Sociodemographic disparities in ambient particulate matter exposure in Austria*

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Abstract

We assess to what extent municipalities with socioeconomically vulnerable populations are disproportionately exposed to particulate matter in Austria. Although air quality in Austria has improved over the last decades, thresholds for safe air quality are still exceeded in large parts of the country and disparities both across and within Austrian regions exist. Particulate matter accounts for the largest environmental health damages of all ambient air pollutants. We use municipality level data on particulate matter exposure from the European Environmental Agency and sociodemographic data from Statistics Austria for 2015. We find that foreign citizens are disproportionately exposed to higher levels of particulate matter in Austria. This finding is robust with regards to different controls, regional fixed effects, and different particulate matter exposure indicators. Exposure disparities by citizenship are stronger in urban areas, where the large majority of foreign citizens live. We also find that citizens with low educational attainment are exposed to higher levels of particulate matter. The latter disparities are stronger in rural areas, where the majority of people with low educational attainment live. The relationship between income and air pollution follows an inverted U-shape in most specifications. High turning points and wide Fieller confidence intervals, however, suggest that the relationship is positive for most of the distribution and insignificant or negative for very high incomes. Overall, we find evidence that socioeconomically vulnerable municipalities are exposed to higher levels of particulate matter.

Keywords: sociodemographic environmental disparities, environmental inequality, air pollution

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1. Introduction

Environmental and public health authorities consider ambient air pollution the single largest environmental health risk today (EEA, 2018a; WHO, 2016). Despite trend–declines in emissions in the last two decades in most industrialized countries, EU and WHO air quality standards are still unmet in large parts of Europe. Of all ambient air pollutants, particulate matter (PM_{10} and $PM_{2.5}$) safety thresholds are most frequently exceeded. Austria shows similar patterns, compared to EU wide averages, with declines in air pollution, including particulate matter, but continued exposure above WHO thresholds for large shares of the Austrian population. In 2016, 21% of the Austrian population were exposed to levels above the PM_{10} threshold and 81% to levels above the $PM_{2.5}$ threshold according to the 2005 air quality guidelines (Horálek et al., 2019).[1]

Particulate matter also accounts for the highest human health damages of all air pollutants in Europe, as well as Austria. Due to their small size, fine particles infiltrate the body's respiratory and circulatory system and cause a variety of cardiovascular, cerebrovascular, cancerous, pulmonary, and respiratory diseases. With improvements in our understanding of the exact mechanisms, mortality rates and premature deths attributable to particulate matter have been continuously corrected upwards (EEA, 2019a,b; WHO, 2019). In 2015, 11,293 deaths (or 132 per 100,000) were attributable to air pollution (mostly particulate matter) in Austria, and life expectancy declined by around 2.2 years on average due to air pollution exposure in the EU (Lelieveld et al., 2019, 2020).

Exposure to and impacts of air pollution are not distributed equally globally and within countries. Globally, especially developing countries are disproportionately affected by poor air quality and the associated health risks. Of the 4.4 million premature deaths attributable to air pollution globally, almost 90% occurred in low- and middle-income regions (WHO, 2019). Within Europe, poor and socioeconomically vulnerable NUTS 2 regions are exposed to higher levels of air pollution (EEA, 2018b). Little however is currently known about air pollution exposure disparities in Austria.

In this paper, we conduct the first empirical analysis of sociodemographic disparities in particulate matter exposure in Austria. Our unit of observation is the municipality level (2,122 observations), the finest level of spatial resolution for which the Austrian Statistical Office (Statistik

[1] In 2021 the thresholds for both pollutants were further reduced. This paper uses the 2005 thresholds.

Austria) provides consistent income and sociodemographic data for the whole country[2]. We use data on PM_{10} and $PM_{2.5}$ exposure from the EU interpolated air quality maps for 2015. The latter provide data on the annual average of particulate matter exposure at the grid cell level and are mostly used for EU–wide air quality assessments (e.g. Horálek et al., 2018, 2019). In order to merge the two databases, we aggregate the grid cell particulate matter data to the municipality level. To assess robustness of the pollution variables used, we compute four different municipality level indicators of PM_{10} and $PM_{2.5}$ exposure respectively, that differently account for population weighting and pollution hot spots within municipalities. We then estimate a multivariate cross–sectional model, explaining particulate matter exposure with the percentage of foreign citizens, the percentage with low educational attainment, income and income square, as well as NUTS 2 or NUTS 3 regional fixed effects.

We find that foreign citizens are disproportionately exposed to higher levels of particulate matter in Austria. This finding is robust with regards to different controls, regional fixed effects, and different particulate matter exposure indicators. Exposure disparities by citizenship are stronger in urban areas, where the large majority of foreign citizens lives. We also find that citizens with low educational attainment are exposed to higher levels of particulate matter. The latter disparities are stronger in rural areas, where the majority of people with low educational attainment live. The relationship between income and air pollution follows an inverted U-shape in most specifications. High turning points and wide Fieller confidence intervals, however, suggest that the relationship is positive or insignificant for most of the income distribution. Overall, we find evidence that socioeconomically vulnerable regions are exposed to higher levels of particulate matter.

The remainder of this paper is structured as follows. Section 2 discusses the related literature, section 3 describes data and methodology, section 4 presents our empirical results, and section 5 concludes.

2. Literature Review

The unequal distribution of environmental hazards by race/ethnicity, income, educational attainment, and other sociodemographic characteristics has been documented in many empirical

[2]Due to data privacy issues, sociodemographic data at finer spatial resolutions are only available for densely populated areas and thus do not include the entire Austrian population. This could bias findings on environmental disparities.

studies for the United States (for an overview, see for example Ringquist, 2005 and Mohai et al., 2009). In Europe, by comparison, this research field is only emerging as the availability and quality of environmental and sociodemographic data is improving and environmental justice is becoming an increasingly important policy issue. We will briefly review the empirical US-based literature, since it has shaped the research designs of the emerging European studies, including ours. We will then give an overview of the emerging European studies.

To empirically assess sociodemographic environmental disparities, data on environmental hazards are merged with sociodemographic data at the finest spatial level of disaggregation available and correlations between exposure to environmental hazards and sociodemographic characteristics are analyzed. The earliest environmental data consistently available for the United States and studied by environmental inequality scholars from the early 1980s onwards were hazardous waste facilities (Bullard, 1983; Anderton et al., 1994; Been and Gupta, 1997) and from the late 1980s onwards toxic releases from industrial facilities published in a database by the US Environmental Protection Agency (Perlin et al., 1995; Brooks and Sethi, 1997; Arora and Cason, 1999; Sadd et al., 1999). While most of the above studies found that poor and minority populations were disproportionately living near these hazardous sites, they also raised some important methodological issues for assessing environmental inequality.

2.1. How near is near?

The above studies merged point-source environmental data with administrative sociodemographic data. The most common way of doing so is called the "unit-hazard coincidence approach", assuming that the spatial unit that hosts a facility is also the (only) one adversely affected. Since environmental hazards don't stop at administrative borders such as zip codes or census tracts, later studies then switched to "distance–based" approaches, which defined buffers around environmental hazards and compared the sociodemographic characteristics of units in the buffer zone to those outside (Mohai and Saha, 2006; Chakraborty et al., 2011). This, however, raises the important question of "how near is near": how wide should the buffers be and – even more importantly – is the existing unit of analysis fine enough to avoid aggregation bias, which would result in findings at a broader spatial scale not being valid for finer ones (Anderton et al., 1994). While data improvements in the US have allowed researchers to address these problems and have resulted in studies refining the unit of analysis from the geographically broad and heterogeneous zip codes to fine-scaled census tracts or block groups, some of the first European studies now face the same challenges (for example, the first EU–wide assessment of environmental inequalities by the EEA (2018b) uses NUTS 2 regions as unit of observation). In this study, we use the municipality level, a fine spatial unit of analysis for Austria, which is comparable in its geographical resolution to census tracts in the US.[3]

2.2. Emissions versus pollution exposure

From the late 1990s onwards, two air pollution exposure databases have become available for the US that report spatially fine grained concentrations of air pollution exposure by using emissions and meteorological data and simulating their fate and transport. One of them is the Risk Screening Environmental Indicators (RSEI) model, which models the fate and transport from toxic releases at industrial facilities and provides fine grained grid cell concentration data. Studies assessing industrial air toxic disparities have aggregated these data to the block group or census tract level and have found disproportionate exposure of poor and minority populations (Ash and Fetter, 2004; Downey et al., 2008; Ash et al., 2013; Zwickl et al., 2014; Boyce et al., 2016). The second dataset is the National Air Toxic Assessment (NATA), which models the dispersion of different point source and mobile emissions, and in contrast to RSEI includes the main criteria air pollutants, such as particulate matter. Studies assessing pollution exposure disparities from these wider sources also consistently find that poor and minority neighborhoods are exposed to higher levels of air pollution (Apelberg et al., 2005; Pastor et al., 2005; Morello-Frosch and Shenassa, 2006). In our study we will also use modeled atmospheric concentration data on air pollution exposure, however, in contrast to the above studies that include a large number of pollutants (and often excluding the main ambient air pollutants), we will focus on particulate matter exposure, which is also most relevant for Austria (see section 3). Focusing on one pollutant instead of an indicator including toxicity-weighted sums of different pollutants also has the distinct advantage that it is most relevant for policy makers, who regulate each pollutant separately.

