

# Denser cities: a blessing or a curse?

A study on the relationship between urban population density and air pollution



*Photo credit: UN Environment Program (2022)*

**Abstract:** *Air pollution is a typical negative congestion force associated with urban living. This paper has looked at a panel of European cities to determine the effect of population density on air pollution between cities. Using satellite readings of PM<sub>2.5</sub> concentration, this paper has used long-difference estimations to uncover the effect of population density on particulate matter concentrations. We have found that a two times standard deviation increase in population density leads to an increase in particulate matter of 1.405  $\mu\text{g}/\text{m}^3$ . This is a pretty sizeable effect, seeing as the mean particulate matter concentration in our dataset is 12.647  $\mu\text{g}/\text{m}^3$ . Through our sensitivity analyses, we see that our findings appear to be robust when checking for non-linearity and sample selection bias.*

Mattijs Gruppen - 2615581

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Vrije Universiteit Amsterdam

Supervised by prof. dr. J.N. van Ommeren

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## Table of contents

1. Introduction .....	3
2. Literature overview.....	5
3. Theoretical Framework and Method .....	7
3.1 Theoretical framework .....	7
3.2 Endogeneity issues .....	8
3.3 Method.....	8
4. Data and descriptives .....	10
4.1 Data .....	10
4.2 Descriptives .....	13
5. Results.....	15
5.1 OLS estimate .....	15
5.2 Long-difference estimates .....	15
5.3 Sensitivity Analyses .....	17
6. Discussion .....	22
6.1 Chosen specifications.....	22
6.2 Potential mechanisms that drive results .....	22
6.2.1 Sectoral composition.....	22
6.2.2 Emissions from commuting .....	23
6.3 Other determinants of local air pollution .....	23
6.4 Future research.....	23
7. Conclusion .....	24
8. Acknowledgments .....	25
References.....	26

## 1. Introduction

In the year 2018, an estimated 55.3% of the world's population lived in urban settlements. The United Nations predict this number to rise to almost 60% in 2030, at which point one in every three people will live in a city larger than 500,000 inhabitants (United Nations, Department of Economic and Social Affairs, 2018). There exists an ever-growing body of literature that looks at the consequences of increasing urban living. The existing literature provides strong evidence that increased urban living is associated with welfare-enhancing agglomeration benefits (Ahlfeldt & Pietrostefani, 2019; Combes & Gobillon, 2015). Increasing density does not only come with positive effects. However, increasing density is also associated with congestion forces such as higher crime rates, more expensive rental prices, higher commuting times and a possible decrease in air quality (Kahn, 2013). This paper follows this line of reasoning by discussing one of the elements of costs of agglomeration, namely the relationship between population density and urban air pollution. As we will show in section two, the existing literature is conflicting and there is relatively little evidence that looks at the relationship between population density and urban air pollution. This study will hope to fill this existing gap in the literature.

Air pollution is a serious issue for cities worldwide. Large cities in developing countries have high levels of air pollution. But this is also an issue in more developed countries. Several cities within the European Union have been subject to legal cases because they have transgressed the legal thresholds of pollution. This makes this subject an important and relevant policy issue.

The local air quality of an urban area is a very important determinant of the quality of life. Air pollution can be the cause of serious health problems. Health problems that are associated with bad air quality are most notably infections of the respiratory system, lung cancer, strokes and heart diseases (Mannucci et al., 2015). According to the World Health Organization, air pollution was the cause of about 600,000 premature deaths in 2010 in the WHO European region alone. It was estimated that the overall annual cost of health impacts and mortality from air pollution for European countries was about \$1.575 trillion dollar (WHO Regional Office for Europe OECD, 2015). Recent studies have suggested that air quality also affects other parts of human life, such as crime, labour productivity, and the outcome of education (Carozzi & Roth, 2020). These additional factors could mean that the total cost of air pollution is likely to be even higher. This makes air quality an important issue for policy makers worldwide. In an ideal world, the negative externality that is air pollution would be internalized through first-best pricing through, for example, a Pigouvian tax. But since this is not realistic, the effect of urban structures on urban air quality is clearly important for social welfare.

The pollutant studied in this paper is particulate matter concentration. Exposure to particulate matter has been found to lead to negative health effects at all levels (Feng et al., 2016). The World Health Organization has set a long term exposure threshold of  $10 \mu\text{g}/\text{m}^3$  to significantly reduce adverse health effects.

There is little existing research that seriously tackles the causality problem while trying to find evidence on the relation between urban density and local air pollution. Existing literature finds conflicting results, is mostly based on cross-sectional data and is focussed on very specific

regions (see the next section). This paper hopes to contribute to the existing literature by providing a credible estimate for European cities.

This paper will attempt to answer the following research question: *What is the effect of urban density on the local air pollutant  $PM_{2.5}$  in European cities?* We use data from a panel of 666 European cities in the years 2000 and 2015. We present ordinary least squares and long-difference estimates, followed by a series of sensitivity analyses.

This paper is structured as follows. Section two will provide an overview of the existing body of literature. Section three provides a theoretical framework and will show the methods used. Section four will present the used data and its descriptives. Section five will show the results and provide a sensitivity analysis. Section six will give a discussion and section seven will provide a conclusion with the key takeaways of this paper.

## 2. Literature overview

This study contributes to the ever-expanding literature that looks at the relation between city structure and urban air pollution. Air pollution is a great issue worldwide. As population is expected to grow, total emissions of pollution are expected to grow as well (Castells-Quintana et al., 2021). The relation between emission, population growth and density is not as straightforward as might appear.

Several studies have looked into the dynamics between population and urban air pollution. Borck & Pflüger (2019) present a theoretical framework that analyses the driving factors between population size and pollution. This theoretical framework, modified to apply to the setting of this study is presented in section 3. In theory, pollution could either increase or decrease with an increase in population size (Borck & Schrauth, 2021).

Larson & Yezer (2015) study the relation between city size and density and energy consumption. They find that if city growth is driven by differences in amenities, per capita energy use falls modestly. They look at the relationship between density and energy consumption by looking at spatial policies, namely the introduction of green belts and building height restrictions. They find that an increase in density by the implementation of a green belt or the relaxing of building height restrictions leads to a decrease in energy consumption per capita (Larson & Yezer, 2015). Similar evidence is found by Borck & Brueckner (2018) who find that increasing building heights induces a higher density, which generates a more compact city that ultimately leads to lower energy use per capita and thus lower emissions (Borck & Brueckner, 2018). Several other studies have looked at the relation between city size or density and household energy consumption. These papers mostly find that inhabitants of denser cities consume less energy per capita (Blaudin de Thé et al., 2021; Glaeser & Kahn, 2010). There are several reasons why denser cities can lead to lower energy consumption. Firstly, inhabitants of denser cities use less fuel. This is due to shorter possible commuting times and greater availability of public transport systems (Karathodorou et al., 2010). Furthermore, denser cities have (on average) smaller dwellings and more energy-efficient high-rise buildings. The greater availability and use of public transit have also been found to reduce air pollution (Bauernschuster et al., 2017).

