Strategic Air Pollution Monitoring:
A European review

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Abstract

Air pollution is a growing public concern due to its effects on health and mortality, and numerous policy initiatives have been applied to reduce it. These policies usually impose fines or regulations to local zones if they surpass some pollution limits of population exposure. Grainger et al. (2017) and Grainger and Schreiber (2019) theorise and try to show that, in the US, non-aligned interests created by these policies might induce local administrations to strategically position air quality stations to reduce pollution measurements and avoid non-attainment. I use a similar methodology to test if this behaviour is also present in the European Union using relative pollution distribution around sited stations and a probability model of station placement. My results coincide with previous research for the US and suggest stations are positioned in relatively cleaner locations as the average level of pollution increases and that zones in attainment choose cleaner locations than zones in non-attainment, suggesting that pollution measurements might be endogenous to the attainment status of a given zone.

***Keywords* —** Air Pollution Monitoring, Environmental Regulation, Air Quality, PM2.5, PM10, Economic Geography

1 Introduction

Due to a large body of research pointing out the adverse effects of air pollution and a growing political concern since the late 1970s[1], increasingly strict legislation on pollution levels has been implemented in multiple countries (Holman et al., 2015). The European Union (EU) Air Quality Directive[2] imposes limits on particulate matter (PM), and other various pollutants. These directives divide the EU territory into various Environmental Zones and automatically monitor their concentration of various pollutants with a network of air quality stations, setting various regional limits for concentration and the consequences for surpassing them.

As documented by Grainger et al. (2017) similar policies in the US such as the Clean Air Act seem to have resulted in incentives to local regulators to strategically avoid siting pollution monitors in locations with poorer air quality, modifying the overall measures of pollution and therefore, the attainment to the policy.

The main questions I aim to answer are: (1) Do air quality stations in the EU systematically positioned in low-pollution locations? (2) Does this seem to respond to incentives to avoid fines from the European Commission's directives? (3) Is this a uniform phenomenon or is it localised in some countries?

To test these questions I borrow the main methodology of Grainger et al. (2017) and apply it to the European context. I use detailed estimates of pollution from van Donkelaar et al. (2016) to look at the pollution level where the station is sited relative to its surroundings. It is crucial to know if there have been systematic errors or biases in air-quality data collection, even more if those are driven by the air quality legislation itself, making it an endogenous variable.

The rest of my report is structured as follows: In Section 2 I explain the EU legislation and put my research in context with the current literature, Section 3 describes the multiple data sources and summarises their information, Section 4 explains the research design, Section 5 describes the results and Section 6 concludes.

[1] https://ec.europa.eu/environment/air/quality/index.htm

[2] EU directives are legislations that allow member states to choose how they comply with the limit or objective. I will refer specifically to a series of directives that build up air quality standards in the EU and especially directive 2008/50/EC.

2 Background and literature review

PM is a way to name small particles of various materials. The most conventional measurement of PM are PM10 and PM2.5 with the number referring to the diameter of the particle in micrometres and their concentration in the air is measured on micrograms per cubic meter (μg/m^3). Both PM10 and PM2.5 are emitted, mainly, by commercial, institutional and household heating, especially wood in Eastern European countries (EEA, 2016). PM2.5 and PM10 have both been linked as causes of higher mortality and morbidity, especially to cardiopulmonary diseases, respiratory infections, bronchus, asthma, and lung cancers, affecting especially those older than 65 years old and among children (less than 17-year-old) (EPA, 2004). In the EU member states, Watkiss et al. (2005) estimate that PM caused 348,000 premature deaths in the year 2000, far ahead of the second more deadly pollutant, ozone, who caused around 21,000 deaths.

The main guidance for this project is the research of Grainger et al. (2017) in which they develop an analytical model to "study the incentives a local regulator faces with respect to sitting new pollution monitors". They conclude that regulators close but below non-attainment have the incentive to avoid sitting pollution monitors in high polluted locations and attempt to test their model with data on the attainment status of zones, the geographic position of stations within those zones, their time of siting and the levels of pollution surrounding a given station. In this project, I focus on looking if there is any evidence of strategic position monitoring in the EU while using and evaluating the methods they use for the US. While EU and US cases are fairly similar, some modifications are based on the different EU geographical and regulatory reality.

The overall structure of the EU and US Air quality legislation is the same. Both divide their territory into zones -counties for the US and (changing) Environmental Zones in the EU-, monitor their air pollution levels with a network of air quality stations and set pollution limits for short (usually a number of days) and long time averages (1 year for the EU, 3 years for the US). The attainment status is decided on aggregate zone statistics and given yearly for each zone.

Although the EU Air Quality directive has one of the most strict limits on PM10 worldwide it is not as stringent with its PM2.5 limits. As pointed out by Wolff and Perry (2010), the common geo-location of PM10 and PM2.5 stations and the ratios of PM10 and PM 2.5 in Europe imply that the EU PM10 limit is likely to set the lower bound for PM2.5 pollution. This is the reason I include both PM10 and PM2.5 stations and evaluate attainment status based on both pollutants.

One significant difference for this study is that while in the US the environmental zone (county) coincides with the administration that decides the placement of new monitors and suffers all the consequences of non-attainment, in the EU the incentives for strategic position placement are not that closely aligned. EU Environmental Zones (referred as "zones" hereafter) are usually big enough to compromise multiple administrative boundaries and can change from one year to the next. Furthermore, although the policy implications go directly to the given zone, the financial consequences of non-attainment are placed both to the zone's administration/s and the EU member state. Finally, the organism responsible of the placement and retirement of stations is usually responsible for a region larger than the zone (states in Germany, regions in Italy, autonomous communities in Spain) or even a national environment body. All of this makes strategic position placement in the EU harder and less likely than in the US.

This is not to say that there are no incentives at all, various regional and national governments have been either threatened by fines or strongly incentivised to pursue decisive policy action by European directives. If a given zone surpasses the limit value set for any pollutant plus a given margin of tolerance, it has to develop a detailed "Clean Action Plan" that credibly sets the path to attainment (with various costly environmental policies). The member state can be penalised financially if the non-attainment continues or the Clean Action Plan is judged not strong enough by the EC. The European Commission (EC) has opened infringement procedures against 16 Member States[3] and the EU Court of Justice has already handed down judgements in Bulgaria and Poland (EC, 2018).

Figure 1 provides a graphical explanation of limit values, margins of tolerance and non-attainment in the EC directives. Attainment status for groups 1, 2, and 3 from the Figure 1 are referred in the rest of the paper as "Dirty", "Marginal", and "Clean" zones, respectively, taking into account their PM10 and PM2.5 concentration levels.

[3] Belgium, Bulgaria, the Czech Republic, Germany, Greece, Spain, France, Hungary, Italy, Latvia, Portugal, Poland, Romania, Sweden, Slovakia and Slovenia.

