

Pollution, Density and Urban Access Regulations: European Evidence *

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Abstract

In recent decades, European municipal governments have developed anti-pollution policies such as urban access regulations to mitigate the exposure of inhabitants to pollutants. Given that population density translates into higher levels of exposure to harmful pollutants, in this paper, we wonder about its translation to inhabitants in urban areas. Using a granular-level geospatial panel dataset, we first provide estimates of the elasticity between population density / economic activity and pollution exposure for the European continent. Then, we quantify the effect of urban access regulations on pollution exposure in the context of an event study design. We find that the elasticity between population density and pollution exposure is around 6% (half that in the US) and that after 5 years of an urban access regulation implementation, pollution exposure is reduced by 2.5%.

Keywords: Agglomeration economies, urban access regulations, pollution, PM2.5

JEL Codes: I10, Q53, Q58, R11, R12

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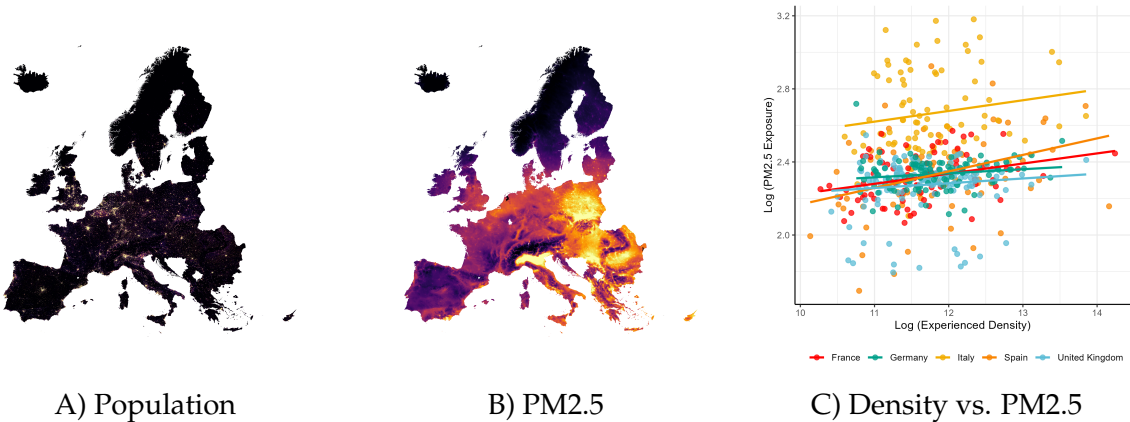
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1 Introduction

Agglomeration economies are known to have benefits like productivity and amenities and costs such as congestion or pollution (Duranton and Puga, 2020). Among these costs, pollution has recently attracted some attention due to its negative impact on the health of city dwellers. According to the latest report of the European Environmental Agency (EEA), at least 253,000 deaths in the European Union (EU) in 2021 were attributable to exposure to fine particulate matter (PM2.5) pollution above the threshold of 5 $\mu\text{g}/\text{m}^3$ recommended by the World Health Organization. Moreover, the Europe Green Deal and the zero pollution action plan set a target to reduce the health impacts of air pollution (estimated by the number of premature deaths attributable to fine particulate matter (PM2.5)) by at least 55% by 2030, compared to 2005. While a branch of the literature explores the increased efficiency of cities concerning per capita pollutant emissions (Glaeser and Kahn, 2010), limited attention has been devoted to investigating the relationship between agglomeration economies and pollution exposure. Examining Figure 1, it becomes apparent that there is a potential relationship between the spatial distribution of population (i.e., cities) and the spatial concentration of pollution in the same spatial domain.

Figure 1: Spatial Distribution of Population and Pollution



Notes: Data for 2019. Figures A) and B) are plotted for Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom using data as in section 2. Figure C) shows all cities in 2019 for the top 5 European countries by population. Experienced density is expressed in millions of persons. As seen in C) there's a positive correlation between experienced density and the pollution exposure. For more info. about the data, please consult section 2.

It appears evident that densely populated areas, such as Madrid, London, the Netherlands or Paris, have a higher concentration of pollutants. Indeed, panel C) of Figure 1 illustrates a positive correlation between a measure capturing agglomeration economies (the so-called experienced density) and

the population-weighted PM2.5 exposure for major cities in European countries. In response to EU regulation, local governments throughout Europe have enacted Urban Access Regulations (UARs) in recent decades. These regulations restrict the entry of vehicles including cars, trucks, lorries and other vehicles with combustion engines such as diesel, into city centers. The primary goal of this policy is to diminish emissions and ease traffic congestion in the city center, albeit with the trade-off of higher transportation and transaction costs for residents living outside the UAR-affected area. While significant efforts in the United States have been devoted to quantifying the effects of "clean air" regulations (Currie and Walker, 2019), Europe lags in research, especially in examining the combined effect of economic activity (proxied by ambient population density) and UARs.

In this study, we first quantify the elasticity between economic activity and pollution exposure. Using PM2.5 as the pollutant variable, we rely on instrumental variables to examine the effect of such density on the population-weighted PM2.5 exposure both between and within European cities. The between-cities exercise directly assesses this effect at the city level, whereas the within-cities effect measures the elasticity at the continent level, considering observed units as grid cells representing $1km^2 \times 1km^2$. Our findings indicate that the elasticity of economic activity on PM2.5 exposure at the city level is around 0.06, while at the within-cities level, it is around 0.11. Methodologically, we employ instrumental variables due to the absence of randomization in city exposure assignment. Geological factors, such as soil quality, as in Combes et al. (2010), and the presence of aquifers as in Burchfield et al. (2006), along with historical instruments pioneered by Ciccone and Hall (1993), serve as sources of variation. These factors allow researchers to isolate the front-door path between agglomeration economies and economic outcomes.

Secondly, we analyze the effect of adopting UARs on PM2.5 exposure, finding an elasticity of 0.027. We gathered data through web scraping from a UAR data collection project to achieve this result. Subsequently, we created a panel for all affected (and unaffected) countries and cities, distinguishing between the control group (no UAR) and the treatment group (cities adopting UAR). At this stage, we acknowledge potential bias in our results arising from inherent imbalance of the treatment (few cities adopting the regulation vs. many non-adopting it). Additionally, the challenge of identifying an appropriate control group is noteworthy, given the differences in observable variables between cities introducing UARs (e.g., Barcelona, London, Lyon, Paris, Madrid) and those non-introducing them. The treated cities in our sample exhibit higher population density and PM2.5 exposure, whereas smaller, less dense and less polluted cities tend to abstain from adopting UARs. We acknowledge that the results from this quasi-experiment are subject to several caveats, casting doubts on the causal interpretation of the findings. Despite these considerations, there is indicative evidence suggesting a

positive effect: the adoption of a UAR implies a 2.7% reduction exposure after 5 years of implementation. We derive this elasticity value using a dynamic difference-in-differences research design to accommodate the staggered adoption of the treatment (Sun and Abraham, 2021).

These results have implications for various branches of the economics literature. Firstly, in terms of data and measurement, the measurement of agglomeration economies and the extent of cities is an active area of research within urban economics (Duranton and Rosenthal, 2021). To capture the phenomena of agglomeration economies, we use a recently developed measure of density, the experienced density (Henderson et al., 2021; Duranton and Puga, 2020). Secondly, our study contributes to the urban economics literature by using instruments for the population density in European territories (Combes et al., 2010; Borck and Schrauth, 2022). We provide robust evidence that these instruments possess considerable predictive power.