There exists a large body of literature which has studied the relation between city size and emissions. These papers find conflicting results, based on the type of emission, methods used and areas studied. Several studies have looked at the relation between CO<sub>2</sub> emissions and population size, with contradicting results. Some studies find that emissions tend to increase with city size (Oliveira et al., 2014), while others find that emissions per capita decrease with city size (Castells-Quintana et al., 2021; Glaeser & Kahn, 2010; Gudipudi et al., 2016).

Some studies have looked at other air quality driving forces, again with differing results. Studies find that population size is positively correlated with NO<sub>x</sub> (Lamsal et al., 2013; Sarzynski, 2012) but other studies find that population density is negatively correlated with NO<sub>x</sub> emissions (Borck & Schrauth, 2021; Hilber & Palmer, 2014). Studies that look at the emissions of particulates are even more fractured. Population size has been found to be positively correlated with the emission of particulates (Castells-Quintana et al., 2021; Glaeser, 1998). When looking

at the relation between the emission of  $PM_{10}$  and population density, some studies find a positive relation (Borck & Schrauth, 2021) while others find a negative relation (Castells-Quintana et al., 2021; Hilber & Palmer, 2014). Studies that look at the emissions of even finer particulate matter ( $PM_{2.5}$ ) and population density are divided as well. Carozzi & Roth (2020) and Borck & Schrauth (2021) find a positive relation while Castells-Quintana et al. (2021) find a negative relationship between density and  $PM_{2.5}$  emissions. It is important to note however that the estimate for  $PM_{2.5}$  in Borck & Schrauth (2021) is imprecisely estimated, which means it can only provide an indication of the size of the effect.

The studies named above vary in their methods and study areas. Castells-Quintana et al. (2021) are based on cross-sectional data. This might not be enough however to seriously address the issue of causality. We discuss the issues with causality in section 3. To the best of our knowledge, there are only three papers that seriously address the issue of causality (Borck & Schrauth, 2021; Carozzi & Roth, 2020; Hilber & Palmer, 2014). Borck & Schrauth (2021) and Carozzi & Roth (2020) take an instrumental variable approach, whereas Borck & Schrauth (2021) use geological- and historical population instruments. These instruments have been used by other studies to instrument for population density (P.-P. Combes et al., 2010). Carozzi & Roth (2020) take a similar approach, albeit with slightly different instruments. They use earthquake risks, the presence of aquifers and soil drainage capacity. A second difference between these papers is that Carozzi & Roth (2020) use satellite  $PM_{2.5}$  readings whereas Borck & Schrauth (2021) use ground monitor station readings. Hilber & Palmer (2014) use a panel dataset with fixed effects regressions. All three studies also differ in their study area. Carozzi & Roth (2020) look at American cities, Borck & Schrauth (2021) use a panel dataset from Germany and Hilber & Palmer (2014) look at a panel of worldwide cities. Carozzi & Roth find an estimated elasticity of 0.13, Borck & Schrauth find an estimated elasticity of 0.08 and Hilber & Palmer find an estimated elasticity of -0.02 for the relation between population density and particulate matter concentrations.

There seems to be a lot that can be contributed to this study area. Current studies only seem to focus on smaller study areas such as sole countries or find contradicting results. This is where our study can contribute to the existing body of literature, by looking at a panel of European Functional Urban Areas. In a synthesis on economic effects of density done by Ahlfeldt & Pietrostefani, pollution has been named as one of the areas where more evidence on the effects of density is needed (Ahlfeldt & Pietrostefani, 2019). Both Hilber & Palmer (2014) and Borck & Schrauth (2021) name particulate matter concentration as the part of their research that yields the least statistically strong results, indicating that this is a gap in the literature which needs to be further explored.

### 3. Theoretical Framework and Method

#### 3.1 Theoretical framework

This study tries to determine the relation between air quality, by looking at particulate matter concentration, and population density. Before jumping into an analysis, it is always important to first think about the theoretical side and implications of the relation between population density and urban air quality. This section will present a simple urban economic framework of city structure and pollution. This section follows the reasoning of Borck & Schrauth (2021). The model is an extension and/or combination of earlier theoretical frameworks (Borck & Brueckner, 2018; Borck & Pflüger, 2019; Borck & Tabuchi, 2019; Larson & Yezer, 2015). For a worked-out version of this model, see appendix A in Borck & Schrauth (2021).

Let us consider a circular monocentric city that has  $N$  workers that commute to the central business district (CBD). Households have a utility  $v(c, q, P)$  where  $c$  stands for non-housing consumption,  $q$  stands for square metres of floor housing space and  $P$  stands for pollution concentration. Households that live  $x$  kilometres from the CBD incur commuting costs  $tx$  and pay land rent  $p(x)$ . Mobility ensures that all households acquire an equal utility level throughout the entire city.

The housing market is controlled by profit-maximizing housing developers, that use capital and land under perfect competition. They pay land rent  $r(x)$  where  $x$  again denotes the distance from the CBD and an invariant price for capital that equals  $i$ . In equilibrium, the land rent at the border of the city must be equal to the opportunity cost of land. Let us now try to induce a change in population density. Consider the share of land in the city that is available for housing development at every  $x$ . Let us denote this as  $\gamma$ . As more land becomes available for housing, developers will build more housing at each  $x$  which will increase the overall density in the city.

If we denote the utility that residents can obtain in the rest of the economy as  $u$ , then the population in the city adjusts through migration mechanisms, such that everyone obtains the same outside utility  $u$  everywhere. Following this line of reasoning, this model produces a city where in the city centre, densities are high, dwellings small and buildings tall.

Let us suppose that we increase the share of land that is available for housing development ( $\gamma$ ). This could be due to a change in policy, for example, a government might use a zoning policy to increase the floor/area ratio. As a result of this policy, housing will be constructed and the density in the city increases. As a result of an increase in housing supply, rents reduce and residents' utility rises. This in turn leads to increased outside migration to the city to restore outside utility  $u$ . In the new equilibrium, city size decreases as in-migration is not strong enough to offset the increase in housing supply. The city population has increased and therefore average population density will have increased as well.