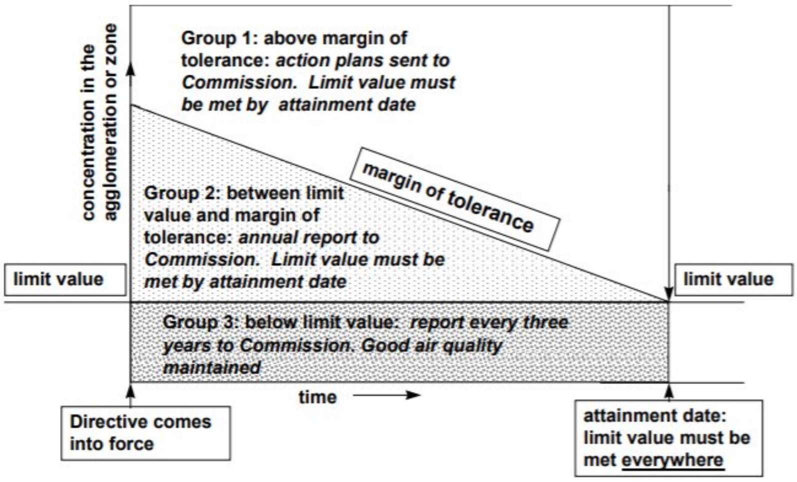


Figure 1: Graphical visualisation of the classification of attainment status in the EU.
Source: Guidance on Assessment under the EU Air Quality Directives EC (2020)

3 Data

To study the strategic position of monitoring stations I need to have the year of sitting, geographic position and attainment status of each individual station monitored by the EC. Furthermore, it is crucial to have the levels of pollution and a set of controls for sufficient locations in the surroundings of each station.

For the geographic position of air quality stations and their attainment status at the time of sitting I use multiple datasets from the Air Quality e-Reporting database (AQeR) from the European Environment Agency (EEA). With data from 2013, it provides detailed information on air quality stations monitored by the EC and Environmental Zones, including when the zone was active, their attainment status for each pollutant and limit in the Air Quality Directive and by how much the limit was exceeded. The perimeter of zones, geographic location of stations and timing of station placement allows me to classify each station with the respective attainment status of the environmental zone at the year when it was sited.

Table 1: Sittings and retirements of stations during the study period

Year	Sittings				Retirements
	Total	Clean	Marginal	Dirty	Total
2013	65	27	26	12	13
2014	63	13	27	23	38
2015	50	1	36	13	35
2016	47	2	36	9	64
2017	25	0	17	8	51
2018	14	0	7	7	63
Total	264	43	149	72	264

Furthermore, AQeR also provides helpful metadata on stations such as their monitoring objective: Traffic, Industrial and Background categories (330, 117 and 651 in my sample, respectively), signal the size of the region its measurements should be representative. Guidance documents of monitor placement and attainment to the EC directives state that while traffic stations should be representative of no more than 200m^2, urban background stations should represent several kilometres (EC, 2020).

To look at the levels of pollution around each individual station I use the satellite- and model-derived rasters of pollution estimates constructed by van Donkelaar et al. (2016). They consist of yearly estimates of PM2.5 mean concentration in a 0.01º x 0.01º definition (approx 1km^2 at the equator). Estimates go from 2001 to 2016 and cover almost all of the European geography. Given there is no availability of estimates for other pollutants at this definition I restrict my analysis to PM2.5. All other estimates of demographic and control values are spatially merged to this geographic definition.

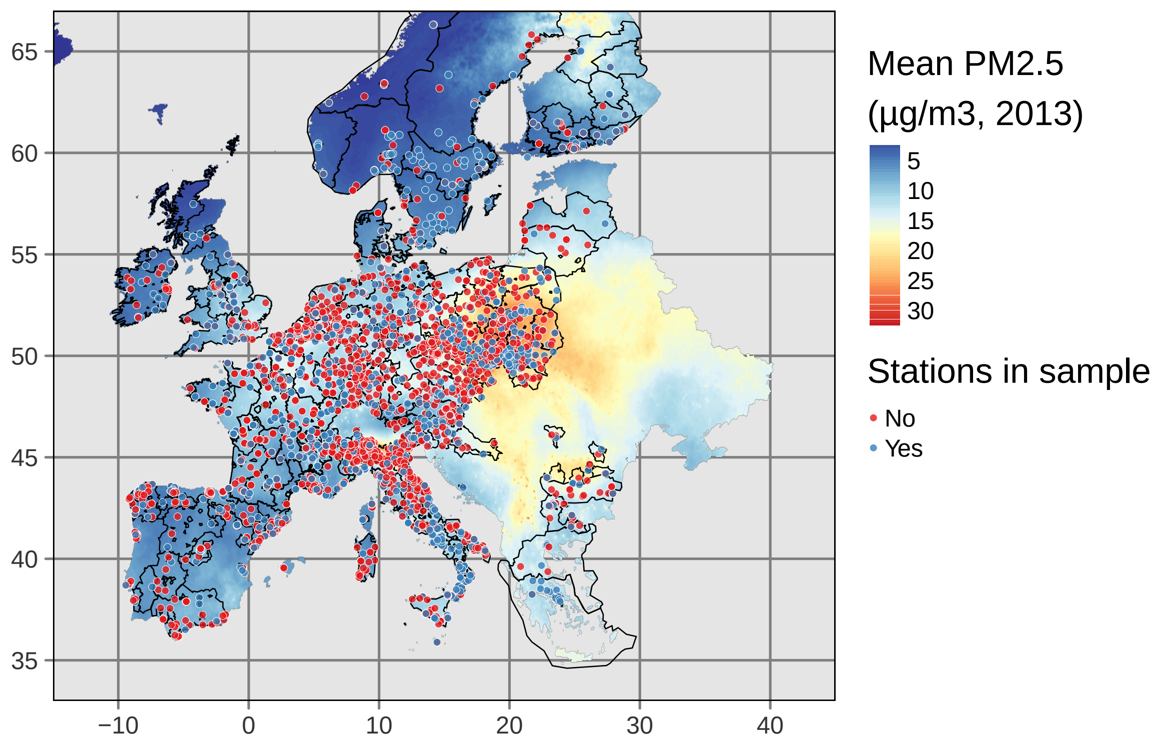


Figure 2: Summary of pollution raster, Environmental Zones that had at least one new station in the sample period (in black) and position of PM10 and PM2.5 stations. Stations in the sample are those inaugurated between 2013 and 2018.

I also incorporate data of multiple demographic and economic variables to act as controls given Grainger and Schreiber (2019) show their importance for station placement in the US. For the whole European geography, I include estimates of GDP from nightlight satellite images from Ghosh et al. (2010), population density estimates from CIESIN (2018), emissions of pollutants by industries from the EEA and land cover from the CORINE database (visual examples can be found in the Appendix Figures 10-12). To fully control for other demographic variables that could affect position, I restrict the sample to France in an alternative specification where I include 1km^2 data on the age distribution, detailed population density, and various wealth-related controls. All data sources and their use can be found in Table 2.

The final number of stations sited in the study period (2013-2018) was 264, well distributed over the 3 different attainment statuses. A detailed count of stations sittings and retirements can be found in Table 1. To have a better idea of the changes and spatial distribution of attainment status Figure 8 in the Appendix summarises all attainment status for each year in the study period and Table 5 gives the number of stations sited in each country per attainment status.