Thirdly, our study is closely related to research examining the elasticity of population density and PM2.5 exposure, with Carozzi and Roth (2023) being the most akin to our paper. We use the same instruments, methodology and data type, albeit for a different territory. Another difference lies in our use of ambient population (average number of people living above a grid cell over a 24-hour period) for calculating the population density / economic activity, whereas Carozzi and Roth (2023) uniformly spread US census population data across grid cells. Despite this difference, our estimates are comparable to theirs, suggesting that our reported elasticity for the European territory is roughly 50% lower than that observed in the United States. The next logical step in this inquiry is to explore the factors contributing to these differences. Another closely related paper conducted by Borck and Schrauth (2022), uses global data to calculate global and country elasticities between population density and exposure to pollutants (PM2.5 and NO3). However, their study relies on less granular data, with cells spanning an area of 10km, and is limited to observations from a single year. In contrast, our analysis utilizes much finer-grained data spanning 14 years, albeit focusing on the European territory. Despite these differences, our estimates align closely with theirs. Moreover, Borck and Schrauth (2021) compute these elasticities for Germany using ground pollution stations, obtaining an estimate of 0.08, which also aligns with our estimate for Europe.

Fourthly, our study is also closely related to the active research field examining the impacts of low-emission zones, zero-emission zones, and other UARs on several economic outcomes and their spillover effects. For instance, Galdon-Sanchez et al. (2023) investigate the effects of Madrid Central, the UAR implemented in Madrid in 2019, on several outcomes including pollution levels and economic activity. Their findings reveal a significant 19% decline in pollution, and a 21% reduction in consumer

spending within the regulated area. The authors use a difference-in-differences approach to capture these effects. Unlike our study, they have access to data detailing the delineation of the UAR. Other papers have focused on driving policy restrictions. [Blackman et al. \(2018\)](#) studies the case for Mexico, [Blackman et al. \(2020\)](#) for Beijing, and [Leape \(2006\)](#) explore the congestion charge in London. Another closely related paper to ours is by [Wolff \(2014\)](#), which explores the effect of Low Emission Zones in Germany. They find that the implementation of these areas resulted in a significant 9% decrease in PM10 levels. Conversely, alternative policies such as building ring roads or investing in public transportation infrastructure did not lead to a decrease in pollution levels.

The remainder of this paper is organized as follows. In section 2, we provide all details about our dataset construction, data sources, and considerations regarding the units of observation emphasizing the potential impact on results based on the chosen unit. In section 3, we address the different econometric issues and strategies employed to address our research questions, including a discussion on the rationale behind our instruments when relevant and valid. In section 4, we present the main results, while section 5 conducts robustness checks for the reliability of our causal claims. Finally, in section 6, we conclude with a summary of the key findings and discuss potential avenues for future research.

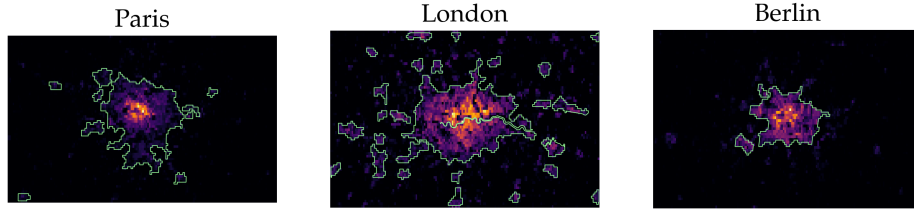
2 Data

In this section we explain the data sources and outline the construction of our units of observation: cities and grid cells (between and within datasets).

2.1 Cities

It is important to note that defining cities using administrative boundaries may introduce measurement error ([Duranton and Rosenthal, 2021](#)). Therefore, to establish city boundaries we rely on the GHS Settlement Model layers (GHS-SMOD). This dataset delineates and classifies settlement typologies based on cell clusters' population size, i.e., population and built-up area densities ([Commission and Eurostat, 2021](#)). We specifically use cells flagged as urban centers, defined as contiguous grid cells with a density of at least 1,500 inhabitants per km^2 of permanent land and with at least 50,000 inhabitants within the cluster with smoothed boundaries. [Figure 2](#) depicts how this delineation works in practice. As expected, big clusters of spatially concentrated economic activity are identified. We use city boundaries based on 2020 data.

Figure 2: Some European Big Cities Delineation



Notes: Ambient population data for 2021 using LandScan data. Cities delineation for this graph comes from 2020 data. Each pixel value is mapped to the population count and it represents $1km^2$. Note that these cities are observed in panel A) of Figure 1: they are "cuts" (clipped grids in the geospatial jargon) of panel A) with the green delineation measuring the city extent.

2.2 Pollution

As our measure of pollution, we rely on PM2.5, also known as Particulate Matter (PM). PM2.5 describes fine inhalable particles with diameters that are generally 2.5 micrometers and smaller. These particles vary in size and shape, composed of hundreds of different chemicals. Some are emitted directly from a source, such as construction sites, unpaved roads, fields, smokestacks or fires. Most particles form in the atmosphere as a result of complex reactions of chemicals like sulfur dioxide and nitrogen oxides, which are pollutants emitted by power plants, industries and automobiles. We obtained the spatial panel data from the European Environment Agency. This dataset provides concentrations of PM2.5 air pollutants on a 1 km grid combining air quality monitoring data in a 'regression-interpolation-merging mapping' methodology and the observational values from air quality monitoring stations used in the interpolation. Subsequently, we construct two panel datasets of the European territory from 2007 to 2021. The first dataset, termed the 'between-cities sample' treats each city as an observation. The second, referred to as the 'within-city dataset', represents each country-year $1km^2 \times 1km^2$ cell as an observation. For the between-cities dataset, we construct pollution exposure. PM2.5 exposure (Y_c) of city c is defined as:

$$Y_c = \sum_{i=1}^{N_c} Y_{ci} \times \frac{Pop_{ci}}{Pop_c} \quad (1)$$

where N is the total number of $1km^2 \times 1km^2$ grid cells within city c , Pop_c is the population of city c , and Pop_{ci} is the observed population of cell i within city c , i.e., the population weighted average of

the exposure to PM2.5 in a given city. For the within dataset, we just proxy the exposure as the given PM2.5 level (Y_{ci}) of that cell.

2.3 Density¹

We use the Oak Ridge National Laboratory LandScan dataset (Sims et al., 2023) to get the density data. This dataset measures the 24-hour average ambient population of the world. The lab constructs the dataset with multiple techniques from geospatial science, remote sensing technology, and machine learning algorithms. The spatial cells are $1km^2$ and are weighted and tailored to match the conditions of the data and the geographical nature of each country/region. Importantly, each cell measures the average number of people living / moving / staying within that cell over a 24-hour period. We believe this detail is a gain over other datasets which are constructed from official census information, as it captures practical and accurate data in real-time. In contrast, the gain over other papers measuring the elasticity between economic activity and pollution exposure is the ability of our dataset to better capture agglomeration economies (Henderson et al., 2021).

We also compare two density measures (D_{ct} in equation 2 in the next section). First, we use the naive density, which is the population count of a grid cell. Given the $1km^2 \times 1km^2$ resolution of each grid cell, the value for each grid cell represents the population density within that km^2 . Second, we construct the experienced density. The central idea of this measure is to reflect the density actually faced by the individual. Administrative boundaries (municipalities) sometimes have heterogeneous sub-units of boundaries (counties) that differ in size, density and many other characteristics. This classification of boundaries can induce measurement error when computing the spatial concentration of economic activity. Roca and Puga (2017) and Henderson et al. (2021) proposed measuring the experienced density by counting the population within a given radius around each individual. In this paper, we set the radius to $10km$. In general, this measure better captures agglomeration economies, as it relates how close the average person within a city is to the concentration of economic activity (Duranton and Puga, 2020).

2.4 Instruments

Following Combes et al. (2010), we introduce soil quality as a source of exogenous variation in population density, using data from the Harmonized World Soil Database (IIASA, 2023). Specifically, we use multiple definitions of soil characteristics, including excess salts, nutrient availability and reten-

¹Although for the sake of simplicity we call it ‘density’, we actually refer to ‘spatial concentration of economic activity’

tion, oxygen availability, rooting conditions, soil toxicity, and workability (see Table 9). Each characteristic is measured on a scale from no limitations to very severe (or non-soil) limitations, providing a comprehensive overview of soil quality. Table 9 displays the share of land by soil characteristic and quality, with an annual average for all the countries in our sample. Additionally, We incorporate historical population density at different lags or time periods, as detailed in the first four rows of Table 8. As expected, historical population density grows over time. We downloaded the data from the History Database of the Global Environment (Goldewijk, 2017). This dataset contains historical population estimates, represented by maps of total, urban and rural population, population density and built-up area. The period covered is 10000 before Common Era (BCE) to 2015 Common Era (CE). Klein Goldewijk et al. (2017) describe how these estimates are calculated. Finally, we incorporate information on aquifer types in the European territory, using data defining six generalized classes of potential groundwater resources with four grades of productivity in terms of general groundwater yield (see Table 8). Highly productive porous aquifers are the most prevalent within a given city, on average. For further details on this data source, see Duscher and Günther (2019).

