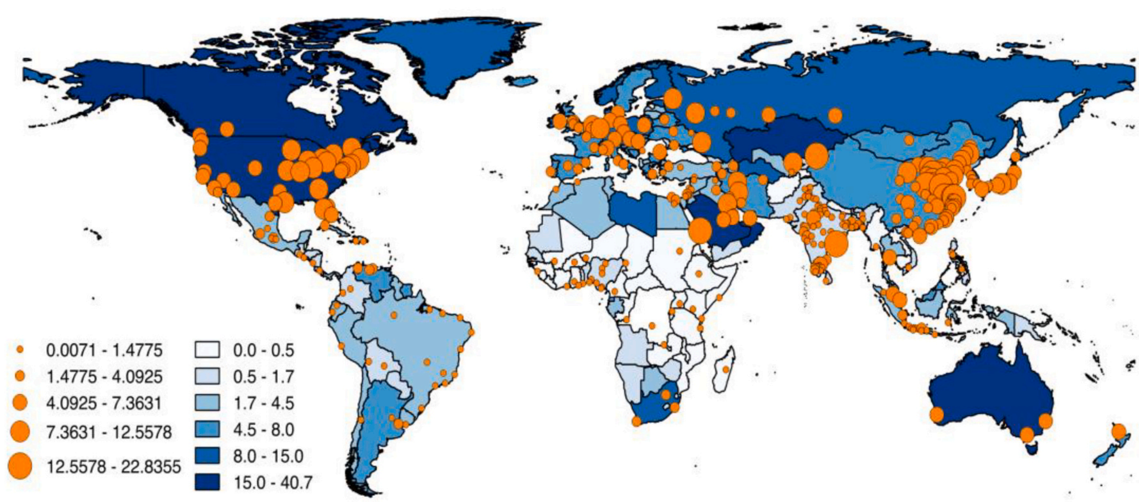

Fig. 1. Map of CO2 Emissions per capita, countries and cities of more than 1 M.
Note: The map shows CO2 emission per capita. For countries, we rely on data from the World Bank, and, for cities, on data from the Global Human Settlement Layers.

emissions. Fig. B.1 in Appendix B shows the marginal effect of the spatial structure of the city depending on city size.[21]

Results in Table 4 suggest that, for relatively small cities, monocentricity is desirable to reduce pollution, but that for larger cities, it is polycentricity what reduces emissions per capita. This is in line our simple theoretical model. One key factor explaining this role of the spatial structure depending on city size is inner-city transport. In relatively small cities, monocentricity means a compact city, which reduces the need and length of commutes. By contrast, in larger cities, monocentricity may imply more and longer commutes. In this case, a more polycentric structure may reduce the length of commutes. In column 5 of Table 4, we test this idea by looking at CO2 emissions from transport. As expected, we find that monocentricity is associated with fewer emissions in relatively small cities, but with more emissions in larger cities.

3.3. Density and pollution at country level

Our main results in Section 3.2 suggest that denser cities pollute less in per capita terms, with their inner structure playing a role. Let us now explore further explore the relationship between density and pollution at the country level. Our look at cities hints at ways to reconcile mixed results from previous papers studying air pollutions in cross-country settings. In particular, our results suggest that we must look at density in urban areas, something not explored in the global literature to date. Traditional measures of population density, divided by calculating the country population by the land area, do not capture what goes on in urban areas. Overall population density might be low because of vast areas of desert or forests, yet within cities, people might huddle close together. Looking at density in urban areas allow us to capture the economies of

[21] According to estimates, the desirability of polycentric structure becomes evident for cities larger than 5 million inhabitants. While this may seem as a large number, our global sample includes cities from 300 thousand inhabitants to agglomerations of more than 30 million. The actual population size from which polycentricity becomes desirable may of course depend on many city characteristics.

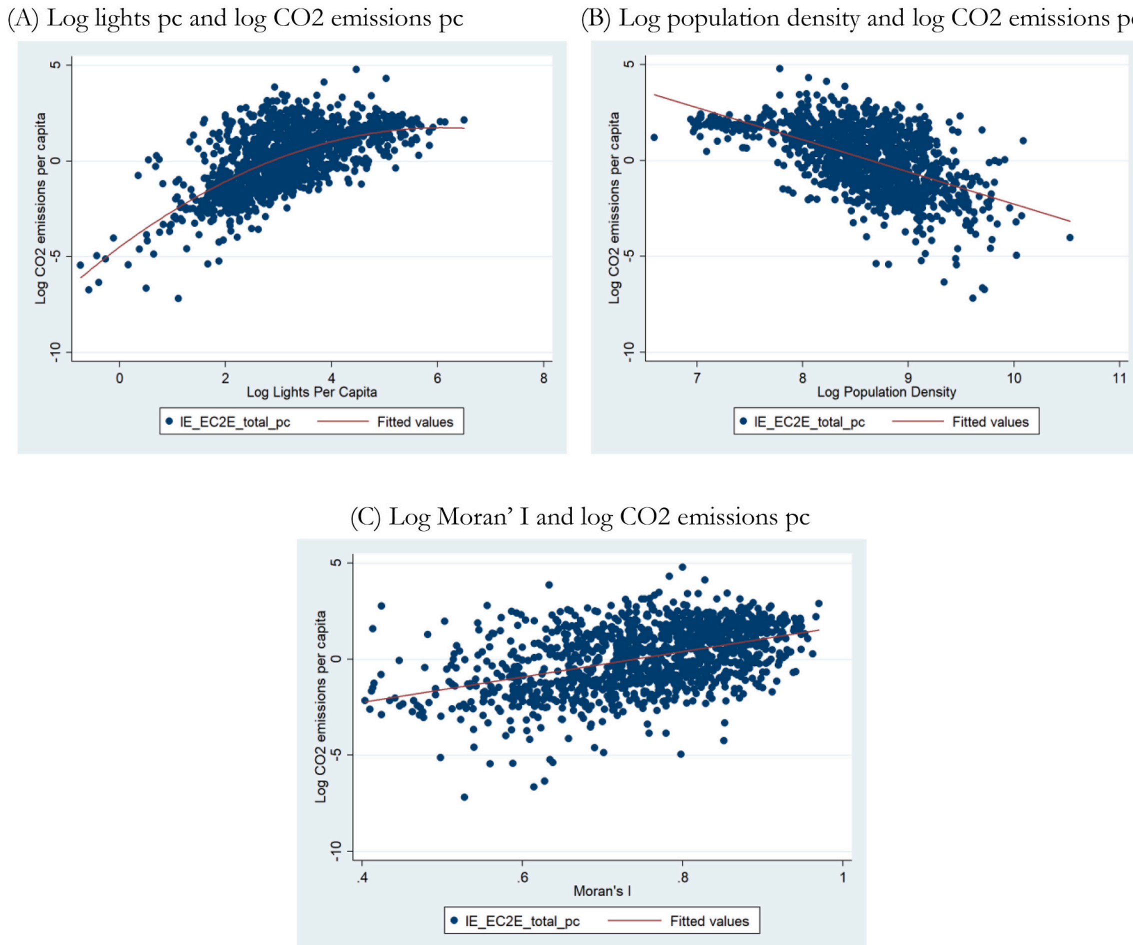

Fig. 2. Scatter plots across 1328 cities for the year 2015.

