# Cleaner Air for Whom?

# Air Quality Policy and Persistent Exposure Disparities

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This version: 15$^{\text{th}}$ June, 2026

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**Abstract**

Focusing on France, this paper quantifies disparities in exposure to fine particulate matter ($PM_{2.5}$) and the role of a recent policy, covering half the population, in their evolution. Within cities, poorer and immigrant-dense neighbourhoods are substantially overexposed to $PM_{2.5}$. These disparities persist between 2006 and 2018 despite a 25% decline in average pollution, in contrast with the United States, where income and racial exposure gaps have narrowed. To evaluate the role of public policies in this stagnation, I exploit the staggered adoption of new city-level air quality plans in a difference-in-differences framework. The plans account for roughly 30% of the observed decline in $PM_{2.5}$, but their effects are concentrated in initially more polluted areas, with differential improvements too small to narrow exposure gaps. Measures targeting the industrial and residential sectors yield the largest reductions in immigrant-dense neighbourhoods, but the most effective measures, which target agriculture, benefit rural areas with the fewest immigrants, so the two effects broadly offset. Additional funding from the national government substantially enhances PPA effectiveness, highlighting the importance of its support in the context of a decentralised policy.

**JEL Codes**: I14, Q53, Q56, R23

**Keywords**: public policy, air pollution, cities, inequality, sectoral emissions

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An early version of this paper has previously circulated under the title "*Inequality in Exposure to Air Pollution in France: Measurement and Impact of a City-Level Public Policy*". This work has been partly funded by French government subsidies managed by the Agence Nationale de la Recherche under the framework of the "Investissements d'avenir" programme reference ANR-17-EURE-001.

The author thanks Lucas Chancel, Olivier Chanel, Gabrielle Fack, François Fontaine, Camille Hémet, Hélène Ollivier, Sefi Roth, Gregor Singer and Louis Sirugue for useful discussions. She also thanks seminar and workshop participants at PSE, Université de Reims Champagne-Ardenne and University of Exeter, and conference attendees in Grenoble (FAERE) and Évry (TEPP), for their comments and suggestions.

# 1 Introduction

Unequal access to clean air may reinforce preexisting health inequalities, both across space and across income groups, and, increasingly, in immigrant-dense neighbourhoods, with consequences that run beyond health to labour market outcomes.[1] In parallel, over the last two decades, most developed countries have experienced substantial improvements in air quality, driven both by technological change and by policies targeting local emissions. It is therefore crucial to evaluate the distributional effects of these policies, as falling average pollution may mask persistent or changing disparities in access to clean air. Yet little is known about how these gains were distributed, or why, including in Europe. In the United States, different waves of the Clean Air Act (CAA) were shown to reduce both *average* exposure and *disparities* across income and racial groups (Bento et al., 2015; Currie and Walker, 2019; Currie et al., 2023; Sager and Singer, 2025). This paper shows that France's flagship air quality policy, which covers half of the country's population, achieved the former objective, but not the latter. Because this policy is decentralised and can target any emitting sector, this paper goes beyond estimating average effects to identify which of the specific local sectoral measures drove the reduction, and why the ones that proved effective did very little to close the gaps.

This paper makes two main contributions: it documents the disparities in exposure to local air pollution and their persistence, and it explains why they persisted by exploiting specificities of the policy aimed at reducing that exposure. First, it provides the first nationwide evidence of both cross-sectional and longitudinal inequality in exposure to fine particulate matter in France, documenting income- and immigration-based disparities that remained stable despite a 25% decline in average pollution. Second, it explains this stagnation by evaluating the central local instrument of French air-quality regulation, called PPA, using a staggered-adoption difference-in-differences design.[2] Because the plans are decentralised, meaning that cities choose which sectors to target and which measures to implement, this paper can go beyond treating the policy as a black box. Local variation in measures taken and sectors targeted allows me to identify which of these contribute to the reduction in local pollution, and to what extent. This distinguishes the analysis from existing work, which either evaluates broad national regulations across many areas without decomposing the mechanisms (the U.S. CAA being the leading example, as in Currie et al., 2023; Sager and Singer, 2025), or studies very specific local measures whose spatial and sectoral scope limits generalisability (e.g., low-emission zones and congestion charges in individual cities, as in Wolff, 2014; Pestel and Wozny, 2021; Green et al., 2020; Herzog, 2024). Such city-level air quality policies exist in all large

[1] The literature on the causal effects of local air pollution on health has brought to light substantial short-term, acute effects (Chay and Greenstone, 2003; Currie et al., 2009; Currie and Walker, 2011; Mink, 2025), but also, more recently, long-run or chronic effects (Anderson, 2020; Bishop et al., 2023; von Hinke and Sørensen, 2023). Another strand of the literature examines its effects on labour market outcomes such as labour supply (Hanna and Oliva, 2015; Aragón et al., 2017; Hoffmann and Rud, 2024), but also productivity (e.g., Chang et al., 2016, 2019; Adhvaryu et al., 2022; Krebs and Luechinger, 2024; Champalaune and Cosentino, 2026) and (wage) earnings (Isen et al., 2017; Champalaune, 2025), all of which can further reinforce existing (labour) income inequalities.

[2] PPA stands for *Plans de Protection de l'Atmosphère*, or *Atmosphere Protection Plans.*

EU countries, making the French case informative beyond its borders.

The PPA policy's decentralised nature is, in geographic terms, also a feature of the U.S. CAA, whose obligations bind at the level of local "non-attainment" areas (Cropper et al., 2025). Yet, air pollution is local in its incidence but not obviously local in its solvability: local authorities differ in capacity and funding, and pollution travels across administrative boundaries. This connects the analysis to a broader literature in the economics of decentralisation, which in the case of environmental outcomes has primarily studied local water pollution management (Sigman, 2014; Lipscomb and Mobarak, 2017). It was also shown that decentralisation may not allow for proper targeting in the case of school decentralisation (Galiani et al., 2008) or in the case of EU transfers to regions, which prove effective in increasing GDP per capita only when local staff are equipped to handle them (Becker et al., 2013). My findings particularly echo this latter paper, as I provide empirical evidence that while decentralisation may allow for more targeted interventions, in particular at the local sectoral level, the central government is still instrumental, since the effects are confined to cities that benefit from its financial and logistical support.

The results show that these plans are responsible for a 1 to 1.5 $\mu g/m^3$ decrease in local fine particulate matter ($PM_{2.5}$) concentration, which represents about a third of the observed total decrease during the study period. This finding is robust to the inclusion of flexible spatial controls. As in the U.S. CAA (Sager and Singer, 2025), larger improvements accrued to initially more polluted neighbourhoods, likely due to decreasing marginal benefits from abatement; but unlike in the United States, this did not translate into larger gains for lower-income or higher-immigrant-share neighbourhoods. Relatedly, the effects only pertain to larger cities ($>$ 250,000 inhabitants), as smaller ones saw little to no decrease following PPA adoption. This contrast points to the role of local capacity. To further substantiate this point, I study a subset of cities that were eligible for a specific state "Breathable city" program, designed to assist them in the design and implementation of air quality measures. I find significant effects are confined to cities that benefitted from this additional help from the state. It thus appears crucial for decentralised policies to come hand in hand with financial and practical support to local governments.

Delving into the content of new air quality plans lets me exploit cross-city variation in the sectors targeted to identify which types of measures drove the observed reductions. I evaluate the relative effectiveness of interventions targeting the transport, manufacturing, residential heating and agricultural sectors, which taken together explain about 75% of the total effect. Lowering speed limits on major road segments has no effect, in line with previous findings (Folgerø et al., 2020; Le Frioux et al., 2024). By contrast, strengthening inspections of polluting manufacturing plants has a significantly positive effect on air quality, while banning open fireplaces and/or promoting housing retrofit subsidies has a smaller but significant impact. Finally, banning agricultural substance spraying on windy days or during pollution peaks proves particularly effective, as it limits the formation of precursors of fine particulates.

Previous research on environmental inequality is also largely US-focused. This literature grew out of early evidence of racial disparities in exposure to toxic waste (Chavis and Lee, 1987) and reports unambiguous income and ethnic gaps in exposure to environmental hazards, including industrial risks (see, e.g., reviews by Mohai et al., 2009; Banzhaf et al., 2019). By comparison, much less is known for Europe, including for France (Fairburn et al., 2019). The French evidence comes mostly from the public health literature and is mixed: while disadvantaged neighbourhoods appear relatively more exposed to air pollution in some cities (Padilla et al., 2014; Bertin et al., 2015), the relationship appears to be U-shaped in others (like Lyon and Grenoble in Padilla et al., 2014; Morelli et al., 2016). But these studies are typically confined to individual cities, and only two have provided inceptive evidence of nationwide disparities in exposure to ambient air pollution (Lavaine, 2015; Ouidir et al., 2017). I thus contribute to this scant though growing literature by exploiting high-resolution satellite-based data, coupled with information on local socioeconomic characteristics at the finest available definition of neighbourhoods in France (called IRIS). This provides the first national-scale evidence on inequality in exposure to fine particulate matter specifically, a pollutant whose associated health burden in mainland France was recently estimated at 48,000 annual early deaths, equivalent to a two-year reduction in life expectancy at 30 on average (Medina et al., 2025). I document that, between cities, average fine particulate concentration displays a U-shaped relationship with income, whereas within cities, neighbourhood-level concentration generally declines with income, with a gradient that appears stronger in the average French city than in London or in the United States (Colmer et al., 2020; Metcalfe and Roth, 2025). To my knowledge, this study is also the first to uncover that neighbourhoods with a high share of immigrants (15% for the top decile) experience statistically significantly and substantially higher fine particulate concentrations than other neighbourhoods in France. Given that about 60% of immigrants were born in African or Asian countries, this pattern hints at the existence of an ethnic gap in exposure to local air pollution akin to that observed in the United States (Zwickl et al., 2014; Currie et al., 2023).

Despite an overall improvement in air quality over the 2006–2018 study period, I find no narrowing of disparities across the neighbourhood-level distributions of income or immigrant share, unlike what is observed in the United States (Currie et al., 2023): initially more polluted neighbourhoods gained the most, but the differential improvement for disadvantaged neighbourhoods was far too small to close the gaps. Disaggregating the effects of the PPA policy down to initial income and immigrant-share ranks enables me to examine the distributional effects of each of the measures taken, by sector. This exercise shows that on the one hand, actions on the residential and manufacturing sectors are somewhat progressive, partly due to the high initial exposure of lower-income and immigrant neighbourhoods to high-emission plants. Because immigrant-dense neighbourhoods are also much less rural on average, the strong effectiveness of interventions on the agricultural sector fully counteracts the progressive effect by immigrant-share rank. These findings thus explain why initial exposure disparities did not close after PPA implementation. They also suggest that targeting residential heating and industry serves both goals at once, by lowering average exposure and narrowing the income and immigrant-share gap. More generally, because polluting sectors are not all located where exposed populations live, this indicates that the distributional effects of air quality policies depend on which sectors, hence which places, local governments choose to target.

The remainder of this paper is organised as follows. Section 2 presents the data on neighbourhood characteristics, fine particulate matter concentration and additional controls. Section 3 describes the cross-sectional patterns of inequality in $PM_{2.5}$ between neighbourhoods in France and their evolution, first using graphical evidence. I then turn to a formal analysis and study the sensitivity of these relationships to controlling for spatial autocorrelation and proxies for the source of $PM_{2.5}$. Section 4 describes the French regulatory context with respect to air quality, while Section 5 presents the identification strategy used to study the impact of the adoption of new air quality plans. Section 6 presents the main results, including the distribution of the effects by income and immigrant share. Section 7 turns to the mechanisms that explain why air quality improved on average, but did not affect disparities in access to clean air, by exploring the role of specific policy actions tied to city capacity and sectoral composition. Section 8 concludes.

# 2 Data sources

## 2.1 Income and neighbourhood characteristics

***Unit of observation*** I make use of IRIS-level data made available by INSEE, the French Bureau of Statistics. IRIS are the equivalent of US census blocks: they are aggregation of housing units delineated by INSEE so as to prepare for the dissemination of census data. They were built using criteria based on both administrative boundaries and demographic characteristics, so as to constitute a homogeneous fraction of a municipality in terms of housing and land use. To this day, all municipalities of more than 10,000 inhabitants, and the majority of municipalities with 5,000 to 10,000 inhabitants are divided into IRIS. By extension, and so as to cover the entire French territory, each municipality that does contain IRIS is an IRIS itself: these are "municipality IRIS".

Appendix Figure B.1 gives a sense of the spatial extent of this neighbourhood definition by showing a map of the Lyon region. As visible on the map, INSEE divides IRIS neighbourhoods into 4 categories: residential (in purple), commercial (in orange), municipality (in beige) and miscellaneous IRIS (in orange).[3] In 2018 at the country scale, there are on average 1,387 inhabitants per unit of observation. During the study period, IRIS and municipalities underwent several changes, especially due to the fact that municipality mergers were common from 2015 on. I provide details on the methodology used to obtain a spatially consistent set of IRIS in Appendix A.1.

[3] By definition, residential IRIS are home to between 1,800 and 5,000 inhabitants and make up 92% of the total 12,802 neighbourhoods. Commercial/industrial IRIS cluster at least 1,000 workers, and no less than twice as many workers as inhabitants. Finally, miscellaneous units are large and specific areas that are sparsely populated, such as parks, forests or harbours, and represent 3% of IRIS.

***Sample selection*** I restrict my sample to residential and municipality IRIS, and drop all units for which I don't observe income in both 2006 and 2018. These are very minor restrictions, and out of the 46,752 initial number of observations, I end up with a sample of 39,925 IRIS. All the IRIS I drop are municipalities with less than 5,000 inhabitants, and on average 114 inhabitants. As Appendix Table A.1 shows, 45% of sampled IRIS are urban, and 55% are rural. Table C.2 in Appendix gives the full descriptive statistics at the IRIS level. For now, we note that the average population in the sample is 1,555 inhabitants, 2,577 when excluding IRIS that are municipalities. The average surface area in the selected sample is 12.43 km$^2$, and 1.76 km$^2$ again excluding municipality IRIS.[4]

***Neighbourhood income and share of immigrants*** Table C.2 provides additional summary statistics. The median of census block median incomes amounts to €20,326[5], which is close to the French median household income during the study period (€19,270 in 2010). However, due to the difference in observation level, the first decile of income is for instance equal to €15,889 on average in my data, compared to €11,040 at the individual level (Argouarc'h and Picard, 2018). The neighbourhood average share of immigrants is 7.5%, but the third quartile is twice as large, and it can go up to almost 80%.

***Other variables of interest*** In addition to income and share of immigrants, the main variables of interest, I select other neighbourhood characteristics found by Pornet et al. (2012) to best mirror individual deprivation in France, as well as measures of the age structure of the neighbourhood, as infants and the elderly are particularly vulnerable to local air pollution (Currie et al., 2009; Deryugina et al., 2019). The full list is described in Appendix Table C.1. Summary statistics of all neighbourhood characteristics are available in Table C.2.

## 2.2 Fine particulate matter concentration

I use $PM_{2.5}$ concentration data from the Atmospheric Composition Analysis Group (ACAG), described in Hammer et al. (2020). ACAG exploits both remote-sensing sources and ground-level monitor data gathered by the European Environment Agency (EEA) in order to deduce the spatial distribution of $PM_{2.5}$ at the global scale. They use satellite-based information on aerosol optical depth (AOD), which measures the extent to which the solar beam is absorbed by suspended particles, as an input into a chemical transport model, GEOS-Chem, to estimate ground-level concentration in $PM_{2.5}$.[6] I observe $PM_{2.5}$ concentration for years 2006 to 2018. The yearly files are made available to the public in raster format in grids of $.01° \times .01°$, i.e., approximately 1.1 km $\times$

[4]Putting restricted-access databases with exact geographic coordinates aside, this is the finest spatial unit of observation available in the French context.

[5]All monetary values are given in 2019 constant euros.

[6]I use the GWR_V4.GL.03 version of the data, described in Hammer et al. (2020). Further information relative to the data is also available on the ACAG website, and information on the GEOS-Chem transport model can be found here: `http://acmg.seas.harvard.edu/geos/`.

1.1 km at the equator. This means that each pixel located in Paris has a west-east side of around 650 m, and a north-south side of around 1.1 km. I infer $PM_{2.5}$ concentration at the IRIS level by computing the weighted average of the level of $PM_{2.5}$ associated with each raster grid that (at least partly) overlaps with each IRIS. I verify that the measure aligns with alternative sources, including monitor data, in Appendix A.2.

Average concentration of fine particulate matter is equal to 10.27 $\mu g/m^3$ in 2018 (12.99 over the whole study period), which complies with the European limit value of 25 $\mu g/m^3$ and almost complies with the 2021 World Health Organisation (WHO) guideline of 10 $\mu g/m^3$, on average. Across neighbourhoods, the distribution of $PM_{2.5}$ concentration ranges from 6.61 to 16.40 $\mu g/m^3$. On the other hand, average concentration weighted by local population, is 13.54 $\mu g/m^3$ in 2018.

### 2.3 Weather data

Weather conditions affect $PM_{2.5}$ levels (see, e.g., Renard and Marchand, 2021, for the case of Paris) as well as individual location choices (Glaeser and Gyourko, 2005; Albouy et al., 2016). Higher temperature favours the photochemical reaction of precursor gases, which creates secondary fine particles. In contrast, rain pushes particles down to the ground, which lowers their atmospheric concentration, and wind disperses them away. I thus extract average wind speed and total precipitation from the Copernicus ERA5 product.[7] There is also seasonal variation in the impact of temperature on air pollutant concentration (Petit et al., 2015). The temperature effect is itself seasonal (Petit et al., 2015): the photochemical channel raises pollution on hot summer days, whereas in winter higher concentrations reflect heating use on colder days. I thus control for summer and winter mean temperature separately.

### 2.4 Sources of $PM_{2.5}$

***Presence of high-emission facilities*** As part of regulation policies on industrial risk, the Ministry for the Environment keeps a register of all high-emission factory plants. The resulting Pollutant Release and Transfer Register (PRTR, or IREP in French), provides a nationwide inventory of production sites that release chemical substances and/or potentially hazardous pollutants released into the air, water and soil.[8] It contains information on the precise geographic location of these plants, which I use to count the number of registered plants that are located within 5 km of the centroid of each IRIS neighbourhood. I use 2006 data, such that this measure provides a proxy for emissions from the manufacturing sector in the vicinity of neighbourhoods prior to treatment.

***Distance to major roads*** I also derive a proxy for air pollution stemming from nearby road traffic by computing the distance of each IRIS centroid to the nearest major road. To this end, I use

[7]The raw datasets were downloaded from the Copernicus Climate Change Service (C3S) Climate Data Store (CDS) (Hersbach et al., 2018). Access here: `10.24381/cds.adbb2d47`

[8]The raw data are available here: `https://www.georisques.gouv.fr/IREP`.

data from BD-TOPO, a product disseminated by IGN, the National Institute of Geographic and Forest Information. I define as "major roads" all roads that are classified as first-order, structural elements of the road network. This measure is meant to capture proximity to busy motorways and ring roads as a source of local pollution. They are of particular interest, as certain PPA zones target them to reduce local air pollution using speed-limit reductions.

# 3 Descriptive evidence

The relationship between $PM_{2.5}$ exposure and neighbourhood income or immigrant share depends critically on the scale of aggregation. Figures 1 and 2 display the gradient in $PM_{2.5}$ by income and immigrant share at three scales: across cities, across neighbourhoods nationally, and within cities. Three patterns emerge. At the national scale, both gradients are non-monotonic: U-shaped for income, essentially flat for immigrant share until a sharp rise at the top of the distribution. Within cities, the income gradient becomes monotonically negative and steep, and the immigrant-share gradient strongly positive. Both gradients have remained remarkably stable over the study period despite a substantial decline in average pollution levels. All values are centred around their yearly mean.

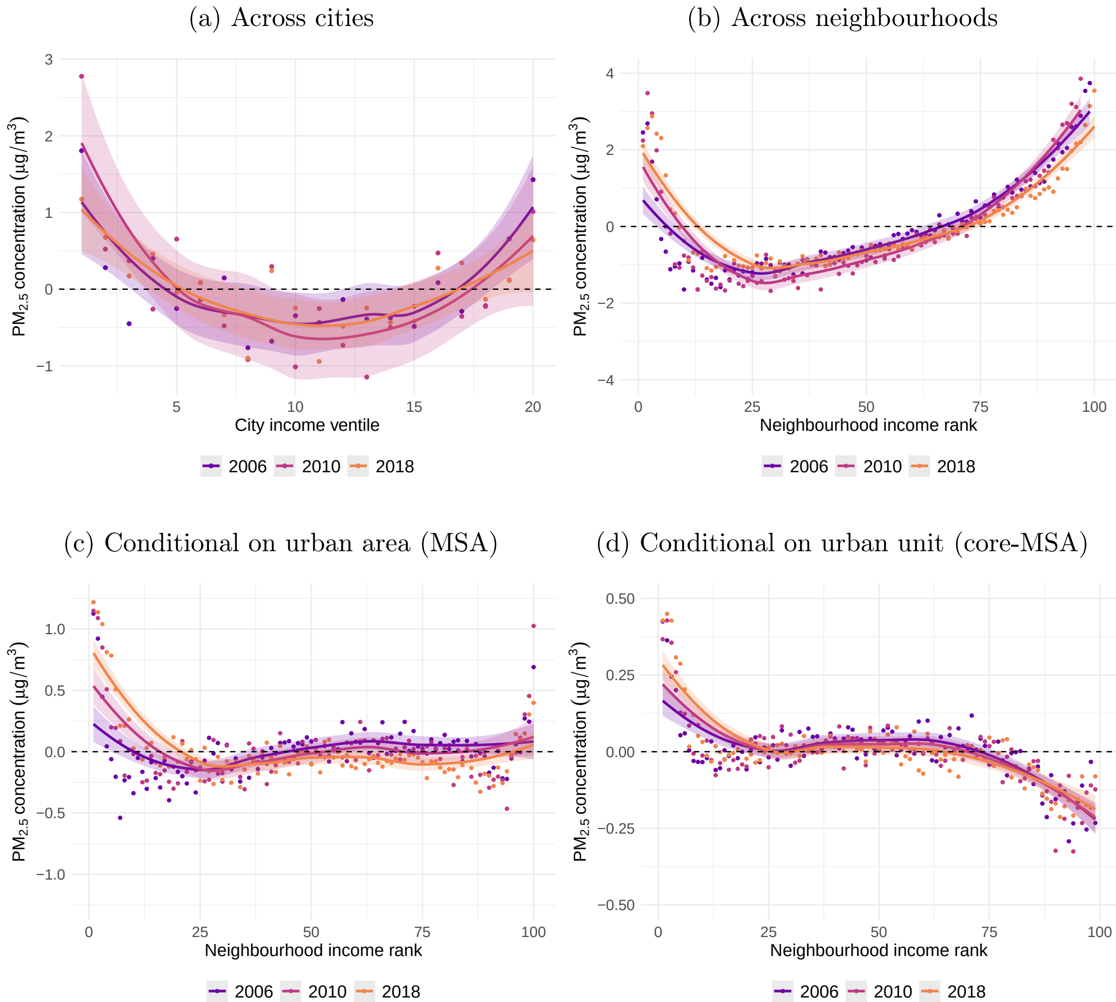
## 3.1 Graphical evidence on disparity patterns

Figures 1 and 2 display the gradient in $PM_{2.5}$ levels by income and immigrant share respectively, first across cities, then across neighbourhoods, and finally within cities. All values are centred around their yearly mean.

