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 (UARs) 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 UARs on pollution exposure using 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 a UAR implementation, pollution exposure is reduced by 2.5%.

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1 Introduction

Agglomeration economies are known to have benefits like productivity and amenities, and also 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, 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 μg/m3 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 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

A) Population B) PM2.5 C) Density vs. PM2.5

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 that areas with higher population density, such as Madrid, London, the Netherlands or Paris, exhibit a greater 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, and lorries as well as 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 behind in research, specially 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 $1km^2x1km^2$. 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, a là 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 allows 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. To obtain this result, we webscraped data from a UAR data collector project. 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 refrain from adopting UARs. We acknowledge that the results from this quasi-experiment comes with many caveats, which poses doubts on the causal interpretation of the results. 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 find this elasticity value using a dynamic difference-in-differences research design to account for 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, measuring 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 with 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 is 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 territory. The next logical step in this inquiry is to explore the factors contributing to these differences. Another closely related paper is by Borck and Schrauth (2022), which 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 (cells with an area of 10km wide), and they only observe one year. In contrast, our analysis uses much finer-grained data spanning 14 years, albeit for the European territory. Despite these differences, our estimates are similar to theirs. Additionally, Borck and Schrauth (2021) compute these elasticities for Germany using ground pollution stations, finding an estimate of 0.08.

Fourthly, our study is also closely related to the active research field measuring the impact of low emission zones, zero emission zones, etc... (UARs) on several economic outcomes and their spillovers. For example, Galdon-Sanchez et al. (2023) investigate the effects of Madrid Central (Madrid's UAR implemented in 2019) on multiple outcomes including pollution 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 observe 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 a 9% decrease in PM10, while alternative policies such as building ring roads or investing in public transportation infrastructure did not yield 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.

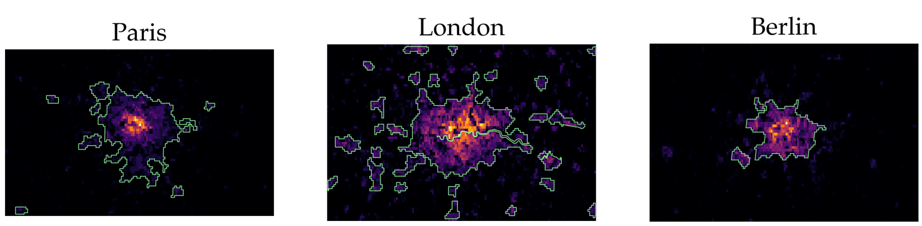
2 Data

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, we establish city boundaries using the GHS Settlement Model layers (GHS-SMOD). This dataset delineates and classifies settlement typologies by a logic of 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 in 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 from 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 the 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:

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

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 Density[1]

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

[1] Although for the sake of simplicity we call it 'density', we actually refer to 'spatial concentration of economic activity'

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 retention, 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 and 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, out 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

[2] Link to the page.

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.

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 varios 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 using 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 reamin static, given that the terrain slope does not exhibit temporal changes.

[3]Data can be found in here.

[4]Data from the European Environmental Agency.

3 Empirical Strategy

3.1 Estimating the elasticity of PM2.5 to population density

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

3.1.1 Instrumenting the population density

When quantifying the elasticity between population density and pollution exposure, some confounding factors arise. Residents in cities tend to self-sort into city centers to benefit from productivity spillovers of agglomeration. Amenities, sectoral specialization, and other factors affect both population density and pollution. Also, there is some reverse causality when quantifying the elasticity since households sort into locations where they are exposed to less pollutants (Heblich et al., 2021). Hence, using a naive OLS estimation to quantify such elasticity would entail a biased estimation. To overcome this issues, we adopt an IV strategy, isolating variation in population density that is uncorrelated with any part of the error term in the main estimation equation. Overall, 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:

$$ln(Y_{ct}) = \beta ln(\hat{D_{ct}}) + \gamma' X_{ct} + \alpha_u + \delta_t + \phi_{ut} + \epsilon_{cut} \tag{2}$$

$$\hat{D_{ct}} = Zln(I_{ct}) + \gamma' X_{ct} + \alpha_u + \delta_t + \phi_{ut} + \epsilon_{cut} \tag{3}$$

In the above equation, if we substitute the index c with i, we specify the equation on the cells and its estimates would provide the within cities estimator. $\hat{D_{ct}}$ stands for the estimated density of the first stage for city c at year t. The specifications include multiple fixed effects since the structure of the samples various heterogeneous factors. First, country fixed effects (denoted by α_u) 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_t) to control for any exogenous shock in the economic cycle, again common to all countries/cities. Finally, the interaction country-year (denoted ϕ_{ut}) to control for unobserved idiosyncratic characteristics, which can impact on pollution exposure both at country-year level.