Table 2: Data Sources

Variable	Use	Source of data with links
Demographic and Economic Controls	**Controls for station sitting location**	
Population density		CIESIN (2018)
Night light as a proxy for Economic Activity		Ghosh et al. (2010)
Additional demographic controls for France		INSEE, Données carroyées à 1km (link)
Other controls	**Controls for station sitting location**	
Sources of industrial pollution		Detailed raster of industrial emissions of NOx, SOx and PM10 (5km x 5km) (link)
Land cover		CORINE data from Copernicus, 2012 (link)[1]
Data on stations	**Position, pollution and year of siting**	
Moment of siting and retirement of stations	Classification of attainment status	AQeR from the EEA (link)
Position of all station	Positioning of stations	AQeR from the EEA
Data on regulation	**To test for strategic placement**	
Assessment methods of monitored zones	Summary of methods	AQeR from the EEA
Compliance results for monitored zones	Classification of attainment status	AQeR from the EEA
Shapefiles of monitored zones	Classification of stations in zones	AQeR from the EEA
Satellite raster of pollution measurements		
PM2.5 mean concentration, yearly, 0.01º x 0.01º	To construct Z-scores around stations	van Donkelaar et al. (2016)

[1]CORINE resolution was reduced from 100m^2 to a 1 km^2 by taking the most common land cover (mode).

4 Research Design

In order to test the hypothesis that the behaviour documented for the US also applies in the EU, I will follow the methodology by Grainger et al. (2017): I look if new monitors, especially in zones that might break of EC limits, are placed in a raster grid with lower pollution with respect to their neighbourhood grids. For that, I create a circular neighbourhood around each station and include all raster grids that inside it as the range of possible positions the regulator could choose for the sited monitor.

Different than Grainger et al. (2017), I choose a circular neighbourhood around each station that varies with the station type because, as explained above, they must be representative of different pollution phenomena. Circular neighbourhoods with a radius of 5, 7 and 10 km are drawn around Traffic, Industrial and Background stations respectively[4,5], values are partially based on the indications drown by EC Guidance under the EU Air Quality Directives (EC, 2020). See Figure 3 for a visual example.

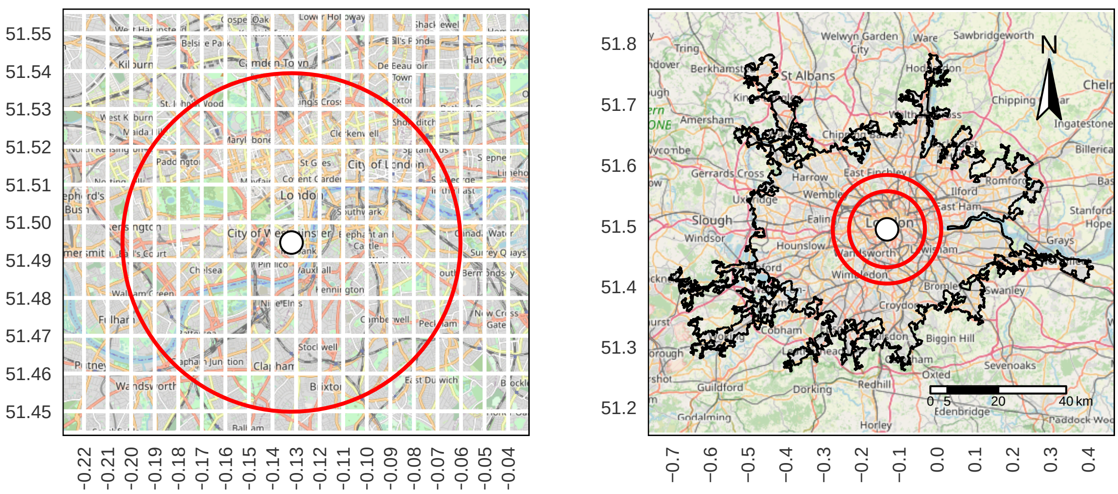


Figure 3: Example of pollution grid definition (0.01º×0.01º - in white), station placement and neighbourhood with a radius of 5 (left), 7 and 10km^2 with London's environmental zone (right). *Base maps from openstreetmap.org*

This allows to calculate the relative difference in pollution of the place where the station was placed and all other possible placement options in the surrounding area by the Z-score of the monitored grid. More specifically, $Zscore_{int} = (pollution_{int} - \overline{pollution_{nt}})/\sigma_{nt}$ with $Zscore_{int}$ being the Z-score of grid i in neighbourhood n at year t.[6]

[4] Analysis was also were also done with a 5km neighbourhood for all stations and results remained unchanged.
[5] The pollution raster data has empty values for large water bodies, avoiding bias around coastal areas.
[6] For years posterior to 2006, for which I do not have pollution estimates, I use the values from 2006. A robustness check with only sittings from 2003 to 2006 is available in the Appendix Table 8 and no significant differences. LISA could also be used to determine strategic placement (mark stations that have low pollution and a spatially lagged high pollution) but I found the Z-score to be more intuitive and simple.

Table 3: Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
Monitor	280,115	0.004	0.06	0	1
Z-score	280,115	0.00	1.00	−8.67	10.25
PM2.5 μg/m^3	280,115	12.80	22.00	0.00	343.24
GDP (Million US$/km^2)	280,115	13.44	6.15	1.60	35.40
Pop. density (persons/km^2)	276,931	805.46	1,919.69	0.00	46,723.82
Industry air pol. (T/25km^2)	280,115	35.06	59.35	0	255
Reporting Year	280,115	-	-	2013	2018
First year station	280,115	-	-	2013	2018
Last year station	74,625	-	-	2013	2021
Inaugurated after 2016	280,115	0.28	0.45	0	1

The summary statistics of temporal and continuous variables can be found in Table 3 with each observation being a 0.01 $\times$ 0.01 raster grid that is inside the neighbourhood of a sited station. Z-scores follow their normalised distribution with mean $= 0$ and standard error $= 1$. Stations that are sited during the study period but after 2016 (last year pollution raster data) represent 28% of the sample.

To formally test the strategic siting of stations, I formalise the decision of placement with a probability model in which the placement of a new monitor within its neighbourhood is a function of its relative pollution (Z-score) interacted with the current attainment status of the Environmental Zone where the station is positioned. The econometric specification is based on Grainger et al. (2017) but has some changes to improve model fit and interpretability such as including interactions of Z-score with pollution levels and with the mean pollution of the zone. The model can be described as:

$$
\begin{aligned}
Monitor_{inzt} = \alpha_0 &+ \alpha_1 Zscore_{inzt} + \alpha_2 Zscore^2_{inzt} \\
&+ \beta_1 Zscore_{inzt} \times Clean_{zt} + \beta_2 Zscore_{inzt} \times Marginal_{zt} \\
&+ \delta Clean_{zt} + \eta Marginal_{zt} \\
&+ \beta_3 Zscore_{inzt} \times PM2.5_{izt} + \beta_4 Zscore_{inzt} \times \overline{PM2.5_{zt}} \\
&+ \sum_j \theta_j X_{jinz} + \sum_q \gamma_q W_{qinz} + \sum_{n=1}^{264} \xi_n S_n + \varepsilon_{inzt} \qquad (1)
\end{aligned}
$$

With $Monitor_{inzt}$ being 1 if the monitor was positioned on that raster grid i, neighbourhood n and zone z at time t. $Zscore_{inzt}$ is the Z-score of grid i with respect to its neighbourhood and $Clean_{zt}$ and $Marginal_{zt}$ are dummies that represent the attainment status of the zone where the monitor is located at time t. $PM2.5_{inzt}$ and $\overline{PM2.5_{zt}}$ are the levels of PM2.5 of a given cell and their mean for a given zone.