***National-scale income disparities*** Panel a of Figure 1 displays the cross-city relationship between $PM_{2.5}$ and income for 769 cities, sorted by income ventile. The relationship follows a U-shape: both low- and high-income cities are more polluted than those in the middle of the income distribution. This is in contrast with the positive gradient already documented in the United States (Hsiang et al., 2019; Colmer et al., 2024), as the pattern actually reflects the coexistence of two distinct types of polluted cities in France. Large cities where economic activity and overall density generate high emissions (e.g., Paris), and smaller northern industrial cities that combine high pollution with low income (e.g., Dunkirk or Douai-Lens).

Turning to neighbourhood-level information, Panel b in Figure 1 displays the unconditional average exposure to $PM_{2.5}$ as a function of a neighbourhood's centile of income, which follows a U-shape. In the French context, statistically more polluted city centres and inner suburbs combine both high- and very low-income neighbourhoods, while outer suburbs have intermediate income levels (Aerts et al., 2015; Floch, 2017). This contrasts with the U.S., where the unconditional cross-neighbourhood gradient is monotonically negative, largely due to suburbs being higher-income than city centres on average (Voorheis, 2017; Colmer et al., 2020).

Figure 1: Gradients in $PM_{2.5}$ concentration by income




*Sources*: $PM_{2.5}$ estimates from ACAG, income and neighbourhood and city definitions from INSEE, area contours from IGN.
*Notes*: Panel (1a) and (1b) display the raw relationship between $PM_{2.5}$ concentration and income, at the urban area and neighbourhood level, respectively. Panels (1c) and (1d) display the residuals of regressions of $PM_{2.5}$ concentration on city fixed effects, against neighbourhood income, using, respectively, the urban area or the urban unit as a city definition. An urban area (MSA, INSEE's *aire urbaine*) comprises peri-urban municipalities, whereas cor-MSAs, or urban units (INSEE's *unités urbaines*, commonly called *agglomérations* in French) only comprise city centres and suburbs. The difference is illustrated in Appendix Figure B.3 in the case of Paris.

***Within-city income disparities*** Figure 1 then conditions $PM_{2.5}$ concentration on the neighbourhood's urban area or urban unit to study within-city inequalities in exposure. The map in Appendix Figure B.3 illustrates the difference between these two definitions for the Paris region. Urban areas are equivalent to American MSAs, comprising the city centre and both inner and outer suburbs (in purple on the map). Urban "units" only comprise the core of the city, i.e., its central municipality and its inner suburbs (in orange on the map). This conditioning renders the patterns shown in Panels c and d of Figure 1. Within cities, neighbourhoods with very low income are considerably more polluted than their higher-income counterparts. In Panel c, only neighbourhoods in the bottom 10% and top 1% of income are overexposed to $PM_{2.5}$. Focusing on urban cores, only neighbourhoods at the bottom 12% are overexposed, while the very top of the distribution is less exposed than the mean, around which 50% of the income distribution gravitates. As shown more formally in Section 3.2, this within-city gradient is stronger than in the U.K., where it is virtually null (Metcalfe and Roth, 2025), and slightly larger than in the U.S. (Colmer et al., 2020).[9]

***Immigrant-share gradients*** At the national scale, both the unconditional and the income-conditional gradients are flat across most of the immigrant-share distribution (Panels a and b). The cross-city relationship (Panel a) mirrors the null cross-city income result. Across neighbourhoods nationally (Panel b), $PM_{2.5}$ rises sharply only above the $75^{th}$ percentile of immigrant share, and conditioning on income does not attenuate the relationship.

Within cities (Panels c and d), the gradient is clearer and steeper. The plain curves show a strong and systematic overexposure of neighbourhoods in the top quintile of the immigrant share distribution, with a particularly sharp rise for the top decile. The gap between the unconditional and income-conditional curves indicates that income mediates part of this relationship. For the top-1% of immigrant shares (between 16.3% and 17.7%, compared to a national average of 10%), differences in income account for about 45% of $PM_{2.5}$ overexposure, but these differences vanish for neighbourhoods below the $80^{th}$ percentile (neighbourhoods with 13.4% of immigrants). All in all, the dashed curves remain J-shaped, indicating that a significant component of the immigrant-share gradient is not explained by income.

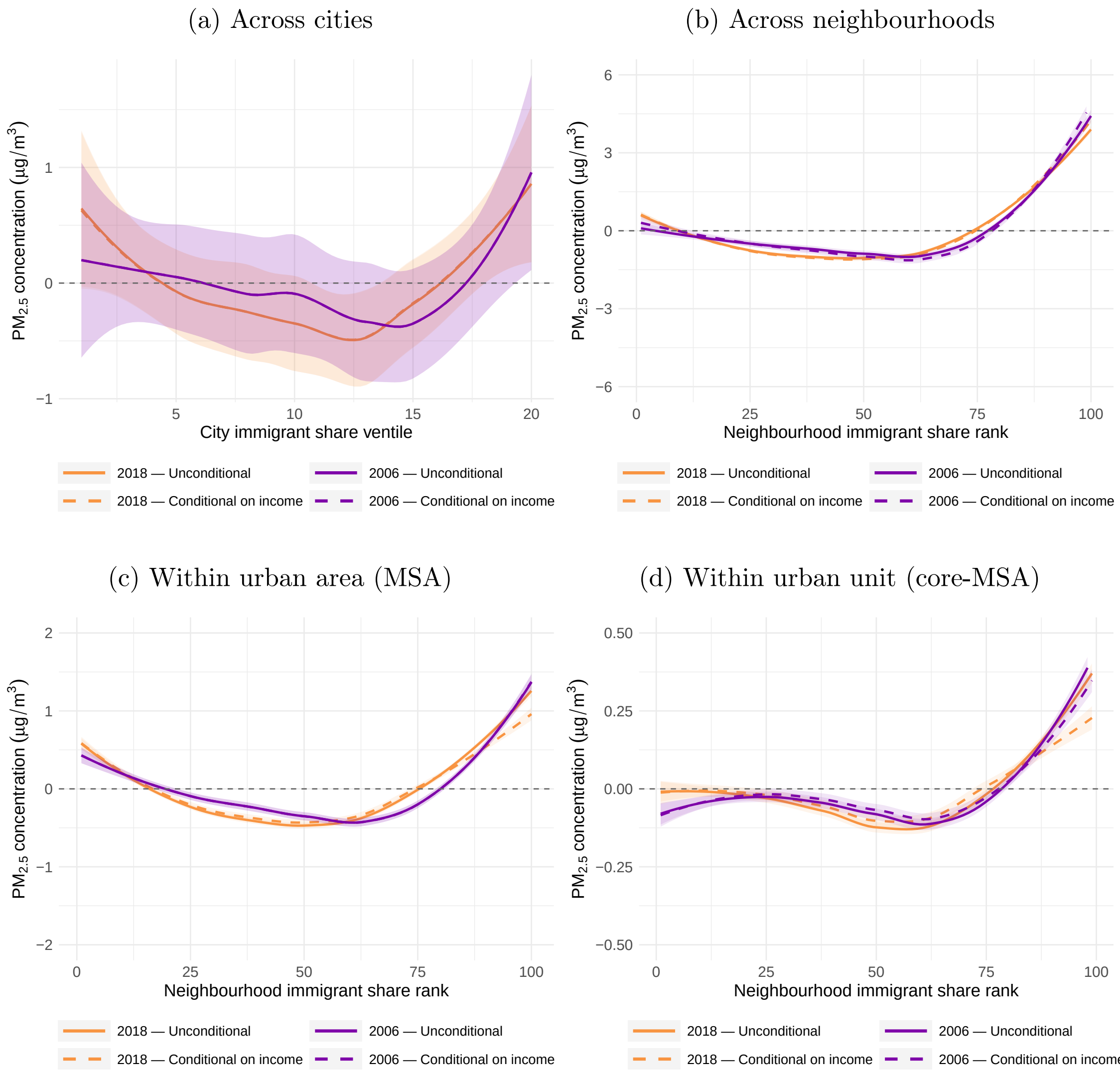
These disparities can be observed at the city level as well: Appendix Figure B.6 gives gradients of $PM_{2.5}$ by decile of immigrant share for the largest 12 cities. Regardless of the city definition (MSA, core-MSA, or PPA zone) and controlling for neighbourhood income, virtually all cities display a positive gradient of $PM_{2.5}$ with respect to the share of immigrants.

***Persistence of disparities over time*** Average $PM_{2.5}$ concentration and population-weighted concentration ("exposure") both declined by about 25% over the study period (Appendix Figure B.7).[10] Yet the gradient curves in Figures 1 and 2 are near-identical for 2006 and 2018: pollution fell, but the shape of the income–$PM_{2.5}$ and immigrant-share–$PM_{2.5}$ gradients remained the same. Appendix Figure B.8 examines this stability more formally through pollution-reduction profiles,

[9] Appendix Figure B.5 repeats the within-city exercise for the 12 largest French cities. Apart from Nantes and Rennes, two Atlantic cities that benefit from prevailing winds reducing particulate stagnation, all cities have $PM_{2.5}$ levels above the 2005 WHO guideline and well above the 2021 guideline of 5 $\mu g/m^3$. The within-city gradient is clearly negative in about half of these cities, fairly flat in Toulouse, Lille, Nice, Nantes and Rennes, and U-shaped in Paris. This heterogeneity likely reflect differences in historical urban design across French cities, as also highlighted in Blaudin de Thé et al. (2021) in the case of car-traffic emissions.

[10] Appendix Figure B.4 also provides evidence on immigrant-share gradients without demeaning the two bottom panels. It shows that prior to 2018, all neighbourhoods have pollution levels above the applicable WHO guideline of 10 $\mu g/m^3$. By 2018, the curves have shifted down, and only neighbourhoods in the 25% of the distribution of immigrant shares do.

Figure 2: Gradients in $PM_{2.5}$ concentration by immigrant share




*Sources*: $PM_{2.5}$ estimates from ACAG, income, immigrant-share and neighbourhood and city definitions from INSEE, area contours from IGN.
*Notes*: Panels (2a) and (2b) display the raw relationship between $PM_{2.5}$ concentration and share of immigrants, controlling for income, at the urban area and neighbourhood level respectively. Panels (2c) and (2d) display the residuals of regressions of $PM_{2.5}$ concentration on city fixed effects and neighbourhood income, against neighbourhood share of immigrants, using, respectively, the urban area or the urban unit as a city definition. An urban area (MSA, INSEE's *aire urbaine*) comprises peri-urban municipalities, whereas core-MSAs, or urban units (INSEE's *unités urbaines*, commonly called *agglomérations* in French) only comprise city centres and inner suburbs. The difference is illustrated in Appendix Figure B.3 in the case of Paris.

in the spirit of Voorheis (2017): while the most polluted neighbourhoods at baseline experienced the largest absolute declines, consistent with mean reversion, the improvement in air quality was distributed relatively evenly across income and immigrant-share ranks. In other words, poorer and higher-immigrant neighbourhoods are consistently more exposed to $PM_{2.5}$ at any point in time, and the recent overall decline did not narrow these gaps. By contrast, both the income–$PM_{2.5}$ gradient and the Black–White exposure gap have narrowed substantially in the United States since the 2000s (Colmer et al., 2024), in particular due to CAA implementation (Currie et al., 2023).

### 3.2 Sectoral correlates and residential segregation

In order to formalise the evidence of the previous sections and to gauge the role of potential correlates, I estimate the following within-city regression:

$$\ln(\mathrm{PM}_{it}) = \alpha + \beta_c \ln(\mathrm{charac}_{it}) + \beta_X X_{it} + \lambda_t + \nu_{c(i)} + \varepsilon_{it} \tag{1}$$

$\ln(\mathrm{PM}_{it})$ is the log of average $PM_{2.5}$ concentration in census block $i$ during year $t$. $\ln(\mathrm{charac}_{it})$ is the log median income or the share of immigrants of census block $i$ in year $t$. $\nu_{c(i)}$ is a city fixed effect and $\lambda_t$ a year fixed effect. $X_{it}$ includes controls for weather conditions. Standard errors are clustered at the city level. Equation (1) does not identify a causal effect, but rather documents correlations net of weather conditions and city-specific time-invariant factors.

***Baseline results*** Table 1 presents the results. Column (1) shows a significantly positive unconditional relationship between neighbourhood income and $PM_{2.5}$, reflecting the fact that larger cities combine both higher pollution and higher income. Introducing city fixed effects in Columns (2) and (3) reverses the sign, confirming the negative within-city gradient shown in Figure 1. The estimates suggest that a one standard deviation increase in neighbourhood income (€5,231, or 25%) is associated with a 0.13 $\mu g/m^3$ lower $PM_{2.5}$. In the bottom panel, the within-city association between immigrant share and $PM_{2.5}$ is positive and gets larger as I control for income, confirming that the immigrant-share gradient is not a reflection of the income gradient.[11]

***The role of spatial patterns and segregation*** Within cities, two reinforcing mechanisms could generate the residual immigrant-share gradient documented in Figure 2. First, immigrant residential segregation is markedly stronger than income segregation in France (Safi, 2009; Préteceille, 2011). Second, polluting activities have been shown to be disproportionately sited near high-immigrant neighbourhoods (see Laurian and Funderburg, 2014, for evidence on waste incinerators). Given that about 60% of immigrants living in France are of African or Asian origin (INSEE, 2025), these patterns are reminiscent of the ethnic gap in $PM_{2.5}$ exposure documented in the United States between Non-Hispanic Whites on the one hand and Blacks and Hispanics on the other (Depro et al., 2015; Kravitz-Wirtz et al., 2016; Currie et al., 2023). To assess how much of the residual

[11] Appendix Table C.4 provides estimates of the within-city correlation between $PM_{2.5}$ concentration and other neighbourhood characteristics. Neighbourhoods with higher shares of elderly residents are more exposed, while those with more toddlers are less so. Since the elderly and young children are particularly vulnerable to $PM_{2.5}$ (Currie et al., 2009; Deryugina et al., 2019), it is worth noting that neighbourhoods with higher shares of elderly are more exposed, while those with more toddlers are less so. More broadly, other measures of neighbourhood deprivation (e.g., unemployment, single-parent share) are positively associated with $PM_{2.5}$.

Table 1: Within-city relationships between $PM_{2.5}$ concentration and income and share of immigrants

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | | | | *Focus on income* | | | | |
| (log) median income | 0.017** | -0.055*** | -0.048*** | -0.046*** | -0.036*** | -0.029*** | -0.046*** | -0.021*** |
| | (0.007) | (0.015) | (0.012) | (0.004) | (0.006) | (0.011) | (0.012) | (0.009) |
| % electric heating | | | | | -0.033 | | | -0.027** |
| | | | | | (0.028) | | | (0.014) |
| (log) # plants within 5 km | | | | | | 0.048*** | | 0.049*** |
| | | | | | | (0.006) | | (0.006) |
| (log) distance major road (km) | | | | | | | 0.0008 | 0.0002 |
| | | | | | | | (0.0005) | (0.0005) |
| $R^2$ | 0.154 | 0.837 | 0.885 | 0.885 | 0.884 | 0.894 | 0.885 | 0.893 |
| | | | | *Focus on share of immigrants* | | | | |
| % immigrants | 0.799*** | 0.957*** | 0.568*** | 0.398*** | 0.380*** | 0.211*** | 0.400*** | 0.189*** |
| | (0.034) | (0.044) | (0.018) | (0.012) | (0.012) | (0.009) | (0.012) | (0.008) |
| % electric heating | | | | | -0.031*** | | | -0.026*** |
| | | | | | (0.002) | | | (0.0012) |
| (log) % of plants within 5 km | | | | | | 0.044*** | | 0.046*** |
| | | | | | | (0.002) | | (0.002) |
| (log) distance major road (km) | | | | | | | 0.0008*** | 0.0003*** |
| | | | | | | | (0.00004) | (0.00005) |
| Control for income | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.540 | 0.551 | 0.846 | 0.934 | 0.888 | 0.895 | 0.889 | 0.893 |
| MSA fixed effect | | Yes | | | | | | |
| Core-MSA fixed effect | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Weather controls | | Yes | Yes | Yes | Yes | Yes | | Yes |
| $s(\text{lon}_i,\ \text{lat}_i)$ | | | | Yes | | | | |
| Observations | 227,106 | 227,106 | 227,106 | 34,988 | 227,106 | 227,106 | 227,106 | 227,106 |

*Sources*: $PM_{2.5}$ estimates from ACAG, neighbourhood characteristics and city definitions from INSEE, area contours from IGN, road network from BD-TOPO IGN product, registered plant data from IREP.
*Notes*: Standard errors clustered at the city level in parentheses. Signif. codes: ***: 0.01, **: 0.05, *: 0.1. Weather controls include mean summer temperature, mean winter temperature, mean precipitation and mean cloud cover. MSAs are INSEE's definition of urban areas, and core-MSAs are INSEE's definition of urban units, which comprise the city centre and inner suburbs (shown in orange in Appendix Figure B.3).

gradient reflects these spatial dynamics rather than a more local relationship, Column (4) adds a thin-plate regression spline of neighbourhood centroid coordinates, $s(x_i, y_i)$, where $x_i$ is longitude and $y_i$ is latitude, which flexibly absorbs smooth geographic variation in $PM_{2.5}$.

The income–$PM_{2.5}$ gradient weakens somewhat, but not significantly so. The immigrant-share gradient, however, drops more substantially. This asymmetry is consistent with the fact that in France, immigrant segregation is markedly stronger than income segregation (Gobillon and Selod, 2007; Safi, 2009; Préteceille, 2011; Quillian and Lagrange, 2016): because immigrants are highly clustered across space, a larger share of the immigrant–$PM_{2.5}$ correlation overlaps with smooth geographic patterns and is accordingly absorbed by the spline. Significance levels are substantially higher in the spatial GAM models, because geographic location is a very strong predictor of $PM_{2.5}$ levels.[12] This spatial control plays the same role throughout the paper, as discussed further in Section 5.3 on the policy evaluation strategy.

[12] The approximate $p$-value of the smoothed term is virtually zero.

***Sectoral correlates*** Columns (5)–(8) introduce proxies for the influence of different emission sectors on neighbourhood $PM_{2.5}$ levels. In Column (5), controlling for the share of electric heating, which does not emit $PM_{2.5}$, weakens both the income and the immigrant-share gradient, though this proxy does not capture the role of residential heating in a precise fashion. Introducing a proxy for manufacturing activity in Column (6) substantially weakens both coefficients of interest: both poorer and high-immigration neighbourhoods tend to be located near high-emission industrial sites, and this proximity accounts for a large part of the observed correlations. Differential proximity to major roads, introduced in Column (7), plays no significant role. This already suggests that targeting major roads is not an efficient tool for reducing income disparities in exposure to local air pollution.

# 4 Regulatory context

As France is a Member State of the European Union, ambient air quality is regulated at both the European and the national level. The PPA policy thus originates in a European regulatory framework, which France transposed into national law and, in turn, devolved to cities by mandating them to design and implement their own air quality measures.

***European regulations*** The 2008 EU Directive on ambient air quality and cleaner air for Europe, among other elements, [13] established that annual concentration in $PM_{2.5}$ had to be lower than 25 $\mu g/m^3$ by the 1st of January, 2015, while it was previously unregulated.[14] The Directive was translated into French law, by decree, on the 21st of October, 2010.[15]

***Translation to French law*** Even before 2008, the LAURE (Law on Air and Rational Use of Energy) of 1996 already compelled urban areas of more than 250,000 inhabitants to implement an Atmosphere Protection Plan (PPA, for *Plan de Protection de l'Atmosphère*). Among other requirements, the latter has to define a precise agenda of measures taken by local authorities so as to meet air quality standards.[16] The 2008 EU Directive led the French government to modify the list of pollutants regulated within the PPA framework: fine particulate matter ($PM_{2.5}$), which was not in-

[13] First, the Directive 2008/50/EC merged the majority of existing legislation on outdoor air quality (apart from the Fourth Daughter Directive 2004/107/EC, which regulates the ambient air concentration of metals, such as mercury and nickel) into a single directive, without any change in existing objectives. Second, it allowed for time extensions for compliance to EU standards regarding the concentration of particulate matter ($PM_{10}$), benzene, and nitrogen dioxide ($NO_2$), up to 2015. Third, it gives the opportunity for Member States to deduct emissions caused by natural sources, such as those emitted through forest fires, when assessing compliance to EU limit values of regulated pollutants.

[14] In terms of exposure, the Commission chose to refer to a three-year annual average exposure (AEI, for Average Exposure Indicator), which must be lower than 20 $\mu g/m^3$. In France, the AEI is computed using monitor data of 49 urban areas. This became legally binding in 2015, i.e., starting for years 2013-2015.

[15] Said decree is available online at `https://www.legifrance.gouv.fr/affichTexte.do?cidTexte=JORFTEXT000022941254&categorieLien=id`.

[16] In addition to the action plan, the elements that a PPA must contain are: a) an inventory of emissions of atmospheric pollutants, b) an evaluation of air quality, c) a description of the sanitary impacts of air pollution, and d) an *ex ante* evaluation of the measures taken, in the form of scenarios.

cluded, was added.[17] Cities were first asked to start monitoring $PM_{2.5}$, while there were less than 10 monitors nationwide before that. Most importantly, they were asked to implement measures aimed at reducing this concentration, working together with the local state services (*préfecture*) such that not only incentive-based or voluntary measures could be implemented, but also regulatory ones. All sectors may also be targeted, including manufacturing, transport, but also the residential or construction sector. Finally, in order to comply with the law, cities are required to evaluate their air quality plan every 5 years, and to revise it if need be. The time needed to evaluate the existing plan, to prepare new measures in conjunction with stakeholders, and to adopt the revised PPA sometimes implies that a longer time period elapses between the adoption of a scheme and its revision. In the sample of large cities, the revised plans were passed an average of 7.3 years after the former one.