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 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 gap between pollution of pre-industrial revolution era and the main source of pollutants today. Moreover, this variable is highly correlated with today's population, specially in Europe, where path dependence 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, can 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 with 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 historical density of 1800 AD 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 influence PM2.5 directly, except through population density: neither the subsurface characteristics (soil quality and presence of aquifers) nor the 1800 AD population density can affect the average PM2.5 level in a current 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, precipitations and wind speed. It might be the case that weather conditions affect pollution levels. For instance, PM2.5 levels rise during summer periods, and dissapear during episodes of heavy precipitation 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 ruggedness. Terrain ruggedness refers to the average grid-cell difference in elevation between a cell and the terrain surrounding (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 at 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 household sorting into denser places and the PM2.5 in the environment.

3.2 The Effect of UAR on Pollution Exposure

To calculate the effect of UARs on pollution exposure, we will first use a simple difference-in-difference strategy by simply adding the treatment term T measured by θ in equation 4. We estimate the model, again, using TSLS with all controls for fixed effects. In this sense, the term $\sum_{j=-6,\neq-1}^{6} \theta_{ct}$ capture the diff-in-diff causal effect. Then, as we have a panel dataset, we can ask what is the effect of such regulation after the implementation of any regulation. Since we are dealing with a staggered treatment (cities adopt regulations at different times), there is evidence 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 implementation of this dynamic difference-in-difference event study has the following form:

$$ln(Y_{ct}) = \sum_{j=-6,\neq -1}^{6} \theta_{ct} + \beta ln(\hat{D_{ct}}) + \gamma' X_{ct} + \alpha_u + \delta_t + \phi_{ut} + \epsilon_{cut} \tag{4}$$

where the impact of the UARs on PM2.5 exposure is measured by parameters θ. Models for dynamic treatment effects, modified for use with staggered rollout, can help in the case of staggered difference-in-differences since separate out the time periods when the effects take place.

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.

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 of the relation (the first part of the equation 2) 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 PM2.5 exposure. However, it is important to recognize possible bias in the estimate due to several reasons, all of them pointing to endogeneity of population density. As discussed in section 3, households may be strategically located in areas (such as suburbs) with lower exposure to harmful pollutants. Additionally, there may be omitted variable bias as households select areas benefiting from amenities and other positive spillovers of agglomeration economies. Furthermore, the correlation of population density could suffer measurement errors due to the uneven spatial distribution of economic activity. Taking all these considerations into account, we then argue that IV estimation is necessary to correct for bias.

In the second part of Table 10, we can observe how the elasticity of the pollution exposure varies with respect to density, doubling its value in the fully specified model. Despite 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. A first tentative conclusion we can draw is that the magnitude of the bias in the elasticity between density and pollution exposure range in the difference between 0.029 and 0.046, if we believe that one of these estimates is consistent.

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 PM2.5 exposure within the range 3.3% to 11%. This substantial variation underscores the downward bias present in the OLS coefficients, attributable both to confounding factors influencing density and the reverse causality between density and PM2.5 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 estimation of equation 2. Also very remarkable is the similar magnitude of the coefficient when using the experienced density measure, 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***	0.033***	0.110***
	(0.003)	(0.002)	(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
Adjusted R^2	0.833	0.834	0.781
F-test (1st stage), Log (Population)	119.7	5,781.2	17.1

Log (Experienced Dens.)	0.054***	0.060***	0.060**
	(0.003)	(0.004)	(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
Adjusted R^2	0.836	0.835	0.835
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 displays 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 other instruments, 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 instance, 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 time 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 country (Bulgaria), exhibit above-average effects of density on pollution exposure of city inhabitants, with all other variables held constant. In contrast, Nordic countries (Denmark, 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	Aquifiers
Log (Pop.)	0.344***	0.142***	0.579***
	(0.021)	(0.005)	(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
Adjusted R^2	-0.762	0.249	-3.42
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.