[3] Both, the average population size of a US census tract as well as of an Austrian municipality is 4000 inhabitants. Compared to census tracts, Austrian municipalities differ less in size, but more in population. This has implications for the role of population weighting, which we will discuss in section 4.

2.3. *Disparities between versus within regions*

Another important methodological question that has so far been neglected in the emerging European literature is the distinction of disparities within versus between regions. Ash and Fetter (2004) and Zwickl et al. (2014) have illustrated that while Hispanics tend to live in the cleaner US cities, within these cities they disproportionately live in more polluted neighborhoods. In the above case, environmental disparities within cities would not have been identified without including city fixed effects in the analysis. It is, however, also possible that environmental disparities are driven by between-region or between-country effects and do not hold within finer geographical units. The first regional analysis of environmental disparities in the EU, EEA (2018b), for example, found that socioeconomically vulnerable regions (mainly located in Southern and Eastern European countries) are exposed to higher levels of air pollution. This study, however, does not include country-level or broader regional fixed effects to explore whether environmental disparities can also be identified within countries or finer regional units. To address this shortcoming, we will include NUTS 2 or NUTS 3 fixed effects to compare between versus within regional disparities in Austria[4].

2.4. *European case studies*

The first European studies were conducted in the United Kingdom and focused on the unequal geographic distribution of polluting industrial sites (Walker et al., 2005), landfills (Richardson et al., 2010), air pollution exposure disparities (Brainard et al., 2002; Mitchell and Dorling, 2003; Barnes and Chatterton, 2017), or multiple environmental hazards (Wheeler, 2004). While the sociodemographic variables investigated varied, most of these studies found evidence for disproportionate burdens of environmental hazards for socioeconomically vulnerable groups. While some of these studies are nation–wide (Mitchell and Dorling, 2003; Wheeler, 2004; Barnes and Chatterton, 2017), the majority focuses on a specific region or city. For the US, Zwickl et al. (2014) found strong regional disparities in environmental inequality patterns. If such disparities would also exist in the UK, case study evidence might not apply to other regions. The subsequently growing European literature has investigated disparities in proximity to industrial facilities (Neier, 2021 and Glatter-Götz et al., 2019 for Austria), exposure to ambient air quality (Rüttenauer, 2018 for Germany, Germani et al., 2014 for Italian provinces, Stroh et al., 2005 for a Swedish region, and

[4] Austria is divided into 9 NUTS 2 regions (federal provinces) and 35 NUTS 3 regions, see table A.3 and figure A.1

Fecht et al., 2015 for England and the Netherlands), noise (Tonne et al., 2018 for London, Havard et al., 2011 for Paris), and limited access to green space (Lakes et al., 2014 for Berlin). Compared to the United States, where the key sociodemographic variables are race/ethnicity and income, in most European studies a broader set of variables are examined, including educational attainment, occupation, citizenship, and country of origin.

2.5. Germany and Austria

Rüttenauer (2018) assesses associations between the share of foreign minorities, toxicity-weighted industrial air pollution and the proximity to polluting facilities in Germany using grid cell demographic data from the German Census and point–source emissions data from the European Pollutant Release and Transfer Register (EPRTR). While the fine spatial resolution is a distinct advantage of the grid cell data, for data privacy reasons they only include information on densely populated areas and thus exclude a part of the German population. Rüttenauer (2018) draws 2km buffers around each of the 4971 industrial facilities and calculates a single toxicity-weighted pollution indicator comparable to toxic releases from the US RSEI, but excluding main ambient air pollutants such as particulate matter. The main socioeconomic variable of interest is the percentage of foreign citizens. Rüttenauer (2018) estimates a spatial model that allows for spatial dependence both in the error term as well as for spatial spillover effects. He finds a positive, significant association between the share of minorities and both proximity to industrial facilities as well as toxicity–weighted emissions. Moreover, large spatial spillover effects suggest that the sociodemographic characteristics of adjacent locations also affect each location itself.

Glatter-Götz et al. (2019) examine the socioeconomic composition of residents living in the immediate vicinity of polluting facilities compared to national averages, using data on the 247 Austrian industrial facilities included in the EPRTR. They obtained sociodemographic data from the Register based Labor Market Statistics 2013 for 1km buffers around the facilities and compared the socioeconomic characteristics of the population located in 1km circular buffer zones around polluting industrial facilities to the aggregated sociodemographic data of all the people living outside the buffers. They find that the population living within the buffers is characterized by higher shares of unemployed, immigrants and low educational attainment, compared to national averages. However, the differences are small and almost non-existent for Vienna.

Neier (2021) analyzes the socioeconomic correlates of industrial air emissions for Austria. In contrast to Glatter-Götz et al. (2019), he not only assesses the incidence of polluting facilities, but also their toxicity-weighted air pollution impacts. Similar to Rüttenauer (2018), he used very fine-scale grid cell data for the socioeconomic variables, but only includes observations in densely populated areas due to data confidentiality reasons. Neier (2021) constructs 1km, 2km and 5km buffers around the facilities and applies two different empirical strategies to assess the sociodemographic correlates of industrial air pollution. First, he applies a randomization strategy, where he compares the sociodemographic characteristics of areas with facilities to the characteristics of areas with randomly allocated facilities. He concludes from this that the percentage of foreigners is significantly higher in the actual facilities applying the 1km and 2km buffer, but only insignificantly higher with the 5km buffer. Incomes are insignificantly lower in all three cases. Second, Neier (2021) estimates a spatial model similar to Rüttenauer (2018) that allows to control for spatial dependence both in the dependent variable as well as in the error term. He finds robust evidence that the percentage of foreigners increases industrial air pollution exposure risk, and that this effect is higher in urban than rural areas. For other socioeconomic variables, including income, no clear patterns can be detected.

3. Data and Method

To assess how air pollution is dispersed across municipalities by sociodemographic characteristics, we generate a cross-sectional dataset for the year 2015, merging grid cell particulate matter exposure data aggregated to the municipality level with sociodemographic data at the same level. Our dataset includes a total of 2,122 observations, representing all existing municipalities in Austria in 2015.

3.1. Air pollution indicators

Particulate matter exposure data (PM_{10} and $PM_{2.5}$ in micrograms per cubic meter ($\mu g/m_3$)) for 2015 is obtained from the interpolated air quality maps provided by the European Monitoring and Evaluation Programme (EMEP) of the European Environmental Agency (EEA) for grid cells of 1km*1km. These data are generated by using air emissions data from monitors and polluting sources such as industrial facilities and a fate–and–transport model, which includes information on pollution dispersion as well as geographical and meteorological parameters (Horálek et al., 2018) to obtain an estimate of pollution exposure for each grid. We also add 1km*1km grid cell data on population density from the Global Human Settlement Layer provided by the Joint Research Centre of the European Commission.