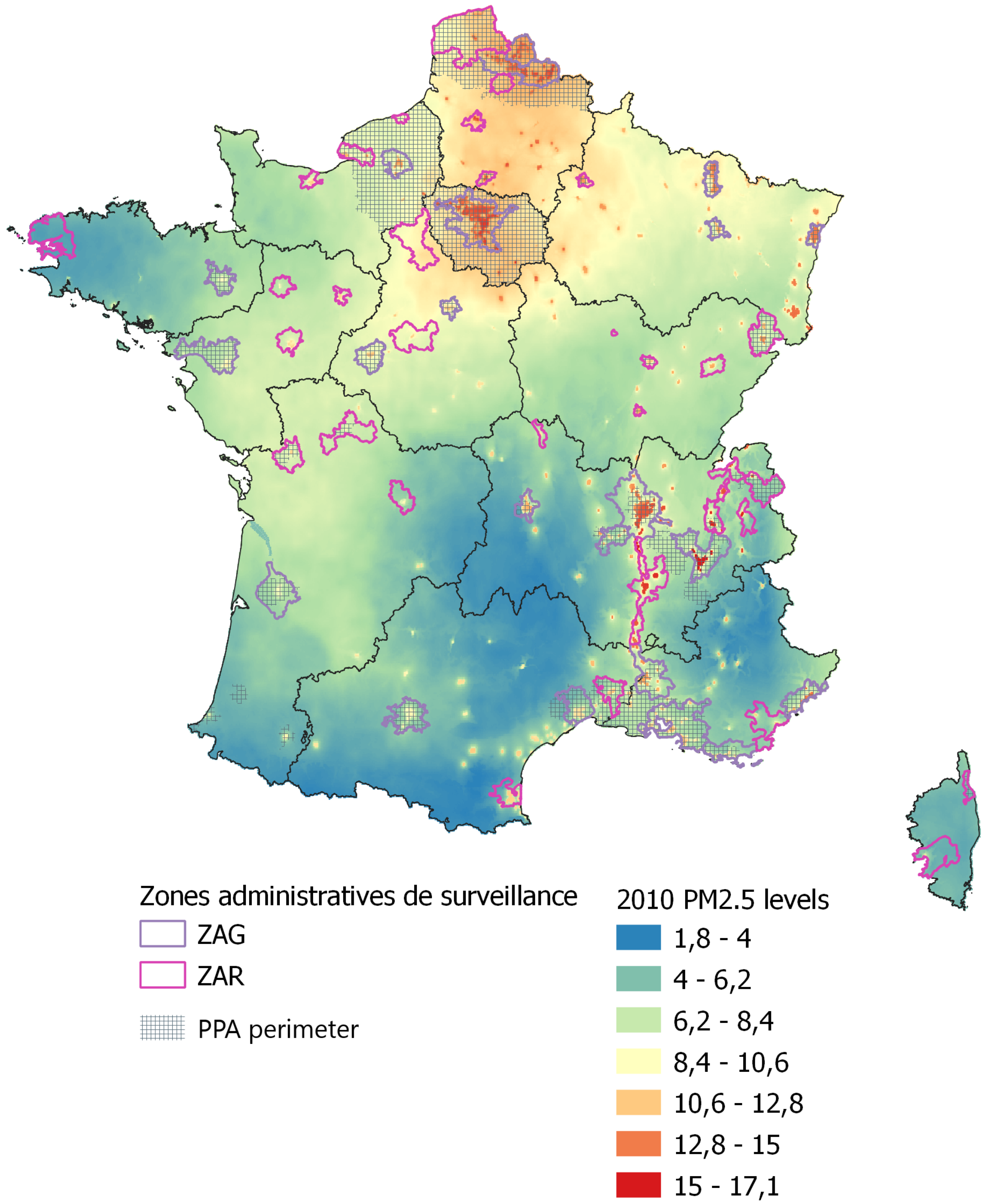
***Definition of targeted cities*** As part of the nationwide system of air quality monitoring, and in order to meet European requirements, the French territory is divided into administrative monitoring zones (hereafter, ZAS, for *Zones Administratives de Surveillance*). These zones are delineated by taking into account local air pollution level, exposed population, emission sources, and the climate prevailing in these zones, as well as the impact of their creation on the cost of the national monitoring system. ZAS can be of two types:

1. ZAG, i.e. risk zones within a conurbation: these include an urban area of more than 250,000 inhabitants, or have a high population density (threshold set by the government);
2. ZAR, i.e. risk zones outside a conurbation: they do not meet ZAG population (density) criteria but their air quality does not meet requirements, or is susceptible not to.

Since the 2010 decree, Atmosphere Protection Plans may be implemented if at least one of these conditions is fulfilled: a) the zone comprises an urban area of more than 250,000 inhabitants, b) limit or target concentrations of at least one pollutant are exceeded within the zone, and/or c) there is a risk that limit or target concentrations will be exceeded within the zone. Given these criteria, cities that are henceforth named "large PPA zones", or "large cities" are all ZAG. These are cities that were already covered by a PPA before the 2008 Directive, due to the 1996 LAURE. On the other hand, all cities that adopted their very first PPA after 2010, hereafter called "small/smaller PPA zones", are ZAR, that were treated not because of their size, but because of their pollution levels. In practice, these are medium-sized cities (50-300,000 inhabitants). Never-treated cities are also all ZAR/medium-sized cities (95-380,000 inhabitants). Tables C.5, C.6, and C.7 in Appendix provide a breakdown of the number of observations and inhabitants by city and by treatment year, for large PPA zones, small PPA zones, and never-treated cities, respectively.

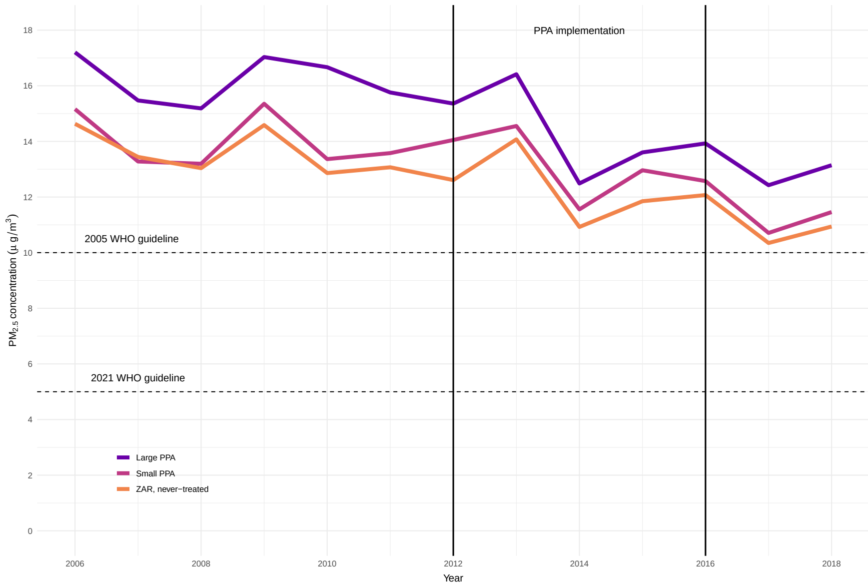
[17] Although measures that aimed at decreasing concentration in other air pollutants like $PM_{10}$ which were implemented beforehand likely already helped reduce $PM_{2.5}$ concentration, the date of implementation of post-2010 PPAs constitutes a new shock.

Figure 3: Administrative monitoring, PPA zones and 2010 $PM_{2.5}$ concentration




*Sources*: $PM_{2.5}$ estimates from ACAG, PPA-zone year of adoption and delineation from municipality list from PPA schemes, administrative region boundaries from IGN, ZAS boundaries from 2008 decree.
*Notes:* ZAG stands for *Zone à risques - Agglomération* – these are large cities of more than 250,000 inhabitants, at least partly covered by a PPA zone due to their population size. ZAR stands for *Zone à risque - hors agglomération* – these are smaller PPA zones, that is, medium-sized cities of 160,000 inhabitants on average. The former, in purple, cover large urban areas, while the latter, in pink, cover smaller urban areas. Although the perimeters of the monitoring zones and the PPA zones do not necessarily exactly coincide, all ZAG are covered by a PPA, while some areas classified as ZAR have implemented a PPA, and some have not.

Figure 4: Evolution of $PM_{2.5}$ concentration – Large and small PPA zones




*Sources*: ACAG, IGN, PPA schemes, 2008 ZAS decree.
*Notes*: Large PPA zones in purple, small PPA zones in pink, never-treated cities in orange.

***Spatial extent*** To give a sense of the spatial extent of these policies, Figure 3 maps 2010 $PM_{2.5}$ concentration in mainland France, overlaid with monitoring zone and PPA zone boundaries. Tiled areas correspond to PPA zones, ZAG are delineated by a purple border, and ZAR are delineated by a pink border. PPA and ZAS perimeters do not exactly match, as the former is often chosen so as to match with urban planning schemes, in particular urban mobility plans, while the latter is chosen on the basis of population or local air pollution.[18]

By 2016, 14,729 neighbourhoods (30% of the total), belonging to 5,500 municipalities (18% of the total) belong to a zone covered by a PPA. Sample restrictions described in Section 5.2 drive the yearly number of IRIS observations down to 14,391, with 12,612 census blocks in large PPA zones and 996 census blocks in small PPA zones. The selected areas represent a total of 31 million inhabitants in 2010, that is, 52% of the mainland French population.

***Motivating evidence*** Figure 4 displays the evolution of $PM_{2.5}$ concentration throughout the study period in large PPA zones (purple), small PPA zones (pink) and never-treated smaller cities (orange). By construction, urban areas covered by a PPA are more polluted than the national average throughout the study period. More specifically, although they fulfil the EU requirement of 25 $\mu g/m^3$ on average, large PPA zones never reached the WHO guideline of 10 $\mu g/m^3$. Still, similarly to the average national reduction of 27% in $PM_{2.5}$ concentration that occurred between

[18]For instance, in the case of the Paris region, the PPA perimeter is larger than the ZAS monitoring zone perimeter: it corresponds to the administrative region boundaries, since the urban mobility plan is elaborated at this level (called PDUIF, for *Plan de Déplacement Urbain d'Île-de-France*).

2009 and 2018, average $PM_{2.5}$ concentration decreased by 25% on average in large PPA zones, and 21% in smaller PPA zones.

# 5 Identification strategy

## 5.1 Staggered difference-in-differences

I perform a staggered difference-in-differences (DiD) estimation of the effects of revised local air quality plan implementation on local $PM_{2.5}$ levels. Due to variation in the date of treatment across cities, not-yet-treated cities are used as a partial control group, complemented by medium-sized cities ("ZAS") not covered by a PPA as a never-treated control group. Based on the information of Section 4, I select this complementary set of control cities based on the monitoring zone classification, and use ZAR which were left untreated because their pollution levels were deemed unlikely to exceed EU guidelines.[19]

***Estimated equations*** The baseline event-study equation writes:

$$\mathrm{PM}_{i(z)t} = \alpha + \sum_{\tau=-10}^{4} \mu_\tau \, \mathbb{1}\{t - E_z = \tau\} + X'_{it}\eta + \gamma_i + \lambda_t + \varepsilon_{it} \tag{2}$$

where $\mathrm{PM}_{it}$ is $\mathrm{PM}_{2.5}$ in neighbourhood $i$, located in PPA zone $z$, observed during calendar year $t$. $\mathbb{1}\{t - E_{z(i)} = \tau\}$ is a binary variable equal to 1 if neighbourhood $i$ is at relative time $\tau$ from PPA adoption (which is approved at the level of PPA zone $z$). The coefficients of interest $\mu_\tau$ capture the evolution of $\mathrm{PM}_{2.5}$ prior to and after the event. The reference categories are $\tau = \{-7,\ -1\}$.[20] The coefficients $\mu_\tau$ thus measure the impact of the revised plan relative to a linear path between the two reference periods, and a significant post-treatment coefficient indicates a break relative to the linear trend in local $\mathrm{PM}_{2.5}$.

Matrix $X'_{it}$ contains controls for weather conditions, which can affect behaviours that the PPA policy also targets. For instance, warmer winters reduce residential heating demand regardless of whether a PPA is in place. The literature in aerosol science also shows that weather conditions directly affect particulate formation, as higher temperatures favour the photochemical reactions that produce secondary $\mathrm{PM}_{2.5}$ (Petit et al., 2015). Hence, if temperature varies differentially across treated and control areas over time, this would confound the estimated treatment effect. In a similar

[19] As shown in Table C.7 however, I exclude 5 of the 16 ZAR cities not covered by a PPA from the control group, such that I end up with 11 never-treated cities, which amount to 1,390 yearly observations. In all five of these cases, direct proximity and prevailing wind directions would induce a contamination of the control group if they were included.

[20] As noted by Callaway and Sant'Anna (2021) and Borusyak et al. (2024), using a single reference period leads to underidentification due to the collinearity between relative time, calendar time, and the treatment year. Taking $\tau = \{-2,\ -1\}$ as references could seem natural but raises the probability of a non-detectable linear trend; using $\tau = -1$ and the furthest pre-treatment period, here $\tau = -10$, avoids this. See Borusyak et al. (2024) for a further discussion of these issues.

fashion, wind governs the vertical dispersion of particulates, hence their concentration (Deryugina et al., 2019). I thus control for the following meteorological variables to isolate the policy-induced change in $PM_{2.5}$: precipitation, cloud cover, summer and winter temperatures, and wind speed. In some specifications, the $X'_{it}$ matrix also contains a spatial spline discussed in Section 5.3, so as to account for relative neighbourhood location as a potential confounder. Standard errors are clustered at the PPA-zone level, the scale at which treatment is assigned. Because the CS and BJS estimators are imputation estimators that first generate a cohort $\times$ time ATT before aggregation, I must rely on a two-step procedure. I first residualise $PM_{2.5}$ on time-varying controls, and then estimate the DiD specification on the residuals. For these estimators, I bootstrap the standard errors.

In a second step, Subsection 6.2 and Section 7 allow for heterogeneous effects by interacting the event-time indicators with an initial neighbourhood characteristic:

$$\mathrm{PM}_{it} = \alpha + \sum_{\tau=-10}^{4} \mathbb{1}\{t - E_z = \tau\}\,(\mu_\tau + \beta_\tau \,\mathrm{charac}_i) + X'_{it}\eta + \gamma_t + \lambda_i + \varepsilon_{it} \tag{3}$$

where $\mathrm{charac}_i$ is a dummy equal to 1 when neighbourhood $i$ belongs to the top decile or quartile of a relevant distribution — the national $PM_{2.5}$ distribution, the PPA-zone distribution of income, or the PPA-zone distribution of immigrant shares — in 2009, prior to the wave of PPA renewals. As the panel is balanced in calendar years, it is not balanced in years to/from treatment. Adoption dates and cohort sizes are summarised in Appendix Tables C.5 for large PPA zones, and C.6 for smaller PPA zones.

***Estimator choice*** The estimator proposed by Sun and Abraham (2021), hereafter SA estimator, is used as the headline estimator. SA is designed for staggered-adoption settings with heterogeneous treatment effects and avoids the "forbidden comparisons" problem identified by de Chaisemartin and d'Haultfoeuille (2020); Goodman-Bacon (2021) that biases TWFE estimates under treatment-effect heterogeneity. Every $(g, s)$ cohort-event-time comparison in SA uses an untreated control group (not-yet-treated or never-treated at time $s$), never a previously-treated unit. It identifies a transparent primitive, $ATT(g, s)$, for each cohort $\times$ event-time cell, and then aggregates it to the event-time level, without imposing a parametric outcome model.

For robustness purposes, I report three complementary sets of estimations in the Appendix. The first relies on TWFE, the "naive" estimator. The second, the estimator by Borusyak et al. (2024) (hereafter, BJS), is the main robustness check.BJS, by contrast, fits a TWFE regression on untreated observations and extrapolates it to impute counterfactual $PM_{2.5}$ values for treated units. When untreated cities follow a smooth downward trend over the sample period, the BJS extrapolation projects a steeper counterfactual decline than is observed in the not-yet-treated control group at the relevant calendar year, mechanically widening the implied treatment effect, hence the preference for SA as the main estimator. The third is the estimator developed by Callaway and

Sant'Anna (2021) (hereafter, CS), which aggregates cohort $\times$ calendar-time effects under similar identifying assumptions to SA, but does not natively allow for the introduction of time-varying controls.Standard errors are clustered at the city level using a cluster bootstrap with 200 replications. Across SA, BJS, and CS, the pooled ATT are quantitatively similar.

## 5.2 Identifying assumptions

The causal interpretation of the point estimates relies on two main assumptions: the parallel trend assumption (PTA) and the exogeneity of treatment timing. I formally state each assumption, discuss its plausibility, and present sensitivity analyses based on recent advances in the staggered DiD literature.

### 5.2.1 Parallel trends and treatment timing exogeneity

***Parallel trends*** The key identification assumption is that, absent the adoption of a new PPA, local air pollution trends would have evolved similarly in treated and control neighbourhoods. Let $\text{PM}_{i,t}(0)$ denote the counterfactual pollution level of neighbourhood $i$ at in year $t$ in the absence of treatment, and $C_i$ denote a dummy equal to 1 for a neighbourhood belonging to a never-treated city, and 0 to a treated city. When using the full set of control units, including never-treated cities, the assumption requires that, conditional on initial characteristics:

$$E[\text{PM}_t(0) - \text{PM}_{t-1}(0) \mid C = 0, \text{charac} = a] = E[\text{PM}_t(0) - \text{PM}_{t-1}(0) \mid C = 1, \text{charac} = a] \quad (4)$$

When using only not-yet-treated units as controls, the analogous assumption is:

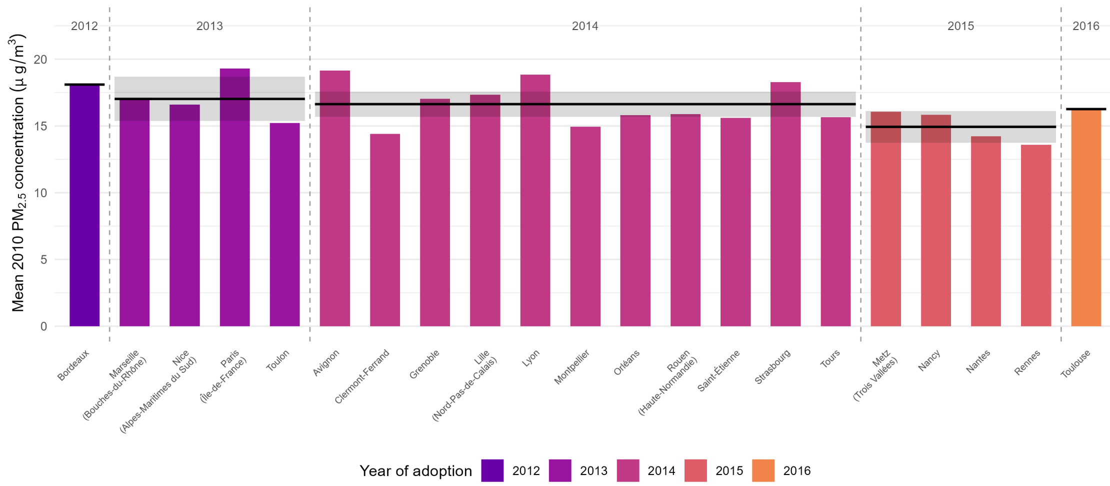
$$E[\text{PM}_t(0) - \text{PM}_{t-1}(0) \mid G_{t_0} = 1, \text{charac} = a] = E[\text{PM}_t(0) - \text{PM}_{t-1}(0) \mid D_s = 0, \text{charac} = a] \quad (5)$$

where $G_{t_0}$ a binary variable equal to 1 if a neighbourhood is first treated in period $t_0$, and $D_s$ a binary variable equal to 1 if the neighbourhood is treated in period $s \geq t \geq t_0$.

Both versions condition on initial neighbourhood characteristics to allow for differential trends across observable types. The not-yet-treated comparison restricts the control set to other PPA zones that have not yet revised their air quality schemes, while the never-treated comparison additionally draws on ZAR that were never subject to a PPA.

Several features of the setting support the PTA, including the absence of self-selection into treatment. For large PPA zones, treatment status is formally determined by a population threshold (250,000 inhabitants). For medium-sized cities, this is less obvious, since treatment assignment occurs based on initial pollution levels, but, as summary statistics in Table C.8 show, small PPA zones have the same initial $\text{PM}_{2.5}$ concentration as never-treated cities, at 15 $\mu\text{g/m}^3$. In addition, Figure 4 shows that raw pre-treatment trends in $\text{PM}_{2.5}$ concentration are largely parallel across treated and never-treated areas, despite the fact that large (treated) cities are more polluted throughout. IRIS

Figure 5: Mean 2010 $PM_{2.5}$ concentration by city and year of PPA adoption




*Sources*: $PM_{2.5}$ estimates from ACAG, PPA-zone year of adoption and delineation from PPA schemes.
*Note*: This graph groups city-level 2010 $PM_{2.5}$ concentrations by year of adoption. The black lines show the treatment cohort mean, with the corresponding 95% confidence interval as the shaded area. Appendix Figure B.9 provides the same information for small PPA zones.

fixed effects also absorb persistent differences in pollution levels across neighbourhoods, which is the main source of concern given that more polluted areas tend to experience steeper declines (recalling Appendix Figure B.8).

In addition, I restrict the pool of never-treated control areas by excluding cities that are geographically close or downwind of treated urban areas, so as to avoid contamination of the control group through pollution spillovers.[21] Complementary regressions that restrict the control group to not-yet-treated units yield similar results, though with slightly smaller point estimates.

***Treatment timing exogeneity*** The second assumption requires that the outcome in the year prior to treatment is unaffected by the upcoming adoption, and that the treatment date is not strategically manipulated. This rules out anticipation effects and endogenous timing of PPA adoption. Several institutional features make manipulation of the treatment date unlikely. The treatment date corresponds to the signature by the prefect(s), who are appointed rather than elected, reducing incentives for politically motivated timing. The signature also follows a lengthy consultation process involving multiple stakeholders and, in many cases, coordination across several *départements*, making it costly to shift the date.[22] Empirically, Figure 5 shows that average 2010 $PM_{2.5}$ concentration does not differ significantly across PPA adoption cohorts, confirmed by the multinomial logit esti-

[21]The excluded cities are Amiens (between the North region and Paris, both treated), Chartres-Dreux (adjacent to the Paris and Normandy PPAs), Fréjus-Draguignan (downwind of Nice, via the Gregale and Levant winds), Vallée du Rhône (downwind of Lyon via the Mistral wind), and Moulins (too small, with only 18 neighbourhoods). The full list of retained control areas is shown in Table C.7.

[22]See for instance this decision by *Conseil d'État*, equivalent to the Supreme Court in a number of countries, sentencing the state for failing to sufficiently reduce atmospheric pollution: Penalty imposed by Conseil d'État.

mation in Table C.9, which regresses the year of PPA adoption on 2010 $PM_{2.5}$ levels and reveals no significant correlation.

### 5.2.2 No sensitivity to parallel trend violations

Figure B.13a, which shows the leads and lags around the treatment date in large cities, does display a mild upward-sloping pattern in pre-treatment differences. This is consistent with the gradual wearing-off of the effects of the previous PPA, typically adopted around 7 years before the new one. Then, a clear break in this trend occurs at the time of treatment. However, conventional pre-trend tests based on the non-significance of event-study coefficients have strong limitations. Indeed, TWFE pre-treatment estimates, shown in orange in the Figure, are biased under treatment effect heterogeneity (de Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; Borusyak et al., 2024). The recent staggered DiD estimators also produce pre-treatment estimates whose properties make visual inspection of pre-treatment trends unreliable (Roth, 2026). More fundamentally, insignificant pre-trends do not imply that the PTA holds.