β_1 and β_2 are the main coefficients of interest showing if there is any significant difference in how Z-score affects the probability of a monitor if the attainment status changes. β_3 controls for the effect of increases in Z-score that are due to greater levels in PM2.5 of that given cell and β_4 controls for the effects of increased PM2.5 in all the environmental zone, a proxy related with attainment that cleans β_1 and β_2 of the effect of general increases in pollution. X is a matrix of controls at the raster grid level such as predicted GDP, population density, amount of industrial emissions and CORINE land cover dummies. W is a set of interactions between PM2.5 levels and treatment status to control for strategic position over the general level of pollution and S is a matrix of station dummies to account for stations' fixed effects (ξ_n).

To the best of my knowledge, in the EU there is no explicit guidance to place stations to characterise vulnerable populations as in the US. The EC guidance is mostly based on having a "representative sample" of population exposure. To test if demographic variables might strongly affect the estimates (as they can be a criterion for station positioning) I do an alternative specification with detailed French demographic data including age, population density and income controls as there is no unique close-to-1km^2 grid definition demographic data for the whole of EU geography.

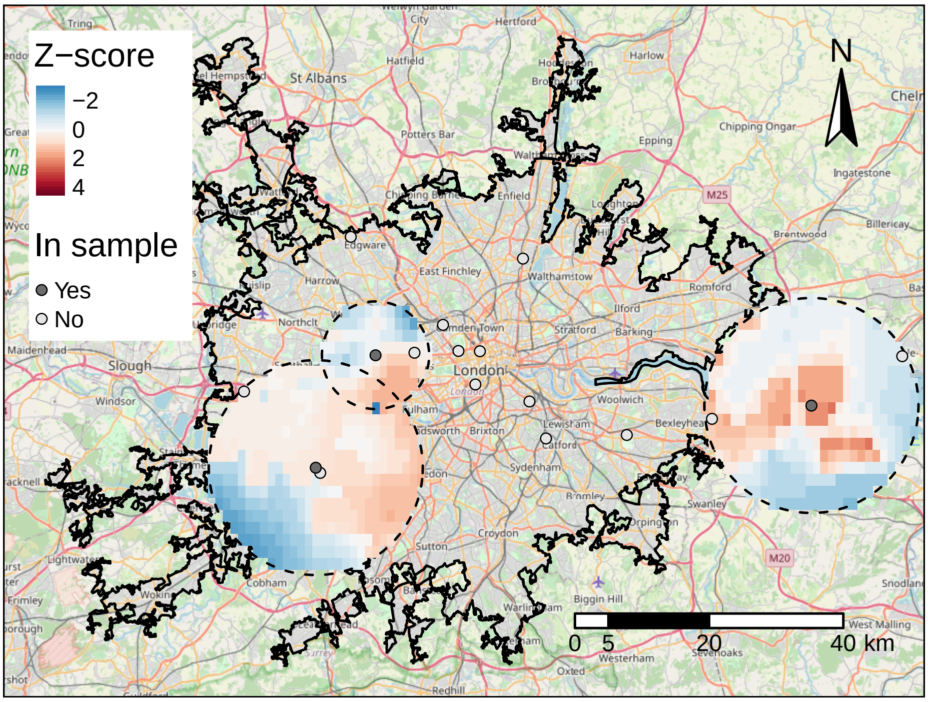


Figure 4: Example of localised Z-scores around new stations and London's environmental zone. Stations that don't have a buffer were placed outside of the study period.
Base map from openstreetmap.org

5 Results:

To analyse if there is any systematic difference between the placement of monitors by attainment status with a probability model, I first consider other descriptive evidence of strategic station positioning. For instance, looking at Figure 5 we can see that stations are positioned on a relatively more polluted location when the zone is classified as “Dirty” than when the attainment status is“Marginal” or “Clean”

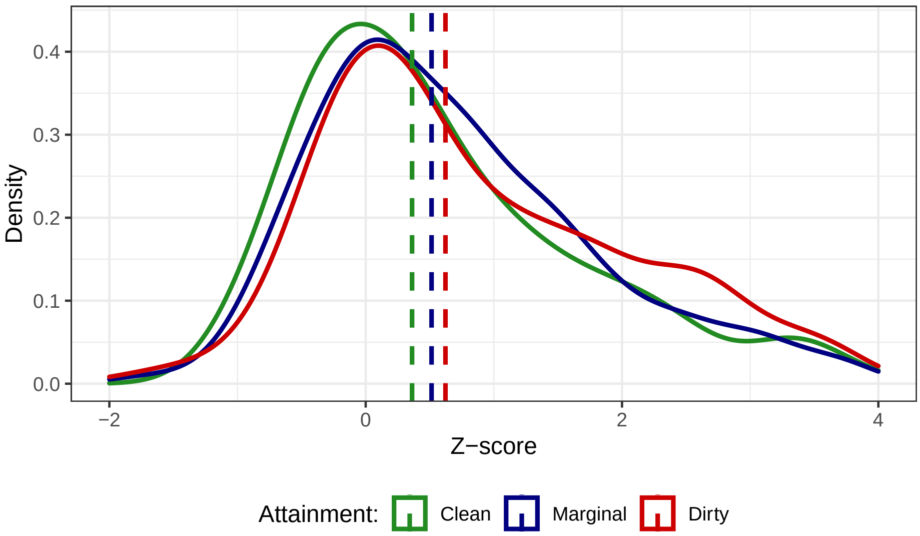


Figure 5: Distribution of Z-scores of new stations on the year they were sited by attainment status of that year. The vertical lines indicate the mean of each category.

But multiple confounding factors could create this distribution, for example, stations, especially in big cities that stay “Dirty” zones might be placed close to where more economic (and population) activity is present during the day. Or, possibly, stations sited to control for industrial emissions sources (a 10% of our sample), would need be in an intermediate distance of the polluting source to have representative measurements of population exposure, affecting their Z-score.

With this in mind, both linear and probit models were constructed with clustered standard errors at different levels and various controls. The variance of the coefficients stayed constant or even slightly declined with clustering in increasingly smaller groups (from the country to each individual station’s neighbourhood). This indicates that ϵ_{int}, as described before, is not spatially correlated or is even negatively correlated, creating confidence on the estimates and coinciding with what is expected as comparisons are already being made *within* each station neighbourhood due to the station fixed effects. The final results with standard errors clustered at the station level can be found in Table 4.