Table 2
Main results at city level, CO2 emissions.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	logCO2pc	logCO2pc	logCO2pc	logCO2pc	logCO2pc	logCO2pc
log(pop)	0.1592***	0.1508***	−0.3409***			
	(0.0322)	(0.0305)	(0.0986)			
log(density)				−0.5447***	−0.3389***	−0.2237***
				(0.0393)	(0.0320)	(0.0517)
log(lightspc)		0.1983**	0.1338***		0.1927**	0.1351***
		(0.0890)	(0.0429)		(0.0812)	(0.0436)
log(industry)		1.0282***	1.1179***		1.0607***	1.0395***
		(0.3359)	(0.1280)		(0.3279)	(0.1259)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	–	YES	YES	–
City effects	NO	RE	FE	NO	RE	FE
Observations	3342	1406	1406	3342	1406	1406
No. of cities	952	788	788	952	788	788
No. countries	131	106	106	131	106	106
R-Square	0.694	0.67	0.282	0.694	0.68	0.288

Note: Robust standard errors (clustered by city) in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

scale that come with proximity, and that could justify a reducing-effect of density, something that total population density and urban rates, as traditionally considered in the literature, cannot properly do.

3.3.1. Cross-country data and stylized facts

To study the relationship between population density and air pollution at country level, we build a global panel dataset, including information for more up to 196 countries with data from 1960 to 2010 in 5-year observations. For pollution, we focus here on CO2 emissions (in tons) as the most important Green-House Gas (GHG), but also given data availability and in line with related papers performing cross-country analyses (e.g. Cole and Neumayer, 2004; Martínez-Zarzoso et al., 2007). We look at total population, population density and urbanization rates, defined as the share of the population living in urban areas. This data comes from different sources, including the World Bank and the Penn World Tables. However, one innovation of this paper is to go

Table 3
Main results at city level, PM2.5 emissions.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. variable:	logPM2.5pc	logPM2.5pc	logPM2.5pc	logPM2.5pc	logPM2.5pc	logPM2.5pc
log(pop)	0.2115***	0.2348***	−0.0497			
	(0.0322)	(0.0377)	(0.2608)			
log(density)				−0.4085***	−0.2956***	−0.2306**
				(0.0377)	(0.0547)	(0.0959)
log(lightspc)		0.1272**	0.0500		0.1332**	0.0614
		(0.0608)	(0.0429)		(0.0629)	(0.0402)
log(industry)		0.7272**	0.7603***		0.7855**	0.7580***
		(0.3336)	(0.1073)		(0.3407)	(0.1234)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	–	YES	YES	–
City effect	NO	RE	FE	NO	RE	FE
Observations	3491	1450	1450	3491	1450	1450
No. of cities	952	809	809	952	809	809
No. countries	142	117	117	142	117	117
R-Square	0.63	0.701	0.342	0.639	0.681	0.36

Note: Robust standard errors (clustered by city) in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4
The role of city structure.

	(1)	(3)	(2)	(4)	(5)
Dependent variable:	logCO2pc	logCO2pc	logCO2pc	logCO2pc	logCO2transport_pc
log(pop)	−0.5479***	−1.4775***			−1.5688***
	(0.0966)	(0.2875)			(0.1485)
log(density)			−0.6111***	−0.4157	
			(0.0961)	(0.3568)	
Moran's I	−2.2502***	−18.1739***	−1.8964***	0.6078	−15.3478***
	(0.3139)	(4.4946)	(0.3123)	(3.7921)	(2.4525)
log(pop)*Moran's I		1.1951***			1.0053***
		(0.3444)			(0.1861)
log(density)*Moran's I				−0.2611	
				(0.4049)	
Year FE	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Observations	2588	2588	2588	2588	3722
No. of cities	943	943	943	943	1242
No. of countries	129	129	129	129	146
R-Square	0.209	0.216	0.25	0.251	0.479

Note: Robust standard errors (clustered by city) in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

further in terms of population density: we use the European Commission's novel GHSL data (Florczyk et al., 2019), which combines Landsat satellite imagery on built-up area with census information (Pesaresi and Freire, 2016). For the years 1975, 1990, 2000 and 2015, the GHSL data classifies each pixel in a global grid of 1 km by 1 km resolution according to the urban structure it belongs to, in particular whether it is high-density urban center (more than 1500 people per sq. km), urban cluster (smaller towns or the outskirts of large cities) or rural. This distinction allows us to compute the average population density in urban areas as well as in urban centers.[22] For our econometric analysis, and following our specification, we also control for other variables, like GDP per capita, industry share, and others. Table C.1 in Appendix C gives definitions and sources for the variables used.

Table C.2 in Appendix C presents main descriptive statistics for our main variables at the country level, distinguishing between developed and developing countries based on the World Bank classification. Figs. C.1.a and C.1.b, in Appendix C, provide maps of CO2 emission per capita and per GDP, respectively, in the year 2010. Some clear stylized facts emerge. First, we see a clear increase in CO2 emissions in the last 50 years, with in CO2 emissions per capita more than doubling. While developed regions still have higher levels of CO2 emissions per capita, the increase has been particularly pronounced in developing countries. In terms of CO2 per GDP, the increase has been more subdued and was entirely driven by developing countries: CO2 per GDP in developing countries in 2010 has even overtaken the corresponding emissions in developed countries. Differences in emissions per GDP reflect important difference in fossil-fuel energy efficiency across countries. Regarding density, while we also see a clear increase in population density, our new variable *density in urban areas* has actually decreased worldwide. This is in line with recent findings (see for instance OECD, 2018) and probably reflecting sub-urbanization in many countries in the last decades. Distinguishing countries by level of development, density in urban areas, as well as density in urban centers, is much higher in developing countries. This is illustrated in Fig. 3, which maps the global distribution of density in urban areas. We see that reaches high values in many African, Latin American and South Asian countries. Countries such as Egypt and Sudan might have a large landmass and therefore a rather low total population density, but with the desert covering most of landmass, density in urban areas is extraordinarily high.

Table C.3 in Appendix C shows correlations between our main variables, while Fig. C.2 presents some scatter plots among them. There is a

[22] For density in urban areas, we aggregate all population living in areas identified as urban and dived by total area identified as urban. For density in center areas we do the same but only considering center areas.