Aggregating grid cell pollution data to any broader geographic level raises two important methodological questions. First, should equal weights be given to all grids or should grids with more inhabitants receive more weight? Since this question is not straightforward to answer, we provide both indicators:

- Mean exposure of PM_{10} or $PM_{2.5}$ and
- Population–weighted mean exposure of PM_{10} or $PM_{2.5}$

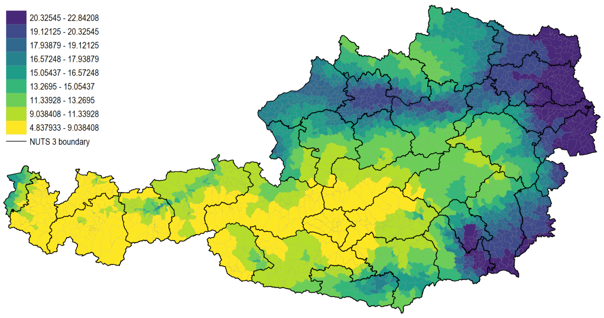
Second, should non–linear effects of pollution exposure and pollution hot spots be taken into account? If grid cell exposure is spatially aggregated to the municipality, a municipality which is half clean and half heavily polluted will end up with similar average exposure compared to a municipality which has medium levels of pollution throughout. Due to non–linear health effects of particulate matter exposure, the overall public health impacts of particulate matter in these two municipalities might be substantially different. Moreover, pollution hot spots might remain undetected. In addition to taking spatial averages, we therefore also calculate two variables including critical thresholds:

- The percentage of the municipality's population above the WHO threshold for PM_{10} or $PM_{2.5}$, according to the 2005 air quality guidelines and
- The percentage of the municipality's surface above the respective WHO thresholds

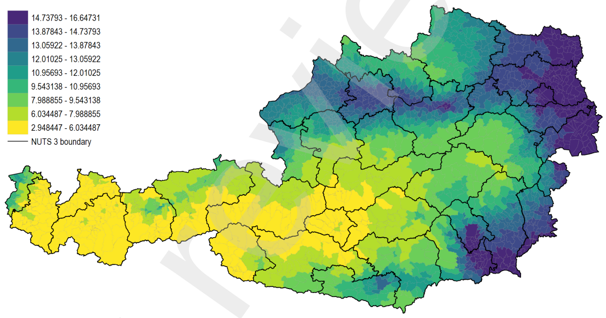
The difference between the latter two again is generated by unequal population density across the municipality. From a human health perspective, whether a pollution hot spot is located in an area with few or many inhabitants is of course critical.

We thus have four different air pollution exposure variables at the municipality level for PM_{10} and $PM_{2.5}$ each. Figure 3.1 compares the first two indicators mean exposure (a,b) and population weighted mean exposure (c,d) for PM_{10} (a,c) and $PM_{2.5}$ (b,d). All four figures show a clear east–west divide, where particulate matter exposure is higher in the eastern regions including Vienna, Burgenland, Lower Austria and Upper Austria. While similar patterns for both pollutants can be observed, population weighting while generating the indicator makes some differences, especially in the South. This justifies the use of different indicators for robustness. We will, however, use the first indicator, mean exposure, as a baseline.

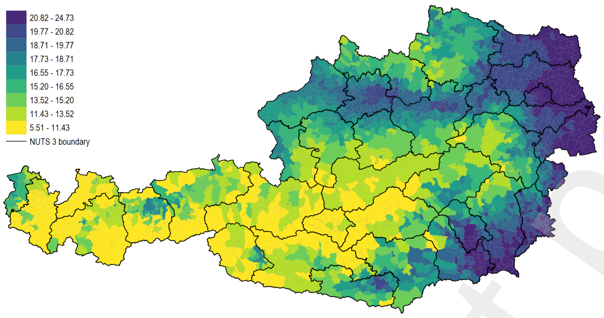
Figure 3.1: Regional air quality maps for PM_{10} and $PM_{2.5}$ (2015)



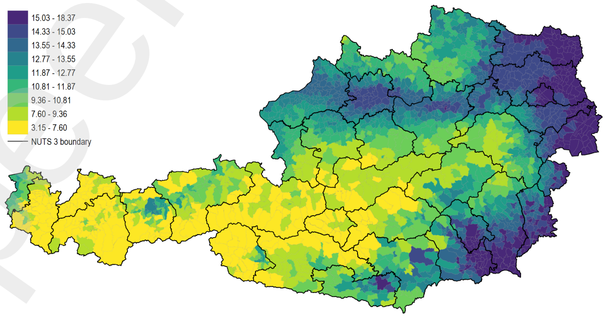
(a) Mean exposure of PM_{10} (μg/m^3)



(b) Mean exposure of $PM_{2.5}$ (μg/m^3)



(c) Pop. weighted mean exposure of PM_{10} (μg/m^3)



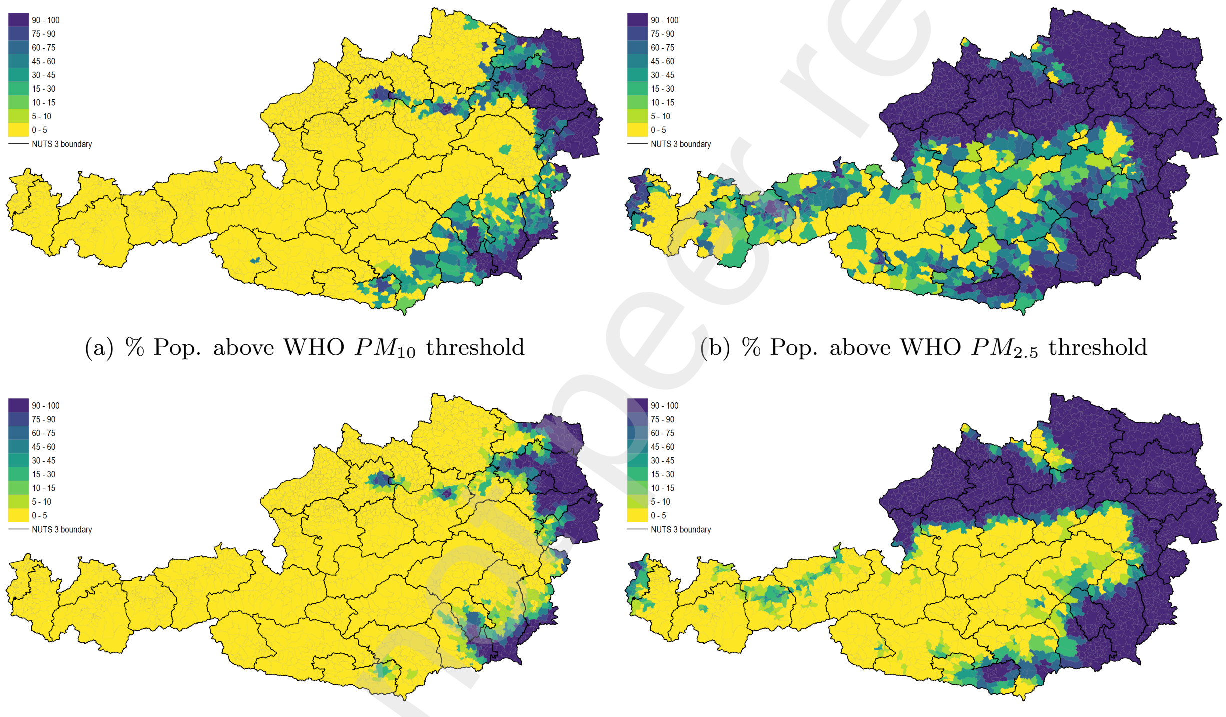
(d) Pop. weighted mean exposure of $PM_{2.5}$ (μg/m^3)

Note: Figure 3.1 presents the spatial dispersion of (population weighted) mean exposure of PM_{10} and $PM_{2.5}$. The darker the color, the higher the level of pollution. *Sources*: Own calculations, air pollution data retrieved from EEA.

Figure 3.2 compares the latter two indicators, the percentage of the municipality's population above the WHO threshold (a,b) and the percentage of the municipality's surface above the threshold (c,d) again for PM_{10} (a,c) and $PM_{2.5}$ (b,d). The figures again show clear east-west disparities and strong differences across NUTS 3 regions. Comparing the first with the second columns we see that in many municipalities the percentage of people exposed to critical pollution concentrations is substantially higher than the share of area, which suggests that pollution exposure is correlated with population density.[5]

[5] Areas where the discrepancies in this direction are large are predominantly located in alpine, mountain, and forest areas, where most of the municipality's surface is loosely populated and more dense settlement mainly only occurs around high-frequented main roads, highways, industrial facilities, and transportation hubs in the valley.

Figure 3.2: Regional air quality maps for PM_{10} and $PM_{2.5}$ (2015)



(a) % Pop. above WHO PM_{10} threshold

(b) % Pop. above WHO $PM_{2.5}$ threshold

(c) %Area above WHO PM_{10} threshold

(d) %Area above WHO $PM_{2.5}$ threshold

Note: Figure 3.2 presents the percentage of population and area exposed to PM_{10} and $PM_{2.5}$ concentrations above the WHO threshold. The darker the color the higher share of exposed area or population. *Sources*: Own calculations, air pollution data retrieved from EEA.

3.2. Sociodemographic indicators

We include three sociodemographic indicators available for all Austrian municipalities for 2015:

- *FOREIGN* indicates the percentage of people without Austrian citizenship and is obtained from the Register Based Labour Market and Employment Statistics 2015. Unfortunately it is not possible to disaggregate foreign citizens by the country of origin at the municipality level.