Table 4: Probit probability model

y: $Pr(Monitor = 1)$	Simple	+E. controls	+CORINE	Grainger et al. (2017)	Final
Z-score	0.280***	0.214***	0.174***	0.0970***	0.177***
	(0.0196)	(0.0199)	(0.0198)	(0.0273)	(0.0524)
Z-score^2	-0.00453	-0.000704	-0.00280		-0.0121*
	(0.00373)	(0.00392)	(0.00401)		(0.00636)
Clean	0.0491***	0.0878***	0.0890***	0.377	0.272
	(0.0157)	(0.0224)	(0.0233)	(0.638)	(0.641)
Marginal	0.0234	0.0494**	0.0501**	0.410	0.431
	(0.0157)	(0.0231)	(0.0237)	(0.613)	(0.638)
Clean×Z-score	-0.0881***	-0.122***	-0.119***	-0.107***	-0.137***
	(0.0270)	(0.0282)	(0.0279)	(0.0331)	(0.0385)
Marginal×Z-score	-0.0441**	-0.0717***	-0.0698***	-0.0510	-0.0775*
	(0.0220)	(0.0230)	(0.0231)	(0.0345)	(0.0411)
PM25				0.107***	0.0894**
				(0.0368)	(0.0425)
Clean×PM25				-0.0186	-0.0102
				(0.0422)	(0.0424)
Marginal×PM25				-0.0249	-0.0266
				(0.0460)	(0.0477)
PM25×Z-score					0.0113
					(0.00719)
Mean zone PM2.5×Z-score					-0.0145*
					(0.00742)
Constant	-2.851***	-2.871***	-2.099***	-3.600***	-3.343***
	(0.0134)	(0.0212)	(0.0819)	(0.526)	(0.601)
Pollution Station FE	✓	✓	✓	✓	✓
Controls (GDP, Pop. density, Emissions)		✓	✓	✓	✓
CORINE			✓	✓	✓
Observations (grids)	280115	276931	275398	275398	275398
BIC	13711.5	13196.6	13071.1	13075.5	13107.1
p-val of joint significance of β_1 and β_2	0.00470	0.00005	0.00007	0.00526	0.00175

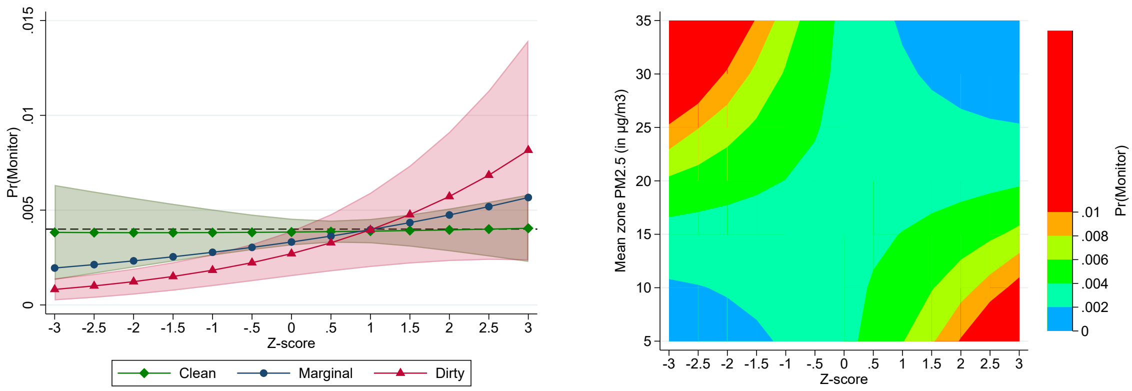
Standard errors in parentheses and clustered by pollution station.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

It is important to point out that the models do not exploit any source of random or quasi-random variation and, although they can be interpreted as very strong correlations, their interpretation as causal effects wold be based on the strong assumption of conditional independence. That is, conditional in all controls included and station fixed effects, the treatment assignment (the attainment status of its zone) was as randomly assigned.

To look if the variation of demographic characteristics within a given buffer zone was likely to be a confounding factor a robustness test was performed with French data. 1km^2 demographic variables regarding income, family composition and age distribution were included into the model and although some were strongly significant there was no significant change in the coefficients of interest (see Table 7 in the Appendix). Furthermore, as opposed to Grainger and Schreiber (2019), no evidence of discrimination based on wealth was found.

From an inspection of the results in Table 4, we can see that stations are usually placed in relatively polluted locations. Furthermore, estimates for the interactions of Clean and Marginal with Z-Score are negative and significant, showing that, *ceteris paribus*, the probability of sitting a monitor was reduced by its Z-score when the zone was either Clean or Marginal, with respect to the base category (Dirty). In general, all common and significant coefficients with Grainger et al. (2017) share the same sign as their results and very close in overall magnitude. To better interpret the magnitude of coefficients, Figure 6 shows the marginal effects and predicted probabilities for each attainment status relative to the Z-score.



(a) Probabilities with 95% C.I for "Clean" and "Dirty". The dashed line (0.004) is the sample proportion of grids with a monitor (the unconditional probability)

(b) Probabilities of sitting a monitor by Z-score and mean PM2.5. While low pollution zones choose high Z-scores, high pollution zones do the opposite.

Figure 6: Predicted probabilities of siting a station according to the Z-score, the attainment status and mean PM2.5 levels, inferred from "Final" model in Table 4.

As shown in Figure 6, everything else equal, while "Clean" stations don't seem to take into account the relative pollution into their positioning, "Marginal" and "Dirty" stations are sited in relatively polluted locations. We can see this is significant for various levels of Z-score. For example, we can see that grids with pollution 1 standard deviation below the mean (Z-score = -1) the probability of sitting a "Dirty" station is nearly half as much as a "Clean" station (49% less). Grainger and Schreiber (2019) find this reduction to be 42% for the US. Furthermore, I find a negative and significant coefficient for "Mean zone PM2.5$\times$Z-score", meaning that the probability of siting a station in a dirty location is reduced as a zone has more average pollution, effectively understating pollution levels.

My results make me differ from some of the conclusions from Grainger et al. (2017), who focus in comparing Marginal and Dirty locations but ignore the significance both they and I have regarding the siting of "Clean" stations[7]. Results for ozone in the US and PM2.5 in the EU would imply "Clean" zones would be even more strategic than "Marginal" zones, which does not coincide with their analytical model. As shown in Figure 6, the probability of siting a station in relatively polluted areas is monotonically increasing with the consequences of attainment status with "Clean" zones being where the regulators choose least polluted locations.[8] My hypothesis is that pollution stations are sited to minimise both regulatory pressure from the air quality regulations and public pressure from voters, choosing less polluted locations to avoid non-attendance (keep the "Clean" status) and to avoid public critique for not having clean air.

Finally, I investigated if this behaviour varies between countries by restricting the sample to countries that had stations sited in each of the 3 categories of attainment[9]. The results show significant variance between countries with some countries having significant negative coefficients (Italy) and others having non-significant results. As the results for all of the EU, all countries except Sweden have lower coefficients for "Clean" than "Marginal" interactions. Heterogeneity is sufficiently large to avoid claiming that the coefficients are representative for all EU countries given a strong effect in some countries such as Italy can be driving the overall results. Results from the overall regression should be interpreted more as a weighted average of various local effects than a uniform relation for all countries.