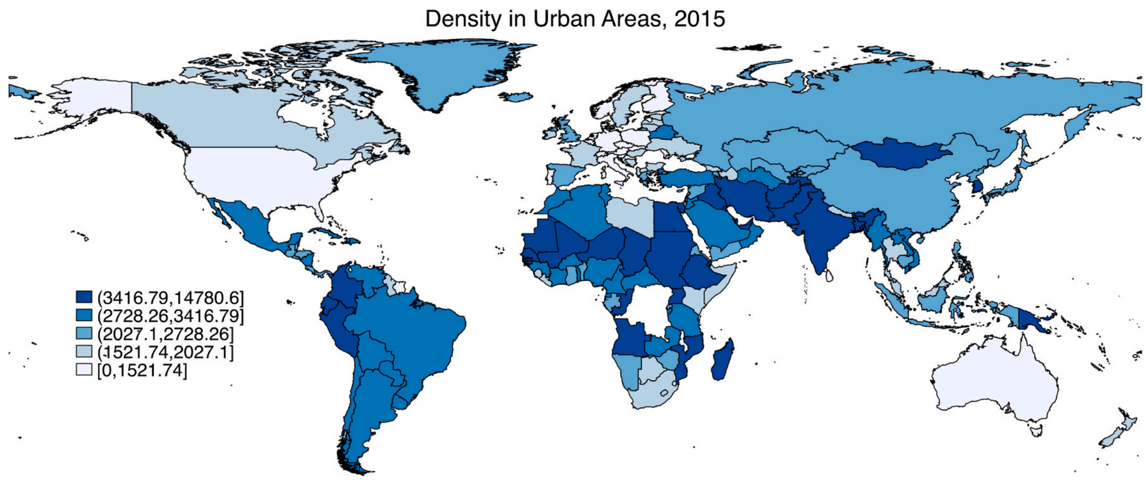

Fig. 3. Density in urban areas, 2015.
Note: The map shows data on density in urban areas in 2015 as constructed by us using data from the Global Human Settlement Layers.

clear association between income per capita and emissions per capita. However, countries with higher income per capita tend to be more energy efficient; they show lower levels of emissions per GDP. The share of industry to GDP and the level of urbanization are also positively associated with emissions per capita. Regarding density, we see no clear association with emissions per capita. However, and interestingly, we do see a clear and negative association between density in urban areas (and urban centers) and emissions per capita.

3.3.2. Econometric results at the country level

Table 5 presents our main econometric results at the country level, using CO2 emissions (in tons) as the dependent variable. As shown in column 1, a larger population is associated with higher CO2 emissions, with a coefficient larger than one, meaning that population growth entails an increase in emissions that is more than proportional. In other words, emissions per capita increase. Moreover, because at the country level an increase of population basically translates into an increase in population density, results in column 1 suggest that emissions per capita increase with population density. As column 2 shows, our result for population holds when controlling for technology and affluence, as suggested by the IPAT model; higher income per capita, and higher share of industry to GDP, are all associated with higher CO2 emissions, as expected. Interestingly, the simple STIRPAT specification is able to explain up to 76% of the within-variance in CO2 emissions. In column 3 we replace total population with population density; the coefficient for density is virtually identical to the coefficient for population in column 2. In column 4, we control for the urban rate, finding a positive and highly significant coefficient. Controlling for the urban rate also reduces the magnitude of the coefficient for density. Finally, in columns 5 and 6, we benefit from the GHSL data and introduce density in urban areas, considering all urban areas (column 5) or central areas only – i.e., those with more than 1500 people per sq. km (column 6). Using GHSL data significantly reduces our sample size, but still leaves us with information for 160 countries in column 5 and 144 in column 6. In both cases the coefficient is negative and statistically significant, being highly significant in the case of density in central areas.

In Table C.4 in Appendix C, we allow for more flexible specifications. First, we consider income per capita in linear and quadratic form to control for the EKC. Results yield the right signs for the EKC, but coefficients are non-significant.[23] We then allow the coefficient for density to vary for developing vs. developed countries and find a coefficient larger than one for developing countries while smaller than one for developed countries. This suggests a differential density-emissions relationship, with emissions per capita going up with density in developing countries while going down in developed countries, in line with previous findings (Shi, 2003; Martínez-Zarzoso et al., 2007). In the same spirit, we allow the coefficient for the urban rate and for density in urban areas to vary for developing vs. developed countries. The emissions-increasing role of urbanization seems to be driven mainly by developing countries (in line with Ponce de León and Marshall, 2014, and Poumanyvong and Kaneko, 2010). Similarly, the emissions-decreasing role of density in urban areas seems also driven by developing countries.[24]

In summary, our results at the country level suggest that while higher density at the national level is associated with higher emissions per capita, the opposite happens with density in urban areas; higher density in urban areas is associated with lower emissions (both total and per capita), especially when considering central areas. These results are in line with and reinforce our city-level results. Our result on density in urban areas is novel and seems to suggest that increasing density in urban areas helps countervail the emissions-increasing effect of overall population density. The size of the coefficients suggests that a 1% increase in density in urban areas is associated with around a 0.22% decrease in emissions, a non-negligible magnitude.[25]

4. Discussion and conclusions

In this paper, we have taken a global view at air pollution looking at countries and cities worldwide. We have focused on emissions (CO2 and PM2.5) and studied the role played by the spatial distribution of population and economic activity. We have done so using i) a large sample of 1244 (big) cities in 146 countries around the world with data for the last two decades, and ii) a large panel of (196) countries with data from 1960 to 2010. With these different units of analysis, we better understand and detail the spatial distribution of the population-emissions relationship.

We have contributed to the literature in several ways. First, we have

[23] In a regression where we only consider income per capita in linear and quadratic form, without further controls, we do find a significant coefficient in line with the literature.

[24] Our results may also highlight different population dynamics between developing and developed countries: in the former, population growth is much higher and a fast process of urbanization has recently been taking place (see e.g. Castells-Quintana, 2017).

[25] We do not pretend to interpret our coefficients in causal terms. However, endogeneity concerns are mitigated as we control for time-invariant characteristics and a large list of time-variant factors.

Table 5
Main results at country level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	log(CO2)	log(CO2)	log(CO2)	log(CO2)	log(CO2)	log(CO2)
log(pop)	1.2258***	1.2378***				
	(0.1906)	(0.1844)				
log(density)			1.2671***	1.0601***	1.0964***	1.2412***
			(0.1818)	(0.1760)	(0.2333)	(0.2423)
log(income)		0.7599***	0.7627***	0.7581***	0.7756***	0.7230***
		(0.0852)	(0.0834)	(0.0833)	(0.1043)	(0.1061)
log(industry_share)		0.3449***	0.3175***	0.2758***	0.2188*	0.1812
		(0.0882)	(0.0838)	(0.0782)	(0.1149)	(0.1263)
log(urb)				0.5304***	0.7188***	0.6341***
				(0.1467)	(0.1887)	(0.2311)
log(density in urban areas)					−0.2018*	
					(0.1052)	
log(density in center areas)						−0.2238***
						(0.0562)
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
Observations	1879	1140	1140	1114	340	307
No. of countries	192	176	176	176	160	144
R-Square (within)	0.688	0.764	0.737	0.749	0.694	0.679

Note: The dependent variable is CO2 emissions in tons.
Robust standard errors (clustered by country) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

provided a global analysis of pollution looking at up to 196 countries and more than 1200 cities (when previous papers have at most looked at 75 cities). Second, we bridge the gap between a country- and city-level analysis by introducing novel measures for density in urban areas at the country level. By considering density in urban areas, we can disentangle the effect of overall population density and more people living in urban areas (i.e., the urban rate), as traditionally done in the country-level literature, from the effect of population density in urban areas. In addition, backed by a theoretical framework, we have studied the role of city characteristics, such as population size, density and urban structure, as determining factors in the evolution of emissions per capita.