- *LOW_EDUC* is defined as the percentage of people aged 15 years and older without secondary or tertiary education and is also obtained from the Register Based Labour Market and Employment Statistics 2015.

- *INC* is defined as the sum of employee wages (gross) and self-employment earnings (less tax deductible expenses), excluding transfer payments, before total tax, and divided by the number of income taxpayers and is obtained from the Integrated Wage and Income Tax Statistics 2015.

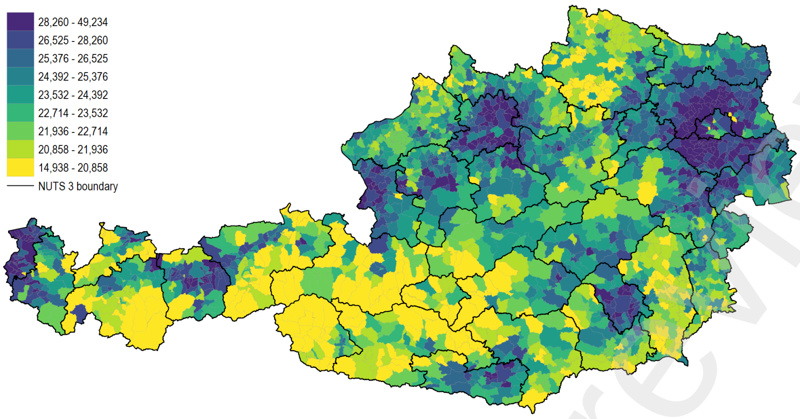
Figure 3.3 visualizes spatial variations in the three sociodemographic variables. For Austria as a whole, in 2015 the annual average income was about 24,500 EUR, the percentage of low skilled people 27% and the total share of foreign citizens 7.5%. While particulate matter exposure shows a clear east-west divide, the sociodemographic variables mainly differ by urbanization: For example, the average annual income is about 28,000 EUR in urban and 24,000 EUR in rural municipalities and the population share with low educational attainment amounts to 25% in urban and 27% in rural areas. The percentage of foreign citizens is higher in urban (12.9%) compared to rural municipalities (6.8%) (see also table A.4). Due to these differences, we will also control for degree of urbanization in some specifications.

3.3. Method

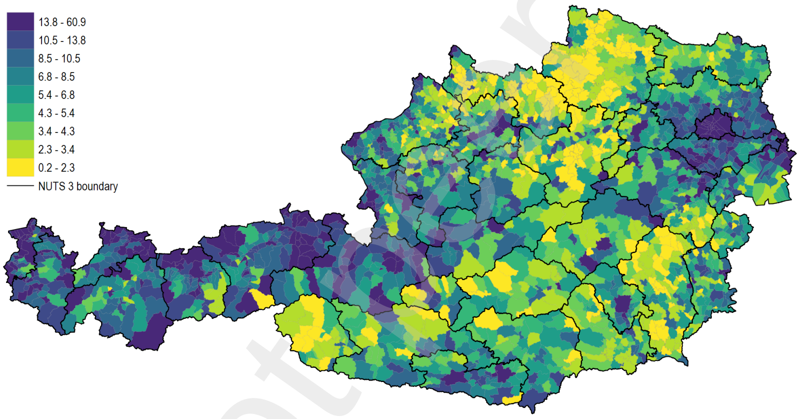
To assess sociodemographic disparities in particulate matter exposure, we estimate a multivariate model, explaining particulate matter exposure by the three sociodemographic variables:

Municipalities with lower shares of exposed people than area, in contrast, are mainly located in lowland regions where most of the area is used for forestry and agriculture, causing environmental stress for the cultivated land. At the same time, due to the geographic location in flat areas, a higher share of surface is habitable and the main areas of settlement tend to be larger in size but less spatially concentrated than in municipalities situated in mountainous regions.

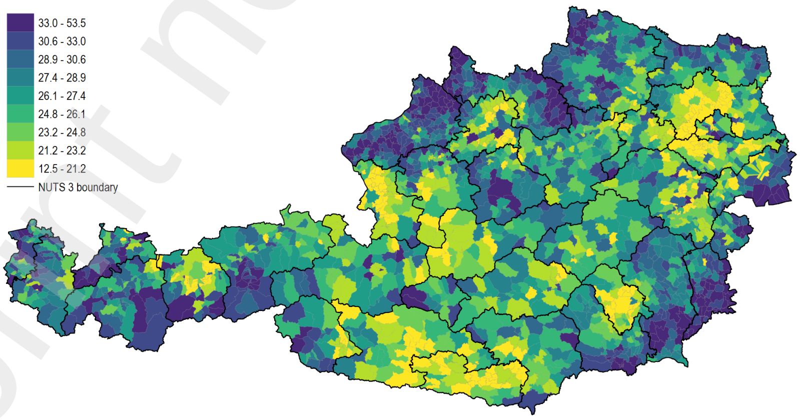
Figure 3.3: Regional sociodemographic maps (2015)



(a) Annual average income (in €)



(b) Foreign citizens (in %)



(c) Low skilled (in %)

Note: Figure 3.3 present the regional distribution of income, foreign and low-skilled citizens. The darker the color the higher the income and the share of foreign or low-skilled people. *Sources*: Own calculations, data retrieved from Statistics Austria.

$$EXP_{mr} = r + \beta_1 FOREIGN_{mr} + \beta_2 LOW\_EDUC_{mr} + \beta_3 INC_{mr} + \beta_4 INC^2_{mr} + \delta_r + \epsilon_{mr}$$

Where EXP_{mr} is a vector of the four different indicators of particulate matter exposure in municipality m in region r, $FOREIGN_{mr}$ is the share of foreign citizens, LOW_EDUC_{mr} is the share with low educational attainment, INC_{mr} is average income divided by 10,000, INC^2_{mr} is the quadratic term of income divided by 10,000 to capture potential non–linearities, δ_m are NUTS 2 or NUTS 3 fixed effects, and ϵ_{mr} is the error term. Due to the uneven size of municipalities (ranging from 51 to almost 280,000 inhabitants), we include population weights in the baseline specifications, however we will also investigate the role of population weighting. We then explore heterogeneity by splitting the sample into urban and rural municipalities. To control for spatial autocorrelation, standard errors are clustered at the NUTS 3 level in all estimations.

4. Results

4.1. Baseline results

Table 4.1: Explaining mean particulate matter exposure by the percentage of foreign residents

	ln(PM 10)			ln(PM 2.5)		
	(1)	(2)	(3)	(4)	(5)	(6)
FOREIGN	0.011***	0.010***	0.005***	0.011***	0.010***	0.006***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Observations	2122	2122	2122	2122	2122	2122
R-squared	0.134	0.588	0.838	0.108	0.608	0.853
Fixed effects	None	NUTS 2	NUTS 3	None	NUTS 2	NUTS 3
Pop weights	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Cluster-robust standard errors in parentheses. *Sources*: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

In table 4.1, we start to assess disproportionate particulate matter exposure by the sociodemographic characteristics of the municipality by explaining pollution exposure by the percentage of foreign citizens. Our dependent variable is average exposure of PM_{10} in columns 1-3 and average exposure of $PM_{2.5}$ in columns 4-6 (we will present results for the three other pollution indicators in subsection 4.2). We include population weights in all specifications (we will discuss the role of population weights in subsection 4.3). Columns 1 and 4 report results without any fixed effects for PM_{10} and $PM_{2.5}$ respectively, columns 2 and 5 report results with NUTS 2 fixed effects, columns 3 and 6 report results with NUTS 3 (the finest regional) fixed effects. We find that the percentage of foreigners is significantly correlated with pollution exposure in all six specifications. The coefficients range between 0.005 in the specifications with NUTS 3 fixed effects and 0.011 in the specification without any fixed effects. A coefficient of 0.005 implies that a 1 percentage point increase in the share of foreign residents increases pollution exposure by 0.5 percent.