What does this change in density mean for the pollution concentration? Let us assume that emissions of pollution are equal to the sum of residential energy emissions and commuting emissions. Residential energy emissions rise as more housing is built which causes an increase in residential energy consumption. Additionally, there are more residents due to migration which means aggregate commuting will also increase, which in turn increases overall

emissions. Because the city's land area has decreased, overall pollution concentration increases too. Therefore, the model predicts that cities that have a higher population density will also have a higher pollution concentration.

This simple theoretical model tends to ignore some possible countervailing forces. One of such forces is a more extensive supply of public transit in denser cities, due to higher economies of scale. Public transit typically produces fewer emissions per person kilometre than cars. This would mean traffic emissions would be less in a denser city (Bauernschuster et al., 2017; Blaudin de Thé et al., 2021; Duranton & Turner, 2018; Stevens, 2017). Furthermore, people in denser cities, especially in the city centre, tend to live in more energy-efficient high-rise buildings. This would lead to a decrease in residential energy consumption per capita (Borck & Brueckner, 2018). Borck & Schrauth show however that if they include these two forces in a stylized way using realistic parameter values, the relation remains positive (Borck & Schrauth, 2021). When taking into account the considerations made under this theoretical framework, we predict that a higher population density should result in higher pollution by emission.

### 3.2 Endogeneity issues

The theoretical framework of section 3.1 immediately highlights some of the challenges and issues that have to be taken into account when designing an identification strategy. The framework suggests two causes of endogeneity when looking at the relationship between population density and urban air pollution. Firstly, there might be unobserved variables that induce a change in density that could be correlated with density. For example, there could be big differences in land use and environmental policy making between different cities and countries. Secondly, pollution might be an endogenous variable. The model states that pollution concentration  $P$  directly influences the utility of an inhabitant in the city. Higher pollution concentration could cause a decrease in utility, which in turn leads to migration out of the city, or sorting mechanisms within the city (Heblich et al., 2021).

### 3.3 Method

This study focuses on the relationship between particulate matter concentration and population density. This means the analysis will focus on estimating a regression of pollution on density.

The baseline estimation takes the following form:

$$PM2.5_{it} = \alpha + \beta_1(PD_{it}) + \beta_2X_{it} + \varepsilon_{it}$$

Where  $i$  indexes grid cells at time  $t$ .  $PD$  is population density,  $X$  denotes a vector of control variables and  $\varepsilon$  denotes the error term.

This estimation has several flaws, however. Because of the nature of the data, we can be sure that this estimation suffers from omitted variable bias. More densely populated cities could differ from less densely populated cities in their geography, industrial structure or other unobserved variables that could affect the emission of  $PM_{2.5}$ . To deal with this problem, this study has chosen a long-difference specification, from the years 2000 until 2015. There are several upsides to choosing for this specific specification. Firstly, because we have a panel dataset, this long-difference estimation deals with all time-invariant factors that could influence



the emission of particulate matter, such as geography or weather conditions (Borck & Schrauth, 2021). If denser cities have more amenities which attract ‘green’ households, these ‘green’ households could influence local pollution policies. In turn, this means that the correlation between density and pollution could be driven by household selection. Fixed effects at a city level address this selection bias. As we only have data for two years (2000 and 2015), there is no difference to a fixed-effect specification. However, Borck & Schrauth (2021) suggest that even with a panel data set of more than two years, a long-difference specification might be preferred as the yearly within variation of population density is pretty small. This means that fixed effects would take out a lot of the interesting variation and the variable of interest would be less precisely estimated (Borck & Schrauth, 2021).

Our first difference specification takes the following form:

$$\Delta(PM2.5_{it}) = \alpha + \beta_1 \Delta(PD_{it}) + \beta_2 \Delta X_{it} + \beta_3 \Delta C_t + \varepsilon_{it}$$

Where  $i$  is the unit of measurement ( $i$  denotes the city at time  $t$ ) and  $C_t$  is a vector of country dummies which hope to capture differences in policy making between different countries. Our parameter of interest is  $\beta_1$ , which shows the effect of population density on  $PM_{2.5}$  concentrations.

## 4. Data and descriptives

This section will first give a description of the data used and afterwards will provide descriptive statistics of the variables of interest.

### 4.1 Data

For this analysis, a combination of several datasets will be used to determine the relationship between urban density and local air pollution.

The first variable used in this study is local air pollution. This study will focus on particulate matter with a diameter of 25.000 microns, hereafter known as PM<sub>2.5</sub>. Data on PM<sub>2.5</sub> has been obtained from the atmospheric composition analysis group. They provide annual estimations of ground-level fine particulate matter by combining Aerosol Optical Depth (AOD) retrievals from several satellites (NASA's MODIS, MISR and SeaWiFS) with the GEOS-Chem chemical transport model. These are subsequently calibrated using data from ground monitoring stations using a Geographically Weighted Regression (Hammer et al., 2020; Van Donkelaar et al., 2019). The study group provides these estimates on a global scale but also calculates them for more focused regions. This study has taken the European dataset, which has been calibrated by using ground station data from the European Environment Agency Air Quality e-Reporting system. For a thorough description of how this dataset is derived, see Van Donkelaar et al. (2019). The data on particulate matter is provided at a very fine scale, namely at a 0.1° x 0.1° raster. This raster has been polygonised and will provide the backbone for the dataset. The grid cell size is defined in coordinate degrees. This will mean the total surface area of each cell will vary slightly depending on latitude (Budic et al., 2016). Figure 1 provides an illustration of the particulate matter concentration in the year 2000. One major benefit of using satellite-derived data over the use of data from ground measuring stations is the total coverage of this dataset. Furthermore, ground monitoring stations are not randomly placed, which means that working with data from ground monitoring stations could affect the estimated results. A possible drawback of using satellite data over ground-based readings is that the estimates are likely to be less precise.



Figure 1: Particulate matter concentration in 2000 (Source: Donkelaar et. al, 2019).

The next variable of importance is population density. Population has been derived from the Global Human Settlement Layer (GHSL). This is a dataset provided by the European Union, which maps global spatial information on the human presence on the globe over time. The dataset used is the GHS-POP dataset, which provides global population data in a resolution of 250x250 metres in the years 1975, 1990, 2000 and 2015. This spatial raster depicts the distribution of population, provided as the number of people per cell (Florczyk et al., 2019). For a full description of the data set, see Florczyk et al. (2019). The data on population is aggregated to the grid cells on PM<sub>2.5</sub> by overlaying the polygon grid on PM<sub>2.5</sub> with the raster grid of population and aggregating the population data to the polygon grid with the assumption that population is uniformly spatially distributed within the GHS-POP raster cells. Population density is subsequently defined as the number of people present in a cell divided by the surface area of the cell. Figure 2 shows the population grid as derived from the GHSL.