Our unique data set has revealed large differences in air pollution not only across countries, but more importantly across cities worldwide. We have shown that denser cities exhibit lower emissions per capita. This negative relationship between city density and emissions per capita is robust to several controls and different estimation techniques and identification strategies. Using our global sample of cities, we have also found evidence of the Environmental Kuznets Curve (EKC), suggesting that emissions per capita go up with income levels at early stages of development, but then decline as development proceeds. This is the first time that the EKC curve is reported in a global sample of cities. Moreover, we have found that the spatial structure of cities also plays an important role; on average, a relatively small-monocentric (compact) city pollutes less compared to relatively small-dispersed one. But large-polycentric cities pollute less compared to large-monocentric ones. This differentiated result by city size seems to be related to transport emissions. Our results are the city-level are supported by new insights we gain at the country-level: While higher total population density and urbanization are associated with higher CO2 emissions per capita, the opposite happens when we look at density in urban areas; higher density in urban areas is associated with lower emissions per capita. In line with theoretical insights, this suggests that while urban life, especially at early stages of development, may be more polluting, higher density in urban areas comes with lower emissions per capita.

In terms of policy implications, our results suggest that policymakers concerned with pollution should pay attention not only at population dynamics but also at the evolution of the spatial distribution of population, both at the country and city level. Based on our results, fostering denser urban areas may lead to lower emissions per capita. Similarly, as cities grow, a more spatially decentralized (i.e., polycentric) structure should be encouraged.

Finally, our results call for further research. While we have taken a global view, the evolution of emissions per capita is likely to depend on several specificities of countries and cities that deserve careful analysis on a case to case basis. The role of different types of infrastructure, institutional settings, production and consumption patterns, as well as social preferences, not studied in this paper, deserves a more detailed analysis. In sum, a better understanding of emissions patterns will prove to be of upmost value to guide policies aimed at reducing air pollution and its dangerous consequences.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Data and additional results at city level

Table A.1
Definitions and Sources for the variables used in our city-level analysis.

Variable	Time Span	Source
CO2 per capita	1975, 1990, 2000, 2015	Constructed using the European Commission's GHSL Urban Centre Database, which is itself based on the European Commission's in-house Emissions Database for Global Atmospheric Research (EDGAR v4.3.2)
PM 2.5 per capita	1975, 1990, 2000, 2015	Constructed using the European Commission's GHSL Urban Centre Database, which is itself based on based the Global Burden of Disease (GBD) 2017 data
Population	1975, 1990, 2000, 2015	European Commission's GHSL Urban Centre Database (see Florczyk et al., 2019 for details)
Density	1975, 1990, 2000, 2015	Constructed using the European Commission's GHSL Urban Centre Database
Lights per capita	1992–2013	Constructed using Satellite Data of Night-time lights, top-coding-corrected (see Bluhm and Krause, 2018)
Spatial Gini coefficient in light	1992–2013	Constructed using Satellite Data of Night-time lights, top-coding-corrected
Moran's I: spatial autocorrelation	1992–2013	Constructed using Satellite Data of Night-time lights, top-coding-corrected

Table A.2
Correlation of Variables, 1244 Cities, all available years.

	CO2 pc	PM2.5 pc	Population	Density	Light pc	Light Gini
PM2.5 pc	0.437					
Population	0.011	−0.004				
Density	−0.286	−0.161	0.085			
Light pc	0.300	0.000	0.048	−0.368		
Light Gini	−0.054	0.090	0.251	−0.045	0.092	
Moran's I	0.197	0.164	0.400	−0.345	0.296	0.449

Note: CO2_pc are the per capita non-short cycle CO2 emissions for all sectors, PM 2.5 pc the corresponding per capita emissions of particulate matter, Density denotes population density, Light p.c. is the light per capita measured in DN, Gini is the Gini coefficient of inequality in lights, Moran is Moran's I Spatial Autocorrelation Coefficient.

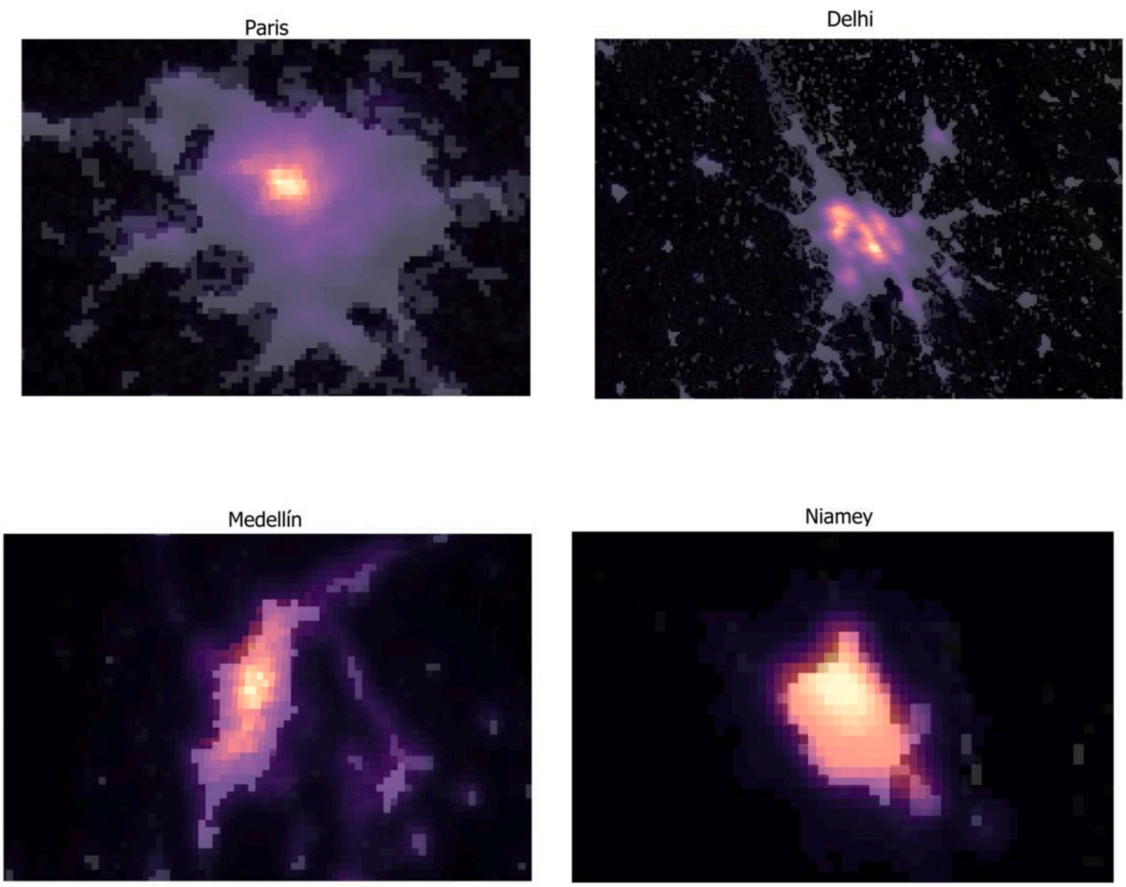


Fig. A.1. Spatial structure of four different cities.
Note: The four pictures present maps of four different cities (Paris, Delhi, Medellín and Niamey), illustrating the distribution of night-time lights across the pixels of the built-up area. Night-time lights in the year 2013 are depicted with respect to each city's maximum luminosity, with brighter colors (yellow, orange, red) denoting higher values and darker colors (purple, black) lower values. The urban extent of the city based on the GHSL data of 2015 forms the backdrop. The strongest monocentricity of these four cities is exhibited by Paris (Moran's I of 0.9502), followed by Delhi (0.9352) while both Medellín (Moran's I of 0.7686) and Niamey (Moran's I of 0.6617) are rather fragmented.