Table 4.2: Explaining mean particulate matter exposure by the percentage of foreign residents and income

	ln(PM 10)			ln(PM 2.5)		
	(1)	(2)	(3)	(4)	(5)	(6)
FOREIGN	0.010^{**}	0.009^{***}	0.007^{***}	0.009^{**}	0.009^{***}	0.007^{***}
	(0.004)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
INC	0.992^{**}	1.050^{***}	0.684^{***}	1.042^{**}	1.096^{***}	0.694^{***}
	(0.412)	(0.273)	(0.185)	(0.472)	(0.298)	(0.190)
INC^2	-0.135^{**}	-0.154^{***}	-0.103^{***}	-0.143^{*}	-0.161^{***}	-0.104^{***}
	(0.063)	(0.041)	(0.028)	(0.072)	(0.045)	(0.029)
Observations	2122	2122	2122	2122	2122	2122
R-squared	0.247	0.663	0.856	0.212	0.676	0.869
INC turn. point	3.671	3.410	3.328	3.651	3.396	3.332
U-shape test (p-val)	0.056	0.001	0.000	0.069	0.001	0.001
Fieller interval	[3.446, 5.125]	[3.321, 3.559]	[3.255, 3.408]	[3.430, 5.854]	[3.313, 3.550]	[3.269, 3.413]
Fixed effects	None	NUTS 2	NUTS 3	None	NUTS 2	NUTS 3
Pop weights	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Cluster-robust standard errors in parentheses. *Sources*: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

In table 4.2, we additionally control for income and income square. Overall, foreigners in Austria live in municipalities with higher incomes (68% of foreigners live in municipalities whose average income is above the national median), because they disproportionately live in urban areas (which we will discuss in section 4.4). We again use mean exposure of PM_{10} and $PM_{2.5}$ as dependent variables, population weights, and gradually introduce finer fixed effects. Controlling for income, we also find that the percent of foreigners is statistically significant in all specifications with coefficients in a similar order of magnitude, now ranging from 0.007 to 0.010. Since the coefficients of income are positive and the coefficients for income square negative, this points towards an inverted U-shaped relationship between income and pollution exposure. Below the regression, we report the p-values of a test for the presence of a non–linear relationship (see Lind and Mehlum, 2010), where the null hypothesis of no inverted U-shaped relationship is tested against the alternative hypothesis of an inverted U-shaped relationship. We also report the turning points of the quadratic income function as well as the 90% Fieller confidence intervals. The relationship between income and pollution exposure can be considered positive and significant up to the lower confidence interval, insignificant from zero around the turning point between the lower and the upper confidence interval, and negative and significant above the upper confidence interval. In all six specifications, we can reject the null of no inverted U-shaped relationship at the 10% level, at the 5% level only in the specifications with fixed effects. The turning points of the income function are between 33,000 and 37,000 euros and thus far above the average municipality income of 24,000 euros. The lower 90% Fieller confidence intervals are between 32,000-34,000 euros in the six specifications. This suggests that the relationship between income and pollution is positive and significant up to a value of around 32,000-34,000 euros, after which it is statistically indifferent from 0. The upper confidence intervals range between 34,000 euros and values outside of the income distribution (the highest municipality's income is around 49,000 euros), which suggests that in some cases there is no significant negative relationship between income and pollution exposure for higher incomes.[6]

In table 4.3, we additionally control for the percentage of people with low educational attainment in the municipality. This again has little effect on the coefficients of the percentage of foreign citizens as well as on the quadratic income function. The share of residents with low educational attainment ranges from 0.007 to 0.013 and is significant in all specifications, except for those without any fixed effects. This suggests that while overall across Austria, we do not find disparities by educational attainment, when zooming into regional labor markets and investigate disparities within NUTS 2 and NUTS 3 regions, we also find that people with low educational attainment are disproportionately affected by pollution exposure. The inclusion of additional sociodemographic variables does not strongly affect the coefficients of foreigners and income. We will refer to table 4.3 (and specifically columns 3 and 6) as baseline specifications for PM_{10} and $PM_{2.5}$ respectively.

4.2. Alternative pollution indicators

In table 4.4 we report the results of table 4.3 with the percentage of the population above the WHO threshold instead of average particulate matter exposure. The coefficient of foreigners is always positive and significant, except for specification 4 (mean $PM_{2.5}$ without fixed effects).

[6]While previous studies have included income and income square, and some of them have reported turning points, they did not calculate the corresponding Fieller confidence intervals and thus cannot meaningfully report which parts of the quadratic income function are statistically significant.

Table 4.3: Baseline specification: Explaining average particulate matter exposure by the percentage of foreign residents, low educational attainment, and income

	ln(PM 10)			ln(PM 2.5)		
	(1)	(2)	(3)	(4)	(5)	(6)
FOREIGN	0.009**	0.007***	0.006***	0.008*	0.008***	0.006***
	(0.004)	(0.002)	(0.001)	(0.004)	(0.002)	(0.001)
LOW_EDUC	0.009	0.012***	0.007***	0.009	0.013***	0.007***
	(0.008)	(0.004)	(0.002)	(0.009)	(0.004)	(0.002)
INC	1.097**	1.293***	0.818***	1.151**	1.347***	0.820***
	(0.439)	(0.231)	(0.144)	(0.503)	(0.257)	(0.147)
INC^2	−0.139**	−0.175***	−0.114***	−0.147**	−0.183***	−0.115***
	(0.063)	(0.035)	(0.022)	(0.072)	(0.039)	(0.023)
Observations	2122	2122	2122	2122	2122	2122
R-squared	0.261	0.680	0.860	0.225	0.692	0.872
INC turn. point	3.932	3.693	3.584	3.908	3.678	3.572
U-shape test (p-val)	0.086	0.001	0.000	0.097	0.001	0.000
Fieller interval	[3.480, 5.671]	[3.502, 4.006]	[3.434, 3.832]	[3.441, 6.271]	[3.483, 4.002]	[3.411, 3.843]
Fixed effects	None	NUTS 2	NUTS 3	None	NUTS 2	NUTS 3
Pop weights	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Cluster-robust standard errors in parentheses. *Sources*: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

Table 4.4: = Table 4.3. with the percentage of the municipality's population above the WHO particulate matter threshold as dependent variable

	% pop above PM 10 WHO threshold			% pop above PM 2.5 WHO threshold		
	(1)	(2)	(3)	(4)	(5)	(6)
FOREIGN	2.505***	1.296***	0.869**	0.336	0.470*	0.553***
	(0.657)	(0.434)	(0.377)	(0.277)	(0.233)	(0.174)
LOW_EDUC	−0.979	0.460	0.657*	1.572**	1.929***	1.210***
	(1.175)	(0.625)	(0.364)	(0.599)	(0.416)	(0.290)
INC	17.715	96.742***	81.907***	152.606***	167.997***	114.150***
	(64.442)	(34.154)	(27.305)	(44.939)	(36.138)	(21.567)
INC^2	−0.677	−12.877**	−12.052**	−20.648***	−22.992***	−15.501***
	(10.434)	(5.898)	(4.724)	(6.519)	(5.423)	(3.205)
Observations	2122	2122	2122	2122	2122	2122
R-squared	0.298	0.638	0.789	0.237	0.472	0.685
INC turn. point	13.075	3.756	3.398	3.695	3.653	3.682
U-shape test (p-val)	.	0.125	0.048	0.009	0.001	0.000
Fieller interval	[., .]	[3.206, 7.079]	[2.888, 4.865]	[3.476, 4.132]	[3.479, 3.958]	[3.510, 3.951]
Fixed effects	None	NUTS 2	NUTS 3	None	NUTS 2	NUTS 3
Pop weights	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Cluster-robust standard errors in parentheses. *Sources*: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

A coefficient of 2.5 suggests that a 1 percentage point increase in foreign citizens increases the likelihood that a municipality is above the WHO threshold by 2.5 percentage points. The coefficient for low educational attainment is only significant in specifications 3-6. The differences between the results from the PM_{10} and $PM_{2.5}$ specifications are generally higher in table 4.4, which might have be due to the latter pollution indicators being very sensitive towards the thresholds used (especially since many people live very close around the threshold). The test for the presence of an inverted U-shaped relationship between income and pollution exposure is accepted at the 10% level in all specifications except for the first and second, and at the 5% level in specifications 3, 5, and 6. Results with population weighted average exposure in table B.1 and with the percentage of the municipality's surface above the WHO threshold in table B.2 are reported in the appendix and generally show similar results.