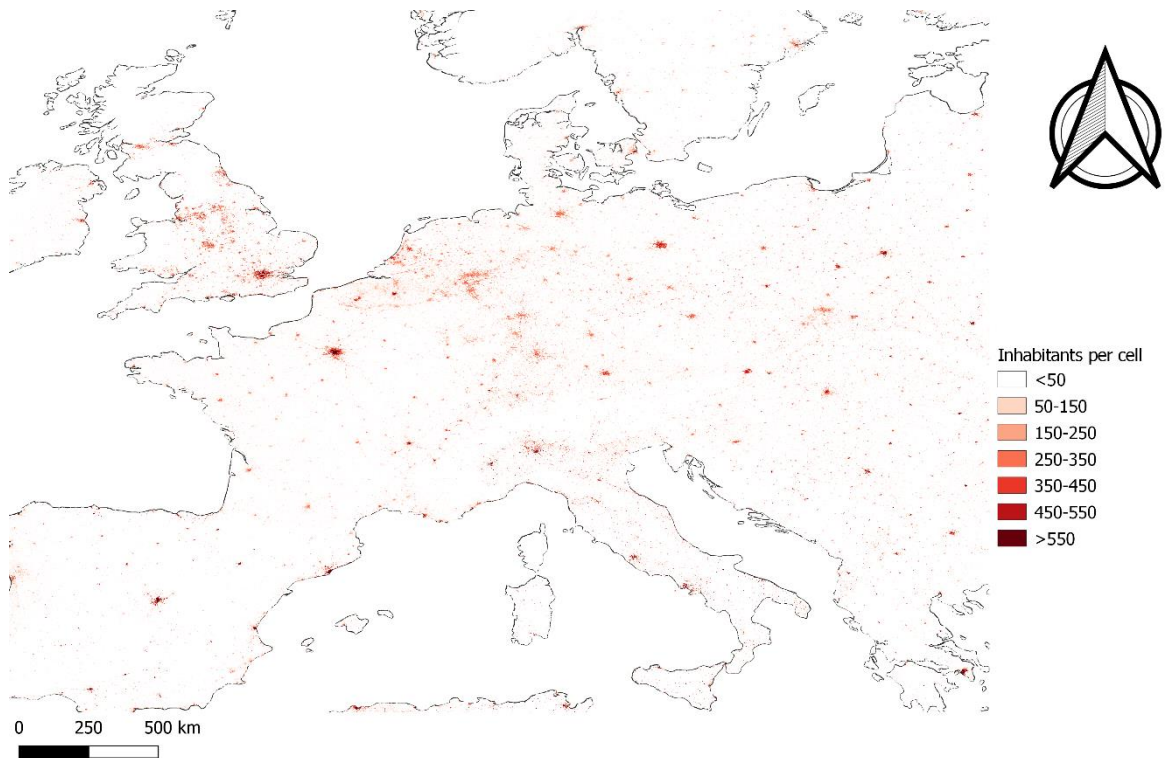


Figure 2: Population grid as derived from the GHSL (source: Florczyk et. al, 2019).

This study focuses on pollution and population density at a more aggregated level, namely at the city level. A uniform definition of cities is therefore necessary for analysis at a European level. This study takes the definition of cities by looking at FUA's (functional urban areas) as has been defined by the Organisation for Economic Co-operation and Development (OECD) and the European Commission (Dijkstra & P. Veneri, 2019). FUA's are defined in several steps. Firstly, a population grid makes it possible to define urban centres, which are defined as a cluster of contiguous cells of more than 50,000 inhabitants and a high density. Next cities are identified as one or more local units that have at least 50% of their inhabitants inside these urban centres. Finally, commuting zones are determined by looking at a set of contiguous local units that have at least 15% of their inhabitants working within the city. The combination of the city with its commuting zone constitutes a FUA (Dijkstra & P. Veneri, 2019). An illustration

of the functional urban areas can be seen in figure 3 below. Data on population and particulate matter is aggregated from the polygonised grid to the FUA level.

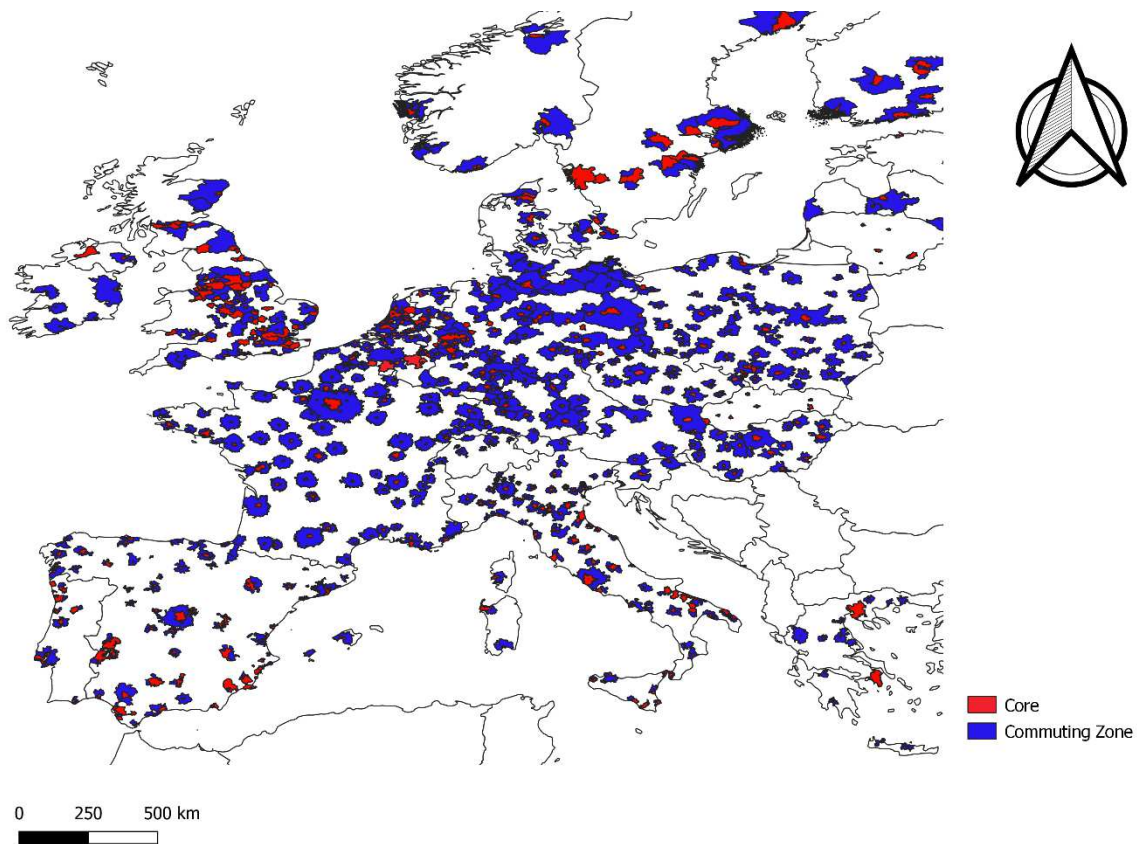


Figure 3: European Functional Urban Areas (source: Dijkstra & P. Veneri, 2019 ).