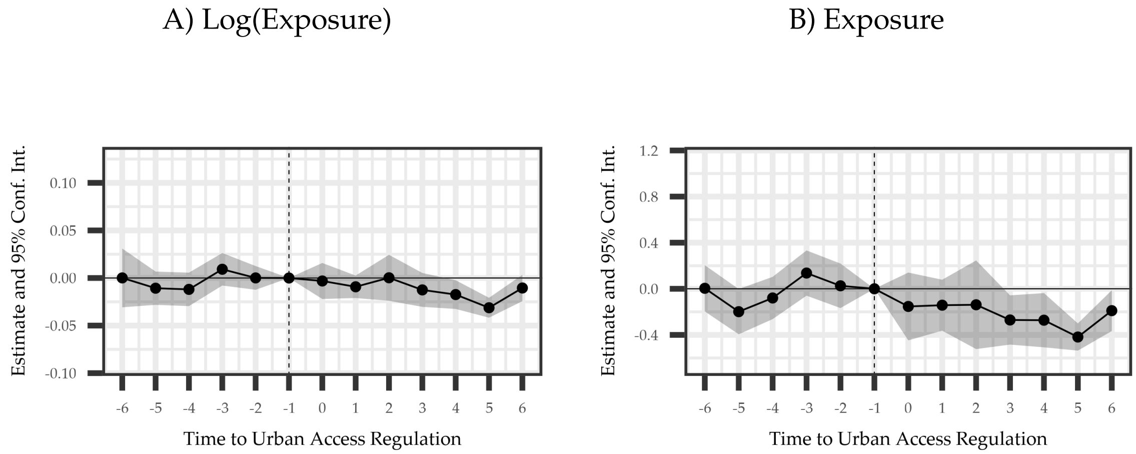
Table 4: Treatment Effect of Urban Access Regulation on PM2.5 Exposure

	(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
Adjusted R^2	0.789	0.794
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 is 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.

Figure 3: Dynamic Difference-in-Differences Event Study



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.

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 analyze. 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, we believe that there is evidence to hypothesize that UARs do indeed reduce PM2.5 exposure. In our exercise, this constitutes more 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). Geospatial data releases take time and institutions producing such data are constantly researching. Therefore, estimating the impact of the adoption of a UAR with so little historical data is very challenging. Furthermore, since the control and treated samples are not balanced, we should 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 to provide an estimate in an active area of research, although with a lot of 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 within our context. The first set of results employ historical density as 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 and 1500 AD.

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

	100 AD	1000 AD	1500 AD	1800 AD
Log (Experienced Density)	0.074***	0.077***	0.070***	0.060***
	(0.007)	(0.005)	(0.005)	(0.004)
Observations	12,180	12,180	12,180	12,180
Adjusted R^2	0.833	0.832	0.834	0.835
F-test (1st stage)	1,387.3	1,409.2	2,075.6	2,837.9
Log (Pop.)	0.221***	0.190***	0.169***	0.142***
	(0.007)	(0.006)	(0.006)	(0.005)
Observations	47,852,785	47,852,785	47,852,785	47,852,785
Adjusted R^2	-0.004	0.117	0.184	0.249
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 labeled 'water' in all regressions - to account for this effect of the business cycle.

Also, examining Table 13 in the Appendix reveals significant estimates of the elasticity through different specifications of the soil quality instrument. In the first row, the elasticity is computed 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 check whether the positive elasticity is derived from 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 size of the elasticity. The results can be seen in Table 14. Using both historical density and the presence of aquifers as instruments yields an elasticity of 0.059-0.062. Subsequently, after incorporating polynomials of the total population, the elasticity figures do not vary significantly from those reported in tables 2 or 12, indicating that results are not being driven by city size. Surprisingly, only when adding a third polynomial, the sign of the elasticity changes. However, we argue that the third polynomial could produce the effect of overfitting the curve. Overall, urban sprawl does not appear to be a driving factor, as the same explanation holds when examining 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 unequal consequences, in terms of health as well as income, on individuals 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 reduce inequalities.