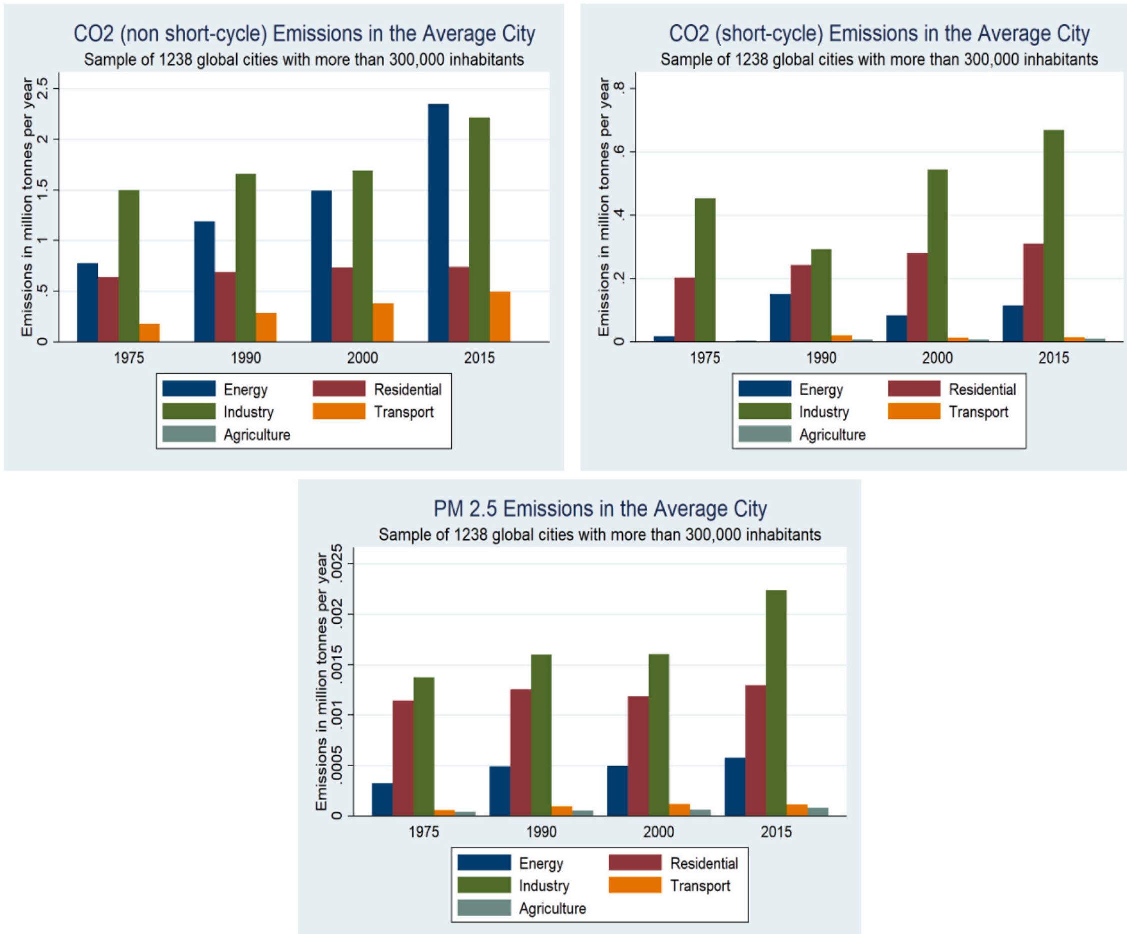


Fig. A.2. Time trends of different emission types.

Table A.3
Correlations by industry.

	Energy	Residential	Industry	Transport
Residential	0.492			
Industry	0.478	0.589		
Transport	0.489	0.795	0.652	
Agriculture	0.154	0.101	0.174	0.263

Note: correlation of Non-Short Cycle CO2 Emissions by Sector, 1244 Cities, all years.

Table A.4
The EKC at city level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	logCO2pc	logCO2pc	logCO2pc	logCO2pc	logPM2.5pc	logPM2.5pc	logPM2.5pc	logPM2.5pc
log(pop)	0.1488***	−0.5626***			0.2283***	−0.2789**		
	(0.0289)	(0.0972)			(0.0285)	(0.1186)		
log(density)			−0.5133***	−0.6544***			−0.3556***	−0.4288***
			(0.0719)	(0.1025)			(0.0526)	(0.0788)
log(lightspc)	0.7004***	0.4862***	0.5285***	0.4081***	0.3517***	0.3204***	0.3304***	0.2972***
	(0.1182)	(0.1682)	(0.0813)	(0.1557)	(0.0699)	(0.0578)	(0.0624)	(0.0526)
$\log(\text{lightspc})^2$	−0.0617***	−0.0551**	−0.0478***	−0.0438**	−0.0293**	−0.0554***	−0.0264***	−0.0538***
	(0.0184)	(0.0234)	(0.0120)	(0.0216)	(0.0121)	(0.0096)	(0.0096)	(0.0086)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	–	YES	–	YES	–	YES	–
City FE	NO	YES	NO	YES	NO	YES	NO	YES
Observations	2588	2588	2588	2588	2694	2694	2694	2694
No. of cities	943	943	943	943	968	968	968	968
No. of countries	129	129	129	129	142	142	142	142
R-Square	0.701	0.174	0.822	0.431	0.67	0.188	0.656	0.235

Note: Robust standard errors (clustered by city) in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.5
Further robustness checks.

	(1) FD	(2) FD-IV	(3) Deep Diff	(4) Deep CS.	(5) IV	(6) IV
Dep. variable:	logCO2pc	logCO2pc	logCO2pc	logCO2pc	logCO2pc	logCO2pc
log(density)	−0.5429***	−1.4800***	−0.2775***	−0.3342***	−0.7399*	−0.7400**
	(0.0659)	(0.2655)	(0.0807)	(0.0539)	(0.4468)	(0.4262)
log(lightspc)	0.1952***	0.1122***	0.0365	0.2011***		−0.0002
	(0.0363)	(0.0442)	(0.0579)	(0.0679)		(0.0715)
Year FE	YES	YES	–	–	–	–
Country FE	–	–	YES	YES	YES	YES
Observations	1633	1632	814	905	328	328
No. of cities	831	788	814	905	328	328
No. countries	119	119	108	119	86	86
F-test of excluded instruments		54.01***			6.87**	11.15***

Note: Columns 1 and 2 are estimated by first-differences using our panel data. In column 3, all variables are calculated as changes between 1990 and 2015. In columns 4 to 6, logCO2pc is measured in 2015 and right-hand-side variables are measured in 1990, with log(density) instrumented with historical population data. Robust standard errors (clustered by city in columns 1 and 2 and by country in columns 3 and 4) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix B. The role of the structure of cities

A theoretical framework

We briefly characterize the conceptual framework behind our empirical analysis at the city level. The model follows the consensus of the literature and is in particular based on the insights of Borck and Tabuchi (2018).