## 4.2 Descriptives

Before moving on to the empirical strategy and core results of this study, it is important to first have a look at the descriptives of the data used.

Table 1 below provides descriptive statistics of the variables of interest. From this table, several conclusions can be drawn. Firstly, there is substantial variation in density in cities, in both years of estimation. Secondly, there seems to be little change in the mean population density from 2000-2015. The mean population density seems to stay relatively stable at around 400 people per square kilometre. When looking at the particulate matter concentration, a downward trend can be spotted. The mean particulate matter concentration seems to have fallen between 2000 and 2015, from  $13.95 \mu\text{g}/\text{m}^3$  to  $11.35 \mu\text{g}/\text{m}^3$ . Lastly, we see that there is large variation in the size of cities. Cities range from a surface area of  $13.93 \text{ km}^2$  to  $17599.37 \text{ km}^2$  with a mean city size of  $1449.73 \text{ km}^2$ .

Table 1: Descriptive statistics.

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
Population density 2000	People/km <sup>2</sup>	669	384.797	464.540	16.790	3627.781
Population density 2015	People/km <sup>2</sup>	669	403.236	490.935	17.717	4327.426
Pm <sub>2.5</sub> 2015	µg/m <sup>3</sup>	666	11.347	4.690	2.845	31.420
Pm <sub>2.5</sub> 2000	µg/m <sup>3</sup>	666	13.946	5.078	4.771	41.116
Population density	People/km <sup>2</sup>	1338	394.016	477.83	16.790	4327.426
Pm <sub>2.5</sub>	µg/m <sup>3</sup>	1332	12.647	5.056	2.845	41.116
ΔPm <sub>2.5</sub>	µg/m <sup>3</sup>	666	-2.599	1.731	-9.868	2.435
Δ Population Density	People/km <sup>2</sup>	669	18.440	82.224	-646.903	784.874
Area	Km <sup>2</sup>	669	1449.733	1759.476	13.928	17599.369

Figure 4 below shows a scatterplot of population density and particulate matter concentration. This scatter plot suggests a slight positive relationship between our variables of interest. Interesting to note is that the densest cities do not seem to automatically have the highest particulate matter concentration. This can be for a multitude of reasons, for example, differences in local policy-making in these cities.

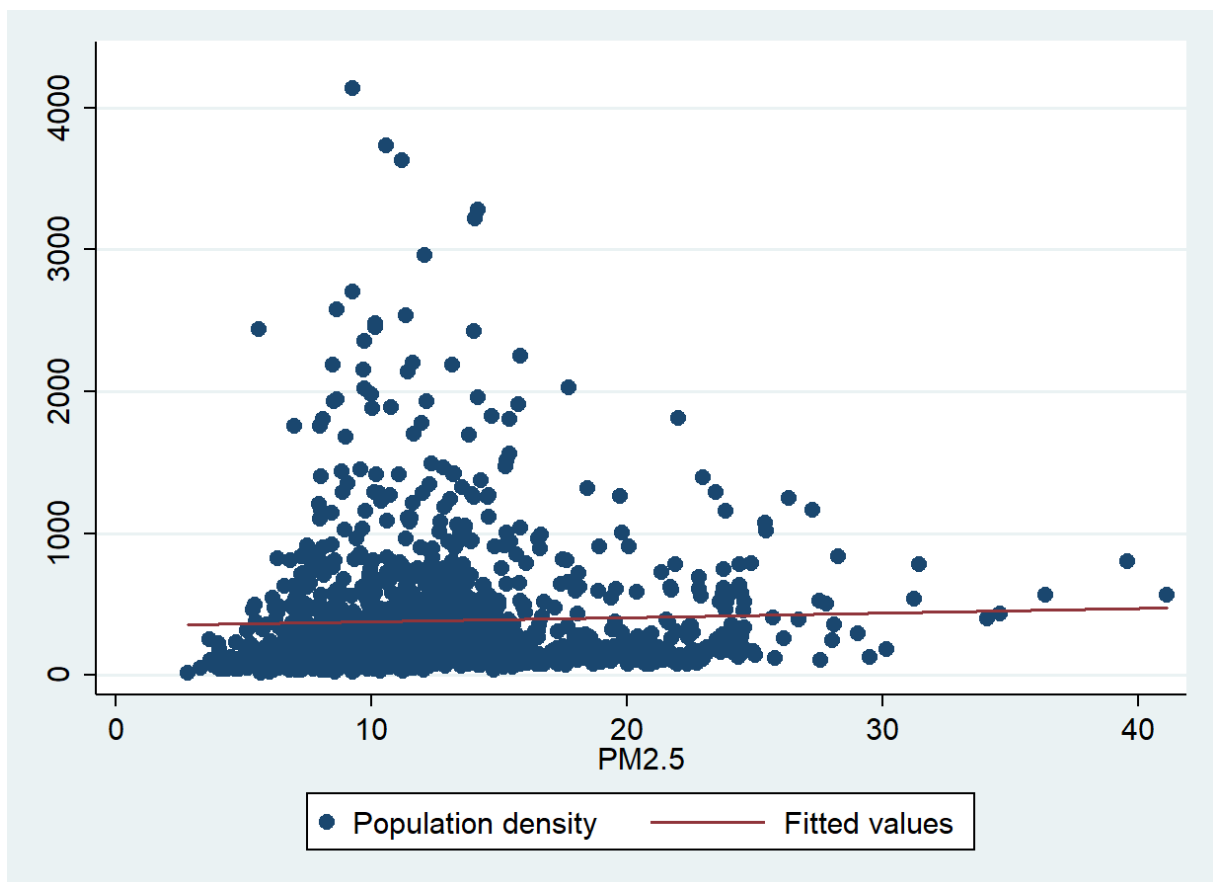


Figure 4: Scatterplot of population density and particulate matter concentration.

## 5. Results

This section will present the results of this paper.

### 5.1 OLS estimate

Table 2: OLS estimates.

	(1) PM <sub>2.5</sub>
Population density	0.000400 (0.000257)
Constant	12.49*** (0.173)
<i>N</i>	1332
adj. <i>R</i> <sup>2</sup>	0.001

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

It is always important to start the analysis with a baseline ordinary least squares estimate. This estimate can be found in column 1 of table 2 above. We can see that if population density were to increase with 1, PM<sub>2.5</sub> concentration would increase by 0.0004  $\mu\text{g}/\text{m}^3$ . This effect is not statistically significant however.