For the analysis of the two questions, we construct geographic and spatial data taken from multiple sources: 1) A sample of a set of cities with a set of variables that characterize them, so that it is possible to explore the effects between cities (between-cities). 2) A sample formed by the cells of $1km^2 \times 1km^2$ cells with the same characteristics of the European territory (33 countries), so that it is possible to analyse the differential effects internal to the cities (within-cities). 3) Data covering the location and time of the introduction of UARs in the EU.

The exercise faces several methodological problems. First, the potential for the population density to be endogenous, which makes it necessary to find relevant instruments (correlated with it) and exogenous instruments (uncorrelated with the error term of the model). Second, the difficulty of finding adequate controls to estimate the causal effect on pollution exposure of the introduction of UARs. Since regulation during the time span of our sample affects big cities and does not affect small cities, it is difficult to construct a balance sample (in terms of observable variables) to be sure that the estimate constitute a causal effect of the regulation.

Regarding the first research question, we find that there is a significant and positive effect of density on such exposure, being our preferred estimate an elasticity of 0.06. This is 50% lower than the reported elasticity in other studies for the US. This finding suggests that agglomeration economies have different externalities and spillovers on each side of the ocean. We believe that this is a very interesting field of research, which requires further investigation into the reasons for these divergences. It would be interesting to test whether the composition of industry or land occupation affects this negative spillover in a disparate way in both areas. It could also be examined whether the inclusion of obvious sources of pollution (power plants) from a historical perspective would explain the differences, although our suspicion is that this is not the main source of uncertainty in our estimates.

Concerning the second research question, we find that the effect of adopting an UAR has a slightly significant and negative effect on pollution exposure, of about 2.7%. The main drawback of estimating this effect is twofold. First, our data is not official and so we're not sure about the data quality; not due to operation reasons but for the very source - the data comes from privately-held project and there are no guarantees that using this data may yield reliable estimates. Second, we do not observe the past recent years (2022 onwards). Geospatial data releases take time and institutions producing such data are constantly researching. Thus, to estimate the impact of the adoption of a UAR with such little historical data is very challenging. Furthermore, since the control and treated samples are not balanced, we should 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 to provide an estimate in an active area of research, although with a lot of room for improvement. For instance, not only regarding data quality, the estimation procedure can be improved by using the within-cities dataset. Specifically, we think that studying some spatial difference-in-differences estimator could shed more light on such UAR adoption effects. It could be the case that adopting an UAR could result in a negative spillover for the periphery of the city, since other factors being constant such as transportation levels, there is a restriction to drive in the city center and so there is more pollutant transit outside the extent of the UAR area. In fact, we believe that this fact may be contaminating our estimates, so that we do not find such desired significant and high effect, although we observe a pattern of positive effect of adopting a UAR.

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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 millimiters 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 millimiters 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 withn 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 millimiters 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^{***}		0.032^{***}		0.029^{***}	
	(0.003)		(0.003)		(0.001)	
Log(Exp. Dens.)		0.017^{***}		0.028^{***}		0.046^{***}
		(0.004)		(0.004)		(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^{***}	0.069^{***}	0.070^{***}
	(3.45×10^{-5})	(3.18×10^{-5})	(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***	0.040***	0.041***	0.041***	0.035***	0.035***	0.033***	0.033***	0.122***	0.113***	0.114***	0.110***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.033)	(0.031)	(0.027)	(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
Adjusted R^2	0.828	0.829	0.833	0.833	0.828	0.830	0.834	0.834	0.759	0.774	0.776	0.781
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***	0.053***	0.054***	0.054***	0.061***	0.062***	0.060***	0.060***	0.018	0.052	0.062**	0.060**
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.032)	(0.036)	(0.031)	(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
Adjusted R^2	0.831	0.832	0.836	0.836	0.830	0.832	0.835	0.835	0.828	0.832	0.835	0.835
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) aquifiers 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)
Incrementally							
Log (Exp. Dens)	0.070***	0.058***	0.056***	0.057***	0.058***	0.055***	0.054***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
F-test (1st stage)	2.21	3.22	3.38	6.24	6.29	5.49	
Separately							
Log (Exp. Dens)	0.070***	0.061***	0.058***	0.062***	0.056***	0.044***	0.067***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(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
City Area: ***NO***				
Log (Exp. Dens)	0.062***	0.045	0.008	-0.029
	(0.003)	(0.029)	(0.027)	(0.056)
F-test (1st stage)	424.5	27.6	33.7	14.5
City Area: ***YES***				
Log (Exp. Dens)	0.059*	0.034	0.021	0.072
	(0.035)	(0.024)	(0.027)	(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	-0.002	0.046**	-0.026***	0.023		-0.046***	-0.085	0.021	0.049	-0.016	-0.046
	(0.057)	(0.007)	(0.018)	(0.004)	(0.021)		(0.006)	(0.105)	(0.015)	(0.035)	(0.019)	(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
Adjusted R^2	0.863	0.920	0.859	0.834	0.755	0.338	0.968	0.668	0.838	0.546	0.915	0.842
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