I therefore rely on the sensitivity analysis proposed by Rambachan and Roth (2023), which bounds the post-treatment effects under controlled violations of the PTA by comparing them to the largest deviation observed in the pre-treatment period. Figure B.10 shows the evidence for the full control group and Figure B.11 for the not-yet-treated group. I focus on commenting Figure B.10 using the full set of control units, as the tests yield almost identical results across the two. The relative magnitude analysis (Panels (a) and (c)) yields a breakdown value of $\bar{M} = 1$. This means that the estimated treatment effect remains significant even when allowing for a post-treatment PTA violation that would be as large as the largest existing pre-treatment deviation. In other words, the results shown in Section 6 are robust to time-varying post-treatment unobserved heterogeneity that would generate variations as large as those that are observed prior to the treatment. In this context, the main concern would be smooth secular trends in local air quality yielding an overestimation of the effects, as documented by Sager and Singer (2025) in the context of the U.S. Clean Air Act. The smoothness restriction analysis (Panels (b) and (d)) shows that the estimators used here are largely robust to this. At $M = 0$, the significantly negative point estimate in Panels (b) and (d) implies that the treatment effect lies significantly below a basic linear extrapolation of the pre-treatment trends. In Panel (d) this is the case up until $M = 0.75$, meaning that the effect I detect lies significantly below a 75% downward deviation in the linear extrapolation of the pre-treatment trends. This rules out concerns of smooth differential trends invalidating the results.

## 5.3 Robustness to smooth spatial confounders

***Why spatial structure matters*** Air pollution is distributed continuously across space. Clustering standard errors at the PPA-zone level accounts for within-zone correlation, but it does not address the fact that pollution levels in nearby neighbourhoods are mechanically correlated regardless of administrative boundaries. For instance, it does not account for correlations between two adjacent neighbourhoods that are located across two PPA zones, which biases the estimation of standard errors. More importantly, relative neighbourhood location also matters for the estimation of point estimates themselves. Proximity to emission sources, topography, and prevailing wind patterns generate spatial structure in air pollution that, if uncontrolled, may confound the estimated treatment effects.

***The spatial spline as a flexible control*** As in Section 3.2, I use a thin-plate regression spline $s(x_i, y_i)$ of IRIS centroid coordinates, estimated within a Generalised Additive Model (GAM), to flexibly absorb smooth spatial patterns in $PM_{2.5}$. The spline captures the spatial structure of air pollution non-parametrically, absorbing confounders that vary continuously across geographic space, such as variations in elevation or wind patterns, including those that are unobserved or difficult to measure directly. Equation (2) augmented with the spatial spline becomes:

$$\mathrm{PM}_{i(z)t} = \alpha + \sum_{\tau=-7}^{4} \mu_\tau \, \mathbb{1}\{t - E_z = \tau\} + X_{it}'\eta + s(x_i, y_i) + \gamma_i + \lambda_t + \varepsilon_{it} \tag{6}$$

Because the spline is a smooth function of coordinates, it absorbs spatial confounders that operate at a scale broader than the individual neighbourhood while leaving within-neighbourhood variation over time (the identifying variation for the treatment effect) intact. The thin-plate regression spline penalty is governed by a smoothing parameter that is estimated from the data by restricted maximum likelihood. The basis dimension $k$ is set such that the fREML-estimated effective degrees of freedom lie below $k$, verified using the diagnostic of Wood (2017).[23]

# 6 Results

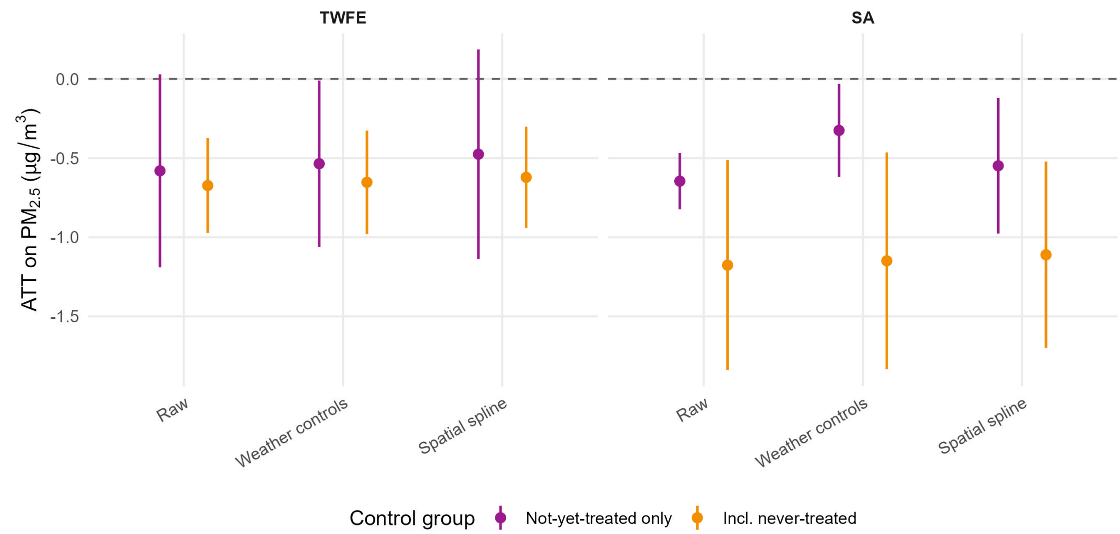
## 6.1 Average effect of PPA on local air quality

Figure 6 provides the main estimates of the average treatment effect, obtained by estimating equation (2) using TWFE (on the left) and the SA estimator (on the right), for large PPA zones in Panel 6a and small PPA zones in Panel 6b. Appendix Figure B.12 shows the robustness of these results to the use of other modern DiD estimators (BJS and CS). Purple points show results using only the not-yet-treated as controls, and orange points use both the not-yet-treated and the never-treated as additional controls. For both types of cities, the coefficients are always more precisely estimated when using the alternative control group which excludes never-treated cities, likely due to heterogeneity across never- and ever-treated cities. On the right-hand side (CS), the point estimates are also less negative once never-treated cities are included as controls, though not statistically significantly so, which is the reverse pattern of TWFE. This is likely attributable to the fact that as opposed to TWFE, which give in an inappropriately high weight to never-treated units

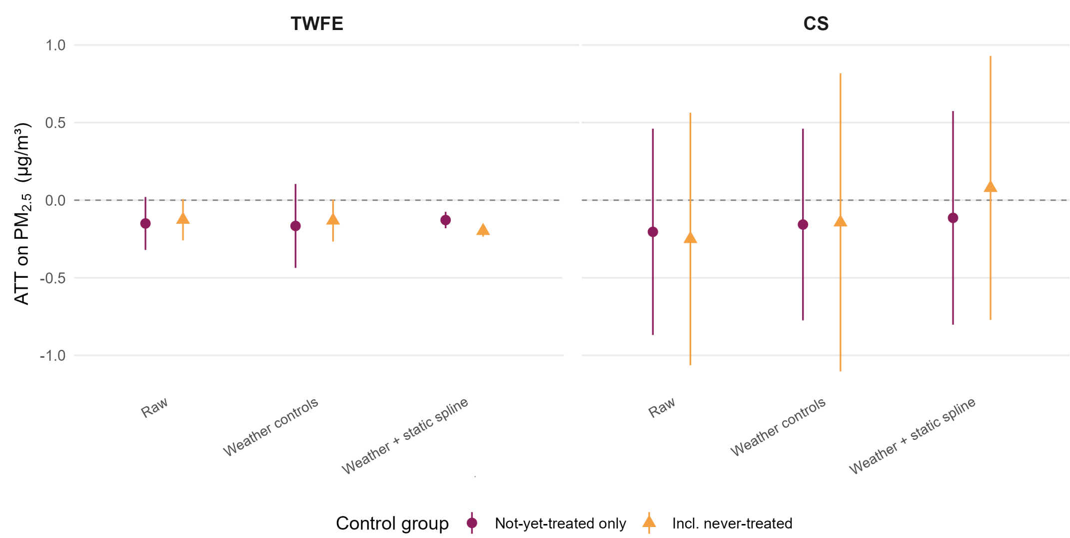
[23]In my preferred specification, the fitted EDF is 183 against a basis ceiling of k = 200.

Figure 6: Average treatment effects in large and small PPA zones

(a) Large PPA zones




(b) Small PPA zones




*Sources*: ACAG, INSEE, IGN, Copernicus CDS, PPA schemes.
*Notes*: Standard errors clustered at the ZAS level in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.
Estimates of coefficients $\mu_\tau$ in equation (2) using only not-yet-treated units as the control group in purple, and the full control group including both not-yet- and never-treated units in orange. Graphs on the left-hand side use the TWFE estimator while those on the right-hand side use the SA estimator. The vertical bars correspond to the 95% confidence interval. When a spatial spline is used in combination with the SA estimator, it enters a first-stage regression that residualises $PM_{2.5}$ levels: the results shown are from a second-stage regression where the dependent variable is residualised $PM_{2.5}$, and standard errors are estimated using 200 bootstrap draws.

(Goodman-Bacon, 2021), the SA method appropriately weighs not-yet-treated, late-adopting urban controls compared to more rural never-treated medium-sized cities.

***Large PPA zones*** The implementation of a new PPA has a significantly negative effect on $PM_{2.5}$ concentration in large cities according to all specifications. Focusing on preferred estimates computed using the SA method and the full control group, the adoption of the new PPA leads to a decrease of about 1.3 μg/m$^3$ in $PM_{2.5}$ levels, which represents a bit more than a third of the overall decrease of 3.4 μg/m$^3$ from 16.3 to 12.9 μg/m$^3$.[24] Turning to event-study coefficients shown in Figure B.13a, I find that the effect of the treatment is rather flat up to the second year following adoption $\tau = 2$, and then gradually increases in magnitude, to go from about -1 μg/m$^3$ to -1.5 μg/m$^3$. This intensifying impact of the PPA likely reflects that fact that new measures are being implemented, come into effect, or manage to tangibly curb emissions a few years after its adoption. Section 7 delves into the measures undertaken in more detail.

***Small PPA zones*** According to the results of Panel (6b), the effect of PPA adoption on $PM_{2.5}$ concentration in smaller cities is very close to zero according to TWFE estimates (), and null according to CS estimations. This is partly due to lower precision, but it is safe to assume that there is no effect. This null effect may be attributed to the fact that smaller cities do not have the necessary means to actually act on local air quality: they have more limited funds, more limited human capital resources (especially on this topic), and likely less bargaining power to obtain help from state agencies on the matter. The latter point may also be related to the fact that they have lower initial pollution levels (14.6 μg/m$^3$ in 2009, as opposed to 17.1 μg/m$^3$ in large cities), which also entails they have less room for improvement.

## 6.2 Cleaner air for whom?

Section 3 established that prior to PPA revision, neighbourhoods with low income and/or a high immigrant population were overexposed to $PM_{2.5}$, and that these disparities remained throughout the study period. This section shows that while local $PM_{2.5}$ decreased more in initially more polluted neighbourhoods, neighbourhoods in the bottom 25% of the income distribution did not benefit from statistically significantly larger decreases in $PM_{2.5}$, while those in the top 10% of the immigrant-share distribution did, but to a small extent.

***Initial pollution levels*** The first row of Table 2 shows that initially more polluted neighbourhoods benefitted from larger improvements in air quality. As in recent work on the U.S. Clean Air Act (Sager and Singer, 2025), the additional decrease for the top quartile of the pre-treatment $PM_{2.5}$ distribution reaches -0.27 μg/m$^3$, about 20% of the average effect (-1.21 μg/m$^3$). This effect persists in row 4, which controls for income and immigrant share, and even slightly rises to 25%

[24] Table C.10 in Appendix provides results that mirror those of Figure 6a, but weighted by neighbourhood population. They can thus be interpreted as showing the effect at the individual level for inhabitants of treated neighbourhoods. All point estimates are very close to those obtained without population weighting.

Table 2: Disparities in the effects of PPA revision – Large PPA zones

| | Average effect (SE) | Interaction term (SE) |
|---|---|---|
| | *Separate regressions* | |
| Top 25% initial $PM_{2.5}$ | -1.21*** (0.32) | -0.27*** (0.09) |
| Bottom 25% income | -1.28*** (0.33) | -0.06** (0.02) |
| Top 10% immigrant share | -1.28*** (0.33) | -0.15*** (0.04) |
| | *Same regression* | |
| Top 25% initial $PM_{2.5}$ | | -0.31*** (0.07) |
| Bottom 25% income | -1.21*** (0.32) | 0.00 (0.02) |
| Top 10% immigrant share | | -0.06** (0.02) |

*Sources*: ACAG, INSEE, IGN, Copernicus CDS, PPA schemes.
*Notes*: Standard errors clustered at the ZAS level in parentheses. $^{*}$ $p < .10$, $^{**}$ $p < .05$, $^{***}$ $p < .01$.
All estimations are performed using the SA estimator and both not-yet- and never-treated units as a control group, and include weather controls.

$(-0.31/-1.21)$. This result may be explained by diminishing marginal returns: a more polluted neighbourhood has more room for improvement, whereas once the air is cleaner and the remaining emissions harder to abate, it becomes difficult to obtain further reductions. In this sense, even small measures likely have stronger impacts where local air pollution is high. I discuss heterogeneity in the type of interventions taken within PPA at greater length in Section 7.

***Trends by income and share of immigrants*** The second and third rows of Table 2 report the additional effect accruing to the bottom income quartile and to the top immigrant-share decile. Both are negative and statistically significant, but small, as they amount to roughly 6% and 16% of the average effect. Most importantly, when introducing all three interaction terms together into the same "horse-race" regression as done in the last three rows of the table, the additional effect for low-income neighbourhoods vanishes, while the additional effect for high-immigrant neighbourhoods halves. The latter represents 5% of the total effect once differential initial income and exposure are taken into account. All in all, although they were shown to be more vulnerable to local air pollution (Hsiang et al., 2019), disadvantaged neighbourhoods benefit slightly more because they are initially more polluted, not because the PPA policy would target disadvantage.[25]

***City centres vs suburbs*** Conditionally on wanting to target more polluted neighbourhoods, policy-makers may be more likely to specifically target city centres, since they are the showcase of cities. This would be in line with our result above that more populated and polluted neighbourhoods see larger effects. Instead, with redistributive effects in mind, they may be more likely to specifically target highly polluted close suburbs, whose inhabitants are less economically advantaged.

Table 3 reports the main regression estimated separately on city centres, suburbs, and rural

[25] Indeed, holding exposure constant, vulnerability to fine particulates is higher among less healthy individuals (Deryugina et al., 2019), and health outcomes correlate with income.

Table 3: Heterogeneity in treatment effects by neighbourhood type

| Neighbourhood type | ATT (SE) | N | # IRIS |
|---|---|---|---|
| City centres | -1.04*** (0.39) | 51,805 | 3,985 |
| Suburbs | -1.36** (0.34) | 83,629 | 6,433 |
| Rural areas | -1.24*** (0.41) | 11,362 | 874 |

*Notes*: Bootstrapped standard errors clustered at the ZAS level in parentheses. $^{*}\ p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$. All estimations performed using the SA estimator and both not-yet and never-treated units as a control group.

areas. Suburbs appear to have benefitted from a larger improvement in air quality than city centres, though not statistically significantly so. This likely reflects differences in the effectiveness of the measures available in each of these settings. In dense city centres, transport is one of the few available levers, yet such measures can fail to reduce car use and may displace traffic rather than eliminate it. Suburbs, by contrast, have more single-family, owner-occupied housing, which makes residential retrofit subsidies easier to implement than in the multi-family, renter-occupied centre. I examine the transport and residential heating channels in the next section.

# 7 Mechanisms

This section explores the channels through which the PPA policy affects $PM_{2.5}$ levels, by leveraging two features of the policy. First, implementation is decentralised to the city level, allowing the analysis to examine the role of local capacity. Second, as PPAs can include measures spanning a wide range of sectors, this generates variation in both the sectors targeted and the specific measures adopted. The second part of the section uses this variation to characterise which types of interventions are associated with larger improvements in air quality, distinguishing between measures targeting the manufacturing, residential, agricultural and transport sectors. The final part builds on the sectoral decomposition to explain how neighbourhoods in the lower end of the income distribution or higher end of the immigrant-share distribution did not obtain larger air quality gains.

## 7.1 City size and capacity

The high degree of decentralisation of the policy, down from the national level to the city level, implies that the effectiveness of the PPA largely relies on local capacity to both choose appropriate interventions, and to implement and enforce them. This section shows that, consistent with the earlier finding that effects are larger in more polluted areas, $PM_{2.5}$ reductions increase with city size. The second part of the section also shows that independently from the high initial pollution effect, cities that benefitted from additional support from the state did see larger improvements.

***City population*** The first panel of Table 4 show the results of a regression interacting treatment status with quartiles of city population, using the first quartile ($<$ 450,000 inhab.) as the

Table 4: Effect of capacity – Size and the "Breathable city" program

| Interacted variable | | Average effect (SE) | Interaction term (SE) |
|---|---|---|---|
| Population quartile (ref: 1) | 2 | -0.048 (0.33) | -0.31 (0.36) |
| | 3 | | -1.19*** (0.19) |
| | 4 | | -2.25*** (0.36) |
| Breathable city (ref: No) | Yes | -0.23 (0.34) | -1.07*** (0.38) |
| | In same zone as Yes | | -0.98** (0.36) |

*Sources*: ACAG, INSEE, IGN, Copernicus CDS, PPA schemes, Ministry of Ecology.
*Notes*: Standard errors clustered at the ZAS level in parentheses. $^{*}$ $p < .10$, $^{**}$ $p < .05$, $^{***}$ $p < .01$.
All estimations performed using the SA estimator and both not-yet- and never-treated units as a control group. The first quartile of ZAS population corresponds to 446,784 inhabitants, the second (median) to 966,301 inhabitants, and the third to 2,134,194 inhabitants. Minimum population is 271,753 inhabitants (Orléans), and maximum population is 12,209,027 (Paris). Central Paris is excluded from the "Breathable city" regression, as it is part of the program but has substantially higher initial capacity and knowledge on air pollution than other cities. Including it renders a coefficient of -1.13 (SE: 0.36).

reference.[26] The interacted coefficients show that the effects of the PPA policy concentrated in cities whose population was higher than the median of around 1 million inhabitants, and focusing on rows 2-3 shows that the effect is twice as large for cities in the top quartile as compared to the 3$^{rd}$.

***The role of government financial and practical guidance*** As Section 4 explains, the PPA policy is very decentralised, in the sense that local authorities have close to full decision-making autonomy in the elaboration of the list of air quality measures that they wish to implement. This implies that there may be large disparities in the ability of each to select the measures that are most likely to be effective, but also to actually implement them. This may be due to a lack of staff trained on air quality issues, a lack of sufficient funds to hire them, or a lack of sufficient funds to offer a housing retrofit subsidy. I investigate this channel by interacting the treatment variable with whether a city was selected as part of the "Breathable in 5 years" program.[27] This project was launched in June 2015 by the Ministry for Ecology and was aimed to encourage the emergence of volunteer "laboratory cities" to implement "radical measures" to reduce $NO_2$ and $PM_{10}$ concentration. It relied on ADEME, the Environment Agency, to support selected cities. 12 large cities already treated by a PPA were selected, out of 36.[28] Average population in Breathable cities is 1.1 million, and 1.4 million inhabitants in PPA zones not part of the program, such that city size is not a confounder here. The corresponding results are provided in the lower panel of Table

[26] Given that treated cities are by construction larger than never-treated cities, the support of the variable differs according to treatment status, which calls for caution.

[27] More precisely, cities (in the statistical sense) or PPA zones themselves were not eligible as such. The administrative level that could apply was the municipality federation (EPCI in French), a group of municipalities that come together to jointly fulfil some of their prerogatives, such as levying local taxes, or sharing public goods to benefit from economies of scale (e.g., water management, or cultural and sports facilities). The Greater Paris region and all large urban cores and their close suburbs, have this status.

[28] PPA zones where at least part of the territory was selected were, in alphabetical order: Avignon, Bordeaux, Grenoble, Lyon, Montpellier, Nice, Paris, Rouen, Saint-Étienne, Strasbourg, Toulouse and three in the Nord-Pas-de-Calais PPA zone: Arras, Lille and Côte d'Opale.

4. They show that only two groups of neighbourhoods saw statistically significant improvements in local $PM_{2.5}$: those directly covered by the program, and those in a PPA zone where at least part of the territory was covered. This points to the importance of providing financial and logistical support to local governments when policy is decentralised. It is also worth highlighting the fact that spillovers of the program to nearby neighbourhoods that were not strictly part of it, but part of the same PPA zone, are strong, as the estimated effect is less than 10% smaller than in Breathable neighbourhoods.

### 7.2 Sectoral mechanisms

This section focuses on sectoral specialisation and targeting as a source of heterogeneity in the effectiveness of the PPA policy, by analysing the specific actions pledged by cities in their PPA. Perhaps surprisingly, there is little variation in the types of measures that local authorities list in their PPA scheme. As shown in Appendix Table C.12, all of them decide on at least one intervention that targets the transport sector, the industrial sector, and the residential sector, and some target the agricultural sector as well.[29] For the industrial and transport sectors, as all cities take similar actions, I rely on initial measures of the strength of exposure to these sectors as proxies for the intensity of the policy. For the residential and agricultural sectors, I am able to use actual listed policy actions that are implemented in some cities, but not others. All results are shown in Table 5. A natural concern is that these variables are correlated with baseline pollution, so the interactions might reflect larger reductions in initially dirtier neighbourhoods rather than sector-specific responses; but the precise zero obtained for the transport proxy (Panel 1) speaks against this, as a proxy capturing only baseline exposure would load there too.

***Transport: speed limits*** I start by road-transport-related actions, which in all cases take the form of speed limits on major roads. I thus test for their effectiveness by interacting treatment status with neighbourhood proximity to a major road. The first panel of Table 5 and row 1 in the fifth panel both show a precise zero for the interaction term. This provides suggestive evidence that lowering speed limits on major roads is largely ineffective, which is in line with previous findings (Folgerø et al., 2020; Le Frioux et al., 2024). This is also consistent with the above result on city centres *vs* suburbs, and echoes the result of Bou Sleiman (2023), who shows that the pedestrianisation of a Parisian riverbank displaced traffic away from this road to the ring road, worsening air quality nearby, instead of triggering a significant modal switch to public transport and an improvement in air quality.[30]

[29] As cities are granted close to full autonomy on this policy, there is no systematic monitoring of the implementation of these actions. As such, the estimates provided here could be seen as intention-to-treat effects (ITT).

[30] The lowering of speed limits has one advantage in that it is a very cheap regulatory tool. But, as shown here, it is also largely ineffective. As such, this can also explain the more recent trend towards the implementation of low-emission zones (LEZ) that ban polluting vehicles altogether, a more stringent but also likely more effective regulatory tool.

Table 5: Heterogeneity by sector targeted

| Variable | Base effect (SE) | Interaction term (SE) |
|---|---|---|
| | *(1) Transport sector* | |
| (log) distance to major road | -1.33*** (0.32) | 0.01 (0.01) |
| | *(2) Manufacturing sector* | |
| (log) # registered plants within 5 km | -0.98** (0.36) | -0.24** (0.10) |
| | *(3) Residential sector* | |
| Dummy for clean heating systems | -1.11*** (0.40) | -0.38 (0.37) |
| Dummy heating × % non-electric | -1.15*** (0.39) | -0.39 (0.44) |
| | *(4) Agricultural sector* | |
| Dummy spraying ban × % rural | -1.07*** (0.33) | -5.40*** (0.58) |
| | *(5) All sectors in the same regression* | |
| (log) distance to major road | | 0.00 (0.01) |
| (log) # registered plants within 5 km | -0.36 (0.36) | -0.26*** (0.06) |
| Dummy heating × % non-electric | | -0.69* (0.36) |
| Dummy spraying ban × % rural | | -7.85*** (1.08) |

*Notes*: Standard errors clustered at the ZAS level in parentheses. $^{*}$ $p < .10$, $^{**}$ $p < .05$, $^{***}$ $p < .01$.
All regressions include weather controls. The rows in the first 4 panels all show The dummy for "clean heating systems" is equal to 1 for cities that choose to ban open fireplaces, and/or to promote and subsidise cleaner residential heating systems. The dummy for "spraying ban" is equal to 1 for cities that choose to ban substance spraying on windy days or during pollution peaks, and more broadly raise farmer awareness on pollutant emissions. There are 10 such cities out of the 21 treated cities.