We consider an economy with R number of cities. In each city, population size, P, is endogenous, while total population N is exogenous. Each city is characterized by a Central Business District (CBD) and an endogenous border denoted x. All individuals commute to the CBD and have identical preferences[26]:

$$U = q^{\alpha} h^{1-\alpha} I^{-\mu}, \tag{B1}$$

where q is the numéraire, h the housing consumption and I the negative externality coming from pollution. Consumers maximize their utility under the following budget constraint,

$$w = q + \mathrm{r}h + tx, \tag{B2}$$

where r is the housing price, t is the commuting cost per unit of distance, and x is the distance to the border. After maximization, the housing consumption is given by

$$h = \frac{\alpha(w - tx)}{r}, \tag{B3}$$

and considering that workers are mobile across and within locations, the housing rent is now equal to

$$r = (w - tx)^{\frac{1}{\alpha}} I^{-\frac{\beta}{\alpha}} v^{-\frac{1}{\alpha}}, \tag{B4}$$

with $v = \alpha^{-\alpha}(1-\alpha)^{(1-\alpha)}\overline{U}$. The bid rent depends on the wage rate, the commuting time at the border and pollution. Notice that at the spatial equilibrium the rent will be equal to the opportunity cost of land r_A.

The city border x solves the total population constraint given by

$$P = \int_0^{\overline{x}} \frac{1}{h} dx, \tag{B5}$$

where $\frac{1}{h}$ is the population density at x, such that P is the total population that fits into a border x.

Assuming that production in each city is characterized by external economies of scale capturing agglomeration effects, with $\gamma < \alpha$:

$Y = P^{1+\gamma}$, and the individual wage rate $w = P^{\gamma}$

Solving the city border Eq. (5) by using the housing rent (3, 4) implies that the equilibrium city border is given by

$$\overline{x} = \frac{P^{\gamma}\left[1 - {r_A}^{\alpha}(r_A + tn)^{-\alpha}\right]}{t} \tag{B6}$$

To fully solve the equilibrium, optimal housing demand (3) and optimal rent (4) are replaced into the utility function (1), which gives the indirect utility in equilibrium, given by

[26] A Cobb-Douglas function is quite common, without being determinant. Denant et al. (2018) have chosen a quasi-linear utility specification that does not affect qualitatively their results.

$$V = P^{\gamma}(r + tP)^{-\alpha} I^{-\mu} \tag{B7}$$

We can observe the traditional market trade-off: as population P increases, utility increases due to agglomeration forces while it decreases because of longer commuting distances t and competing for land r.

This simple model allows to identify the equilibrium population at the city level, using the migration condition that relies on the indirect utility differential $V(P_i) - V(P_j)$. Setting $V^{'(P_i)} = 0$, and considering first pollution has a global phenomenon that affect utility but does not affect location choices, the equilibrium population level that solves the differential is equal to

$$P = \frac{\gamma r}{(\alpha - \gamma)\mathrm{t}} \tag{B8}$$

As underlined by Henderson (1974) and Borck and Tabuchi (2018), the equilibrium population is not necessarily equal to the optimal city size, which is derived from the maximization of indirect utility with respect to population.

Now, to obtain the optimal value of P we replace $I = (P^{\theta}A^{\varphi}T)$ in the indirect utility we obtain:

$$V(P) = T^{-\mu}(A)^{-\varphi\mu}P^{\gamma-\theta\mu}(r_A + tP)^{-\alpha}$$

which once maximized with respect to P gives the optimal population:

$$P^{*} = \frac{(\gamma + (1-\theta)\mu)r_A}{(\alpha - \gamma - (1-\theta)\mu)\mathrm{t}} \tag{B9}$$

which depends on θ and μ, namely the pollution elasticity and its disutility, α -the housing share, γ -the economies of scale, and t -the commuting costs. Population P is strictly defined within a border x so that it can be interpreted as city size but also population density.

To analyze under which conditions population is optimal, basically comparing P and P^*, values for parameters α, γ and μ must be set. Following the literature, we can set $\alpha = 0.24$ (according to Davis and Ortalo-Magné, 2011); $\gamma = 0.05$ (according to Combes and Gobillon, 2015) and $\mu = 0.022$ (according to Borck and Tabuchi, 2018). In this case, the equilibrium population density is sub-optimal for any value of $\theta > 1$ and positive values of rent and commuting costs. In other words, *if the pollution elasticity is higher than one, it means that city size (or population density) is not high enough to lead to a decrease in emissions* per capita.

So far, this version of the model of Borck and Tabuchi (2018) has considered cities to be symmetric. But what if locations are considered to differ from each other? To answer this, we go beyond the existing literature and assume that locations differ from each other, by their amenities or by their structure. In particular, we assume that cities are characterized by the following indirect utility:

$$V(P_i) = B_i P_i^{\gamma}(r_A + tP_i)^{-\alpha} I_i^{-\mu} \tag{B10}$$

where $B = Z\rho$ is the interaction between a level of amenities (infrastructures, geographic position…) and a degree of polycentricity. The main idea here is to assume that a polycentric city offers a better access to amenities and more efficient infrastructures (Fujita et al., 2001; Dieleman et al., 2002; Li et al., 2018).

As above, pollution is given by $I = (P^{\theta}A^{\varphi}T)$ and, considering free migration, we obtain the equilibrium value of B,

$$B_i = \left(\frac{P_1}{P_i}\right)^{\gamma}\left(\frac{r_A + tP_i}{r_A + tP_1}\right)^{\alpha}\frac{P_i^{\theta}A_i^{\varphi}T_i}{P_1^{\theta}A_1^{\varphi}T_1}\rho_i \tag{B11}$$

Replacing B_i in the indirect utility (10) and maximizing with respect to P_i, we find a new optimality condition, *up to a normalization*. With $\theta < 1$, such that emissions per capita decrease with density (as suggested by our empirical results), $\alpha = 0.24$, $\gamma = 0.05$ and $\mu = 0.022$, *the optimal density is higher than equilibrium population in polycentric cities. This suggests that, for larger cities, polycentricity may be more desirable and lead to a decrease in emissions* per capita.

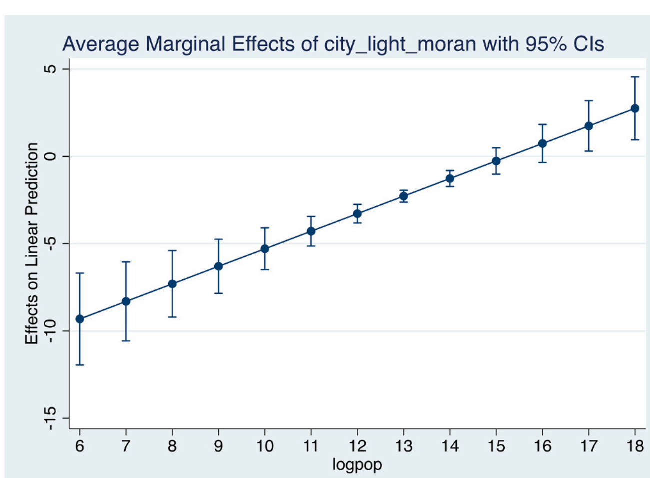


Fig. B.1. Marginal effects of structure depending on city size.
Note: Marginal effects of Moran's I (our measure of monocentricity) depending on total population size of cities, and using coefficients from Table 5.

Appendix C. Data and additional results at country level

Table C.1
Definitions and sources, variables at country level.