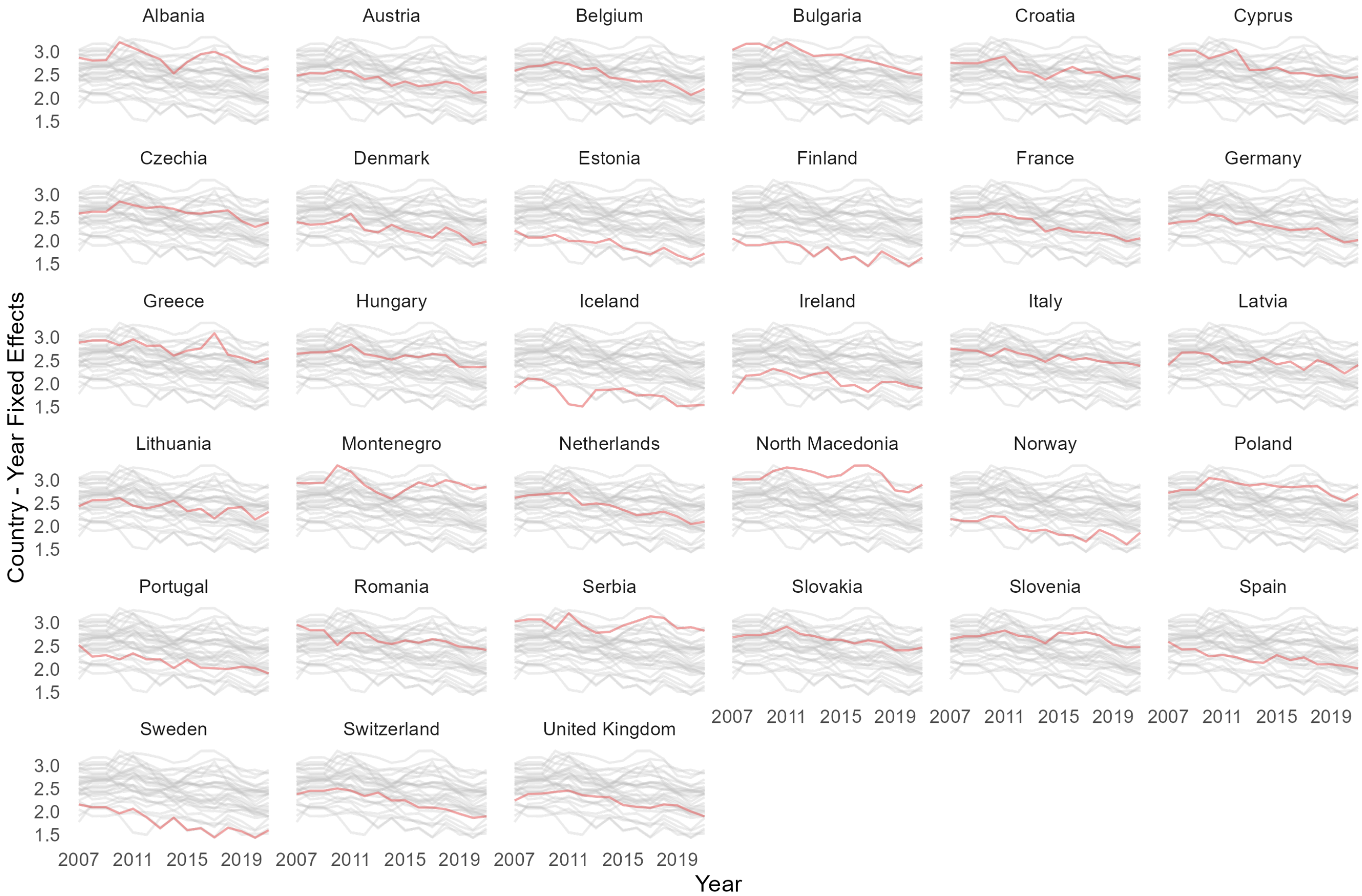

Figure 4: Country-Year Fixed Effects Coefficients