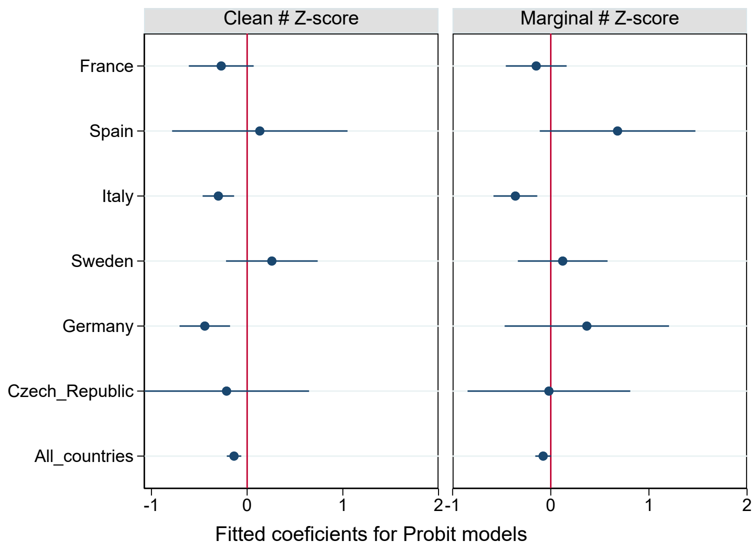


Figure 7: Coefficients of interest (β_1 and β_2) when modelling countries individually and all countries together, "Dirty" being the omitted category. Lines represent 95% confidence intervals from clustered SE at the station level.

[7] In their principal results regarding strategic positioning on ozone both the equivalents to β_1 and β_2 are significant and negative, with β_1 being significantly smaller than β_2.

[8] Closer to the more recent conclusions of Grainger and Schreiber (2019).

[9] The number of sited stations by country and attainment status can be found in Table 5, in the Appendix.

6 Conclusions

With present EU and US regulations in air quality, local bodies are both responsible to maintain pollution exposure below certain thresholds and to decide the positioning of air quality stations that measure pollution exposure. With data from the US Grainger et al. (2017) and Grainger and Schreiber (2019) investigate if stations from zones below the threshold are systematically positioned in less polluted locations and find significant results.

I use a similar methodology by creating round neighbourhoods around each station, calculating local z-scores of pollution and fitting a cross-sectional probability model of station sitting for the EU to test if attainment status changes the probability of sitting a monitor in polluted locations. My results for the EU coincide with those from Grainger and Schreiber (2019) in significance and magnitude and show that a given location 1 standard deviation below the mean of pollution (Z-score = -1) has half the probabilities of having a monitor if its zone is fully in attainment ("Clean") relative to being in non-attainment ("Dirty"). Their results for the US predict a 42% reduction in probability. Furthermore, I find that zones with higher average pollution systematically choose less polluted locations. Finally, I look at the spatial variability of this phenomenon for various countries and conclude it shows significant variability between countries.

These results imply that, to some extent, data based on EC-monitored stations (1) comes, generally, from high pollution places (2) is endogenous to the attainment status given levels of air pollution are relatively understated for zones in attainment and (3) is endogenous to the mean pollution level of the zone where they are positioned, with more polluted zones choosing relatively less polluted places for their monitors. These conclusions question both the quality of the data that comes out of EC monitored stations and the use of attainment status as a source of exogenous variation in pollution levels in the literature.

Although this work gives confident estimates of systematic differences in the sitting of air quality monitors by attainment status, it does not claim a causal relationship. To further investigate this issue, a sharp regression discontinuity design in which stations in zones just above and below the attainment threshold could prove useful. As there are multiple pollutants that can drive non-attainment, a method with a "double discontinuity" as the one used by Card et al. (2007) could be a good way forward.

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Appendices

Table 5: Number of stations sited for each country and attainment status

	Clean	Marginal	Dirty
Austria	0	56	2
Belgium	0	18	0
Bulgaria	0	1	5
Croatia	1	1	2
Czechia	10	3	31
Denmark	2	1	0
Finland	5	22	0
France	22	139	21
Germany	1	119	7
Greece	10	1	9
Ireland	12	0	0
Italy	134	45	20
Latvia	0	1	0
Lithuania	0	1	0
Luxembourg	1	2	0
Malta	1	0	0
Netherlands	9	0	1
Norway	0	24	1
Poland	0	3	137
Portugal	4	2	0
Romania	6	1	1
Slovakia	0	3	3
Slovenia	0	1	4
Spain	3	72	4
Sweden	11	25	32
United Kingdom	4	41	0

The attainment status of a station corresponds with the attainment status of its zone at the year when it was sited.

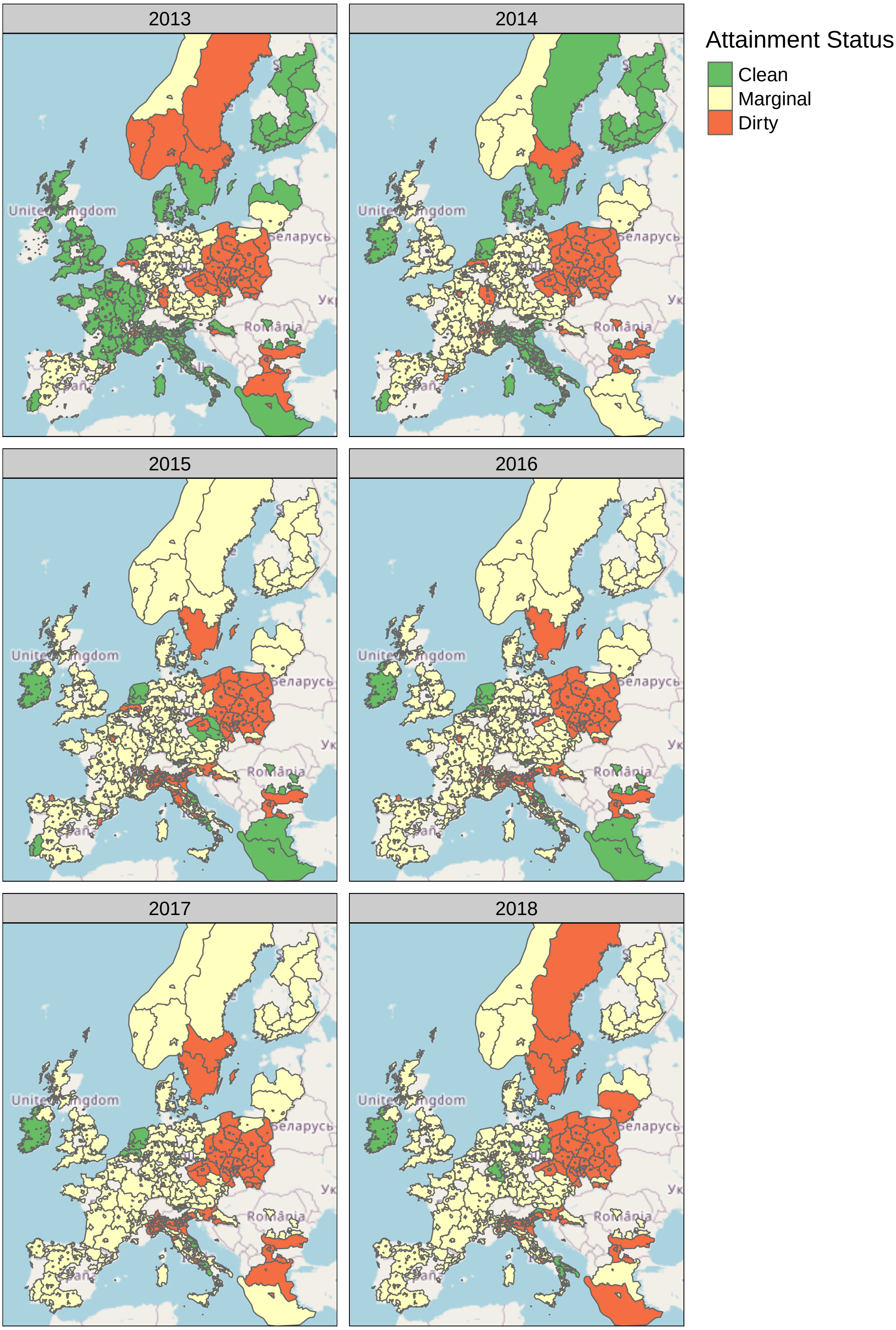

Figure 8: Attainment status for PM2.5 and PM10 for the study period and all Environmental Zones studied (those that had at least one station positioned in 2013-2018).
Base map from openstreetmap.org