Variable	Time Span	Source
Total CO2 Emissions	1960–2010	World Bank – World Development Indicators based on data from the Carbon Dioxide Information Analysis Center, Environmental Sciences Division, Oak Ridge National Laboratory, Tennessee, U.S.
CO2 Emissions per capita	1960–2010	World Bank – World Development Indicators
CO2 Emissions per GDP	1960–2010	World Bank – World Development Indicators
Total Particulate Matter (2.5)	1960–2010	World Bank – World Development Indicators
Total Population	1960–2010	World Bank – World Development Indicators
Income per capita	1960–2010	Real GDP per capita from Penn World Tables 7.1
Industry Share	1965–2010	World Bank – World Development Indicators
Urban Rate	1960–2010	World Bank – World Development Indicators
Density	1965–2010	World Bank – World Development Indicators
Density in Urban Areas	1975, 1990, 2000, 2015	Constructed using data from Global Human Settlement Layers, see Pesaresi and Freire (2016) for details
Density in Urban Centers	1975, 1990, 2000, 2015	Constructed using data from Global Human Settlement Layers, see Pesaresi and Freire (2016) for details

Table C.2
Descriptive statistics at country level (182 countries), main variables.

	Beginning of Sample			End of Sample		
	World	Dev'd	Dev'ing	World	Dev'd	Dev'ing
CO2	44.37	148.80	12.23	163.99	304.10	122.34
	(251.59)	(498.27)	(74.66)	(766.81)	(849.99)	(738.27)
CO2 pc	2.0906	6.2927	0.8373	4.9744	10.4519	3.3460
	(4.5115)	(7.6636)	(1.5584)	(6.4040)	(7.2383)	(5.1294)
CO2/GDP	0.4240	0.4506	0.4146	0.5045	0.3343	0.55754
	(0.7044)	(0.3009)	(0.8026)	(0.4299)	(0.2162)	(0.4654)
Pop	15.26	18.72	14.25	34.87	26.45	37.32
	(60.28)	(36.08)	(65.74)	(134.30)	(54.30)	(149.86)
GDPpc	4.15	10.09	1.97	13.39	33.73	6.95
	(4.66)	(4.92)	(1.76)	(16.80)	(20.68)	(8.07)
Industry	21.73	17.26	21.87	28.38	27.52	28.66
	(10.40)	(0.00)	(10.54)	(13.53)	(11.42)	(14.18)
Urban rate	36.03	60.94	28.76	57.09	76.91	51.32
	(23.77)	(18.39)	(19.97)	(23.89)	(15.12)	(22.89)
Density	164.32	261.52	136.36	312.16	475.78	264.49
	(810.71)	(685.99)	(843.23)	(1470.65)	(1449.37)	(1478.14)
Density	3276.84	2695.49	3458.13	2700.42	2337.65	3014.42
Urb.Areas	(3427.02)	(3161.42)	(3175.92)	(2292.86)	(2337.93)	(2372.55)
Density	8901.46	4353.15	10,531.83	5779.49	3962.14	6452.98
Urb.Centers	(18,709.2)	(3486.37)	(22,086.59)	(3825.70)	(2804.69)	(3951.34)

Note: The table presents country-level summary statistics at the beginning and end of sample period. The beginning is 1960 (exception: density and industry from 1965, density in urban areas and urban centers from 1975), the end is 2010 (exception: density in urban areas and urban centers from 2015). Standard deviations in parentheses. The variables are total CO2 emissions (in millions of tons), CO2 per capita (tons per capita), CO2 per GDP (kg per US$ of GDP), PM25 per capita (micrograms per cubic meter per 1000 people), population in million inhabitants, real GDP in 1000 USD, the urban rate in percent, industry share as percentage of GDP, density as well as density in urban areas and urban centers in people per sq-km.

Table C.3
Correlations, main variables at country level.

	CO2 pc	GDPpc	Industry	Urb	Density	D.Urb.Areas
GDPpc	0.755					
Industry	0.379	0.206				
Urb	0.492	0.639	0.332			
Density	0.010	0.177	−0.059	0.231		
Density in Urb Areas	−0.065	−0.151	−0.020	−0.030	0.508	
Density in Urb Center	−0.100	−0.123	0.000	−0.135	0.126	0.489

Notes: The correlations are computed across all available countries and time periods.
For more information on the variables, see Table B.1.

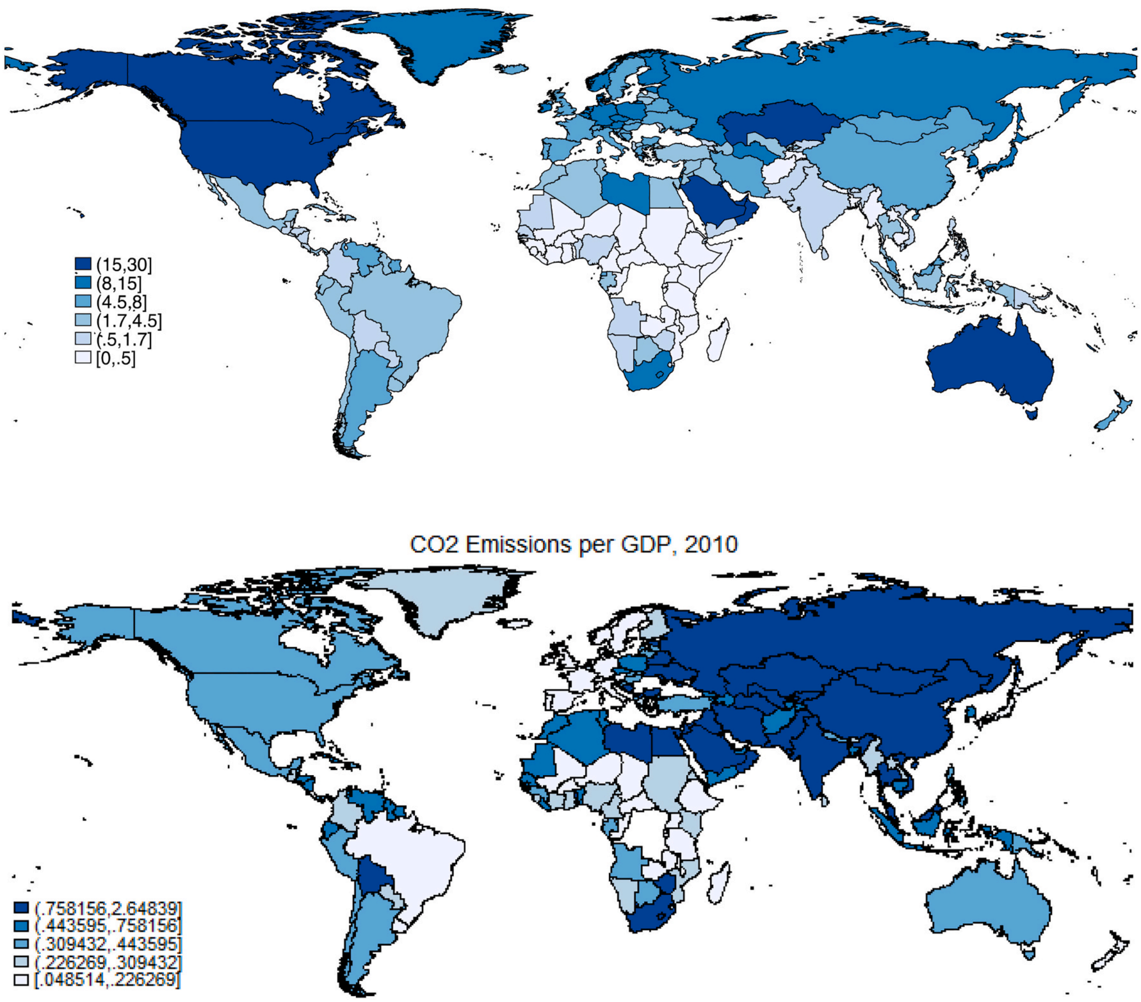
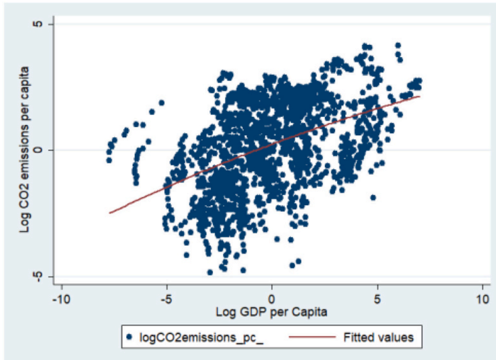
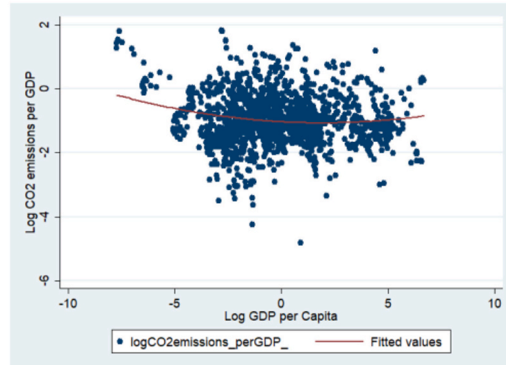