2.5 Urban Access Regulations

We use webscrapped data to construct a panel dataset of urban access regulations along the European continent, specifically gathering information from the Urban Access Regulations project.² While the project does not aim for comprehensive coverage of every urban area, it endeavors to include as many cities and towns as possible. Table provides an overview of the affected countries by these regulations. It is worth noting that only 12 out of 33 countries are affected by the regulations, and within each country, the panel is markedly unbalanced, with treated cities representing a small share of each country's total number of cities. It's essential to highlight that our dataset only includes information on the city where the UAR is being adopted, and not the geographical boundary of the regulated zone for each regulation. In comparison to studies like Galdon-Sanchez et al. (2023), which uses the geographical boundary of Madrid Central (the main UAR established in 2019) to assess its impact on several economic outcomes, our dataset lacks this key characteristic. This absence may have consequences as the spatial distribution of economic activity and pollutant emission is crucial. Consequently, studying PM2.5 exposure at the city level with the introduction of an exogenous shock (the UAR) may not yield desired estimates, given that the inner boundaries where the UAR is applied are within the city delimitation. Despite this limitation, there is some room for evaluating the impact of UAR treatments.

²Data can be found in the following website: <https://urbanaccessregulations.eu/>

Table 1: Countries with at least 1 city with any type of UAR

	Regulation	Mean Density	Mean Exposure	Regulation Start	N. Cities
Austria	No	73 700.82	14.50		7
	Yes	988 967.80	16.68	2016	1
Belgium	No	99 469.84	14.39		14
	Yes	169 872.36	15.04	2020	3
France	No	151 425.92	12.94		72
	Yes	261 189.50	13.71	2017	7
Germany	No	80 045.82	12.92		70
	Yes	281 597.24	13.09	2013	32
Italy	No	129 742.11	16.71		78
	Yes	294 551.17	21.39	2019	10
Latvia	No	25 360.93	13.41		2
	Yes	294 011.33	15.71	2008	1
Netherlands	No	80 584.58	13.67		38
	Yes	1 171 691.13	14	2020	1
Norway	No	33 897.35	7.38		5
	Yes	325 846.33	10.33	2016	1
Poland	No	94 090.11	22.41		60
	Yes	187 307.63	17.74	2015	2
Spain	No	93 175.56	12.33		80
	Yes	2 223 144.57	13.65	2019	2
Sweden	No	47 742.20	7.32		15
	Yes	507 337.33	6.87	2020	1
United Kingdom	No	95 297.46	10.98		137
	Yes	963 319.26	9.31	2018	6

Notes: Yearly (2007-2021) averages.

We define the treatment in our quasi-experiment as the initiation of the first observed regulation affecting a city. For simplicity, we do not distinguish between various types of regulations (such as low emission zones, zero emission zones, charging schemes for vehicles, etc.), focusing only on the intensive margin of UARs. Due to data quality issues, we assume also that subsequent periods following the initiation of observed treatment for a given city will be considered as time periods with treatment.

2.6 Controls

Table 6 presents the main descriptive characteristics of the controls used in our between-cities sample, while Table 7 details those used in the within-sample. Climate related controls are sourced from [Cornes et al. \(2018\)](#), using the E-OBS dataset. It is provided on regular latitude-longitude grids with spatial resolutions of 0.1° and has a daily resolution. Covering a significant portion of the European continent, from northern Scandinavia to southern Spain and north Africa, and extending from Iceland to Russia at 40°E ., the E-OBS dataset's coverage dynamically changes over time due to fluctuations in station scope. We use three variables -daily observations of temperature, precipitation and wind-

initially aggregating them at the monthly level and subsequently at the yearly level. The daily mean air temperature is measured near the surface, typically at height of 2 meters. Total daily precipitation, including rain, snow, and hail is measured as the height of the equivalent liquid water in a square meter. Wind speed is quantified as the daily mean wind speed at a height of 10 meters.

For trade-related variables, we use data from Natural Earth Data,³ an open source public domain map dataset providing information on various geological features of the earth at various resolutions. This dataset includes physical data such as land, oceans, reefs, rivers, as well as boundaries and city names. Using the coasts dataset, we define a city as coastal if its centroid is located within 50km of the nearest coastline. Additionally, we calculate the distance to the closest coastline and the nearest river, measured in km. Subsequently, we use an elevation European map,⁴ we compute the average terrain ruggedness, as in [Nunn and Puga \(2012\)](#).

Finally, our last control variable focuses on the emission of pollutant power plants, and we obtain the data from the Global Power Plant Database ([Global Energy Observatory, 2018](#)). We compute the distance of each city to the nearest pollutant-emitting oil, coal, and gas power plants. However, it is essential to acknowledge the potential introduction of look-ahead bias in our analysis, since this dataset is constructed as of June 2018. Thus, for years beyond 2018, the assigned power plant proximity for cities might not accurately reflect the current closest power plant. It is noteworthy that climate-related controls are contingent on a yearly basis, trade-related variables are dependent on city-centroid, and geological variables remain static, given that the terrain slope does not exhibit temporal changes.

3 Empirical Strategy

3.1 Estimating the elasticity of PM2.5 to population density

This section presents the methodological approach used to estimate the model parameters. Our baseline method is Ordinary Least Squares (OLS), but we have the challenge that our main variable is potentially endogenous. Thus, we switch to an Instrumental Variables (IV) method and present several tests to show the relevance and validity of the instruments. Since our preferred method is IV, the answer to the second research question on the effect of regulation on PM2.5 exposure only uses IV.

³Data can be found in the following website: <https://www.naturalearthdata.com/>.

⁴Data from the [European Environmental Agency](#).

3.1.1 Instrumenting the population density

When quantifying the elasticity between population density and pollution exposure, some confounding factors arise. Urban residents tend to self-sort into city centers to benefit from the productivity spillovers of agglomeration. Amenities, sectoral specialization, and other factors affect both population density and pollution. In addition, there is some reverse causality when quantifying the elasticity as households sort into locations where they are exposed to fewer pollutants (Heblich et al., 2021). Therefore, using a naive OLS estimation to quantify such elasticity would entail a biased estimation. To overcome this problem, we adopt an IV strategy, isolating variation in population density uncorrelated with any part of the error term in the main estimation equation. In general, the successful application of IV in urban economics over the past decades is well-documented (Card, 2001; Baum-Snow, 2007; Rosenthal and Strange, 2008; Combes et al., 2011; Couture et al., 2018).