### 5.2 Long-difference estimates

Table 3: Long-difference estimates.

	(1) $\Delta\text{PM}_{2.5}$	(2) $\Delta\text{PM}_{2.5}$
$\Delta$ Population Density	0.00142* (0.000718)	0.00147* (0.000662)
Constant	-2.622*** (0.0695)	-2.606*** (0.444)
Country fixed effects	No	Yes
<i>N</i>	666	666
adj. <i>R</i> <sup>2</sup>	0.002	0.431

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 3 above shows our main regression results. Column 1 shows the results of our basic regression, which is a long-difference regression of the change in population density on the change in particulate matter concentration in the time period 2000-2015. The effect of change in population density is 0.00142, which means when population density changes by 1, the change in particulate matter increases by 0.00142  $\mu\text{g}/\text{m}^3$ . This effect is significant at the 5%

confidence level. We can see that if we compare this result with our baseline OLS estimate in table 2, the value of the coefficient has gotten significantly larger. This would indicate a positive bias under ordinary least squares. This can be rationalized by the presence of sorting mechanics. Air pollution may lead to lower equilibrium densities if households spatially sort in response. To get a sense of if this effect is big, we can look at what happens if population density would increase by two times the standard deviation. The standard deviation of population density is 477.83 (see section 4.2). This means that if population density would increase with two standard deviations, particulate matter would increase by  $1.357 \mu\text{g}/\text{m}^3$ . When considering that the mean  $\text{PM}_{2.5}$  concentration is  $12.647 \mu\text{g}/\text{m}^3$ , we can say this effect is substantial. The constant shows that in the time period 2000-2015, particulate matter has decreased significantly, namely by -2.622. This is statistically significant at the 0.01% confidence level.

We can ask ourselves how trustworthy these results are. These results do not take into account differences in policy making between countries. Countries can put different restrictions on the emissions of particulate matter which are not shown in this regression. Therefore, we also run this regression with country fixed effects included. These results can be seen in column 2. The effect of change in population density is 0.00147, which means when population density changes by 1, particulate matter concentration increases by  $0.00147 \mu\text{g}/\text{m}^3$ . This effect is statistically significant at the 5% confidence level. The size of the effect has increased a little bit, but is very comparable to the effect of the regression in column 1. Once again, we can see how big this effect is if population density were to increase by two standard deviations. If population density in 2015 were to increase by two standard deviations, particulate matter would increase by  $1.405 \mu\text{g}/\text{m}^3$ . The constant is also very comparable in size to the first regression and once again indicates that in the considered time period particulate matter concentrations have decreased significantly by -2.606. This effect is statistically significant at the 0.01% confidence level.

*Table 4: Long-difference estimates with a log-log specification.*

	(1)	(2)
	$\Delta \text{Ln PM}_{2.5}$	$\Delta \text{Ln PM}_{2.5}$
$\Delta \text{Ln Population Density}$	-0.183* (0.0735)	0.0836 (0.131)
Constant	-0.220*** (0.0325)	-0.208*** (0.0104)
Country fixed effects	No	Yes
$N$	666	666
adj. $R^2$	0.016	0.599

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$



As economists, we prefer to have elasticities when we investigate the relationship between air pollution and population density. Therefore, we also include a log-log specification, where the estimated coefficient can be interpreted as an elasticity. The outcome of these regressions can be found above in table 4. Column 1 shows a baseline estimate that does not include country fixed effects, column 2 shows a regression estimate that does include country fixed effects. Column 1 gives us a pretty surprising result. It indicates that if population density were to increase by one percent,  $PM_{2.5}$  would decrease by 0.183 percent. This effect is statistically significant at the 5% confidence interval. This is a very surprising result, particularly as the expected sign has changed to a negative. This estimate however does not include country fixed effects, so one can wonder if the results are trustworthy. We therefore also run this regression with country fixed effects in column 2. There we can see that the sign changes back to the expected positive. Column 2 indicates that a one percent increase in population density would lead to a 0.0836 percent increase in particulate matter concentration. This effect is not statistically significant, so we cannot say if this estimate is trustworthy. It is interesting to note however that column 2 finds an almost identical result as Borck & Schrauth (2021) find in their paper. They find an estimated elasticity of 0.08 but also say that the value is imprecisely estimated.

We can think for a minute about why the log-log specification gives different results from our preferred estimates in table 3. One explanation could be that the log specification simply does not fit our data as well. The descriptives in section four did not indicate a big skewness to our data, which would give credibility to this line of reasoning. Secondly, we could say that even if the functional form did not match our data very well, but the effect would be statistically very strong, it should not change the outcome of the regression results as much. This indicates that the effect might not be super strong (statistically speaking).

### 5.3 Sensitivity Analyses

In this subsection, we will look at how robust our results are by considering several alternate specifications to see if this changes our results. To compare the alternate specifications, our preferred specification has been included each time as the first regression in column 1 of all tables.

Table 5: Long-difference specification with non-linearity.

	(1)	(2)
	$\Delta PM_{2.5}$	$\Delta PM_{2.5}$
$\Delta$ Population Density	0.00147*	0.00238
$\Delta$ Population Density <sup>2</sup>		-0.000000209 (0.000000253)
Constant	-2.606*** (0.444)	-2.616*** (0.446)
Country fixed effects	Yes	Yes
<i>N</i>	666	666
adj. <i>R</i> <sup>2</sup>	0.431	0.431

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Firstly, we want to check if the effect of population density on particulate matter concentration could be non-linear. To check for non-linearity, we have run a regression which includes the change in population density squared, which can be seen in table 5 above in column 2. In column 2, we can see the effect of change in population density increases to 0.00238. This effect however becomes statistically insignificant. We can see the effect of population density squared as well. This effect is extremely small and negative, but once again insignificant. Therefore, we conclude that non-linear relations do not affect our main results.

Table 6: Probability weighted long-difference estimation.

	(1)	(2)
	$\Delta PM_{2.5}$	$\Delta PM_{2.5}$
$\Delta$ Population Density	0.00147* (0.000662)	0.00226 (0.00226)
Constant	-2.606*** (0.444)	-3.093*** (0.0383)
Country fixed effects	Yes	Yes
Probability weighted regression	No	Yes
<i>N</i>	666	666
adj. <i>R</i> <sup>2</sup>	0.431	0.380

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

It could be the case that our results are the way they are simply because denser cities are larger. As a second robustness test, we have therefore performed a probability weighted regression. The regression weights are based on the area of the cities. Therefore, this specification gives cities with a bigger size a higher weight. This means we can see if bigger cities contribute more or less to the effect of population density on particulate matter concentration. The results can

be found in column 2 of table 6. We can see the effect increases to 0.00226, but it is not statistically significant. The estimated effect does get larger, but due to the insignificance, we cannot say that it is statistically different from our main results.