***Manufacturing sector*** In the vast majority of cases, measures targeting the industrial sector consist in strengthening inspections in the high-emission plants located in the zone covered by the PPA. As described in the descriptives of Section 3, these plants are listed in a national registry, as they are subject to filing a declaration or a formal authorisation. I interact treatment status with the (log) number of such polluting plants within 5 km of the neighbourhood, to gauge the effectiveness of strengthening inspections. Panel 2 and row 2 of Panel 5 of Table 5 show that the effect of the policy is indeed larger in neighbourhoods that are in the vicinity of a large polluting plant. Panel 2 in particular suggests that the effect is about 25% larger in such neighbourhoods.

***Residential heating*** The residential sector, in particular residential heating, is responsible for half of total primary $PM_{2.5}$ emissions before the treatment period (Citepa, 2018), and there is variation in whether cities decide to address the issue. I build a dummy equal to 1 for whether the PPA zone decided to a) ban open fireplaces, b) promote national housing retrofit subsidies for replacing old boilers and open fireplaces,[31] and/or c) implement its own subsidies[32] 10 cities (47%,

[31] When combustion is less complete, as it is often the case when burning wood in open fireplaces or malfunctioning boilers, emissions of fine particulates are higher. Since 2009, the French Environment Agency runs a "heating fund" (*Fonds Chaleur*), through which the state subsidies housing retrofit. Between 2009 and 2014, it has dedicated €1.2 billion to replace old heating systems in both collective and individual housing (source: ADEME, 2015, in French).

[32] As cities write in their PPA, this is generally done at the municipality or municipality federation level, and it is difficult to keep track of all municipalities that implement such programs independently. I thus consider all neighbourhoods belonging to such zones as treated, such that this aggregation accounts for spillovers.

and 60% of neighbourhoods) include at least one of these measures in their PPA.

In practice, row 1 of Panel 3 only uses the dummy to proxy the strength of the intervention, while row 2 of Panel 3 and row 3 of Panel 5 modulate this strength by interacting it with its potential, i.e., with the share of residential heating that is non-electric, hence potentially polluting, in the area. Corresponding estimates suggest that air quality improved more in PPA zones that chose to specifically target the residential sector, although the effect is statistically significant only when controlling for other interventions (Panel 5). In this preferred specification, at the mean share of non-electric heating households (74.15%), local $PM_{2.5}$ declined by $(0.69 \times 0.7415 =)$ 0.51 $\mu g/m^3$ more in neighbourhoods belonging to a PPA zone that adopted an intervention on residential heating. This is in line with the discrepancy in effects between city centres and suburbs found above: open fireplaces are more common in the suburbs than in city centres, and, broadly speaking, inefficient heating systems are more easily replaceable in single-family housing units (in suburbs) than in collective property buildings that are common in city centres.

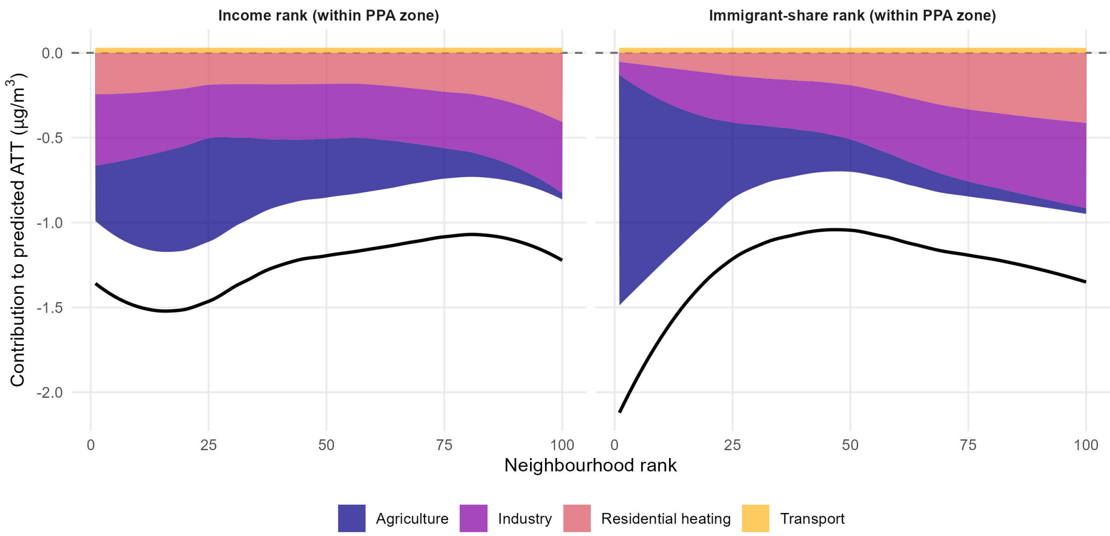
***Agriculture*** Most PPA zones do not implement any measure related to agriculture, simply because they do not have any rural neighbourhoods. This sector however is estimated to be responsible for 7% of primary emissions in 2010 at the national scale, a fraction that is much higher when accounting for secondary particulates (Espina-Martin et al., 2024). Because these particulates travel, agriculture can *in fine* account for a sizeable share of urban $PM_{2.5}$ concentration.[33] Some PPA zones that are partly rural do however take such actions, most of which take the form of raising awareness and promoting good practices, such as avoiding or banning substance spreading on windy days or during pollution peaks.[34] I interact treatment status with the product of the share of rural neighbourhoods and a dummy equal to 1 if the neighbourhood belongs to such a PPA zone in Panel 4 and in row 4 of Panel 5. In both cases, I find that at the mean share of rural neighbourhoods, $PM_{2.5}$ decreased by $(0.076 \times 7.85 =)$ 0.59 $\mu g/m^3$ more in neighbourhoods that belong to a PPA zone that implemented an intervention targeting the agricultural sector.[35] This is 1.5 times more than in neighbourhoods that didn't implement any of the four interventions tested here, and explains the result of Table 3, in which I find that the drop in $PM_{2.5}$ following PPA adoption is somewhat larger in rural areas than in city centres.

[33]Agriculture is almost the sole contributor to ammonia emissions (96% in 2025), mainly through substance spraying. Ammonia has strong chemical reactions with other pollutants associated with fossil fuel combustion, and generates (in technical terms) secondary inorganic compounds that are part of $PM_{2.5}$. These inorganic compounds are primarily emitted by agriculture and made up for 50% of imported $PM_{2.5}$ in Paris in 2011 (Airparif, 2011).

[34]Out of the 21 large PPA zones, 9 contain more than one rural neighbourhood. Out of these, five did implement measures targeting the agricultural sector: Lille (23.9% of neighbourhoods), Nantes (4.5%), Rennes (8.1%), Rouen (17.0%) and Tours (5.7%). The remaining four are Grenoble (16.8%), Montpellier (18.1%), Saint-Etienne (7.5%) and Toulouse (12.5%). Hence, more rural PPA zones aren't more likely to include measures aimed at agricultural emissions.

[35]The agricultural interaction is robust to leave-one-zone-out estimation: across the five implementing zones, the coefficient ranges from -8.19 (SE: 1.22) excluding Rouen, to -7.56 (1.04) excluding Lille (the most influential zone, with the highest rural share among implementers), and remains significant at the 1% level.

Figure 7: Sectoral decomposition of the predicted effect by income and immigrant share




*Sources*: ACAG, INSEE, IGN, Copernicus CDS, PPA schemes.
*Notes*: Predicted effect by 2009 income rank (on the left) and immigrant-share rank (on the right), using the SA estimator. The black line shows the full average predicted ATT by percentile.
The dark blue area is the contribution of the identifiable measure targeting the agricultural sector (product of a dummy equal to one if the city's PPA comprises a measure targeting farmers specifically and the share of rural neighbourhoods).
The purple area is the contribution of a proxy for the measure targeting the industrial sector (log number of registered plants within 5 km).
The coral orange area is the contribution of the identifiable measure targeting the residential sector (product of a dummy equal to one if the city's PPA mentions an open boiler ban and/or a subsidy for boiler replacement and the share of households that don't have electric heating in the neighbourhood).
The yellow area is the contribution of the identifiable measure targeting the transport sector (log distance to the nearest major road).

## 7.3 Explaining the persistence of disparities

Hinging on the same identified measures and proxies as in the previous subsection, I proceed to quantify the contribution of each sector to the overall predicted effect along the PPA-zone-specific income and immigrant-share distributions. To do so, I use the estimated coefficients associated with each sectoral measure from a joint estimation, predict the effect for each observation, which I then group by income or immigrant-share rank. Stacking the individual sectoral contributions produces Figure 7, which shows the results by income percentile on the left, and by immigrant-share percentile on the right.

First, as it is not possible to identify every single PPA measure and thus the associated variation, there is a gap between the black line, which shows the total ATT by percentile, and the contour of the stacked areas. Still, the identified measures account for a total effect of -0.5 to -1.2 $\mu g/m^3$ depending on the variable rank, which represents up to 75% of the total predicted ATT. The effect of transport measures, proxied by neighbourhood distance to a major road, is null.

Overall, the total effect is less strongly negative as income increases, apart from the very bottom of the distribution: the effect of identifiable interventions is mildly progressive, but too small to narrow the baseline gap. This is mostly driven by the intervention targeting the agricultural sector, which has strongly progressive effects due to affluent neighbourhoods being located in city centres. On the other hand, the gradient of the contribution of the manufacturing sector is fairly flat, like, to some extent, the one associated with residential heating.

The results of this exercise generate much starker results in the case of the share of immigrants. Again, this is mostly driven by the measure on agriculture: it is particularly effective, but rural neighbourhoods also have the lowest shares of immigrants. Importantly however, the proxies for the effect of strengthening inspections on polluting plants and for the effect of promoting less polluting residential heating systems appear strongly progressive, in the sense that their effect grows more and more negative as the share of immigrants increases. All in all, it appears that the effectiveness of banning spraying on days with high wind and/or pollution and related interventions targeting agricultural practices does more than cancel out the progressive effect of manufacturing and residential heating measures. This explains the persistence of both income- and immigrant-share-based disparities in exposure to local $PM_{2.5}$ during the study period.

# 8 Conclusion

This paper draws on high-resolution satellite-based data on $PM_{2.5}$ concentration, matched with census-block-level information on income, share of immigrants, and other neighbourhood characteristics, to document patterns of inequality in exposure to local air pollution in France and to evaluate the role of city-level air quality plans in their evolution. Within cities, both poorer and immigrant-dense neighbourhoods are substantially overexposed to $PM_{2.5}$ and these disparities persisted between 2006 and 2018 despite a 25% decline in average pollution. This contrasts with the United States, where exposure gaps along both income and racial lines have narrowed (Currie et al., 2023; Colmer et al., 2024; Sager and Singer, 2025). The PPA policy, which since 2016 covers half of the French population, accounts for a 1 to 1.5 $\mu g/m^3$ reduction in treated neighbourhoods relative to controls, about a third of the observed $PM_{2.5}$ decline. As in the case of the U.S. Clean Air Act (Sager and Singer, 2025), initially more polluted neighbourhoods saw the largest reductions, but, somewhat in contrast with this most recent evidence on the U.S., the differential improvement was too small to close the income or immigrant-share gaps.

The high decentralisation of the policy generates two findings that help explain this pattern. First, effects concentrate in cities supported by the national “Breathable in 5 years” programme, where additional funding and technical assistance assured effectiveness. Without this support from the national government, decentralised plans deliver no detectable reduction in $PM_{2.5}$, a result with broader implications for the design of devolved environmental regulation. Second, because cities choose which sectors to target, the aggregate effect can be decomposed into sectoral channels. Measures targeting the industrial and residential sectors predict larger reductions in high-immigrant neighbourhoods, while measures targeting agriculture predict the opposite, since rural neighbourhoods have the lowest shares of immigrants. The two patterns approximately offset, leaving the aggregate incidence rather flat in the case of income, but partly regressive in the case of immigrant share. This illustrates a more general point: because polluting sectors are not all located where exposed populations live, the distributional effects of an air quality policy depend on which sectors, hence which places, local governments choose to target.

Vulnerability to fine particulates is higher among less healthy individuals (Deryugina et al., 2019), and health correlates with both income and migration patterns. The persistent gaps in exposure documented here therefore imply that the health burden of fine particulate pollution falls highly disproportionately on lower-income, more immigrant-dense neighbourhoods. Individual sorting in response to changes in air quality has been shown to shape environmental disparities elsewhere (Depro et al., 2015), a dimension the present analysis leaves to further research. Whether the exposure disparities identified in this paper will erode through residential sorting depends on two elements. First, the response depends on the degree of capitalisation of air quality into housing prices. The latter is well documented in the United States (Chay and Greenstone, 2005; Bento et al., 2015; Sager and Singer, 2025) but less so in the French context, although available results suggest more limited reactions (Champalaune, 2025). Second, low-income and/or immigrant households are also the least likely to limit their exposure through residential mobility: immigrants in France have a high propensity to live and remain in public housing (Fougère et al., 2013; Verdugo, 2016), and low-income households more generally are less responsive to local amenity changes (Diamond, 2016). Together, these elements suggest that residential sorting alone is unlikely to close the exposure gaps documented here.

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# A Data Appendix

## A.1 Neighbourhood information

### A.1.1 Defining a consistent set of IRIS neighbourhoods

There are several issues arising with the use of a panel of yearly IRIS datasets:

1. Boundary changes;
2. Municipality mergers;
3. Creation of new neighbourhoods;
4. Provision of income data at the IRIS level only for municipalities with more than 10,000 inhabitants, and not for those with 5,000-10,000 inhabitants that are divided into IRIS

These issues are dealt with step by step. Regarding the first issue, I construct a matching file of IRIS identifiers for IRIS that changed boundaries over time. This is arguably not problematic *per se*, since, according to INSEE, IRIS boundaries changed only slightly over the period. Still, part of this work has to be performed by hand, due to missing conversion tables. The corresponding matching table is available upon request.

Second, there was a large wave of mergers of towns during the study period. A rather substantial fraction of these mergers occurred in 2015 and 2016, after the passing of a law that facilitated the creation of new merged cities during this period. This is particularly problematic since data for year $t$ is provided using the geographic breakdown of year $t + 2$. Other mergers occurred before 2015. In this case, it is not possible to only rely on a matching file. When towns are merged, it is the identifier of the chosen "head municipality" (*commune siège*) that becomes the identifier of the new merged town. As such, characteristics associated with the identifier before the merger are simply not comparable to characteristics associated with the same identifier after the merger. For these municipalities, I compute the weighted average of the characteristics of the merged municipalities prior to the merger, at the level of the new municipality.

Third, some municipalities were newly divided into IRIS during the period, and, fourth, for the 915 municipalities of 5,000-10,000 inhabitants, while I observe socio-demographic characteristics at the IRIS level, I observe income at the municipality level. In both cases, I eventually observe some characteristics at the municipality level, and some at the IRIS level. In such a case, I keep all variables at the municipality level, and compute weighted means of IRIS-level variables.

### A.1.2 Sample selection and neighbourhood typology

Table A.1 presents the different types of IRIS neighbourhoods, as identified by INSEE. The first two columns contain the whole set of IRIS, the third and fourth show the typology of sampled IRIS

Table A.1: Typology of sampled neighbourhoods

| Category | Full set of IRIS | | Sampled IRIS | | Large PPA zones | | Small PPA zones | |
|---|---|---|---|---|---|---|---|---|
| | Number | Percent | Number | Percent | Number | Percent | Number | Percent |
| Residential IRIS (H) | 11,801 | 25.2 | 11,635 | 29.1 | 8,474 | 73.8 | 1,094 | 54.4 |
| Municipality IRIS (Z) | 33,950 | 72.6 | 28,290 | 70.9 | 2,331 | 20.3 | 905 | 44.0 |
| Commercial IRIS (A) | 721 | 1.5 | | | 494 | 4.3 | 6 | 0.3 |
| Miscellaneous IRIS (D) | 280 | 0.6 | | | 181 | 1.6 | 5 | 0.2 |
| Urban | 19,000 | 40.6 | 17,806 | 44.6 | 10,605 | 92.4 | 1,580 | 78.6 |
| Rural | 27,752 | 59.4 | 22,119 | 55.4 | 875 | 7.6 | 419 | 20.8 |
| City centre | 7,947 | 36.7 | 7,222 | 18.1 | 3,985 | 34.7 | 984 | 49.0 |
| Suburban | 9,621 | 20.6 | 9,194 | 23.0 | 6,435 | 56.1 | 490 | 24.4 |
| Isolated | 1,432 | 3.1 | 1,390 | 3.5 | 185 | 1.6 | 106 | 5.3 |
| Rural | 27,752 | 40.6 | 22,119 | 55.4 | 875 | 7.6 | 419 | 20.8 |
| | 46,752 | | 39,925 | | 11,480 | | 2,010 | |

*Sources*: INSEE, PPA schemes.
*Notes*: The first typology is the following. Residential IRIS are census blocks that are home to 1,800 to 5,000 inhabitants, which are homogeneous in terms of housing. "Municipality IRIS" are census blocks that correspond to municipalities, because the municipality is not populated enough for it to be divided into smaller entities. Business IRIS cluster at least 1,000 workers, and at least twice as many workers as inhabitants. Miscellaneous IRIS are parks, forests, airports, large prison facilities...
The second and third typologies are linked as follows: rural blocks and (most) isolated ones are classified as rural, while suburban and central blocks are all classified as urban.

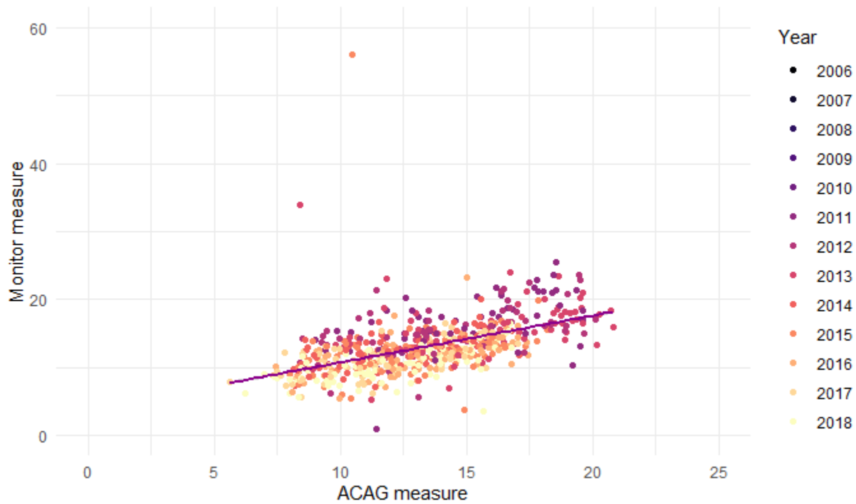
that the descriptive evidence focuses on, and the last four columns show the typology for large and small PPA zones.

To provide the descriptive evidence of Section 3, I select neighbourhoods for which I observe income in both 2006 and 2018, and drop non-residential neighbourhoods, that is, commercial and miscellaneous IRIS. In Section 6, I focus on neighbourhoods that are part of a large PPA zone (columns 5 and 6 of Table A.1) or a small PPA zone (columns 7 and 8 of Table A.1). Unsurprisingly, about 92% of neighbourhoods belonging to large PPA zones are urban, with 35% in city centres, and about 56% in suburbs. However, there are comparatively many more rural neighbourhoods in smaller PPA zones, with 79% only being urban.

## A.2 Fine particulate matter

I exploit reanalysis $PM_{2.5}$ gridded data throughout the paper, as it allows me to cover the entire French territory, at a fine scale, for the entire time period. In contrast, monitor data for this time period is scarce: 97 $PM_{2.5}$ monitors were in place during the study period, which is insufficient. Other gridded datasets, like those provided by INERIS on the basis of the CHIMERE air transport model, are of high quality, but they start in 2009, and thus would prevent me from properly assessing and controlling for pre-treatment trends.

Figure A.1: Monitor observation of $PM_{2.5}$ against ACAG measure




*Notes*: "Monitor measure" from the AASQA network. The "ACAG measure" is the one used in the main text to perform all analyses.

Fowlie et al. (2019) stress that satellite-based predictions of local air pollution, though more precise spatially and more reliable than monitor data, can suffer from measurement error, especially at extreme values. Given that the ACAG data I make use of is calibrated at the global level, and that France has intermediate levels of air pollution over the study period, this issue is not much of a concern here. If anything, this may slightly inflate standard errors, but has no effect on point estimates. To assuage concerns, I validate the data I use in the main text using these alternative sources, for the available time periods and locations.

***AASQA monitor data*** In France, local air quality is monitored by regional associations called AASQA. As part of the European-level air quality monitoring regulations, they transfer their data to the European Environment Agency (EEA). I thus extract the monitor data from the EEA website.[36] I start by aggregating the hourly or daily information to the yearly level. Then, I match each monitor to the neighbourhood it is located in. As shown in Figure A.1, the ACAG re-gridded estimates are very similar to the monitor measures; only two very strong outlying values are not captured. This corresponds to two events that are very local, both in space and in time, and thus does not pose a significant threat. If anything, this would imply that the effects identified in the PPA evaluation are slightly underestimated.

[36]The raw data, at the hourly or daily level (depending on years of collection) can be downloaded here: `https://eeadmz1-downloads-webapp.azurewebsites.net/`.

***INERIS gridded data*** As abovementioned, INERIS, the National institute for the industrial environment and risks, performs the same type of reanalysis as ACAG, but using the CHIMERE chemical air transport model, as opposed to Geos-CHEM for ACAG.[37] It would be appropriate to use these data in the French case, since they are specifically designed for it. However, they go much less far back in time, as they start in 2009. This would prevent me from controlling for as long a pre-treatment trend as with the ACAG data. Still, I provide a similar sanity check as with the monitor data above. Regressing the ACAG measure of $PM_{2.5}$ on the INERIS measure of $PM_{2.5}$, I get a coefficient of 0.872, and an $R^2$ of 0.834.