4.3. The role of population weights

Table 4.5: = Specification 4.3 without population weights

	ln(PM 10)			ln(PM 2.5)		
	(1)	(2)	(3)	(4)	(5)	(6)
FOREIGN	-0.008^{*}	0.003^{*}	0.005^{***}	-0.010^{**}	0.004^{*}	0.005^{***}
	(0.004)	(0.002)	(0.001)	(0.005)	(0.002)	(0.001)
LOW_EDUC	0.016^{***}	0.010^{***}	0.003^{*}	0.018^{***}	0.010^{**}	0.003
	(0.005)	(0.003)	(0.002)	(0.006)	(0.004)	(0.002)
INC	1.553^{***}	1.118^{***}	0.908^{***}	1.685^{***}	1.157^{***}	0.906^{***}
	(0.313)	(0.194)	(0.104)	(0.362)	(0.203)	(0.108)
INC^2	-0.199^{***}	-0.145^{***}	-0.130^{***}	-0.219^{***}	-0.152^{***}	-0.131^{***}
	(0.048)	(0.032)	(0.017)	(0.056)	(0.033)	(0.018)
Observations	2122	2122	2122	2122	2122	2122
R-squared	0.223	0.651	0.844	0.206	0.680	0.863
INC turn. point	3.903	3.843	3.489	3.856	3.804	3.464
U-shape test (p-val)	0.014	0.009	0.000	0.014	0.007	0.000
Fieller interval	[3.612, 4.482]	[3.546, 4.403]	[3.312, 3.724]	[3.566, 4.448]	[3.505, 4.346]	[3.282, 3.706]
Fixed effects	None	NUTS 2	NUTS 3	None	NUTS 2	NUTS 3
Pop weights	No	No	No	No	No	No

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Cluster-robust standard errors in parentheses. *Sources*: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

In the previous sections, we applied population weights to present results that are representative for the Austrian population. The empirical literature on environmental inequality emphasizes, however, that it is important to also report results without any weights to treat every geographical unit equally (independently of whether it has 51 or almost 280,000 residents as in our case), to avoid overlooking disparities in small, rural places. Table 4.5 shows baseline table 4.3 without population weights. The coefficient for foreigners switches and becomes negative and statistically significant in the specification without any fixed effects. In the specifications with fixed effects, the coefficient again is positive and statistically significant, though only around half in size compared to table 4.3. The coefficient for low educational attainment is always positive and statistically significant, except in column 6, and generally drops in size when zooming in finer with regional fixed effects. Population weighting has little effect on the quadratic income function.

4.4. Urban versus rural

Table 4.6: Explaining average $PM_{2.5}$ exposure, rural versus urban municipalities

	(1) Rural	(2) Urban	(3) Rural	(4) Urban	(5) Rural	(6) Urban
FOREIGN	-0.016***	0.014***	0.001	0.008**	0.003**	0.003*
	(0.004)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)
LOW_EDUC	0.024***	-0.009	0.015***	0.002	0.005*	0.003
	(0.005)	(0.011)	(0.005)	(0.004)	(0.003)	(0.003)
INC	1.879***	0.038	1.131***	0.658**	1.016***	0.240
	(0.532)	(0.511)	(0.388)	(0.284)	(0.165)	(0.172)
INC^2	-0.242**	0.002	-0.138*	-0.089**	-0.152***	-0.032
	(0.091)	(0.065)	(0.071)	(0.040)	(0.030)	(0.022)
Observations	1869	253	1869	253	1869	253
R-squared	0.282	0.248	0.646	0.769	0.860	0.901
INC turn. point	3.883	-11.801	4.087	3.678	3.338	3.785
U-shape test (p-val)	0.093	.	0.236	0.026	0.001	0.089
Fieller interval	[3.457, 5.620]	[., .]	[3.391, 12.911]	[3.387, 4.227]	[3.123, 3.722]	[., .]
Fixed effects	None	None	NUTS 2	NUTS 2	NUTS 3	NUTS 3
Pop weights	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. *Sources*: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

The differences between tables 4.3 and 4.5 suggests that foreigners are more adversely affected by pollution exposure in highly populated places, which is also where they disproportionately live. In fact, 75 percent of foreigners in Austria live in urban areas, while overall 52 percent of the Austrian population lives in urban areas. We thus finally split our sample into urban and rural areas, where 12 percent of our observations are classified as urban. Table 4.6 reports results for urban and rural areas with population weights for average $PM_{2.5}$ exposure. Appendix table B.3 reports results without population weights, which are very similar to table B.4, suggesting that the role of population weighting is minor when splitting the sample into urban versus rural. Appendix tables B.4 B.5 report results for average PM_{10} exposure, which are also very similar.

We find that overall in rural areas, the coefficients for foreigners is negative and statistically significant (specification 1) and turns positive and statistically significant with NUTS 3 fixed effects (specification 5). The coefficient for low educational attainment is positive and statistically significant for all three rural specifications, but drops in size from 0.024 to 0.005 with the inclusion of finer fixed effects. In urban areas, where 3 out of 4 foreigners live, the coefficients are positive and statistically significant in all three specifications (2, 4, and 6). However, the coefficients drop in size with the inclusion of finer fixed effects. The coefficient for low educational attainment is not statistically significant in any of the specifications. The test for an inverted U-shaped relationship between income and pollution exposure is accepted at the 10% level in all specifications except for the second and at the 5% level in specifications 4 and 5.

5. Conclusion

We find that foreign citizens are significantly more exposed to particulate matter in Austria. Our findings are robust to excluding the other sociodemographic controls, towards using different measures of particulate matter exposure, as well as towards including no, NUTS 2, and NUTS 3 fixed effects. When splitting our sample into urban and rural neighborhoods, we find that the observed disparities by citizenship are driven by urban neighborhoods, in which 75% of foreign citizens live. The remaining 25% foreigners overall live in the cleaner parts of rural areas, however within these areas they also live in the more polluted municipalities. From an inequality perspective, within regional disparities are of highest interest, since they are most likely driven by environmental injustice in residential segregation, and within regional disparities exist independent of the degree of urbanization.

We also find evidence that citizens with low educational attainment are disproportionately affected by particulate matter exposure. The latter effect is especially driven by rural areas. This suggests that foreigners face a significantly higher pollution burden in urban areas, where they disproportionately live and people with low educational attainment face a higher pollution burden in rural areas, where the majority of low educational attainment residents live.

The relationship between income and pollution exposure is non–linear and follows an inverted U-shaped relationship, as in many previous previous empirical analyses of environmental inequality. We improve upon previous studies by providing a formal test for the presence of an inverted U-shaped relationship between income and pollution exposure based on Lind and Mehlum (2010), which is accepted in most, but not all specifications. Where applicable, we also present 90% Fieller confidence intervals to show the ranges where the income function is statistically significant. The lower confidence interval starts at income levels substantially above the mean income and the upper confidence intervals are often outside of the distribution. This suggests that income is significantly positively correlated with pollution exposure or insignificant from zero for the majority of the distribution. The latter finding can be explained by the fact that income is an important measure of economic and industrial activity.

Our findings are thus in line with the large body of empirical studies documenting sociodemographic disparities in air pollution exposure. While our unit of observation is comparable in size to the US-based studies, our main difference is that we study a single pollutant, particulate matter, which is the number one pollutant in densely populated high income countries in Europe, like Austria. Particulate matter is generally considered to be spatially much less concentrated than, for example, toxic releases by industrial facilities, and also much more correlated with industrial activity in general. It could therefore be expected that environmental inequalities are much smaller. Yet, we still find robust evidence that foreigners and citizens with low educational attainment are disproportionately affected by particulate matter exposure in Austria, independent of whether we control for income.

Future studies could extend this analysis to different European countries (for which municipality-level sociodemographic data exist, but are not harmonized across Europe) and explore different pollutants. Moreover, as both pollution and regional data will become available as time series, it will become possible to assess the causes of the observed disparities.

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Appendix A. Additional summary statistics

Table A.1: Emission Thresholds

	PM_{10} annual averages	$PM_{2.5}$ annual averages
WHO emission threshold (μg/m_3)	20	10
percentage observations above threshold (%)	15	64
percentage population above threshold (%)	21	75

Note: Table A.1 reports the emission thresholds of annual average concentrations of PM_{10} and $PM_{2.5}$ and the percentage of observations (municipalities) and Austrian population above the given emission threshold. Limit values are set in the Ambient Air Quality Guidelines (AQG) of the World Health Organization (WHO).
Source: WHO (2006).