Table 7: Long-difference estimation with population density sample selection.

	(1)	(2)	(3)	(4)
	$\Delta PM_{2.5}$	$\Delta PM_{2.5}$	$\Delta PM_{2.5}$	$\Delta PM_{2.5}$
$\Delta$ Population Density	0.00147* (0.000662)	0.00236* (0.00111)	0.00248** (0.000712)	0.00188* (0.000859)
Constant	-2.606*** (0.444)	-2.744*** (0.0161)	-3.017*** (0.0136)	-4.028*** (0.0234)
Country fixed effects	Yes	Yes	Yes	Yes
Sample selection	-	5 < abs( $\Delta$ Population Density) < 300	10 < abs( $\Delta$ Population Density) < 300	20 < abs( $\Delta$ Population Density) < 300
<i>N</i>	666	512	389	271
adj. <i>R</i> <sup>2</sup>	0.431	0.438	0.431	0.474

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Next, we would like to see what would happen if we take a sample selection and how this would affect the size of the effect of density on particulate matter concentration. This is also to check if our results are affected by outliers in the data, which could be considered as measurement errors. In columns 2, 3 and 4 of table 7, we have taken a sample size selection to see what the effect of density is in these subsets.

Firstly, we take a look at column 2 where we can see a regression run on the subset 5 < absolute( $\Delta$  Population Density) < 300. In this way, we filter out cities with very low or high changes in population density (which could indicate measurement error). The effect rises to 0.00236, which means that if population density changed by 1,  $PM_{2.5}$  would change by 0.00236  $\mu g/m^3$ . This effect is statistically significant at the 5% confidence interval. By filtering away areas with little to no change, we can see that the estimated value rises. We can draw several conclusions from this. Firstly, we can say that the effect of population density on particulate matter concentration is larger in areas where more change happens. This is logical, as we would not expect areas where there is little change in population density to have a big increase in particulate matter concentration. We can see a similar story in columns 3 and 4. Column 3 finds an effect that is similar in size to the one found in column 2 and the regression in column 4 starts to come close to the effect found in our preferred estimate in column 1. All estimates are statistically significant at the 5% confidence interval. We can see from column 4 that the effect is not much larger in cities where change is very large. We can see however that the constant gets larger if we look at cities where population density has changed more. This means that in

cities where population density has changed more, particulate matter concentration tended to decrease more in the years 2000-2015.

Table 8: Long-difference estimation with area sample selection.

	(1)	(2)	(3)
	$\Delta PM_{2.5}$	$\Delta PM_{2.5}$	$\Delta PM_{2.5}$
$\Delta$ Population Density	0.00147* (0.000662)	0.00308 (0.00495)	0.00151 (0.000750)
Constant	-2.606*** (0.444)	-2.626*** (0.0612)	-2.324*** (0.00704)
Country fixed effects	Yes	Yes	Yes
Sample selection	-	Area km <sup>2</sup> >1000	Area km <sup>2</sup> <5000
<i>N</i>	666	317	637
adj. <i>R</i> <sup>2</sup>	0.431	0.329	0.436

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

We would also like to know if the pollution-density relation is larger or smaller depending on city size. Is the effect of population density larger in larger cities? To do this, we have once again done two regressions where we take a subset of the sample. The results can be seen above in table 8. Column 1 shows the estimate of our preferred estimation, column 2 shows a subset of the sample where smaller cities have been filtered away and column 3 shows a subset of the sample where the biggest cities have been filtered away. In column 2 we can see that if population density changed with 1,  $PM_{2.5}$  is expected to go up by 0.00308  $\mu\text{g}/\text{m}^3$ . This would suggest that the effect of population density on particulate matter concentration is larger in bigger cities. The estimate is not statistically significant however and therefore we cannot say it is statistically different from our preferred estimate in column 1. In column 3, we can see that if population density were to go up by 1, particulate matter concentrations will go up by 0.00151  $\mu\text{g}/\text{m}^3$ . This effect is very comparable in size to our estimate in column 1. This estimate is also statistically insignificant, so we cannot draw any further conclusions from this estimate.

Table 9: Long-difference estimation with population density and area sample selection.

	(1)	(2)	(3)
	$\Delta PM_{2.5}$	$\Delta PM_{2.5}$	$\Delta PM_{2.5}$
$\Delta$ Population Density	0.00147* (0.000662)	0.00236* (0.00111)	0.00208 (0.00381)
Constant	-2.606*** (0.444)	-2.744*** (0.0161)	-2.740*** (0.0553)
Country fixed effects	Yes	Yes	Yes
Sample selection	-	5 < abs( $\Delta$ Population Density) < 300 & Area km <sup>2</sup> > 10	5 < abs( $\Delta$ Population Density) < 300 & Area km <sup>2</sup> > 500
<i>N</i>	666	512	334
adj. <i>R</i> <sup>2</sup>	0.431	0.438	0.421

Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Lastly, we combine the sample selections, where we filter both based on the size of the city as well as the absolute change in population density. Column 2 of table 9 filters away the very smallest cities (less than 10 kilometres squared) and cities with either very low or high changes in population density. From column 2, we once again can see that the estimated coefficient rises to 0.00236, which is a very comparable result as found in column 2 of table 7. This effect is statistically significant at the 5% confidence interval. This means if population density were to rise with one, particulate matter concentrations would rise by 0.00236  $\mu\text{g}/\text{m}^3$ . Without the extremely small values of both city size and population density, the estimated coefficient is higher, but not extremely. This is still a realistic estimate. Column 3 filters away the smallest cities (less than 500 kilometres squared) and cities with either very low or high changes in population density. The estimated effect of population density is 0.00208, which means that if population density were to rise with one, particulate matter concentration would rise by 0.00208  $\mu\text{g}/\text{m}^3$ . This is very comparable to the size of the effect found in column 2 but the estimated effect is once again statistically insignificant.

When we look at the sensitivity tests where we check for measurement error by taking subsets of the sample, we can see several things. Firstly, we can say that by taking away small or large observations, which could be interpreted as outliers or measurement error, we can see that in all cases the estimated value of population density on particulate matter increases somewhat. This is not surprising as we expect areas where more change occurs (as a lot of the cities experience relatively little change in population density) to have more change in particulate matter concentration. At the same time, the value does not increase to an incredibly high value that could lead us to believe that the results are driven by measurement error. Furthermore, we see that a lot of the sensitivity analyses return statistically insignificant results. This gives more credence to the fact that the effect of population density on particulate matter concentration, while present, is statistically not super strong.