Table 6: Linear probability model

y: $Pr(Monitor = 1)$	Simple	+E. controls	+CORINE	Grainger et al. (2017)	Final
Z-score	0.00276***	0.00189***	0.00151***	0.00153***	0.00278***
	(0.000231)	(0.000233)	(0.000225)	(0.000328)	(0.000728)
Z-score^2	0.000768***	0.000781***	0.000708***		0.000359***
	(0.000117)	(0.000119)	(0.000116)		(0.000130)
Clean	1.49e-16	0.0000111	0.0000107	-0.00245	-0.00434
	(.)	(0.0000120)	(0.0000116)	(0.00765)	(0.00690)
Marginal	4.58e-16	0.0000198	0.0000180	-0.00114	-0.000806
	(.)	(0.0000162)	(0.0000153)	(0.00609)	(0.00556)
Clean×Z-score	-0.000713*	-0.00111***	-0.00108***	-0.00111**	-0.00182***
	(0.000403)	(0.000400)	(0.000387)	(0.000431)	(0.000526)
Marginal×Z-score	-0.0000705	-0.000593*	-0.000649**	-0.000542	-0.00127**
	(0.000325)	(0.000336)	(0.000327)	(0.000438)	(0.000534)
PM25				0.000659*	0.0000625
				(0.000361)	(0.000331)
Clean×PM25				0.000178	0.000315
				(0.000553)	(0.000499)
Marginal×PM25				0.0000660	0.0000119
				(0.000480)	(0.000436)
PM25×Z-score					0.000516***
					(0.000100)
Mean zone PM2.5×Z-score					-0.000586***
					(0.000105)
Pollution Station FE	✓	✓	✓	✓	✓
Controls (GDP, Pop. density, Emissions)		✓	✓	✓	✓
CORINE			✓	✓	✓
Observations (grids)	280115	276931	276731	276731	276731
BIC	-753490.6	-742507.7	-741996.9	-741882.0	-741995.7
p-val of joint significance of β_1 and β_2	0.168	0.0182	0.0151	0.0378	0.00261

Standard errors in parentheses
Standard Errors are clustered by pollution station.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Models with French demographic data

y: $Pr(Monitor = 1)$	Final Model		+French Controls	
Z-score	0.444	(0.278)	0.474*	(0.271)
Z-score^2	-0.0162	(0.0237)	-0.0127	(0.0229)
Clean	0.981	(2.787)	1.914	(2.824)
Marginal	2.919	(2.063)	2.662	(2.203)
Clean×Z-score	-0.237	(0.227)	-0.278	(0.219)
Marginal×Z-score	-0.0880	(0.216)	-0.137	(0.205)
PM25	0.165	(0.180)	0.109	(0.189)
Clean×PM25	-0.0796	(0.217)	-0.126	(0.221)
Marginal×PM25	-0.205	(0.182)	-0.210	(0.191)
PM25×Z-score	0.0175	(0.0260)	0.0156	(0.0258)
Mean zone PM2.5×Z-score	-0.0323	(0.0285)	-0.0288	(0.0283)
Mean Age			-0.0267	(0.0171)
Persons/km^2			0.000135***	(0.0000239)
Prop. of poor h.			-0.402	(0.752)
Prop. of owners			-0.774***	(0.221)
Prop. uniparental h.			-3.165	(3.038)
Wealth proxy			-0.0000174	(0.0000182)
Prop. of persons >80y			7.964***	(1.960)
Prop. of persons <5y			-1.106	(2.125)
Constant	-4.021*	(2.081)	-1.804	(2.375)
Pollution Station FE	✓		✓	
Controls (GDP, Pop. density, Emissions)	✓		✓	
CORINE	✓		✓	
Observations (grids)	14558		13712	
BIC	1990.8		1933.7	
p-val of joint significance of β_1 and β_2	0.319		0.334	

Standard errors in parentheses

Probit models with the dependent variable being 'Monitor'

Standard Errors are clustered by pollution station.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

From the comparison of both models we can conclude that the inclusion of new variables does not seem affect the estimates of the interactions, only their standard errors.

Table 8: Probit results of final model compared with a restricted sample

y: $Pr(Monitor = 1)$	Final Model	Only 2013-2016
Z-score	0.177***	0.202***
	(0.0524)	(0.0632)
Z-score^2	-0.0121*	-0.0159**
	(0.00636)	(0.00772)
Clean	0.272	0.190
	(0.641)	(0.637)
Marginal	0.431	0.175
	(0.638)	(0.740)
Clean×Z-score	-0.137***	-0.152***
	(0.0385)	(0.0431)
Marginal×Z-score	-0.0775*	-0.101**
	(0.0411)	(0.0502)
PM25	0.0894**	0.0715
	(0.0425)	(0.0465)
Clean×PM25	-0.0102	-0.00457
	(0.0424)	(0.0419)
Marginal×PM25	-0.0266	-0.00648
	(0.0477)	(0.0574)
PM25×Z-score	0.0113	0.0123
	(0.00719)	(0.00826)
Mean zone PM2.5×Z-score	-0.0145*	-0.0148*
	(0.00742)	(0.00858)
Constant	-3.343***	-3.095***
	(0.601)	(0.651)
Pollution Station FE	✓	✓
Controls (GDP, Pop. density, Emissions)	✓	✓
CORINE	✓	✓
Observations (grids)	275398	198248
BIC	13107.1	9662.7
p-val of joint significance of β_1 and β_2	0.00175	0.00202

Standard errors in parentheses

Standard Errors are clustered by pollution station.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