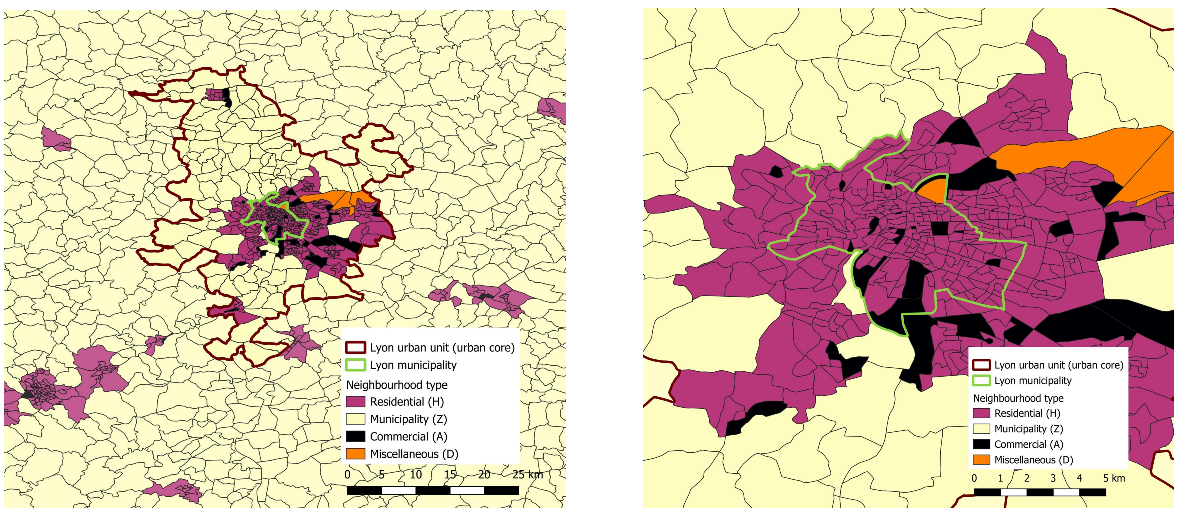
[37]The raw data can be visualised and downloaded here: `https://www.ineris.fr/fr/recherche-appui/risques-chroniques/mesure-prevision-qualite-air/qualite-air-france-metropolitaine`.

# B Appendix Figures

Figure B.1: Representation of the IRIS observation level: Focus on Lyon

(a) Lyon urban unit

(b) Zooming in

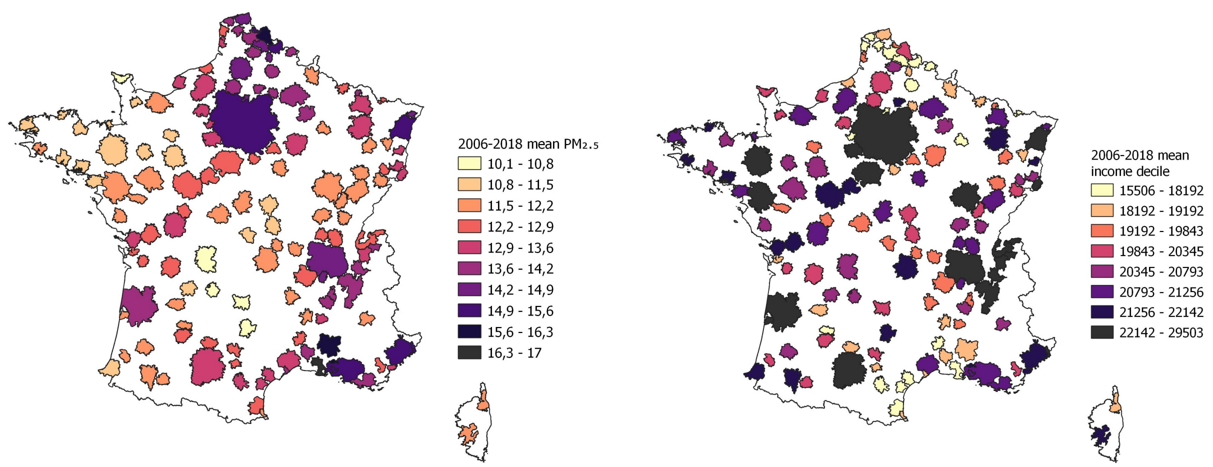



*Sources*: INSEE, IGN.
*Notes*: Panel (a) shows the delineation of the Lyon urban core in dark red. IRIS neighbourhoods are delineated in black. The municipality of Lyon, which is the central municipality of the city, is delineated in green in both panels. Panel (b) zooms into the municipality of Lyon to better show the size of urban IRIS neighbourhoods.
Residential IRIS are in dark pink: they are very small, always less than 1-km wide within the municipality. Commercial/industrial IRIS are in black. All IRIS in beige/light yellow are also municipalities. Miscellaneous IRIS are in orange. Miscellaneous IRIS include parks (like the large triangle-shaped neighbourhood in the north of the municipality of Lyon, visible in Panel (b))), or airports, like the large light orange neighbourhoods east of the municipality.

Figure B.2: $PM_{2.5}$ concentration and median income by decile – MSA level, 2006-2018

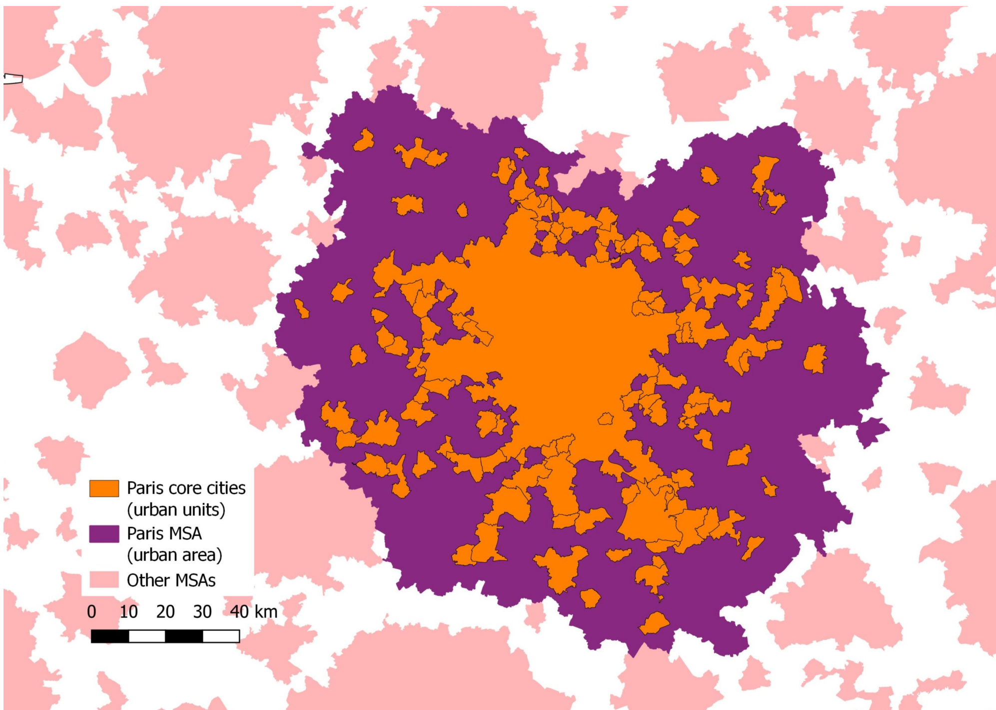
(a) $PM_{2.5}$ concentration

(b) Median income



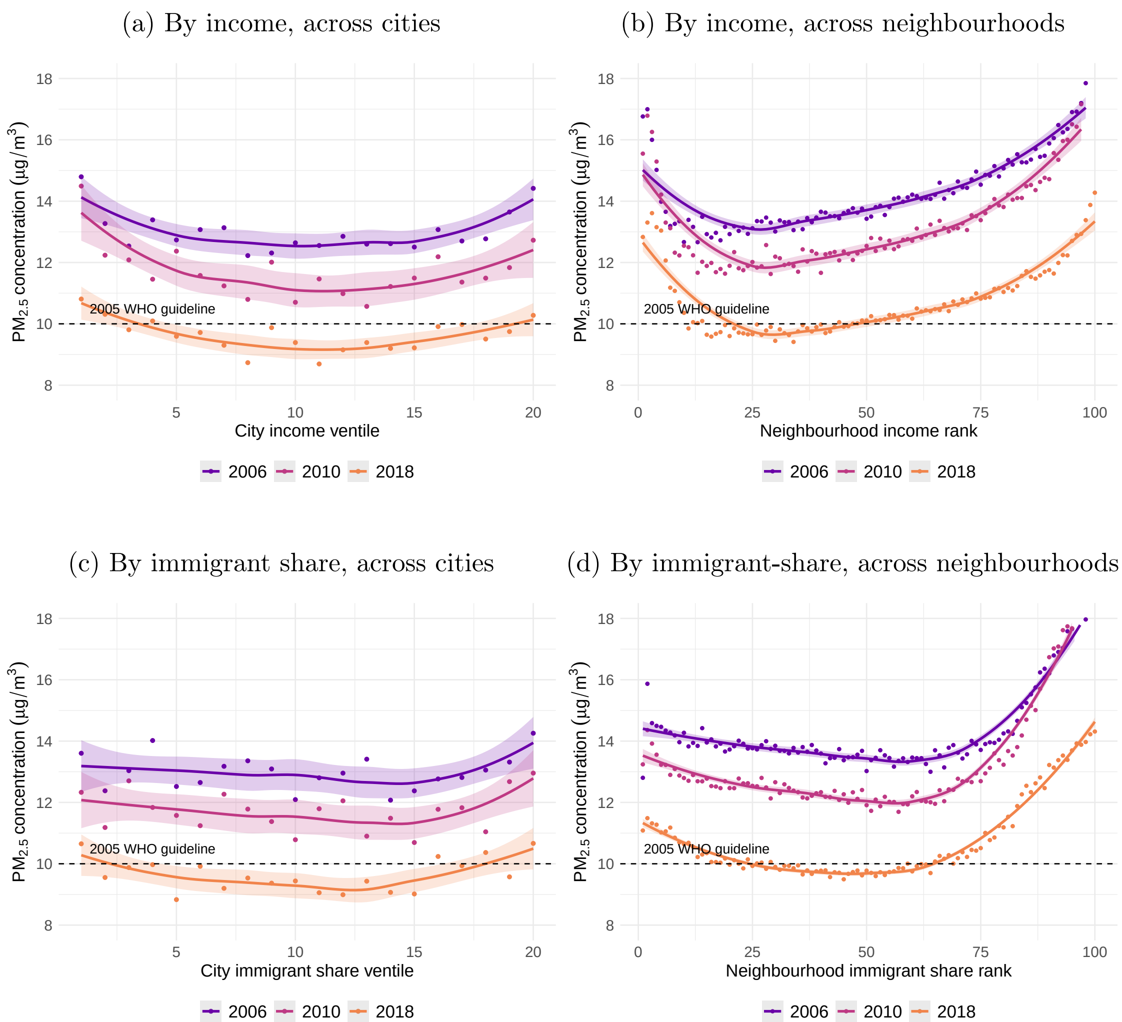

*Sources*: ACAG, INSEE, IGN.
*Notes*: Variables are defined using the mean over years 2006, 2010 and 2018. Some cities, in particular in the north, combine both a high level of local air pollution and low income. Paris, Lyon and the French Riviera are high-income and high-pollution areas.

Figure B.3: Urban area *versus* urban unit: Focus on Paris



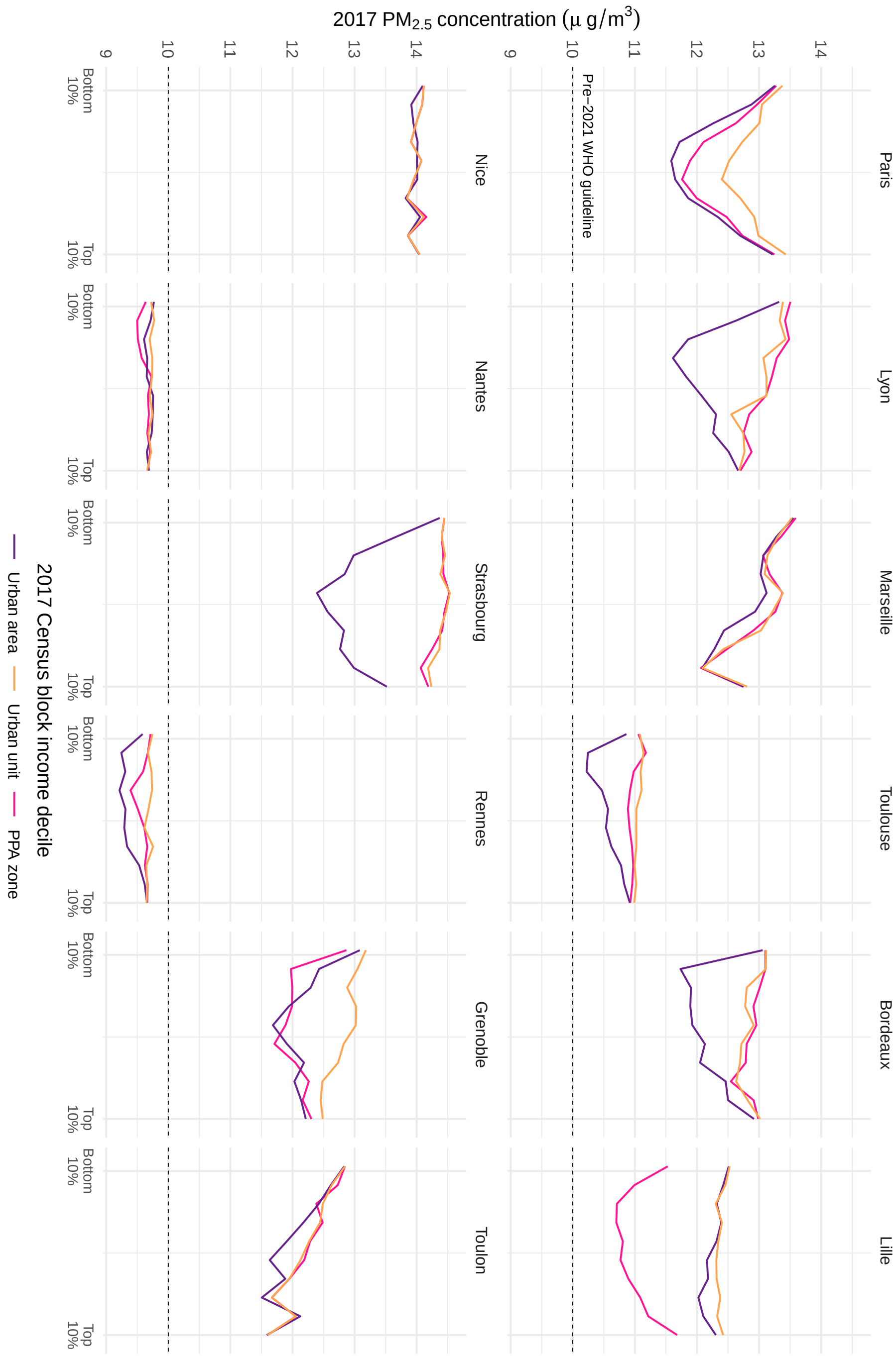

*Sources*: INSEE, IGN.
*Notes*: The map provides an illustration of the different city definitions used in Section 3. In orange, the "urban unit" (*unité urbaine*), or urban core, is a municipality or group of municipalities with a built-up area that is home to at least 2,000 inhabitants, where all housing units must have a nearest neighbour at no more than 200 metres. In addition, each municipality included in the urban unit must have at least half its population in this built-up area.
In orange, the "urban area", equivalent to the Metropolitan Statistical Area (MSA) in the U.S., includes the urban unit, but adds its periphery, or outer suburbs, to it. Outer suburbs are made up of municipalities located around the urban unit that fulfil the "built-up continuum" criterion, and in which at least 40% of the active population works in the urban unit (in orange).

Figure B.4: Gradients in $PM_{2.5}$ concentration by income and immigrant-share, no demeaning




*Sources*: ACAG, INSEE, IGN.
*Notes*: Panel (B.4a) and (B.4b) display the raw relationship between $PM_{2.5}$ concentration and income, at the urban area and neighbourhood level, respectively. Panel (B.4a) and (B.4b) display the raw relationship between $PM_{2.5}$ concentration and immigrant share, controlling for income, at the urban area and neighbourhood level, respectively.

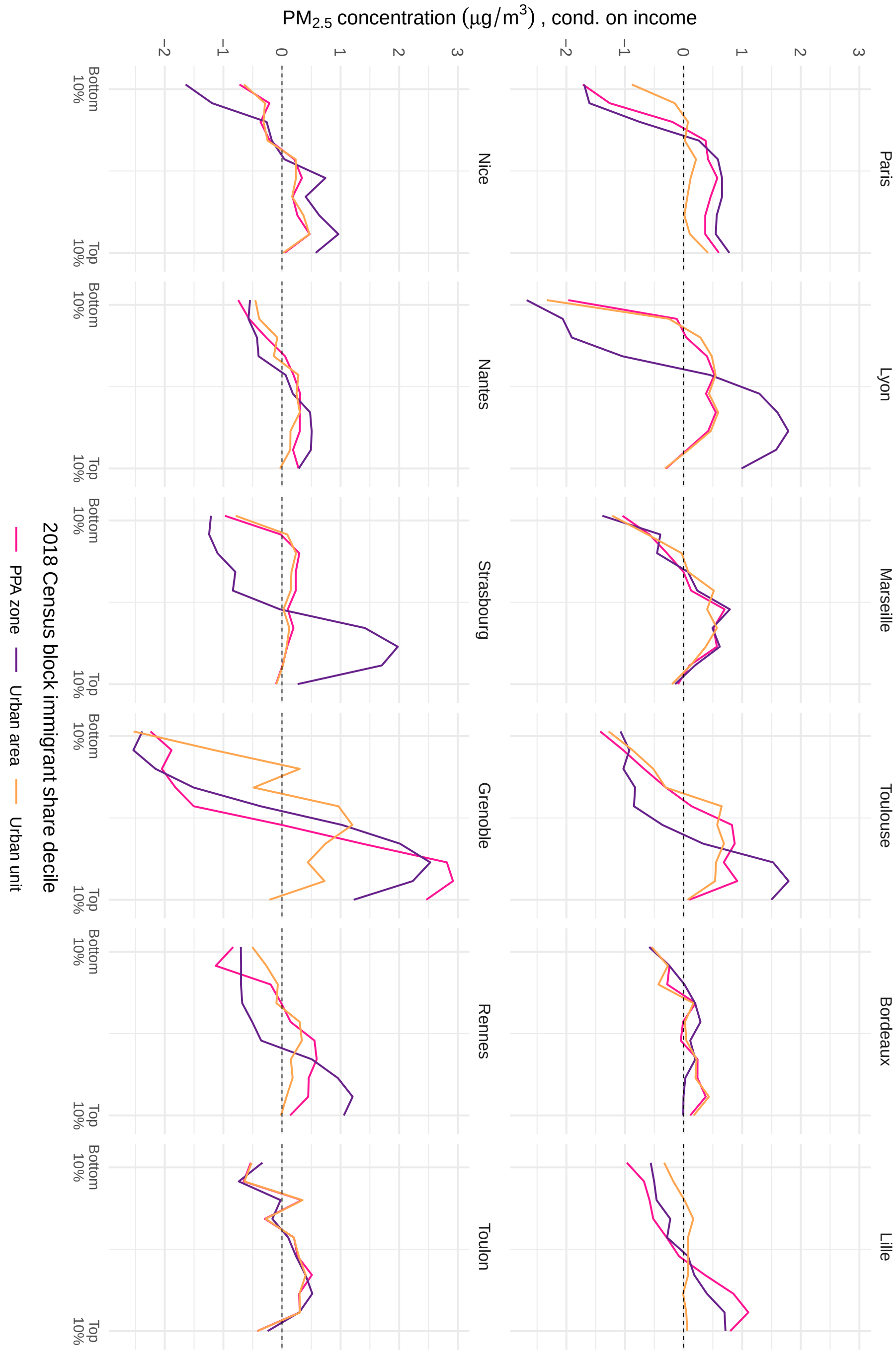
Figure B.5: 2018 average exposure to $PM_{2.5}$ by income decile – 12 largest urban areas




*Sources*: ACAG, INSEE, IGN.

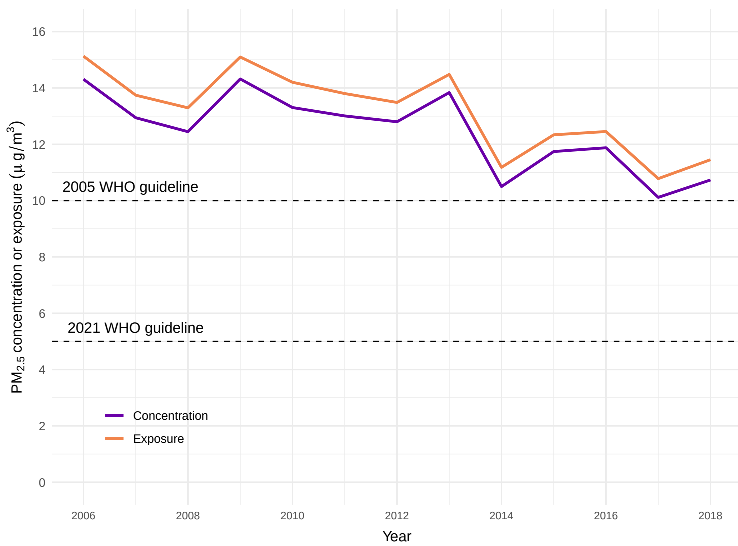
*Notes*: Each graph plots the average exposure by income decile for each urban area. The purple curve was obtained by focusing on the corresponding major city's urban area (MSA, *aire urbaine*, which includes outer suburbs). The orange curve was obtained by focusing on the urban unit (i.e., city centres and inner suburbs only, excluding outer suburbs) of the corresponding major city. The pink curve was obtained by focusing on the PPA zone of the corresponding major city. PPA zone perimeters are not necessarily comparable. In the case of Lille or Paris, it corresponds to the entire administrative region, which expands further into space than the cities themselves. In the case of Rennes or Lyon, it corresponds to the municipality federation ("EPCI"), hence the rough equivalence between the curves.

Figure B.6: 2018 average exposure to $PM_{2.5}$ by immigrant share, controlling for income – 12 largest urban areas




*Sources*: ACAG, INSEE, IGN.
*Notes*: Each graph plots the average exposure by decile of immigrant share for each urban area, controlling for neighbourhood income. The purple curve was obtained by focusing on the corresponding major city's urban area (MSA, *aire urbaine*, which includes outer suburbs). The orange curve was obtained by focusing on the urban unit (i.e., city centres and inner suburbs only, excluding outer suburbs) of the corresponding major city. The pink curve was obtained by focusing on the PPA zone of the corresponding major city.

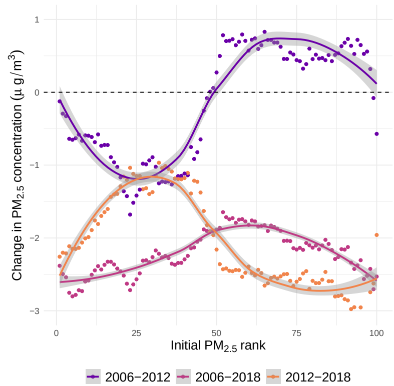
Figure B.7: Evolution of average exposure to $PM_{2.5}$ – 2006-2018



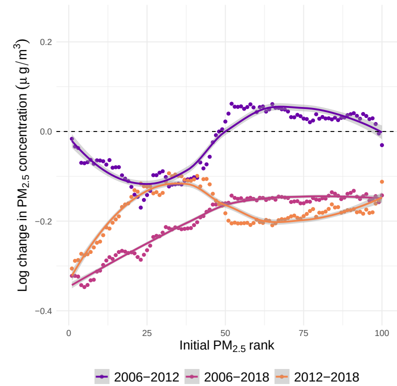

*Sources*: ACAG, INSEE, IGN.
*Notes*: "Concentration" is unweighted, while "exposure" is population-weighted concentration.