Table A.2: Mean Values of Sociodemographic and Air Pollution Variables at NUTS 1 Level

	East Austria (AT1)	South Austria (AT2)	West Austria (AT3)
Mean exposure PM_{10} (μg/m3)	18.149	14.305	13.243
Mean exposure $PM_{2.5}$ (μg/m3)	13.124	10.383	9.361
PW mean exposure PM_{10} (μg/m3)	18.952	16.188	14.655
PW mean exposure $PM_{2.5}$ (μg/m3)	13.624	11.650	10.271
% pop above PM_{10} WHO threshold	43.362	23.436	1.327
% pop above $PM_{2.5}$ WHO threshold	94.351	65.434	62.113
% area above PM_{10} WHO threshold	32.716	13.774	0.759
% area above $PM_{2.5}$ WHO threshold	90.715	47.290	49.525
INC ('000 Eur)	2.534	2.306	2.428
INC^2 ('000 Eur)	6.562	5.382	6.000
FOREIGN (%)	7.190	5.485	8.671
LOW_EDUC (%)	26.475	25.758	27.963

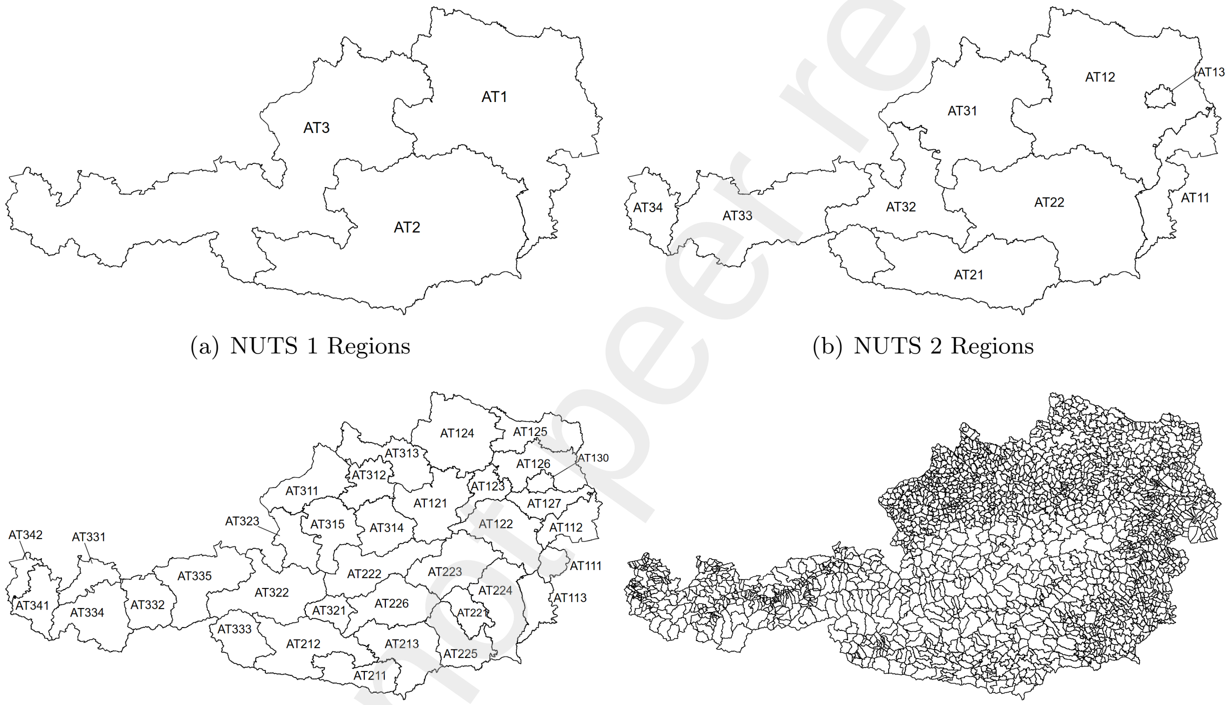
Notes: Table A.2 presents the mean values of all applied air pollution and sociodemographic indicators at the NUTS 1 Level
Sources: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

Table A.3: NUTS Classification Austria

NUTS Level, Code and Name		
NUTS 1 - groups of federal provinces (3)		
AT1 Eastern Austria		
AT2 Southern Austria		
AT3 Western Austria		
NUTS 2 - federal provinces (9)		
AT11 Burgenland		
AT12 Lower Austria		
AT13 Vienna		
AT21 Carinthia		
AT22 Styria		
AT31 Upper Austria		
AT32 Salzburg		
AT33 Tyrol		
AT34 Vorarlberg		
NUTS 3 - political districts (35)		
AT111 Mittelburgenland	AT212 Oberkärnten	AT315 Traunviertel
AT112 Nordburgenland	AT213 Unterkärnten	AT321 Lungau
AT113 Südburgenland	AT221 Graz	AT322 Pinzgau-Pongau
AT121 Mostviertel-Eisenwurzen	AT222 Liezen	AT323 Salzburg und Umgebung
AT122 Niederösterreich-Süd	AT223 Östliche Obersteiermark	AT331 Außerfern
AT123 Sankt Pölten	AT224 Oststeiermatk	AT332 Innsbruck
AT124 Waldviertel	AT225 West- und Südsteiermark	AT333 Osttirol
AT125 Weinviertel	AT226 Westliche Obersteiermark	AT334 Tiroler Oberland
AT126 Wiener Umland/Nordteil	AT311 Innviertel	AT341 Bludenz-Bregenzer Wald
AT127 Wiener Umland/Südteil	AT312 Linz-Wels	AT342 Rheintal-Bodenseegebiet
AT130 Wien	AT313 Mühlviertel	
AT211 Klagenfurt-Villach	AT314 Steyr-Kirchdorf	

Note: Table A.3 presents Austria's NUTS levels (1, 2, 3), NUTS codes and respective names. *Source*: Statistics Austria.

Figure A.1: NUTS Regions and Municipalities in Austria



(a) NUTS 1 Regions

(b) NUTS 2 Regions

(c) NUTS 3 Regions

(d) Municipalities

Note: Figure A.1 presents maps of Austria separated into NUTS 1, NUTS 2, NUTS 3 regions and municipalities. Austria has 3 NUTS 1 regions, 9 NUTS 2 regions, 35 NUTS 3 regions and 2122 municipalities (2015). There are between 15 and 146 municipalities in a NUTS 3 region. Vienna is separated into 23 districts, referred to as municipalities in this paper. *Sources*: Own representations, data and shape files retrieved from Statistics Austria.

Table A.4: Descriptive Statistics of Sociodemographic and Air Pollution Variables

	Mean	SD	Min	Max	N
Rural					
Mean exposure PM_{10} (μg/m3)	15.057	4.289	4.838	22.422	1869
Mean exposure $PM_{2.5}$ (μg/m3)	10.824	3.317	2.948	16.647	1869
PW mean exposure PM_{10} (μg/m3)	16.275	3.834	5.508	23.473	1869
PW mean exposure $PM_{2.5}$ (μg/m3)	11.604	3.016	3.149	17.539	1869
% pop above PM_{10} WHO threshold	19.712	34.806	0.000	100.000	1869
% pop above $PM_{2.5}$ WHO threshold	72.381	39.135	0.000	100.000	1869
% area above PM_{10} WHO threshold	13.621	31.102	0.000	100.000	1869
% area above $PM_{2.5}$ WHO threshold	63.138	45.444	0.000	100.000	1869
INC ('000 Eur)	2.396	0.301	1.494	4.807	1869
INC^2 ('000 Eur)	5.829	1.536	2.232	23.107	1869
FOREIGN (%)	6.792	4.967	0.200	60.900	1869
LOW_EDUC (%)	27.252	4.844	13.500	53.500	1869
Urban					
Mean exposure PM_{10} (μg/m3)	16.473	3.763	8.236	22.842	253
Mean exposure $PM_{2.5}$ (μg/m3)	11.649	2.922	5.159	16.619	253
PW mean exposure PM_{10} (μg/m3)	18.251	2.633	9.494	24.730	253
PW mean exposure $PM_{2.5}$ (μg/m3)	12.869	2.160	6.175	18.368	253
% pop above PM_{10} WHO threshold	29.557	42.399	0.000	100.000	253
% pop above $PM_{2.5}$ WHO threshold	89.491	18.574	0.000	100.000	253
% area above PM_{10} WHO threshold	24.183	38.802	0.000	100.000	253
% area above $PM_{2.5}$ WHO threshold	70.134	37.556	0.000	100.000	253
INC ('000 Eur)	2.786	0.426	2.043	4.923	253
INC^2 ('000 Eur)	7.943	2.689	4.174	24.240	253
FOREIGN (%)	12.785	6.740	2.000	39.800	253
LOW_EDUC (%)	25.052	5.463	12.500	37.700	253
Total					
Mean exposure PM_{10} (μg/m3)	15.226	4.254	4.838	22.842	2122
Mean exposure $PM_{2.5}$ (μg/m3)	10.923	3.282	2.948	16.647	2122
PW mean exposure PM_{10} (μg/m3)	16.511	3.765	5.508	24.730	2122
PW mean exposure $PM_{2.5}$ (μg/m3)	11.755	2.956	3.149	18.368	2122
% pop above PM_{10} WHO threshold	20.886	35.927	0.000	100.000	2122
% pop above $PM_{2.5}$ WHO threshold	74.421	37.691	0.000	100.000	2122
% area above PM_{10} WHO threshold	14.880	32.289	0.000	100.000	2122
% area above $PM_{2.5}$ WHO threshold	63.972	44.627	0.000	100.000	2122
INC ('000 Eur)	2.442	0.342	1.494	4.923	2122
INC^2. ('000 Eur)	6.081	1.846	2.232	24.240	2122
FOREIGN (%)	7.507	5.558	0.200	60.900	2122
LOW_EDUC (%)	26.990	4.972	12.500	53.500	2122