More specifically, we recover our desired elasticity β with the following Two-Stage Least Squares (2SLS) method:

$$\ln(Y_{ict}) = \beta \ln(D_{ict}) + \gamma_1' X_{ict} + \alpha_{1c} + \delta_{1t} + \phi_{1ct} + \epsilon_{ict} \quad (2)$$

$$\ln(D_{ict}) = \theta' Z + \gamma_2' X_{ict} + \alpha_{2c} + \delta_{2t} + \phi_{2ct} + u_{ict} \quad (3)$$

In the above equation, i corresponds to cells, c to countries and t to years. If we specify the equation on the cells, its estimates provide the within-cities estimator. If we only consider the cities, the estimates correspond to the between-cities estimator. D_{ct} is the density, which will be adjusted in the first stage. The specifications include several unobserved effects. First, country fixed effects (denoted by α_{1c} α_{2c}) to control for state-level regulations with common impacts and or other characteristics such as unobserved macroeconomic factors affecting the same pollution exposure in all observation units. Second, yearly fixed effects (δ_{1t} and δ_{2t}) to control for any exogenous shock in the economic cycle, again common to all countries/cities. Finally, the interaction country-year (denoted ϕ_{1ct} and ϕ_{2ct}) to control for unobserved characteristics, which can affect pollution exposure at a country-year level.⁵

We exploit three potential sources of exogenous variation to adjust population density at the first stage. First, we rely on soil quality, as in Combes et al. (2010). Soil can be an important determinant of

⁵Both, ϵ_{ict} and u_{ict} can be decomposed into an unobserved time-invariant individual component (cell or city effect) and a mixed error. We assume that the cell (city) effect is part of the mixed error and is uncorrelated with the regressors in the corresponding equation.

the existence patterns of cities, as its quality can influence the productivity of land (agriculture) and thus can attract more people to exploit it. Second, we rely on historical population density as a long lag instrument, as in [Ciccone and Hall \(1993\)](#). This instrument has been used very often in estimating the benefits and costs of agglomeration economies for US, but not for Europe. To our knowledge, only the work of [Borck and Schrauth \(2022\)](#) uses this instrument on a global scale, but at a lower resolution. On the other hand, if we use the population density of 1800 AD, we assume that there is a sufficient time lag between the pollution at the time of the pre-industrial revolution and today's main source of pollutants. Moreover, this variable is highly correlated with the current population, especially in Europe, where the dependence on the trajectory of cities is quite clear. Finally, the third instrument is the presence of aquifers. Following [Burchfield et al. \(2006\)](#), we assume that urban expansion, and thus population density, may be driven by the presence of aquifers, as urban developers can reduce costs by connecting the water supply network to a natural aquifer.

The instrument related to soil quality is valid as long as there is some path dependence in the spatial distribution of population and the current local pollution factors differ from those in the past ([Combes et al., 2010](#)). To check whether the 1800 AD historical density is robust to multiple historical lags, we compare several historical population densities with our preferred one in section 5. We argue that all these instruments are valid since they cannot directly influence PM2.5 except through population density: neither subsurface characteristics (soil quality and presence of aquifers) nor 1800 AD population density can affect the average PM2.5 level in a present-day city.

We control for multiple observable variables (X vector in equation 2) that may influence PM2.5. Since they are considered strictly exogenous, we use this set of variables in estimating population density at the first state (equation 3). We have encapsulated these controls into four groups. The first includes weather-related variables: temperature, precipitation and wind speed. It might be the case that weather conditions affect pollution levels. For instance, PM2.5 levels rise during summer periods and disappear during episodes of heavy rainfall or wind. It could also affect density, as the location of homes is based on weather conditions ([Rappaport, 2007](#)). Second, we control for geological variables: latitude and terrain ruggedness. Terrain ruggedness refers to the average grid-cell difference in elevation between a cell and the surrounding terrain ([Nunn and Puga, 2012](#)). Pollutants may be concentrated in regions whose elevation is in valleys or riverbanks, as in the Po Valley. Third, trade-related variables: if the city is coastal, the distance to the nearest water source. Following [Carozzi and Roth \(2023\)](#), we use these controls to reduce bias in the first stage estimation of population density. Finally, we include a measure of the distance from a city of power plants open to pollutants, either oil, gas, or coal power plants, to each city or grid cell. These possible emissions from power

plants could also be causing the location of households sorting into denser places and the PM2.5 in the environment.

3.2 The Effect of UAR on Pollution Exposure

We are only able to measure the effect of UARs on pollution exposure in our sample of cities due to missing data that prevents us from integrating it properly into our cell dataset. We think that our panel dataset on cities allows estimating the effect of the implementation of any regulation. To calculate the effect of UARs on pollution exposure, we first use a simple difference-in-difference strategy by adding the treatment term Tct in equation 4. We estimate the model, again, using TSLS with all controls for fixed effects. In this sense, the parameters θ_{cj} capture the diff-in-diff causal effect. Since we are dealing with a staggered treatment (cities adopt regulations at different times), the definition of Tct must consider it. We are aware that not accounting for this heterogeneous adoption may lead to biased estimates (Goodman-Bacon, 2021). For this reason, we use the estimator proposed by Sun and Abraham (2021). The form of the equation of this dynamic difference-in-difference event study has the following form:

$$\ln(Y_{ct}) = \sum_{j=-6, \neq -1}^6 \theta_{cj} T_{ct} + \beta \ln(D_{ct}) + \gamma' X_{ct} + \alpha_c + \delta_t + \phi_{ct} + \epsilon_{ct} \quad (4)$$

where normalization is at $t = -1$ and we allow the impact of the UARs on PM2.5 exposure is measured by parameters θ_{cj} . Again, we adjust in the first step D_{ict} using equation (3).⁶

4 Results

This section presents the main findings of the paper, structured into two subsections. Firstly, we present estimations of how density affects pollution exposure, using several alternative specifications. Secondly, we examine the influence of UARs on pollution exposure while controlling for density and a wide specification of strictly exogenous variables.

⁶Equation (4) allows the causal effect of the introduction of UARs to be different in different countries, but we also estimate a common effect, see Figure 3.

4.1 Pollution and Density

The baseline results of our exercise consider that population density is exogenous, and to save space we present in the first part of Table 10 in the Appendix the naive OLS estimation (equation 2 without instrumenting density) between density and pollution exposure. We explore several specifications, including all the controls described in section 3 and/or different fixed effects. We find that density is significantly (at the 1% level) and positively associated with pollution exposure. In the fully specified model, the coefficient is 0.028, i.e., a 1% increase in population within a given city implies a 2.8% increase in PM_{2.5} exposure. However, it is important to recognize potential bias in the estimate, as several factors suggest endogeneity issues related to population density. As discussed in section 3, households may be strategically located in areas (such as suburbs) with lower exposure to harmful pollutants. Additionally, omitted variable bias may arise due to households choice areas benefiting from amenities and other positive spillovers of agglomeration economies. Furthermore, population density could suffer measurement errors due to the uneven spatial distribution of economic activity. Considering all these factors, we argue that IV estimation is necessary for correcting bias.

In the second part of Table 10, we can observe how the elasticity of the pollution exposure varies concerning density, doubling its value in the fully specified model. Despite any remaining potential bias, this suggests that naive estimation of spatial economic activity induces measurement error. Table 11 presents OLS estimates for the within dataset. The elasticity now stands at 0.046, considering the entire European territory. If we believe that one of these estimates is consistent, a preliminary conclusion we can draw is that the magnitude of the bias in the elasticity between density and pollution exposure ranges in the difference between 0.029 and 0.046.

Turning our attention to the IV estimation of the between-cities sample in Table 2, we observe notable variations in the estimates across different specifications, each incorporating all controls and fixed effects. Using the instruments of aquifer presence and historical density, the elasticity ranges from 0.033 to 0.11. This implies that a 1% increase in density is associated with a corresponding increase in PM_{2.5} exposure within the range 3.3% to 11%. This substantial variation underscores the downward bias present in the OLS coefficients, attributable to confounding factors influencing density and the reverse causality between density and PM_{2.5} exposure. In panel 2 of Table 2, the estimated coefficients are now associated with the experienced density measure. Notably, the coefficient is significant at the 1% level for both the soil quality and historical density instrument. The coefficient of density remains significant at the same level with the rest of the instruments and its magnitude increases. The historical density instrument notably achieves a higher F-Test statistic in the first stage estima-

tion of equation 2. Also very remarkable is the similar magnitude of the coefficient when using the experienced density measure, ranging between 0.056 and 0.06.