Figure B.8: Pollution-reduction profiles

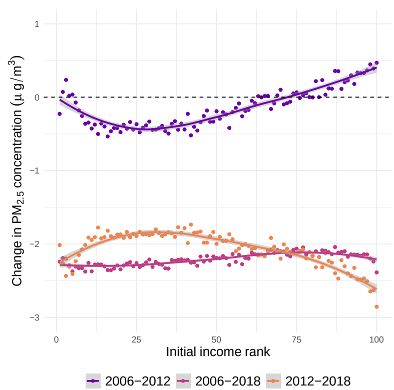
(a) Absolute Δ, by initial $PM_{2.5}$



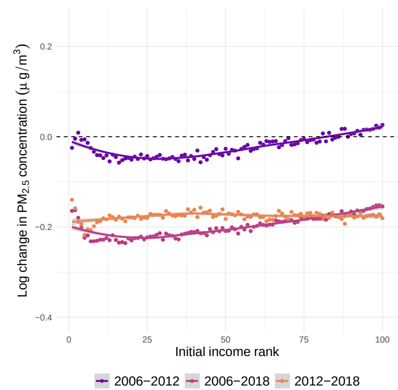

(b) Relative Δ, by initial $PM_{2.5}$



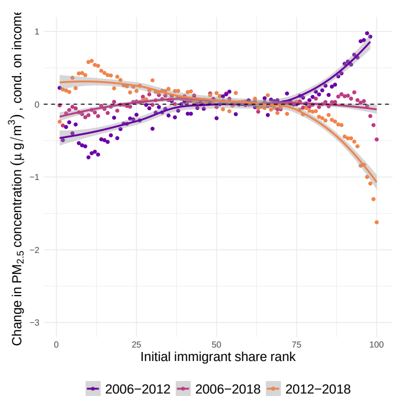

(c) Absolute Δ, by initial income



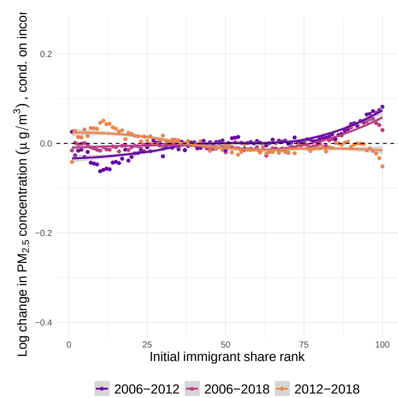

(d) Relative Δ, by initial income




(e) Absolute Δ, by initial immigrant share

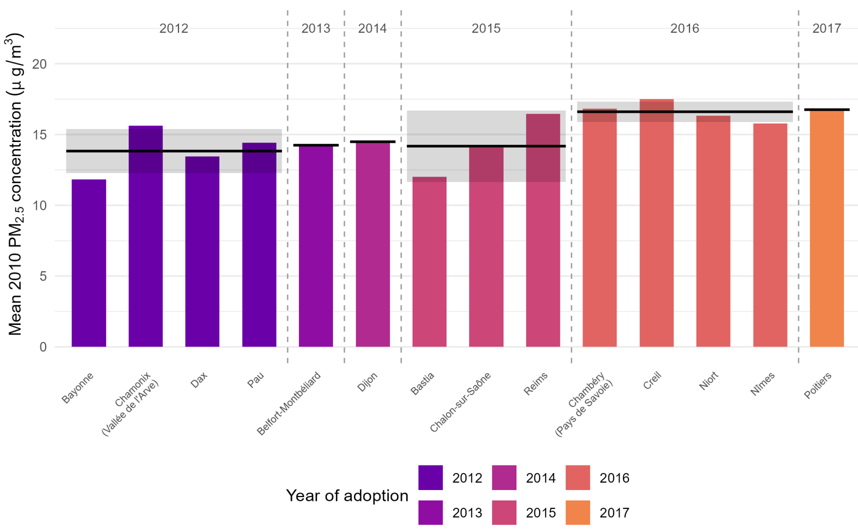



(f) Relative Δ, by initial immigrant share




*Sources*: ACAG, INSEE, IGN.
*Note*: For all periods, initial rank is defined as the centile in the 2006 distribution of IRIS $PM_{2.5}$ concentration (Panels B.8a and B.8b), income (Panels B.8c and B.8d) or immigrant shares (Panels B.8e and B.8f). Panels B.8e and B.8f control for initial differences in income across neighbourhoods.
Panels B.8a and B.8b show profiles that exhibit strong mean reversion: the most polluted neighbourhoods at baseline experienced the largest declines, while the least polluted saw little change. The horizontal profiles by income are much flatter: the change in $PM_{2.5}$ between 2006 and 2018 is broadly similar across income ranks, though slightly regressive in relative terms. Profiles by immigrant share, conditional on income, are also relatively flat over the full period, but the two sub-periods reveal an asymmetry: between 2006 and 2012, air quality deteriorated more in neighbourhoods with higher initial immigrant shares, while between 2012 and 2018 the pattern reversed, with these same neighbourhoods experiencing larger improvements. The two movements broadly cancel out over the full period.

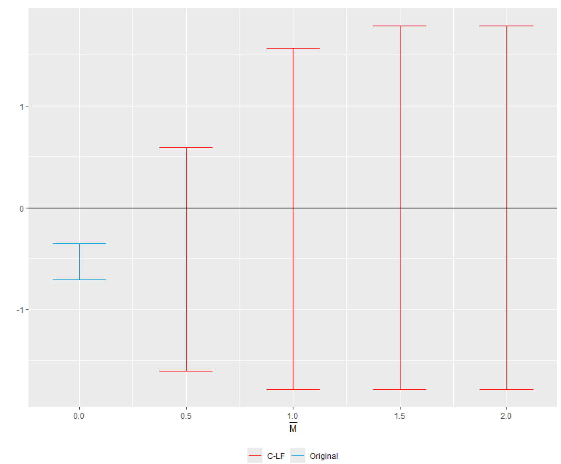
Figure B.9: Mean 2010 $PM_{2.5}$ concentration by year of PPA adoption – Small PPA zones



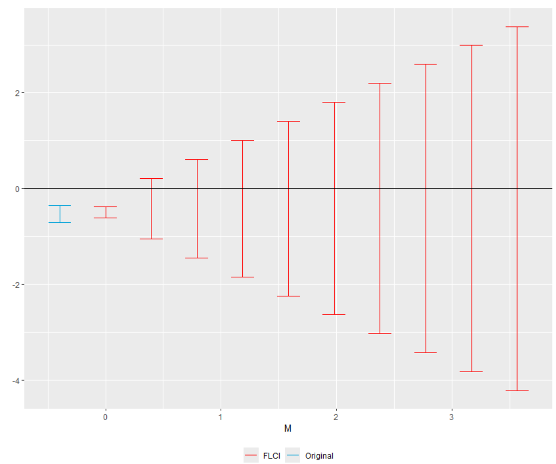

*Sources*: ACAG, IGN, PPA schemes.
*Note*: This graph groups city-level 2010 $PM_{2.5}$ concentrations by year of adoption. The black lines show the treatment cohort mean, with the corresponding 95% confidence interval as the shaded area.

Figure B.10: Pre-trend sensitivity tests - Full control group

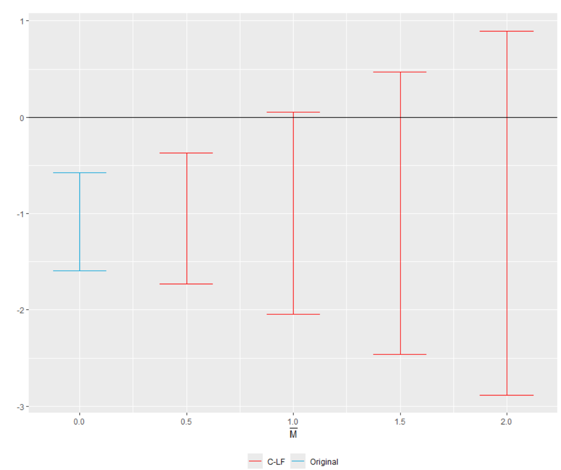
(a) CS2021, magnitude



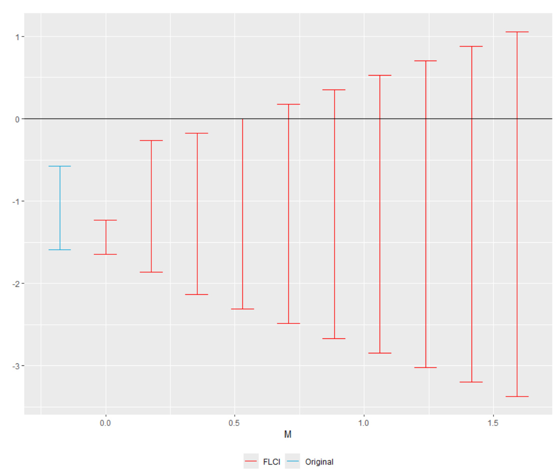

(b) CS2021, smoothness




(c) SA2021, magnitude



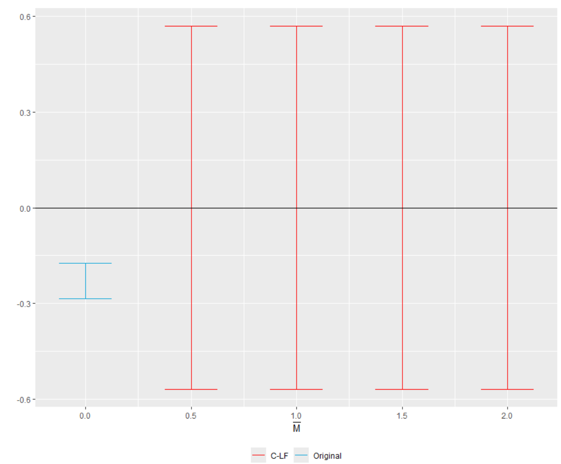

(d) SA2021, smoothness



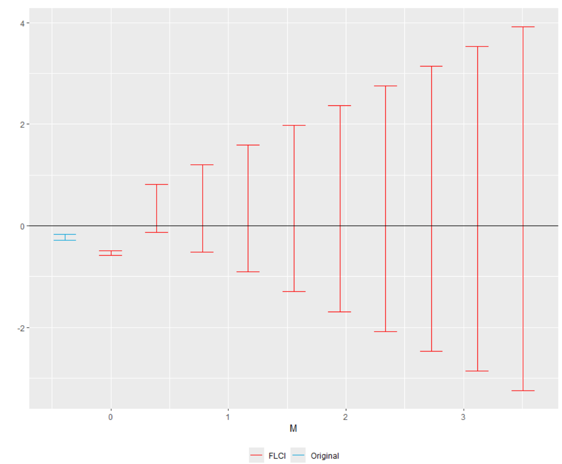

*Sources*: ACAG, INSEE, IGN, Copernicus CDS, PPA schemes.
*Notes*: Relative magnitude sensitivity analysis in Panels (a) and (b), and sensitivity analysis based on smoothness restrictions in Panels (c) and (d), based on Rambachan and Roth (2023) Honest DiD, for estimates shown in Figures 6 and B.12, using the full control group, which includes never-treated cities. CS2021 refers to the method by Callaway and Sant'Anna (2021), and SA2021 refers to that of Sun and Abraham (2021).

Figure B.11: Pre-trend sensitivity tests - Main results: Not-yet-treated control group only

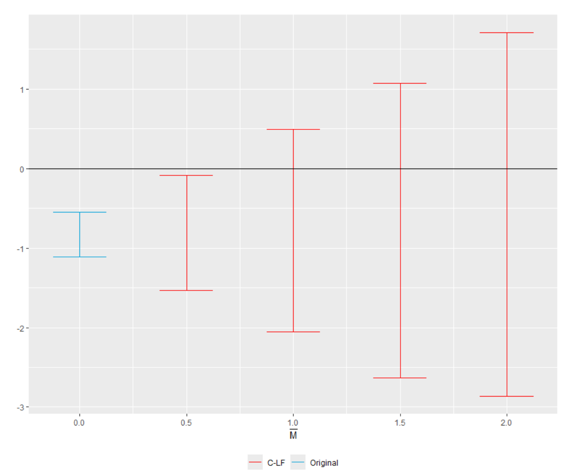
(a) CS2021, magnitude



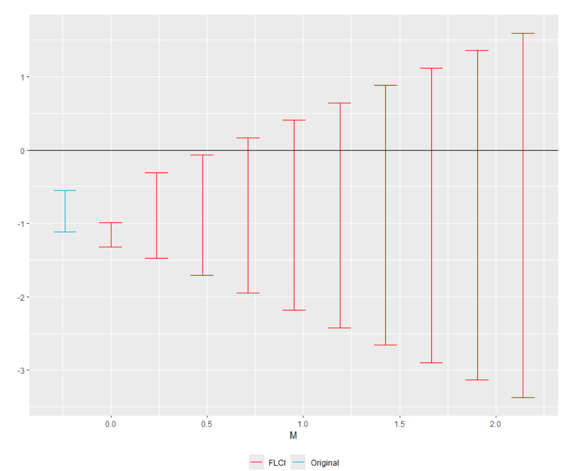

(b) CS2021, smoothness




(c) SA2021, magnitude

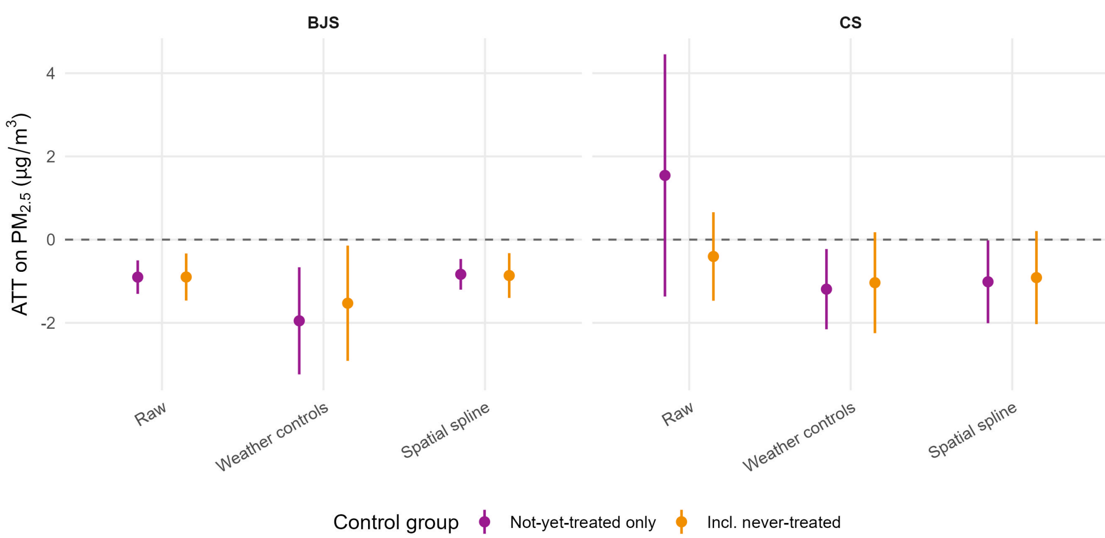



(d) SA2021, smoothness




*Sources*: ACAG, INSEE, IGN, Copernicus CDS, PPA schemes.
*Notes*: Relative magnitude sensitivity analysis in Panels (a) and (c), and sensitivity analysis based on smoothness restrictions in Panels (b) and (d), based on Rambachan and Roth (2023) Honest DiD, for estimates shown in Figures 6 and B.12, using the not-yet-treated control group. CS2021 refers to the method by Callaway and Sant'Anna (2021), and SA2021 refers to that of Sun and Abraham (2021).

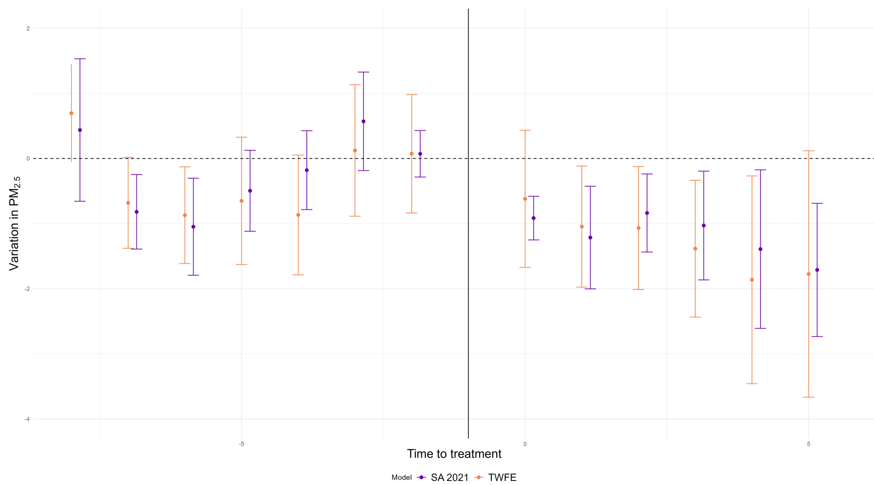
Figure B.12: Robustness of main effects to estimator use



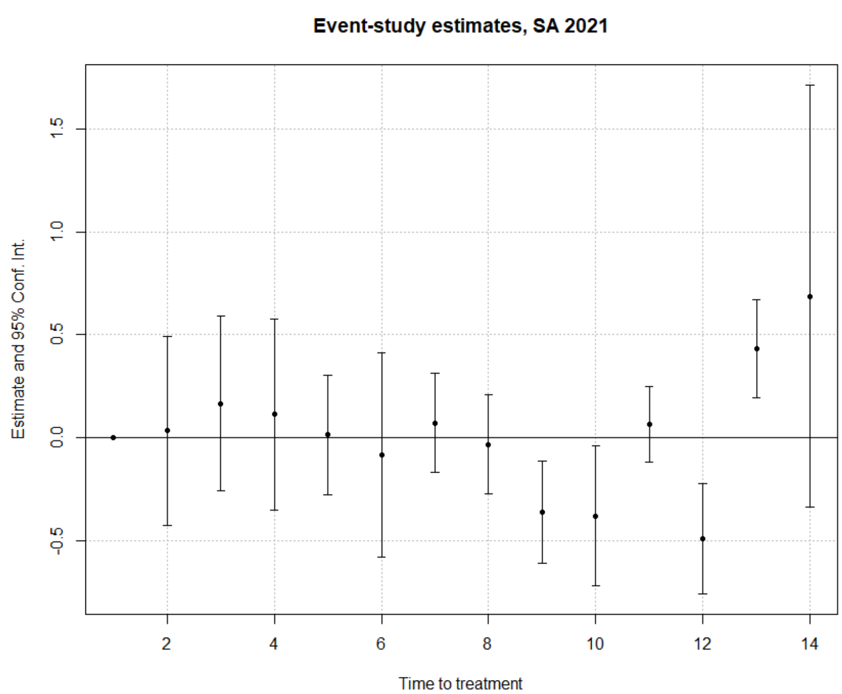

*Sources*: ACAG, INSEE, IGN, Copernicus CDS, PPA schemes.
*Notes*: Standard errors clustered at the ZAS level in parentheses. $^{*}$ $p < .10$, $^{**}$ $p < .05$, $^{***}$ $p < .01$.
Estimates of coefficients $\mu_\tau$ in equation (2) using only not-yet-treated units as the control group in purple, and the full control group including both not-yet- and never-treated units in orange. Graphs on the left-hand side use the BJS estimator while those on the right-hand side use the CS estimator. The vertical bars correspond to the 95% confidence interval. When a spatial spline is used in combination with the estimator, it enters a first-stage regression that residualises $PM_{2.5}$ levels: the results shown are from a second-stage regression where the dependent variable is residualised $PM_{2.5}$, and standard errors are estimated using 200 bootstrap draws.

Figure B.13: Event-study estimates of the effects of PPA revision

(a) Large PPA zones




(b) Small PPA zones




*Sources*: ACAG, INSEE, IGN, Copernicus CDS, PPA schemes.
*Note*: Estimates of coefficients $\mu_\tau$ in equation (2) using the full control group, which includes both not-yet-treated and never-treated cities. The vertical bars correspond to the 95% confidence interval.

# C Appendix Tables

Table C.1: List of observed neighbourhood characteristics

| Category | Variable |
|---|---|
| *Education* | Share of population with at least some tertiary education ("high-skill") |
| *Occupation* | Share of population aged 15+ by occupation:<br>1) Farmers<br>2) Craftsmen, tradesmen, business managers (excl. licensed professionals)<br>3) White-collar jobs: executives and other intellectual professions<br>4) Intermediary: Technicians, foremen, school teachers, nurses, intermediary public servant occupations, and other intermediary occupations<br>5) Employees: Lower civil servant positions, policemen, military, intermediary administrative positions, service workers, and other employees (excluded to avoid multicollinearity)<br>6) Blue-collar jobs: Industrial and craft workers, agricultural workers, drivers, and other blue-collar jobs<br>7) Retired<br>8) Others without occupation: unemployed who never worked, students |
| *Housing* | Share of inhabitants that are homeowners<br>Share of population that live in social housing (HLM)<br>Share of dwellings with all-electric heating |
| *Deprivation measures* | Share of unemployed in population aged 15-64<br>Share of population that live in single-parent households |
| *Age structure* | Share of population between 0 and 5 years old<br>Share of population above 80 years old |

Table C.2: Summary statistics of all variables, IRIS level – Full sample, 2006-2018

| | Mean | SD | Minimum | 1$^{st}$ quartile | Median | 3$^{rd}$ quartile | Maximum |
|---|---|---|---|---|---|---|---|
| $PM_{2.5}$ concentration (µg/m$^3$) | 12.99 | 2.59 | 6.61 | 11.03 | 12.84 | 14.68 | 22.70 |
| Population | 1555.32 | 1537.64 | 77 | 374 | 1042 | 2324 | 25681 |
| Area (km$^2$) | 12.43 | 16.31 | 0.02 | 1.68 | 8.39 | 16.47 | 455.37 |
| Median income (2019 euros) | 20970.78 | 5231.92 | 1678.90 | 18078.84 | 20325.76 | 23065.60 | 73770.40 |
| % Immigrants | 0.07 | 0.07 | 0.00 | 0.02 | 0.04 | 0.08 | 0.79 |
| % Electric heating | 0.25 | 0.14 | 0.00 | 0.15 | 0.24 | 0.33 | 0.96 |
| Distance to major road (km) | 13319.58 | 22354.44 | 0.31 | 2417.51 | 7514.24 | 18007.17 | 294849.99 |
| # polluting plants within 5 km | 4.05 | 4.03 | 1 | 1 | 2 | 5 | 32 |
| % < 5 years old | 0.07 | 0.02 | 0.00 | 0.06 | 0.07 | 0.08 | 0.27 |
| % > 65 years old | 0.21 | 0.08 | -0.08 | 0.16 | 0.20 | 0.26 | 0.70 |
| % Unemployed | 0.08 | 0.04 | 0.00 | 0.06 | 0.07 | 0.10 | 0.53 |
| % Tertiary educated | 0.24 | 0.12 | 0.00 | 0.16 | 0.21 | 0.28 | 0.85 |
| % Farmers | 0.02 | 0.04 | 0.00 | 0.00 | 0.01 | 0.03 | 0.54 |
| % Crafts-/Tradesmen | 0.04 | 0.03 | 0.00 | 0.02 | 0.03 | 0.05 | 0.32 |
| % White-collar | 0.07 | 0.07 | 0.00 | 0.03 | 0.05 | 0.09 | 0.55 |
| % Intermediary occ. | 0.13 | 0.05 | 0.00 | 0.10 | 0.13 | 0.17 | 0.47 |
| % Employees | 0.16 | 0.05 | 0.00 | 0.13 | 0.16 | 0.19 | 0.73 |
| % Blue-collar | 0.14 | 0.07 | 0.00 | 0.10 | 0.14 | 0.19 | 0.57 |
| % Retired | 0.28 | 0.09 | 0.00 | 0.22 | 0.27 | 0.34 | 0.90 |
| % Inactive excl. retired | 0.15 | 0.06 | 0.00 | 0.11 | 0.14 | 0.17 | 0.86 |
| % Homeowners | 0.70 | 0.21 | 0.00 | 0.62 | 0.77 | 0.84 | 1 |
| % Social housing | 0.10 | 0.18 | 0.00 | 0.00 | 0.02 | 0.10 | 1 |
| % Single-parent | 0.09 | 0.05 | 0.00 | 0.05 | 0.08 | 0.12 | 0.52 |

*Notes*: Data from ACAG (row 1), INSEE (rows 2, 4-6, 9-22), IGN (rows 3, 7) and PRTR (row 8). Full sample includes all IRIS neighbourhoods classified as type "H" (residential) or type "Z" (municipality) for which income is observed in both 2006 and 2018.