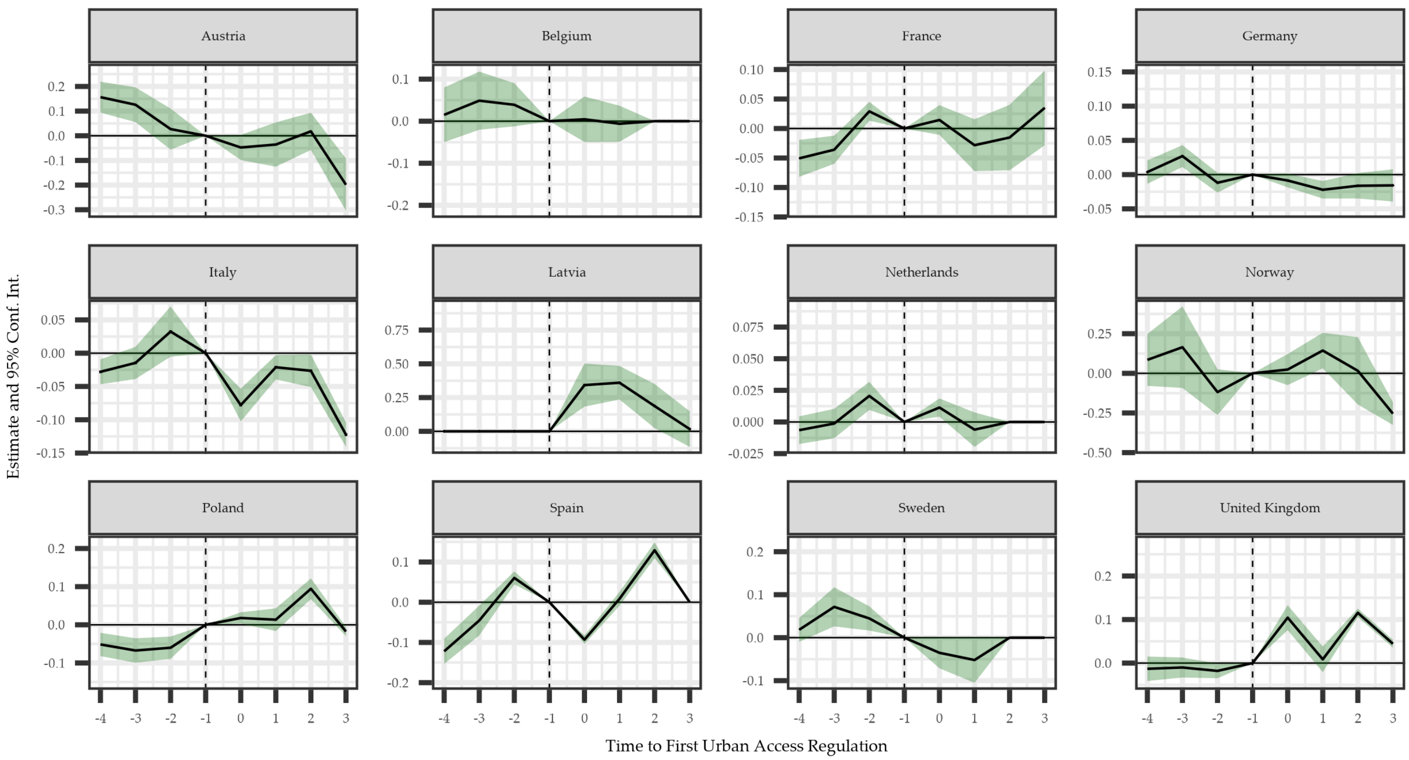

Figure 5: Dynamic Difference-in-Differences by Country