Table 2: Between Cities PM2.5 Exposure IV Estimates with Population

	Soil Quality	Historical Density	Aquifer
Log (Population)	0.041*** (0.003)	0.033*** (0.002)	0.110*** (0.024)
Weather	Yes	Yes	Yes
Geological	Yes	Yes	Yes
Water	Yes	Yes	Yes
Power Plants	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
N	12,180	12,180	12,180
F-test (1st stage), Log (Population)	119.7	5,781.2	17.1
<hr/>			
Log (Experienced Dens.)	0.054*** (0.003)	0.060*** (0.004)	0.060** (0.030)
Weather	Yes	Yes	Yes
Geological	Yes	Yes	Yes
Water	Yes	Yes	Yes
Power Plants	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
N	12,180	12,180	12,180
F-test (1st stage), Log (Exp. Dens.)	106.6	2,837.9	20.8

Notes: Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Clustered (country-year) standard-errors in parentheses. Fixed Effects: Country-year, country and year. Temporal coverage: 2007-2021. Countries: Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom .

All coefficients stabilize at around 0.06. We consider this shift in the coefficient plausible, given the methodology used to calculate the experienced density. Furthermore, Table 12 in the Appendix reports the results of all possible specifications. We note the robustness of the elasticity figure. It falls within the range 0.041 and 0.054 when using the soil instrument (columns (1)-(4)), and is significant at a 1% level. The same pattern can be observed for the aquifer instrument (columns 9-12) and the historical density instrument (columns 5-8).

Comparing these estimates with those of other studies, remarkable similarities emerge. [Carozzi and Roth \(2023\)](#), for example, conclude that their preferred elasticity is 0.14 in the between-cities sample for the US territory, using all geological instruments. Our estimated elasticity of 0.033, using the

(comparable) naive density and the aquifer instrument, aligns closely with their findings. It is important to note that, despite being comparable, these estimates may differ due to variations in data, geographical coverage, and periods used. In another study, [Ahlfeldt and Pietrostefani \(2019\)](#) report an elasticity of 0.12.

Policy-makers may be interested in the historical trend of this elasticity. In Graph 4 in the Appendix, we depict the country-year fixed effects of the second model in Table 2. We observe a diminishing trend over the years, revealing some heterogeneity within the European continent. Less advanced and/or smaller economies, such as Balkan countries (Albania, Serbia, Montenegro, Croatia) or some Eastern European countries (Bulgaria), exhibit above-average effects of density on pollution exposure of city inhabitants, with all other variables held constant. In contrast, Nordic countries (Denmark, and Sweden) present the lowest fixed effect compared to other countries.

Table 3: Within Cities PM2.5 Exposure IV Estimates with Population Counts

	Soil Toxicity	Historical Density	Aquifers
Log (Pop.)	0.344*** (0.021)	0.142*** (0.005)	0.579*** (0.028)
Weather	Yes	Yes	Yes
Geological	Yes	Yes	Yes
Water	Yes	Yes	Yes
Power Plants	Yes	Yes	Yes
FE: Country - year, Country and Year	Yes	Yes	Yes
Observations	47,852,785	47,852,785	47,852,785
F-test (1st stage)	22,423.1	3,222,527.8	136,783.9

Notes: Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Clustered (country-year) standard-errors in parentheses. Fixed Effects: Country-year, country and year. Temporal coverage: 2007-2021. Countries: Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom .

In Table 3 we can see the elasticities estimated using the grid cell (within) dataset. We observe that all elasticities are significant at the 1% level, and the magnitude lies between 0.14 and 0.58. Our preferred estimate in this context is derived from the specification using the historical density instrument. It is important to highlight that, in the first column, we only use the soil toxicity characteristic as the instrument for computational reasons.

4.2 Pollution and Urban Access Regulations

We use the between-cities dataset to measure the effect of adopting a UAR on pollution exposure. Looking at Table 4, we see that the effect of adopting an UAR is slightly negative, and is around 2.7%. This means that, on average, after an implementation of a UAR, the exposure to pollution in cities is 2.7% lower.

Table 4: Treatment Effect of Urban Access Regulation on PM2.5 Exposure

	(1)	(2)
UAR	-0.028*	-0.027*
	(0.015)	(0.014)
Weather	Yes	Yes
Geological	Yes	Yes
Water	Yes	Yes
Power Plants	Yes	Yes
FE	Yes	Yes
Observations	9,675	9,675
F-test (1st stage), Log(Pop.)	5,655.3	
F-test (1st stage), Log (Exp. Dens.)		3,056.2

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Clustered (country-year) standard errors in parentheses. Fixed Effects: Country-year, country and year. Temporal coverage: 2007-2021. Countries: Austria, Belgium, France, Germany, Italy, Latvia, Netherlands, Norway, Poland, Spain, Sweden and United Kingdom

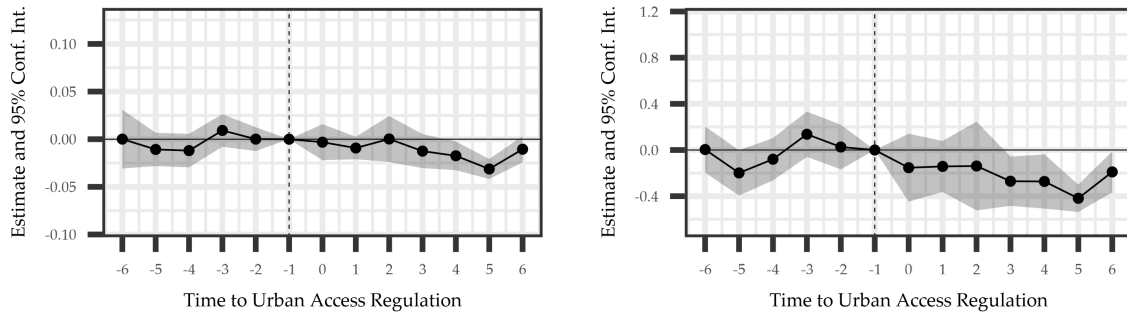
Next, looking at panel A of Figure 3, we see that this effect is only significant at the 4th and 5th lag, with the level of the former (2.5%) matches the effect of the previous reported treatment (2.7%). In panel B, where we only look at exposure levels (without taking logs), the effect appears to be slightly more significant, again reaching its maximum significance at the 4th and 5th lags. This means that the effect of the introduction of UARs is not short-term but long-term, and could have many political, environmental and health implications.

Note that, as we saw in Table 4, the panel is quite unbalanced. Looking at Figure 5 in the Appendix, we observe that those countries with a larger number of treated cities, like Germany, have a significant and negative effect of adopting any UAR. In fact, within this country, there are 32 treated cities out of a total of 102. Furthermore, the parallel trends assumption seems to hold at the light of the pre-treatment effect. If we look, for instance, at Italy, we see that the effect is also negative, but the parallel trends assumption does not hold. Sweden may also be another interesting country to ana-

Figure 3: Dynamic Difference-in-Differences Event Study

A) Log(Exposure)

B) Exposure



Notes: Panel A) shows the effect of adopting any UAR on the logarithm of population weighted cities exposure (see equation 1), and panel B) the exposure, after controlling for all possible controls detailed in section 2, and city, country, year and country-year fixed effects. We use the between-cities dataset for running this exercise and we exclude from the sample countries that never adopted any UAR in any city.

lyze. However, its control group is much larger than the treatment group (1 in 8 cities adopted some municipal regulation), so it is very difficult to draw sensitive conclusions.

Overall, although the event study does not shed much light, mainly due to data limitations, we believe that there is evidence to hypothesize that UARs do indeed reduce PM_{2.5} exposure. In our exercise, this constitutes more of a signal of correlation than causality because of two main drawbacks. First, our data on regulations is not official and so we are not sure about its quality. Second, we do not observe the past recent years (2022 onward). Publishing geospatial data takes time and the institutions that produce them are in constant research. Therefore, estimating the impact of adopting a UAR with so little historical data is very challenging. Furthermore, since the control and treated samples are not balanced, we should be cautious in interpreting the estimate as a causal impact since confounding factors could bias it. However, we believe that our attempt is a first step in providing an estimate in an active area of research, albeit with much room for improvement.