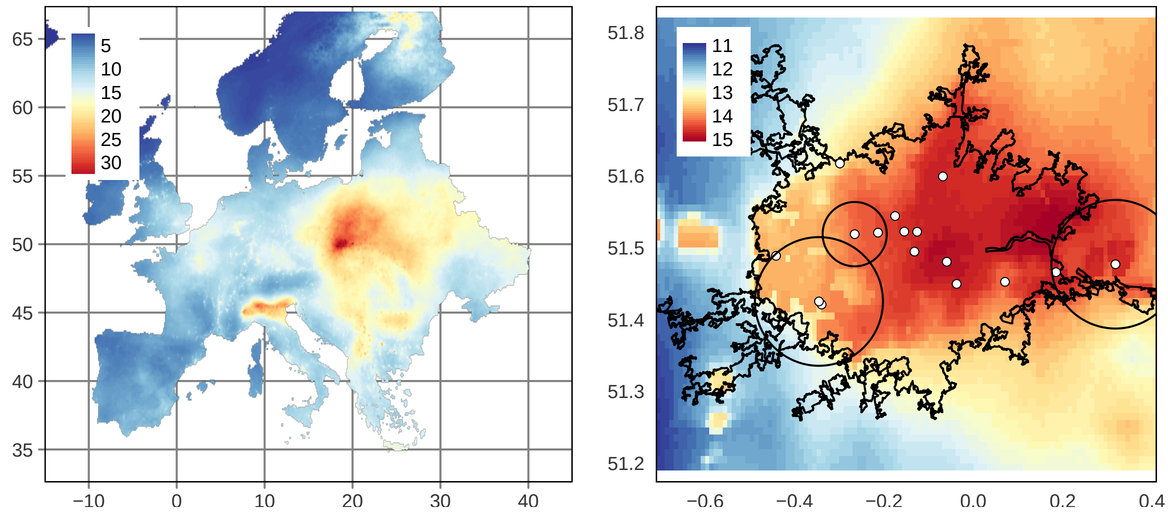

Figure 9: Illustration of pollution raster for 2013 (left) and an example for London with pollution stations and their neighbourhoods (right). Values in μg/m^3.

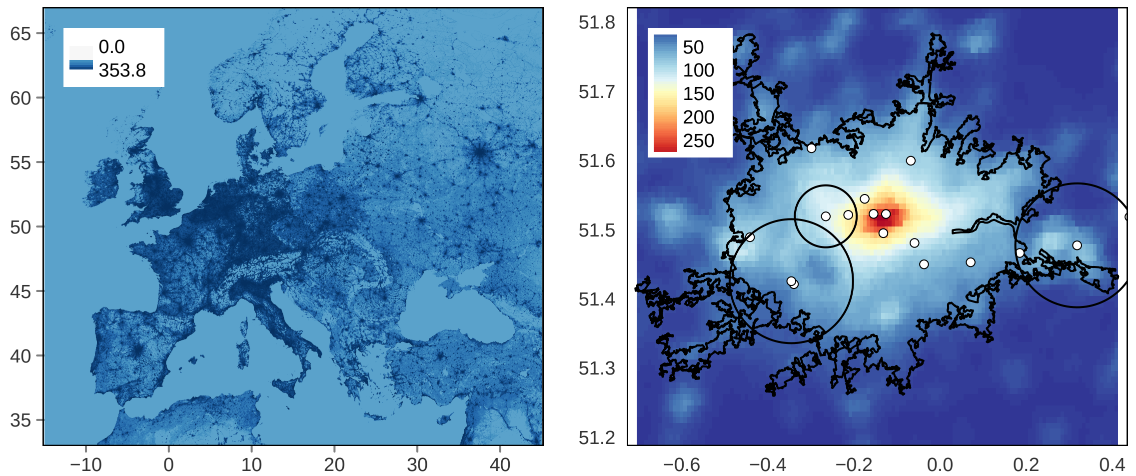

Figure 10: Illustration of GDP raster (Million US$ per km^2) (left) and an example for London with pollution stations and their neighbourhoods (right).

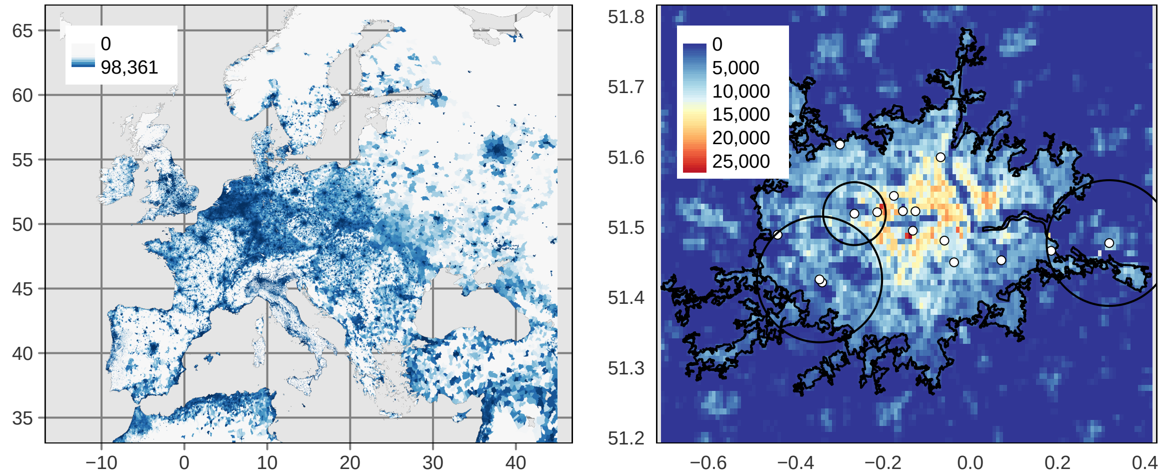

Figure 11: Illustration of population density raster (persons/km^2) (left) and an example for London with pollution stations and their neighbourhoods (right).

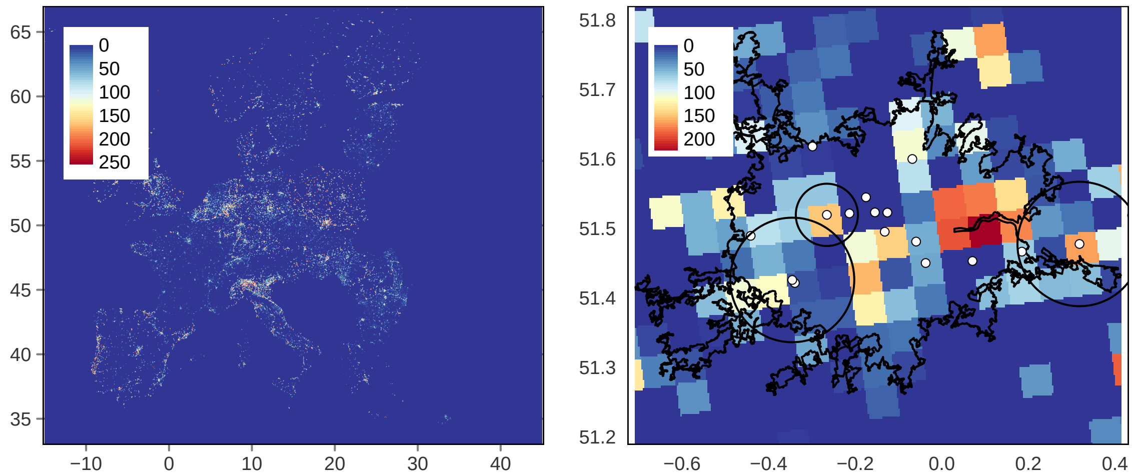

Figure 12: Illustration of industrial pollution raster (added tones of NO_x, SO_x and PM10 per 5km^2, yearly) (left) and an example for London with pollution stations and their neighbourhoods (right).

End