Notes: Table A.4 presents the descriptive statistics (mean, standard deviation, minimum, maximum and number of observations) of all applied air pollution and sociodemographic indicators for the urban/rural sub samples and the total sample.
Sources: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

Appendix B. Additional regressions

Table B.1: = Table 4.3. with population weighted average pollution exposure as dependent variable

	ln(PM 10/pop)			PW ln(PM 2.5/pop)		
	(1)	(2)	(3)	(4)	(5)	(6)
FOREIGN	0.007***	0.007***	0.006***	0.007**	0.007***	0.007***
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.002)
LOW_EDUC	0.004	0.010***	0.007***	0.004	0.011***	0.006**
	(0.006)	(0.003)	(0.002)	(0.007)	(0.004)	(0.003)
INC	0.931***	1.176***	0.883***	1.004**	1.271***	0.907***
	(0.334)	(0.185)	(0.155)	(0.404)	(0.219)	(0.167)
INC^2	−0.129**	−0.163***	−0.124***	−0.141**	−0.177***	−0.129***
	(0.050)	(0.029)	(0.025)	(0.060)	(0.034)	(0.027)
Observations	2122	2122	2122	2122	2122	2122
R-squared	0.270	0.628	0.797	0.228	0.620	0.809
INC turn. point	3.613	3.611	3.557	3.567	3.584	3.529
U-shape test (p-val)	0.027	0.000	0.000	0.033	0.000	0.001
Fieller interval	[3.252, 4.414]	[3.447, 3.865]	[3.406, 3.822]	[3.171, 4.461]	[3.405, 3.865]	[3.365, 3.814]
Fixed effects	None	NUTS 2	NUTS 3	None	NUTS 2	NUTS 3
Pop weights	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. *Sources*: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

Table B.2: = Table 4.3. with the percentage of the municipality's area above the WHO particulate matter threshold as dependent variable

	% area above PM 10 WHO threshold			% area above PM 2.5 WHO threshold		
	(1)	(2)	(3)	(4)	(5)	(6)
FOREIGN	2.611***	1.271***	0.741***	0.616	0.621**	0.501***
	(0.658)	(0.307)	(0.261)	(0.509)	(0.262)	(0.153)
LOW_EDUC	−0.616	0.181	0.393	1.941	1.763***	1.067***
	(0.928)	(0.436)	(0.306)	(1.178)	(0.531)	(0.336)
INC	2.599	63.064**	47.254*	139.316**	142.085***	82.977***
	(55.216)	(26.307)	(25.781)	(57.015)	(34.327)	(18.328)
INC^2	1.338	−9.082**	−8.497*	−16.571**	−18.561***	−10.703***
	(8.839)	(4.409)	(4.314)	(7.870)	(5.103)	(2.426)
Observations	2122	2122	2122	2122	2122	2122
R-squared	0.352	0.641	0.764	0.181	0.579	0.773
INC turn. point	-0.971	3.472	2.780	4.204	3.827	3.876
U-shape test (p-val)	.	0.083	0.055	0.165	0.012	0.001
Fieller interval	[., .]	[2.938, 6.315]	[1.278, 3.424]	[3.646, 7.113]	[3.561, 4.372]	[3.640, 4.163]
Fixed effects	None	NUTS 2	NUTS 3	None	NUTS 2	NUTS 3
Pop weights	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. *Sources*: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

Table B.3: = Table 4.6 without population weights for $PM_{2.5}$

	(1) Rural	(2) Urban	(3) Rural	(4) Urban	(5) Rural	(6) Urban
FOREIGN	-0.014***	0.012***	0.003	0.006*	0.004**	0.006**
	(0.005)	(0.004)	(0.002)	(0.003)	(0.001)	(0.003)
LOW_EDUC	0.019***	-0.009	0.009**	0.000	0.001	0.002
	(0.006)	(0.009)	(0.004)	(0.004)	(0.002)	(0.002)
INC	2.098***	0.118	1.038***	0.582**	0.916***	0.384**
	(0.447)	(0.530)	(0.259)	(0.214)	(0.131)	(0.166)
INC^2	-0.297***	-0.003	-0.135***	-0.076**	-0.139***	-0.050**
	(0.079)	(0.072)	(0.046)	(0.029)	(0.024)	(0.022)
Observations	1869	253	1869	253	1869	253
R-squared	0.238	0.141	0.690	0.719	0.873	0.874
INC turn. point	3.538	17.768	3.844	3.816	3.292	3.802
U-shape test (p-val)	0.012	.	0.082	0.017	0.000	0.018
Fieller interval	[3.218, 4.233]	[., .]	[3.381, 5.392]	[3.433, 4.337]	[3.087, 3.610]	[3.459, 4.177]
Fixed effects	None	None	NUTS 2	NUTS 2	NUTS 3	NUTS 3
Pop weights	No	No	No	No	No	No

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. *Sources*: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

Table B.4: = Table 4.6 with population weights for PM_{10}

	(1) Rural	(2) Urban	(3) Rural	(4) Urban	(5) Rural	(6) Urban
FOREIGN	-0.011***	0.012***	0.003	0.005*	0.003***	0.005**
	(0.004)	(0.004)	(0.002)	(0.003)	(0.001)	(0.002)
LOW_EDUC	0.018***	-0.008	0.009**	0.000	0.002	0.003
	(0.005)	(0.008)	(0.004)	(0.004)	(0.002)	(0.002)
INC	1.890***	0.173	0.999***	0.530**	0.920***	0.361**
	(0.387)	(0.450)	(0.259)	(0.214)	(0.126)	(0.164)
INC^2	-0.262***	-0.012	-0.128***	-0.070**	-0.139***	-0.047**
	(0.067)	(0.061)	(0.046)	(0.029)	(0.023)	(0.021)
Observations	1869	253	1869	253	1869	253
R-squared	0.249	0.158	0.660	0.682	0.854	0.860
INC turn. point	3.600	7.158	3.910	3.800	3.320	3.818
U-shape test (p-val)	0.012	.	0.107	0.024	0.000	0.023
Fieller interval	[3.280, 4.285]	[., .]	[3.422, 5.781]	[3.365, 4.404]	[3.116, 3.638]	[3.445, 4.223]
Fixed effects	None	None	NUTS 2	NUTS 2	NUTS 3	NUTS 3
Pop weights	No	No	No	No	No	No

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. *Sources*: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.

Table B.5: = Table 4.6 without population weights for PM_{10}

	(1) Rural	(2) Urban	(3) Rural	(4) Urban	(5) Rural	(6) Urban
FOREIGN	-0.013***	0.013***	0.001	0.008**	0.003**	0.002**
	(0.004)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)
LOW_EDUC	0.022***	-0.007	0.015***	0.002	0.005**	0.003
	(0.004)	(0.010)	(0.004)	(0.003)	(0.002)	(0.002)
INC	1.684***	0.108	1.054***	0.623**	1.002***	0.214
	(0.493)	(0.460)	(0.383)	(0.292)	(0.158)	(0.170)
INC^2	-0.212**	-0.008	-0.126*	-0.085**	-0.150***	-0.028
	(0.084)	(0.058)	(0.070)	(0.041)	(0.029)	(0.022)
Observations	1869	253	1869	253	1869	253
R-squared	0.288	0.264	0.616	0.749	0.840	0.895
INC turn. point	3.975	6.797	4.186	3.652	3.343	3.800
U-shape test (p-val)	0.128	.	0.280	0.032	0.001	0.113
Fieller interval	[3.498, 6.246]	[., .]	[3.422, 28.179]	[3.332, 4.275]	[3.133, 3.716]	[., .]
Fixed effects	None	None	NUTS 2	NUTS 2	NUTS 3	NUTS 3
Pop weights	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. *Sources*: Own calculations, air pollution data retrieved from EEA, sociodemographic data obtained from Statistics Austria.