5 Robustness Analysis

This section presents some checks to assess the robustness of our instruments. We explore different specifications and employ alternative instruments for testing purposes. In particular, we use historical and experienced density measures to provide additional evidence of their informativeness in capturing agglomeration economies in our context. The first set of results employs historical density

as an instrument at different time lags in the first stage, as illustrated in Table 5. More specifically, we use the historical density figures of 100 AD, 1000 AD, 1500 AD, and 1800 AD.

Table 5: PM2.5 Exposure IV Estimates Robustness: Historical Densities

	100 AD	1000 AD	1500 AD	1800 AD
Log (Experienced Density)	0.074*** (0.007)	0.077*** (0.005)	0.070*** (0.005)	0.060*** (0.004)
Observations	12,180	12,180	12,180	12,180
F-test (1st stage)	1,387.3	1,409.2	2,075.6	2,837.9
Log (Pop.)	0.221*** (0.007)	0.190*** (0.006)	0.169*** (0.006)	0.142*** (0.005)
Observations	47,852,785	47,852,785	47,852,785	47,852,785
F-test (1st stage)	1,250,670.5	1,973,644.1	2,696,604.7	3,222,527.8
Weather	Yes	Yes	Yes	Yes
Geological	Yes	Yes	Yes	Yes
Water	Yes	Yes	Yes	Yes
Power Plants	Yes	Yes	Yes	Yes
FE: Country-Year, country and year	Yes	Yes	Yes	Yes

Notes: Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Clustered (country-year) standard-errors in parentheses. Fixed Effects: Country-year, country and year. Temporal coverage: 2007-2021. Countries: Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom .

These results directly confirm the relevance condition of the instrument, indicating a clear correlation between cities' experienced density in 100 AD and the current experienced density of cities. Furthermore, recognizing that the impact of past density, operating through present density, on pollution exposure, might be subject to the influences of economic growth, we introduce trade-related variables - specifically, the group labelled 'water' in all regressions - to account for this effect of the business cycle.

Also, examination of the Table 13 in the Appendix reveals significant estimates of the elasticity across different specifications of the soil quality instrument. In the first row, the elasticity is calculated incrementally for various soil characteristics by progressively adding each distinct soil quality to the specification. Note that the elasticity of 0.054 in column 7 aligns that of the model in Table 2 when the experienced density is used.

If larger cities display higher pollutant concentration, it raises the possibility that the city size/area

could act as an important confounder between economic activity concentration and pollution concentration. To assess whether the positive elasticity is driven by population size, we present estimates in Table 14, controlling flexibly for population using polynomials of the total sum of the population in a city and city area, similar to Carozzi and Roth (2023). As a final robustness check, we analyze whether the joint inclusion of the historical (1800 AD) and the aquifer instruments is significant and determines the magnitude of the elasticity. The results are displayed in Table 14. Using both historical density and the presence of aquifers as instruments yields an elasticity range of 0.059 to 0.062. Subsequently, after incorporating polynomials of the total population, the elasticity estimates do not significantly differ from those reported in tables 2 or 12, suggesting that results are not being driven by city size alone. Surprisingly, the sign of the elasticity changes only when adding a third polynomial. However, we argue that the third polynomial could lead to overfitting of the model. Overall, urban sprawl does not appear to be a driving factor, as the same explanation holds when examining the results of the second row of Table 14.

6 Conclusion

We planned in this study to answer two research questions. First, we like to estimate the elasticity between population density and pollution exposure in Europe. We did so at the country, city and more granular level with data for $1km^2 \times 1km^2$ cells, trying to highlight both the differential effect between and within cities. Second, we try to analyze the effect of the introduction of UARs on the volume of PM2.5 in some cities to mitigate the exposure of inhabitants to pollutants. The detection of effects of population density on pollution levels can have several direct and/or indirect consequences, e.g., on mortality and morbidity. It can also lead to unequal consequences on individuals, in terms of health as well as income, to the extent that they live and/or work and have to move to locations where pollution exposure is higher. The introduction of environmental policies as UARs can avoid premature deaths and morbidity thus reducing health costs and, potentially, contributing to reducing inequalities.

For the analysis of the two questions, we compiled geographic and spatial data taken from multiple sources: 1) A sample of cities with a set of variables that characterize them, enabling exploration of the effects between cities (between-cities analysis). 2) A sample consisting of $1km^2 \times 1km^2$ cells representing the European territory across 33 countries, allowing for analysis of internal city variations (within-cities analysis). 3) Data detailing the location and timing of UARs introduction in the EU.

The exercise faces several methodological challenges. Firstly, there is a concern that population may

be endogenous, necessitating the identification of relevant instruments (correlated with population density) and exogenous instruments (uncorrelated with the error term of the model). Secondly, there is difficulty in identifying suitable controls to estimate the causal effect of UARs on pollution exposure. Given that regulations during our sample period primarily affect large cities and not small cities, constructing a balanced sample (in terms of observable variables) becomes challenging, making it uncertain whether the estimate truly reflects the causal impact of the regulation.

In relation to the first research question, we find that there is a significant and positive effect of density on pollution exposure, with our preferred estimate showing an elasticity of 0.06. This estimate is 50% lower than the reported elasticity in other studies for the US, indicating potential differences in agglomeration economies and their externalities and spillovers across regions. We believe that this discrepancy presents an intriguing area for further investigation, warranting exploration into the underlying reasons. It would be interesting to examine whether differences in industry composition or land use contribute to varying spillover effects between regions. Additionally, exploring the inclusion of historical sources of pollution, such as power plants, may provide insights into these divergences, although we suspect that this may not be the primary source of uncertainty in our estimates.

Concerning the second research question, we find that the adoption of a UAR has a slightly significant and negative effect on pollution exposure, estimated at about 2.7%. The main drawback of estimating this effect is twofold. First, our data sourced from a privately-held project lacks official validation, raising concerns about data quality. Second, the absence of recent years' data (post-2022) limits our ability to assess the long-term impact of UAR adoption. Moreover, the imbalance between control and treated samples complicates the interpretation of our estimate as causal, as confounding factors could bias the results. Nevertheless, we view our analysis as an initial step in this active area of research, acknowledging substantial room for improvement. To enhance our estimation approach, we propose leveraging the within-cities dataset and exploring spatial difference-in-differences estimators. Such methods could provide deeper insights into the effects of UAR adoption, particularly concerning potential negative spillovers on the city periphery. For instance, restrictions on driving in city centers under UARs might lead to increased pollutant transit in surrounding areas, potentially impacting our estimates. In summary, while our findings suggest a pattern of positive effects from UAR adoption, further research efforts are needed to address data quality issues, improve estimation techniques, and account for spatial dynamics in pollution exposure.

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A Appendix

B Descriptives

Table 6: Descriptive Statistics of Cities characteristics (between)

	Mean	Standard Deviation
Population	0.13	0.34
Experienced Density	0.15	0.15
Pollution Exposure	15.18	5.76
Temperature	8.23	3.38
Precipitation	3.61	1.22
Wind Speed	2.55	1.26
Ruggedness	14.84	14.54
Coast City	0.45	0.50
Water Distance	131.12	148.15
Coast Distance	40.57	46.55
Power Plant Distance	554.98	387.14

Notes: Yearly (2007-2021) averages and standard deviation for Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom . Population and experienced density is expressed in millions of persons, temperature in Celsius degrees, precipitation in millimeters per day, wind speed in meters per second (in thousands) at a 10 meter height above the surface, and all distance variables are expressed in kilometers (km).

Table 7: Descriptive Statistics of Cities characteristics (within)

	Mean	Standard Deviation
Population	105.73	725.91
PM2.5	10.83	5.27
Temperature	6.62	4.50
Precipitation	0.00	0.00
Wind Speed	3.16	1.20
Ruggedness	16.66	20.90
Coast City	0.30	0.46
Water Distance	0.22	0.41
Power Plant Distance	0.15	0.36

Notes: Yearly (2007-2021) averages and standard deviation for Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom . Population and experienced density is expressed in millions of persons, temperature in Celsius degrees, precipitation in millimeters per day, wind speed in meters per second (in thousands) at a 10 meter height above the surface, and all distance variables are expressed in kilometers (km).