## 6. Discussion

In this paper, we have shown that denser cities tend to lead to higher particulate matter concentrations. There are several factors however that were missing in this paper that could tremendously improve its worth and its contribution to the related literature. This section will discuss the chosen specification, potential mechanisms that could drive the found results and recommendations for future research.

### 6.1 Chosen specifications

This paper has opted for a long-difference specification, as this has several benefits. It deals with all time-invariant factors that influence particulate matter concentration at a city level. It is important to address the issue of causality, as many papers in the literature ignore the importance of causality in estimating the effect of population density on local air pollutants. There are only several papers that address the importance of causality (Borck & Schrauth, 2021; Carozzi & Roth, 2020; Hilber & Palmer, 2014). Two of these papers, Borck & Schrauth (2021) and Carozzi & Roth (2020) opt to go for an instrumental variable estimation, as there might be issues with reverse causality that can bias the results. Local air quality can affect the density of cities as people could choose to live in less polluted cities (Heblich et al., 2021). We feel this effect might not be as big as suggested by these papers, however, it still might be relevant. Therefore future research could improve on this paper by including an instrumental variable specification to see if there is a big difference in results. Both Borck & Schrauth (2021) and Carozzi & Roth (2020) include both instrumental variable and fixed effects/long-difference estimations as a robustness test. They conclude that their instrumental variable- and fixed effects specifications find similar results. Consequently, we expect that we would not find any different results in our study field. It would however still provide an interesting prospect for future research. Both papers choose geological instruments (soil characteristics, presence of aquifers and earthquake risks) and historical population instruments. These could be used for Europe as well, for example by using data from the European Soil Database (Panagos et al., 2012).

### 6.2 Potential mechanisms that drive results

This section discusses several possible mechanisms that could drive the results. This section discusses what has been found in the literature about possible driving forces. These possible driving forces are not checked for in this paper. Future research could therefore check to see if similar results can be found using this dataset.

#### 6.2.1 Sectoral composition

It is possible that the sectoral composition differs between cities with differing densities and that this in turn could explain the effect of density on the emission of local air pollutants. If population density drives cities to have a more polluting sectoral composition, this could influence the found results. Borck & Schrauth (2021) find that denser cities are actually more specialized in 'cleaner' forms of industry. They find that including 'dirty' and 'clean' sectoral composition in their regressions leads to very small effects on the density coefficient and therefore is not likely to affect the density-pollution relationship.

This sentiment is echoed by Carozzi & Roth (2020) who check to see if population density can explain observed differences in sectoral composition between cities. Manufacturing work is associated with higher emissions of particulate matter. They find that population density has a very small and mostly insignificant effect in explaining the share of manufacturing work. They conclude that while there may be a small effect of density on the local intensity of air polluting industries, it is unlikely to explain the findings of their proposed density-pollution relation.

The literature suggests that sectoral composition might play a small effect that is unlikely to affect the found relation. It is however not included in this paper and therefore should be considered in future research.

### 6.2.2 Emissions from commuting

Transport, in particular commuting flows, can impact the concentration of air pollutants. Previous research has shown however that denser cities are associated with lower emissions from transport (Bauernschuster et al., 2017; Blaudin de Thé et al., 2021; Duranton & Turner, 2018; Stevens, 2017). Although some of the reported effects are rather small, they unequivocally say that denser cities lead to lower emissions from commuting. Therefore, it is very unlikely that our results are driven by transport-based emissions.

### 6.3 Other determinants of local air pollution

This paper has looked at  $PM_{2.5}$  only as a determinant of local air pollution. There is indeed overwhelming evidence that  $PM_{2.5}$  has a big impact on public health (Feng et al., 2016). It is however not the only determinant of local air quality. Other studies have shown that other pollutants, such as ozone ( $O_3$ ), nitrogenous oxides ( $NO_x$ ) and particulate matters of a different size ( $PM_{10}$ ) also have adverse health effects (Costa et al., 2014; World Health Organization, 2021). Borck & Schrauth (2021) show that although all these local air pollutants affect public health, they do not have the same relation with population density as particulate matter. It is therefore interesting for future research to include these other determinants of local air quality to see what the elasticities between them and population densities are.

### 6.4 Future research

This paper has shown that there is still a lot of room for future research on this topic. According to the results, the relationship between particulate matter and population density is not super strong statistically speaking. This is echoed by Borck & Schrauth (2021) and Hilber & Palmer (2014) who both state that particulate matter is the area of their research that finds the statistically weakest results.

While this study finds results comparable with some of the literature (Borck & Schrauth, 2021; Carozzi & Roth, 2020), other works find conflicting results (Castells-Quintana et al., 2021; Hilber & Palmer, 2014). It should be noted that these two papers that find a negative relation between particulate matter and population density are based on a global overview, whereas this paper, Borck & Schrauth (2021) and Carozzi & Roth (2020) are focused on the western world. This paper focuses on a panel of European cities, Borck & Schrauth (2021) focus on Germany and Carozzi & Roth (2020) focus on the United States. Therefore, it might be interesting for future research to investigate if there are differences in the interaction between density and pollution between developing and developed countries.

## 7. Conclusion

Air pollution is a typical negative congestion force associated with urban living. This paper has looked at a panel of European cities to determine the effect of population density on air pollution between cities. Using satellite readings of PM<sub>2.5</sub> concentration, this paper has used long-difference estimations to uncover the effect of population density on particulate matter concentrations. We have found that a two times standard deviation increase in population density leads to an increase in particulate matter of 1.405  $\mu\text{g}/\text{m}^3$ . This is a pretty sizeable effect, seeing as the mean particulate matter concentration in our dataset is 12.647  $\mu\text{g}/\text{m}^3$ . Through our sensitivity analyses, we see that our findings appear to be robust when checking for non-linearity and sample selection bias. The found estimate is not extremely statistically strong, which is what the literature has shown as well.

The findings of this paper highlight the importance of including local air quality when discussing topics such as densification and urban planning. A common point made by policymakers is that bigger and denser cities are more environmentally friendly as it leads to lower CO<sub>2</sub> emissions per capita. While this may be true, this paper and the associated literature have shown that it is important to not forget the distinction between global and local pollution. This paper has shown that denser cities are actually worse places to live when looking at exposure to particulate matter concentrations, which indicates there could actually be a trade-off between reducing a city's carbon footprint and preserving the local air quality within cities.

This paper contributes to the literature by studying the determinants of air pollution. These types of studies are imperative in understanding the consequences of densification and are necessary when trying to evaluate suitable solutions.



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