Fig. C.1.a and C.1.b. Maps of CO2 Emissions per capita and per GDP, 2010.

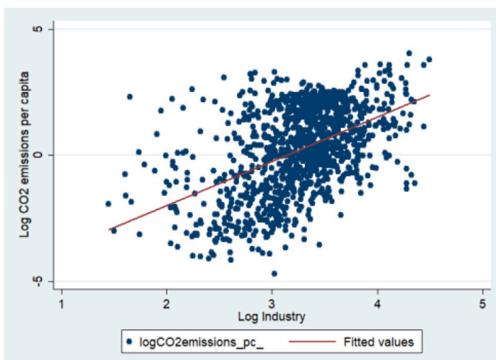
(A) Log GDP pc and log CO2 emissions pc



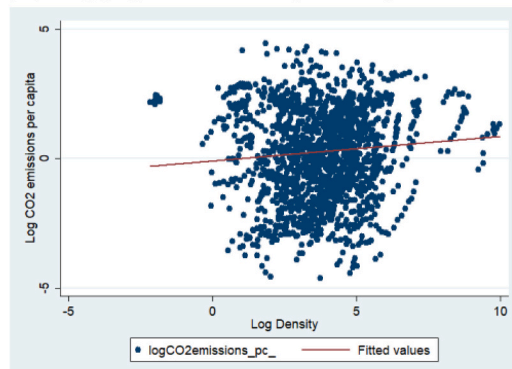
(B) Log GDP pc and log CO2 emissions per GDP



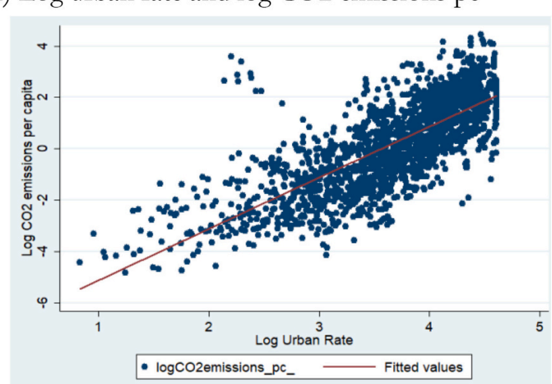
(C) Log industry share and log CO2 emissions pc



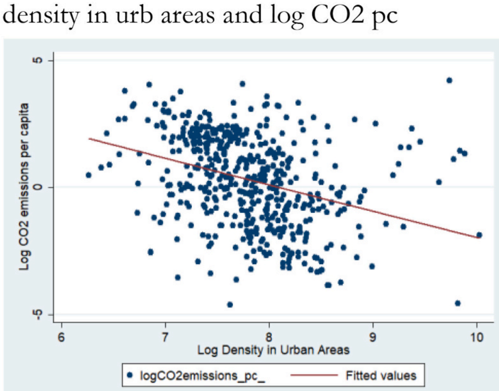
(D) Log population density and log CO2 emissions pc



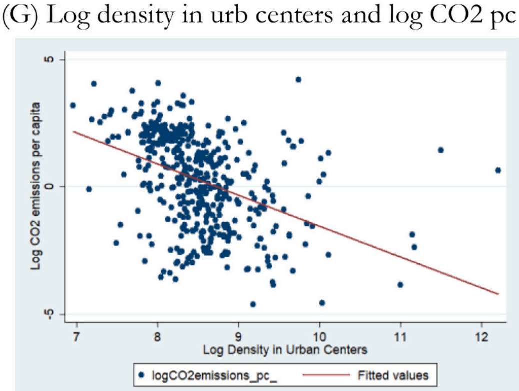
(E) Log urban rate and log CO2 emissions pc



(F) Log density in urb areas and log CO2 pc



(G) Log density in urb centers and log CO2 pc



Note: All plots use all available data for all time periods and countries.

Fig. C.2. Scatter plots between country-level variables.

Table C.4
Robustness checks at country level.

	(1)	(2)	(3)	(4)
Dependent variable:	log(CO2)	log(CO2)	log(CO2)	log(CO2)
log(pop)	1.2320***			
	(0.2062)			
log(density)*developing		1.3232***	1.0909***	1.1690***
		(0.1970)	(0.2114)	(0.3033)
log(density) *developed		0.7103***	0.7944***	1.3005*
		(0.2022)	(0.2178)	(0.6788)
log(income)	0.8096	0.7148	0.5284	1.0313
	(0.5049)	(0.4460)	(0.4230)	(0.8812)
log$(income)^2$	−0.0031	0.0045	0.015	−0.0183
	(0.0309)	(0.0276)	(0.0257)	(0.0511)
log(industry_share)	0.3441***	0.2903***	0.2665***	0.1726
	(0.0875)	(0.0841)	(0.0807)	(0.1341)
log(urb)*developing			0.5080***	0.6168***
			(0.1467)	(0.2260)
log(urb)*developed			−0.2505	−0.2923
			(0.4867)	(0.9235)
log(density in center)*dev'ing				−0.2109***
				(0.0559)
log(density in center) *dev'ed				−0.5426
				(0.8937)
Year FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Observations	1140	1114	1114	304
No. of countries	176	176	176	144
R-Square (within)	0.87	0.741	0.751	0.681

Note: The dependent variable is CO2 emissions in tons. Robust standard errors (clustered by country) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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