Table 8: Descriptive Statistics of Cities instruments (between)

	Mean	Standard Deviation
Population in 100 A.D.	0.10	0.61
Population in 1000 A.D.	0.13	0.79
Population in 1500 A.D.	0.43	1.94
Population in 1800 A.D.	1.47	5.23
Highly productive porous aquifers	0.31	0.38
Low and moderately productive porous aquifers	0.22	0.34
Highly productive fissured aquifers	0.11	0.25
Low and moderately productive fissured aquifers	0.08	0.23
Locally aquiferous rocks, porous or fissured	0.18	0.31
Practically non-aquiferous rocks, porous or fissured	0.10	0.24

Notes: Population is expressed in millions of people. Aquifer variables measure the share of land within a city with such aquifer characteristic. Yearly (2007-2021) averages and standard deviation for Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom. Population and experienced density is expressed in millions of persons, temperature in Celsius degrees, precipitation in millimeters per day, wind speed in meters per second (in thousands) at a 10 meter height above the surface, and all distance variables are expressed in kilometers (km).

Table 9: Cities Soil Quality: Share of Land by Quality

	Excess Salts	Nutrient availability	Nutrient retention	Oxygen availability	Rooting conditions	Toxicity	Workability
Mainly non-soil	0.02	0.03	0.02	0.02	0.02	0.02	0.02
Moderate limitations	0.24	0.24	0.21	0.24	0.24	0.24	0.24
No or slight limitations	0.48	0.50	0.57	0.48	0.48	0.48	0.48
Sever limitations	0.13	0.13	0.09	0.13	0.13	0.13	0.13
Very severe limitations	0.07	0.05	0.04	0.07	0.07	0.07	0.07

Notes: Yearly Averages (2007 - 2021) for Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom .

C Regressions

Table 10: Between OLS Estimates for PM2.5 Exposure

	(1)	(2)	(3)	(4)	(5)	(6)
Log (Pop.)	0.034*** (0.003)		0.032*** (0.003)		0.029*** (0.001)	
Log(Exp. Dens.)		0.017*** (0.004)		0.028*** (0.004)		0.046*** (0.003)
Country - Year					Yes	Yes
Country					Yes	Yes
Year					Yes	Yes
All Controls	No	No	Yes	Yes	Yes	Yes

Notes: Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Clustered (country-year) standard-errors in parentheses. Fixed Effects: Country-year, country and year. Temporal coverage: 2007-2021. Countries: Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom .

Table 11: Within OLS Estimates for PM2.5 Exposure

	(1)	(2)	(3)
Log (Pop.)	0.061*** (3.45×10^{-5})	0.069*** (3.18×10^{-5})	0.070*** (0.001)
Country - Year			Yes
Country			Yes
Year			Yes
Observations	47,852,785	47,852,785	47,852,785
Adjusted R ²	0.061	0.221	0.324

Notes: Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Clustered (country-year) standard-errors in parentheses. Fixed Effects: Country-year, country and year. Temporal coverage: 2007-2021. Countries: Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom .

Table 12: Between Cities PM2.5 Exposure IV Estimates with Population Density

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log (Pop.)	0.041*** (0.003)	0.040*** (0.003)	0.041*** (0.003)	0.041*** (0.003)	0.035*** (0.003)	0.035*** (0.002)	0.033*** (0.002)	0.033*** (0.002)	0.122*** (0.033)	0.113*** (0.031)	0.114*** (0.027)	0.110*** (0.024)
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geological		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Water			Yes	Yes			Yes	Yes			Yes	Yes
Power Plants				Yes				Yes				Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,180	12,180	12,180	12,180	12,180	12,180	12,180	12,180	12,180	12,180	12,180	12,180
F-test (1st St.)	118.0	117.6	119.6	119.7	5,838.6	5,828.9	5,779.4	5,781.2	16.0	14.9	17.0	17.1

Log (Exp. Dens.)	0.051*** (0.004)	0.053*** (0.004)	0.054*** (0.003)	0.054*** (0.003)	0.061*** (0.004)	0.062*** (0.004)	0.060*** (0.004)	0.060*** (0.004)	0.018 (0.032)	0.052 (0.036)	0.062** (0.031)	0.060** (0.030)
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geological		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Water			Yes	Yes			Yes	Yes			Yes	Yes
Power Plants				Yes				Yes				Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,180	12,180	12,180	12,180	12,180	12,180	12,180	12,180	12,180	12,180	12,180	12,180
F-test (1st St.)	97.8	98.1	106.6	106.6	2,951.4	2,944.4	2,836.3	2,837.9	17.8	16.8	20.8	20.8

Notes: Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Clustered (country-year) standard-errors in parentheses. Fixed Effects: Country-year, country and year. Temporal coverage: 2007-2021. Countries: Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom . . Columns (1)-(4) first stage instrument is soil quality, columns (5)-(8) historical density (1800 AD) and columns (9)-(12) aquifers presence.

Table 13: Robustness Check for Between Cities PM2.5 Exposure IV Estimates using Multiple Soil Quality Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Incrementally</i>							
Log (Exp. Dens)	0.070*** (0.004)	0.058*** (0.004)	0.056*** (0.004)	0.057*** (0.004)	0.058*** (0.004)	0.055*** (0.004)	0.054*** (0.003)
F-test (1st stage)	2.21	3.22	3.38	6.24	6.29	5.49	
<i>Separately</i>							
Log (Exp. Dens)	0.070*** (0.004)	0.061*** (0.005)	0.058*** (0.005)	0.062*** (0.005)	0.056*** (0.005)	0.044*** (0.006)	0.067*** (0.004)
F-test (1st stage)	617.7	489.9	472.5	415.5	424.0	407.6	590.9
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geological	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Water	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Power Plants	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,180	12,180	12,180	12,180	12,180	12,180	12,180

Columns 1 to 7 stand for different soil characteristics (ordered): toxicity, nutrient retention, nutrient availability, workability, rooting conditions and excess of salts. *Notes:* Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Clustered (country-year) standard-errors in parentheses. Fixed Effects: Country-year, country and year. Temporal coverage: 2007-2021. Countries: Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom .

Table 14: Robustness Check in Between Cities PM2.5 Exposure IV Estimates for City Size adding City Area

	No Polynomial	Sum Population	2nd Degree Pol	3rd Degree Pol
<i>City Area: NO</i>				
Log (Exp. Dens)	0.062*** (0.003)	0.045 (0.029)	0.008 (0.027)	-0.029 (0.056)
F-test (1st stage)	424.5	27.6	33.7	14.5
<i>City Area: YES</i>				
Log (Exp. Dens)	0.059* (0.035)	0.034 (0.024)	0.021 (0.027)	0.072 (0.078)
F-test (1st stage)	16.8	34.5	32.0	8.95
Weather	Yes	Yes	Yes	Yes
Geological	Yes	Yes	Yes	Yes
Water	Yes	Yes	Yes	Yes
Power Plants	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	12,180	12,180	12,180	12,180

Notes: Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Clustered (country-year) standard-errors in parentheses. Fixed Effects: Country-year, country and year. Temporal coverage: 2007-2021. Countries: Albania, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom. . Column (1) shows adds no polynomial terms of population, column (2) adds the sum of population of a given city, and the following columns add a squared and cubic exponential terms to the sum of population to the control covariates.

Table 15: Treatment Effect of Urban Access Regulation on PM2.5 Exposure

	Austria (1)	Belgium (2)	France (3)	Germany (4)	Italy (5)	Latvia (6)	NL (7)	Norway (8)	Poland (9)	Spain (10)	Sweden (11)	UK (12)
UAR	-0.096 (0.057)	-0.002 (0.007)	0.046** (0.018)	-0.026*** (0.004)	0.023 (0.021)		-0.046*** (0.006)	-0.085 (0.105)	0.021 (0.015)	0.049 (0.035)	-0.016 (0.019)	-0.046 (0.039)
Weather	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geological	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Water	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes
Power Plants	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	120	255	1,185	1,530	1,320	45	585	90	930	1,230	240	2,145
F-test, Log (Pop.)	133.9	1,498.6	1,183.4	1,922.3	1,980.5	-22.3	566.9	89.6	1,481.8	2,429.5	1,746.4	662.1

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. Clustered (country-year) standard errors in parentheses. Fixed Effects: Country-year, country and year. Temporal coverage: 2007-2021. Countries: Austria, Belgium, France, Germany, Italy, Latvia, Netherlands, Norway, Poland, Spain, Sweden and United Kingdom

D Figures

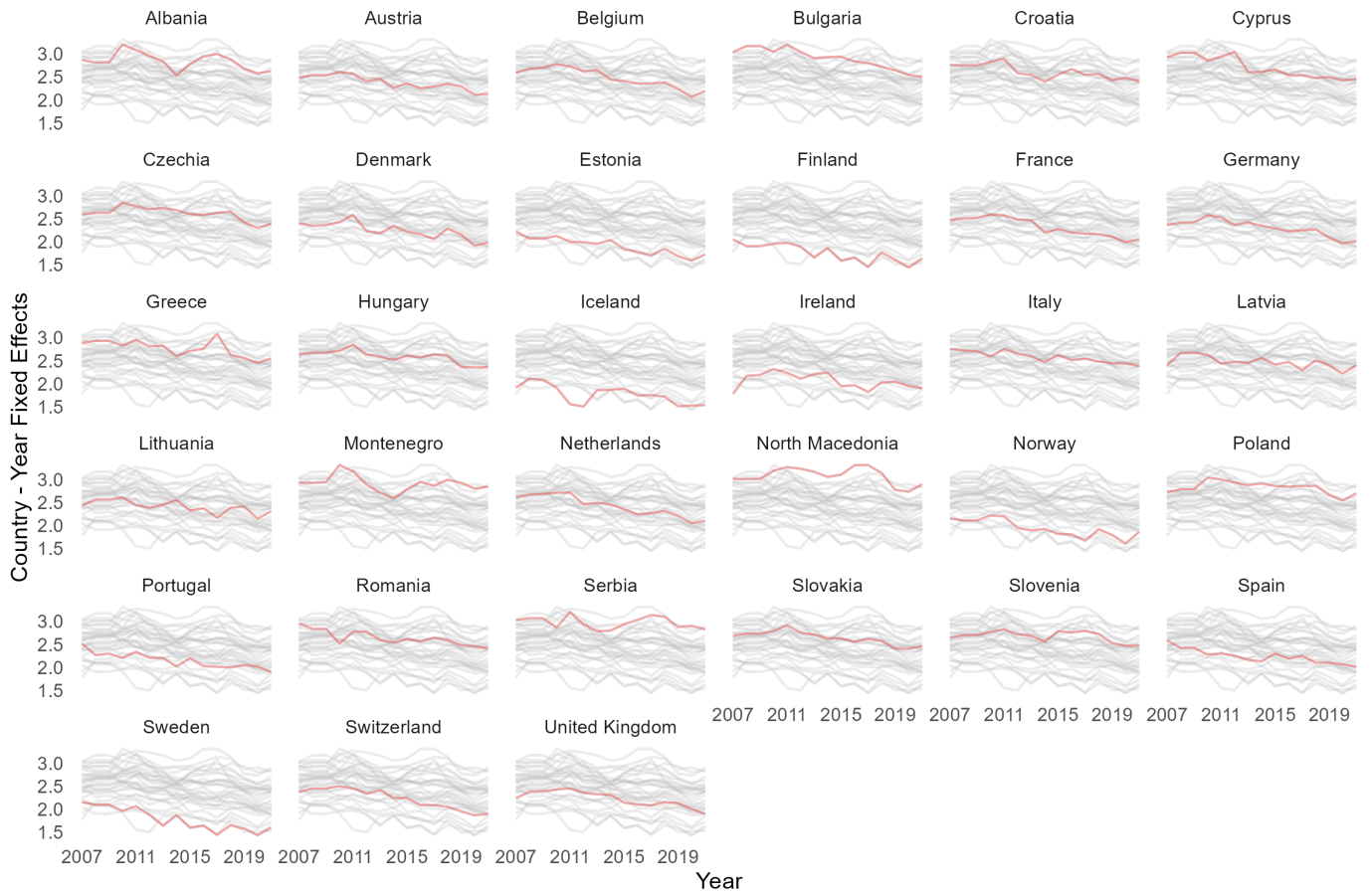


Figure 4: Country-Year Fixed Effects Coefficients

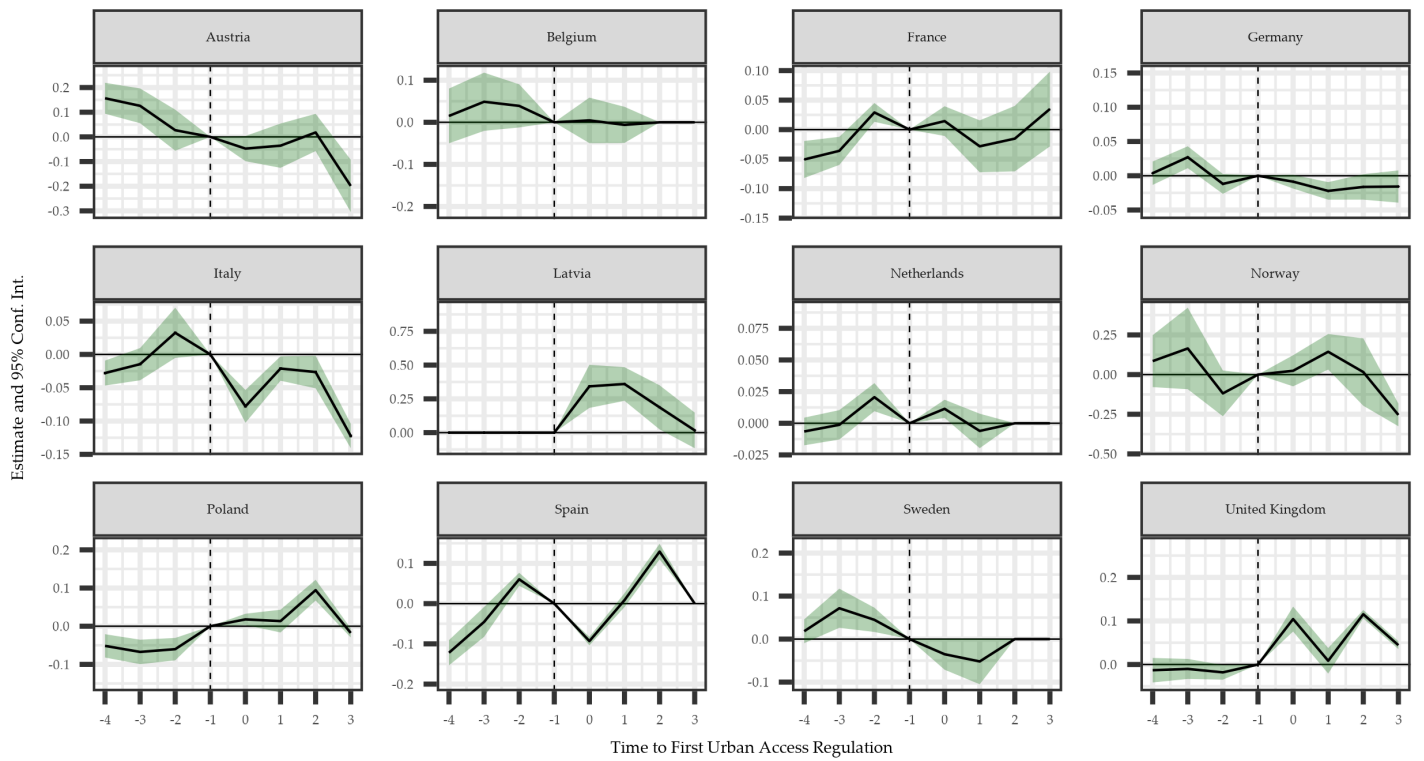


Figure 5: Dynamic Difference-in-Differences by Country