Table C.3: Within-city relationships between $PM_{2.5}$ concentration and income and share of immigrants, weighted by population

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | | | | *Focus on income* | | | | |
| (log) median income | 0.0107 | -0.0589*** | -0.0495*** | -0.587*** | -0.0363*** | -0.0300** | -0.0495*** | -0.0200** |
| | (0.0076) | (0.0157) | (0.0123) | (0.0016) | (0.0062) | (0.0117) | (0.0124) | (0.0083) |
| % electric heating | | | | | -0.0192 | | | -0.0191* |
| | | | | | (0.0253) | | | (0.0112) |
| (log) # plants within 5 km | | | | | | 0.0475*** | | 0.0492*** |
| | | | | | | (0.0067) | | (0.0063) |
| (log) distance to major road (km) | | | | | | | 0.0007 | -0.00005 |
| | | | | | | | (0.0006) | (0.0005) |
| $R^2$ | 0.154 | 0.837 | 0.885 | 0.885 | 0.884 | 0.894 | 0.885 | 0.893 |
| | | | | *Focus on share of immigrants* | | | | |
| % immigrants | 0.7935*** | 0.9227*** | 0.5699*** | 0.4023*** | 0.3748*** | 0.2201*** | 0.4023*** | 0.1824*** |
| | (0.0344) | (0.0445) | (0.0179) | (0.0122) | (0.0123) | (0.0099) | (0.0122) | (0.0076) |
| % electric heating | | | | | -0.0183*** | | | -0.0175*** |
| | | | | | (0.0022) | | | (0.0021) |
| (log) # plants within 5 km | | | | | | 0.0434*** | | 0.0454*** |
| | | | | | | (0.0016) | | (0.0018) |
| (log) distance to major road (km) | | | | | | | 0.0007*** | 0.00001 |
| | | | | | | | (0.00005) | (0.00005) |
| Control for income | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.56345 | 0.57075 | 0.85262 | 0.89125 | 0.88909 | 0.89917 | 0.89126 | 0.89615 |
| MSA fixed effect | | Yes | | | | | | |
| Core-MSA fixed effect | | | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effect | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Weather controls | | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $s(\text{lon}_i,\ \text{lat}_i)$ | | | | Yes | | | | |
| Observations | 227,106 | 227,106 | 227,106 | 34,988 | 227,106 | 227,106 | 227,106 | 227,106 |

*Sources*: ACAG, INSEE, IGN.
*Notes*: Standard errors clustered at the city level in parentheses. Signif. codes: ***: 0.01, **: 0.05, *: 0.1.
Weather controls include mean summer temperature, mean winter temperature, mean precipitation and mean cloud cover. MSAs are INSEE's definition of urban areas, and Core-MSAs are INSEE's definition of urban "units", which comprise the city centre and inner suburbs.

Table C.4: Additional correlates of $PM_{2.5}$ concentration

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| (log) median income | -0.0759*** | -0.0394*** | -0.0640*** | -0.0222*** | -0.1245*** | -0.1110*** | -0.0495*** | -0.0110*** |
| | (0.0017) | (0.0030) | (0.0021) | (0.0015) | (0.0042) | (0.0035) | (0.0050) | (0.0020) |
| % immigrants | | | | 0.4023*** | | | | 0.3989*** |
| | | | | (0.0122) | | | | (0.0123) |
| % < 5 years old | -0.5307*** | | -0.5580*** | | | | | |
| | (0.0257) | | (0.0235) | | | | | |
| % > 65 years old | 0.0538** | | 0.0494** | | | | | |
| | (0.0204) | | (0.0201) | | | | | |
| % single-parent households | | 0.0915*** | 0.1153*** | | | | | |
| | | (0.0132) | (0.0129) | | | | | |
| % tertiary-educated | | | | | 0.2357*** | | | |
| | | | | | (0.0078) | | | |
| % high-skilled | | | | | | 0.3748*** | 0.3086*** | |
| | | | | | | (0.0125) | (0.0125) | |
| % unemployed | | | | | | | 0.4817*** | |
| | | | | | | | (0.0260) | |
| Observations | 227,106 | 227,106 | 227,106 | 227,106 | 227,106 | 227,106 | 227,106 | 227,106 |
| $R^2$ | 0.88906 | 0.88801 | 0.88923 | 0.89125 | 0.89225 | 0.89116 | 0.89262 | 0.89135 |
| Within $R^2$ | 0.14383 | 0.13568 | 0.14510 | 0.16072 | 0.16841 | 0.16003 | 0.17126 | 0.16146 |

*Sources*: ACAG, INSEE, IGN.

Table C.5: Sample of large PPA zones

| Year | Zone | # IRIS | # Municipalities | Surface area (km$^2$) | 2010 population | $PM_{2.5}$ | Breathable city |
|---|---|---|---|---|---|---|---|
| 2012 | Bordeaux | 271 | 53 | 925 | 816,331 | 17.99 | Yes |
| | | 271 | 53 | 925 | 816,331 | 17.99 | |
| 2013 | Marseille (Bouches-du-Rhône) | 668 | 113 | 4,557 | 1,852,642 | 17.23 | No |
| | Nice (Alpes-Maritimes du Sud) | 345 | 52 | 713 | 939,864 | 16.05 | Yes |
| | Paris (Île-de-France) | 4,738 | 1,222 | 11,257 | 11,619,868 | 19.08 | Yes |
| | Toulon | 199 | 26 | 619 | 538,973 | 15.26 | No |
| | | 5,950 | 1,413 | 17,146 | 14,951,347 | 16.91 | |
| 2014 | Avignon | 84 | 22 | 473 | 268,758 | 19.13 | Yes |
| | Clermont-Ferrand | 84 | 22 | 267 | 275,218 | 14.81 | No |
| | Grenoble | 381 | 255 | 3,504 | 739,424 | 16.75 | Yes |
| | Lille (Nord-Pas-de-Calais) | 2,167 | 1,431 | 11,963 | 3,983,717 | 17.06 | Yes |
| | Lyon | 497 | 115 | 1,076 | 1,473,353 | 18.87 | Yes |
| | Montpellier | 195 | 107 | 1,548 | 538,448 | 14.98 | Yes |
| | Orléans | 93 | 22 | 322 | 267,653 | 15.89 | No |
| | Rouen (Haute-Normandie) | 1,453 | 1,177 | 11,716 | 1,799,768 | 15.85 | Yes |
| | Saint-Étienne | 167 | 55 | 764 | 434,407 | 15.55 | Yes |
| | Strasbourg | 162 | 28 | 279 | 456,317 | 18.35 | Yes |
| | Tours | 138 | 40 | 828 | 354,728 | 15.81 | No |
| | | 5,421 | 3,274 | 32,740 | 10,591,791 | 16.64 | |
| 2015 | Metz (Trois Vallées) | 163 | 67 | 465 | 438,735 | 15.75 | No |
| | Nancy | 103 | 38 | 307 | 327,940 | 15.88 | No |
| | Nantes | 255 | 58 | 1,650 | 781,874 | 14.79 | No |
| | Rennes | 134 | 43 | 668 | 403,276 | 13.75 | No |
| | | 655 | 206 | 3,090 | 1,951,825 | 15.04 | |
| 2016 | Toulouse | 315 | 113 | 1,128 | 919,239 | 16.15 | Yes |
| | | 315 | 113 | 1,128 | 919,239 | 16.15 | |
| **Total over large PPA zones** | | **12,612** | **5,059** | **55,029** | **29,230,533** | 16.43 | |
| % of metropolitan France | | 27% | 15% | 10% | 47% | | |

*Sources*: ACAG, INSEE, IGN, PPA schemes, Ministry of Ecology.
*Notes*: For convenience, PPA zones that cover large (administrative) regions are called by the name of the largest city they cover; their actual name is given in parentheses.

Table C.6: Sample of small PPA zones

| Year | Zone | # IRIS | # Municipalities | Surface area (km$^2$) | 2010 population | $PM_{2.5}$ | Breathable city |
|---|---|---|---|---|---|---|---|
| 2012 | Bayonne | 66 | 18 | 298 | 189,255 | 11.8 | Yes |
| | Chamonix (Vallée de l'Arve) | 58 | 41 | 1,236 | 152,719 | 15.53 | Yes |
| | Dax | 30 | 19 | 342 | 53,227 | 13.42 | No |
| | Pau | 60 | 22 | 269 | 164,093 | 14.44 | No |
| | | 214 | 100 | 2,145 | 559,294 | 13.8 | |
| 2013 | Belfort | 220 | 180 | 1,169 | 300,629 | 14.16 | No |
| | | 220 | 180 | 1,169 | 300,629 | 14.16 | |
| 2014 | Dijon | 87 | 15 | 151 | 230,098 | 14.55 | Yes |
| | | 87 | 15 | 151 | 230,098 | 14.55 | |
| 2015 | Bastia | 24 | 11 | 228 | 80,225 | 11.9 | No |
| | Chalon-sur-Saône | 26 | 9 | 79 | 70,092 | 13.94 | No |
| | Reims | 89 | 15 | 142 | 211,512 | 16.5 | Yes |
| | | 139 | 35 | 449 | 361,829 | 14.11 | |
| 2016 | Chambéry | 48 | 24 | 263 | 122,670 | 16.94 | No |
| | Creil | 52 | 29 | 192 | 130,839 | 17.9 | No |
| | Niort | 48 | 27 | 528 | 102,216 | 16.31 | No |
| | Nîmes | 143 | 78 | 1,654 | 355,992 | 15.89 | No |
| | | 291 | 158 | 2,637 | 711,717 | 16.76 | |
| 2017 | Poitiers | 45 | 13 | 257 | 135,150 | 16.73 | No |
| | | 45 | 13 | 257 | 135,150 | 16.73 | |
| **Total over small PPA zones** | | **996** | **501** | **6,808** | **2,298,717** | 15 | |
| % of metropolitan France | | 2% | 1% | 1% | 4% | | |

*Sources*: ACAG, INSEE, IGN, PPA schemes, Ministry of Ecology.
*Notes*: For convenience, PPA zones that cover large (administrative) regions are called by the name of the largest city they cover; their actual name is given in parentheses.

Table C.7: Sample of never-treated cities

| ZAR | # IRIS | # Municipalities | Surface area | 2010 population | $PM_{2.5}$ |
|---|---|---|---|---|---|
| Ajaccio | 54 | 32 | 1,080 | 95,389 | 12.02 |
| Amiens$^{\dagger}$ | 83 | 33 | 298 | 168,670 | 18.36 |
| Angers | 97 | 27 | 539 | 264,242 | 14.81 |
| Besançon | 94 | 49 | 390 | 172,045 | 14.44 |
| Blois | 74 | 56 | 1,176 | 122,869 | 15.33 |
| Brest | 159 | 85 | 1,634 | 381,732 | 13.07 |
| Caen | 97 | 38 | 249 | 238,206 | 14.25 |
| Chartres-Dreux$^{\dagger}$ | 152 | 113 | 1,541 | 217,857 | 16.36 |
| Fréjus-Draguignan$^{\dagger}$ | 78 | 27 | 1,178 | 240,158 | 13.45 |
| Laval | 38 | 20 | 436 | 95,451 | 13.62 |
| Le Mans | 80 | 14 | 201 | 195,340 | 14.33 |
| Limoges | 84 | 27 | 644 | 214,665 | 14.31 |
| Moulins$^{\dagger}$ | 18 | 7 | 173 | 39,470 | 13.64 |
| Perpignan | 87 | 38 | 645 | 257,974 | 13.46 |
| Vallée de la Tarentaise | 28 | 23 | 442 | 54,351 | 15.93 |
| Vallée du Rhône$^{\dagger}$ | 167 | 108 | 1,713 | 398,996 | 16.49 |
| **Full control group** | **1,390** | **697** | **12,339** | **3,157,415** | 14.62 |
| % of metropolitan France | 3% | 2% | 2% | 5% | |

*Sources*: ACAG, INSEE, IGN.
*Notes*: The never-treated control group excludes cities marked with a $^{\dagger}$, since prevailing wind patterns are such that their air quality is likely contaminated by that of nearby treated cities. Amiens is located right between the Lille (Nord-Pas-de-Calais) region and the Paris region, Chartres-Dreux is adjacent to Paris (Île-de-France), Fréjus-Draguignan is adjacent to Marseille (Bouches-du-Rhône), and Valence-Montélimar (Vallée du Rhône) is located right south of Lyon. I also exclude Moulins, which is much too small (only 18 observations a year and 40,000 inhabitants).

Table C.8: Summary statistics – Large and small PPA zones and never-treated cities, 2010

| Variable | Mean | SD | Minimum | 1st quartile | Median | 3rd quartile | Maximum |
|---|---|---|---|---|---|---|---|
| | | | | *Large PPA zones* | | | |
| $PM_{2.5}$ concentration (µg/m$^3$) | 16.95 | 4.01 | 7.60 | 13.30 | 17.85 | 20.50 | 22.70 |
| Population | 2317.676 | 1508.474 | 117 | 1,484 | 2,230 | 2881.25 | 14,484 |
| Area (km$^2$) | 4.363 | 8.567 | 0.018 | 0.243 | 0.764 | 6.184 | 371.032 |
| Median income (2019 euros) | 22542.151 | 7160.265 | 2647.7 | 18136.25 | 21839.4 | 26,103 | 66287.102 |
| % Immigrants | 0.106 | 0.094 | 0 | 0.034 | 0.078 | 0.154 | 0.606 |
| % < 5 years old | 0.077 | 0.023 | 0.008 | 0.062 | 0.076 | 0.091 | 0.203 |
| % > 65 years old | 0.168 | 0.068 | -0.05 | 0.123 | 0.163 | 0.207 | 0.561 |
| % Unemployed | 0.085 | 0.041 | 0 | 0.056 | 0.076 | 0.104 | 0.351 |
| % Tertiary educated | 0.295 | 0.155 | 0.008 | 0.176 | 0.26 | 0.381 | 0.811 |
| Distance to major road (km) | 13.27 | 22.32 | 1.407 | 2.409 | 7.484 | 17.82 | 283.3 |
| # polluting plants within 5 km | 5.74 | 4.793 | 1 | 2 | 4 | 8 | 26 |
| Part of Breathable city program | 0.395 | | | | | | |
| | | | | *Small PPA zones* | | | |
| $PM_{2.5}$ concentration (µg/m$^3$) | 15.058 | 1.646 | 10.135 | 14.135 | 14.7 | 16.449 | 19.4 |
| Population | 2307.949 | 1541.858 | 139 | 1335.75 | 2,136 | 2,931 | 10,446 |
| Area (km$^2$) | 6.836 | 13.318 | 0.049 | 0.443 | 2.703 | 8.574 | 245.038 |
| Median income (2019 euros) | 20811.14 | 4616.985 | 4049.1 | 18856.201 | 21512.7 | 23625.8 | 35891.90 |
| % Immigrants | 0.08 | 0.071 | 0 | 0.038 | 0.059 | 0.092 | 0.501 |
| % < 5 years old | 0.07 | 0.023 | 0.019 | 0.056 | 0.068 | 0.082 | 0.192 |
| % > 65 years old | 0.192 | 0.072 | 0 | 0.142 | 0.187 | 0.235 | 0.513 |
| % Unemployed | 0.087 | 0.047 | 0.014 | 0.057 | 0.077 | 0.104 | 0.391 |
| % Tertiary educated | 0.253 | 0.099 | 0.029 | 0.183 | 0.245 | 0.311 | 0.633 |
| Distance to major road (km) | 13.25 | 19.83 | 0.006 | 2.603 | 8.248 | 18.50 | 217.3 |
| # polluting plants within 5 km | 5.206 | 4.498 | 1 | 1 | 4 | 8 | 22 |
| Part of Breathable city program | 0.23 | | | | | | |
| | | | | *Never-treated cities* | | | |
| $PM_{2.5}$ concentration (µg/m$^3$) | 11.859 | 2.623 | 7.187 | 8.830 | 12.581 | 13.862 | 16.459 |
| Population | 2267.826 | 1466.633 | 141 | 1291.25 | 2,136 | 2853.75 | 11,263 |
| Area (km$^2$) | 9.532 | 13.137 | 0.056 | 0.571 | 4.978 | 13.646 | 128.667 |
| Median income (2019 euros) | 21172.568 | 4673.461 | 2,541 | 19160.626 | 21561.649 | 23756.701 | 45233.102 |
| % Immigrants | 0.068 | 0.067 | 0 | 0.026 | 0.046 | 0.084 | 0.473 |
| % < 5 years old | 0.074 | 0.022 | 0 | 0.059 | 0.072 | 0.085 | 0.183 |
| % > 65 years old | 0.191 | 0.075 | -0.029 | 0.142 | 0.181 | 0.231 | 0.698 |
| % Unemployed | 0.08 | 0.045 | 0 | 0.05 | 0.069 | 0.097 | 0.321 |
| % Tertiary educated | 0.249 | 0.092 | 0.04 | 0.187 | 0.242 | 0.3 | 0.664 |
| Distance to major road (km) | 12.52 | 18.90 | 0.003 | 2.328 | 7.284 | 17.794 | 237.22 |
| # polluting plants within 5 km | 4.158 | 3.046 | 1 | 1 | 3 | 7 | 18 |

*Notes*: Data from ACAG (row 1), INSEE (rows 2, 4-8), IGN (rows 3, 9), PRTR (row 10), Ministry of Ecology (row 11).

Table C.9: Multinomial logit of year of adoption on $PM_{2.5}$ in 2010

| | Coef. | Std Err. | $p$-value | 95% CI |
|---|---|---|---|---|
| 2012 | | *Base outcome* | | |
| 2013 | -1.16 | 1.14 | 0.31 | (-3.39;1.07) |
| 2014 | -1.44 | 1.13 | 0.21 | (-3.66;0.78) |
| 2015 | -1.62 | 1.15 | 0.16 | (-3.87;0.64) |
| 2016 | -1.43 | 1.21 | 0.26 | (-3.80;0.95) |

*Sources*: ACAG, INSEE, IGN, PPA schemes.

Table C.10: Average treatment effects in large PPA zones, weighted by population

| Method | Control group | Estimate (SE) |
|---|---|---|
| TWFE | Never-treated | -0.622*** (0.160) |
| | Not-yet-treated only | -0.536** (0.253) |
| SA | Never-treated | -0.712** (0.245) |
| | Not-yet-treated only | -0.751*** (0.171) |
| BJS | Never-treated | -1.538** (0.706) |
| | Not-yet-treated only | -1.881*** (0.662) |

*Sources*: ACAG, INSEE, IGN, Copernicus CDS, PPA schemes.
*Notes*: Standard errors clustered at the ZAS level in parentheses. $^{*}$ $p < .10$, $^{**}$ $p < .05$, $^{***}$ $p < .01$

Table C.11: Robustness of heterogeneity analysis to control group and estimator use

| Neighbourhood type | Estimator | Control group | ATT (SE) | N | # IRIS |
|---|---|---|---|---|---|
| City centres | SA | Not-yet-treated | -0.53*** (0.19) | 45,617 | 3,509 |
| | CS | Not-yet-treated | -1.20*** (0.49) | 45,617 | 3,509 |
| | BJS | Not-yet-treated | -1.77** (0.74) | 45,617 | 3,509 |
| | BJS | Never-treated | -1.12* (0.69) | 51,805 | 3,985 |
| Suburbs | SA | Not-yet-treated | -0.65*** (0.10) | 81,406 | 6,262 |
| | CS | Not-yet-treated | -1.15** (0.52) | 81,406 | 6,262 |
| | BJS | Not-yet-treated | -2.04** (0.60) | 81,406 | 6,262 |
| | BJS | Never-treated | -1.89*** (0.64) | 83,629 | 6,433 |
| Rural areas | SA | Not-yet-treated | -0.99*** (0.31) | 8,372 | 644 |
| | CS | Not-yet-treated | -1.69** (0.76) | 8,372 | 644 |
| | BJS | Not-yet-treated | -1.82*** (0.56) | 8,372 | 644 |
| | BJS | Never-treated | -0.71 (0.70) | 11,362 | 874 |

*Sources*: ACAG, INSEE, IGN, Copernicus CDS, PPA schemes.
*Notes*: For the CS estimator, the outcome is residualised $PM_{2.5}$ levels after accounting for weather controls (using the whole sample). Number of bootstrap draws: 200.

Table C.12: Number of actions implemented in large PPA zones, by type

| Sector | Number of zones | Share of zones (%) | Number of actions | Mean number of actions by zone | Share in French population (%) | Share in area of France (%) |
|---|---|---|---|---|---|---|
| Agriculture* | 7 | 33 | 13 | 1.86 | 31 | 7.5 |
| Industry | 21 | 100 | 83 | 3.95 | 49 | 11 |
| Residential | 20 | 95 | 90 | 4.50 | 48 | 11 |
| Transport | 21 | 95 | 201 | 9.62 | 49 | 11 |
| Urban planning** | 10 | 48 | 24 | 2.40 | 33 | 5.9 |
| All sectors*** | 21 | 100 | 52 | 2.48 | 49 | 11 |
| Total | 21 | | 463 | 22.0 | | |

*Source*: PPA schemes.
*Notes*: The mean number of actions by city is conditional on any action of the type being implemented in the city. The share of population is the 2017 share of the population of metropolitan France that the covered zones add up to. In the case of the residential sector, only Nantes, in the West, does not list any measure.
*: This concerns only some PPA zones that expand quite far from the city centre and/or are in regions whose economy is oriented towards agriculture, namely, in descending population order: Paris (Île-de-France), Lille (Nord-Pas-de-Calais), Rouen (Haute-Normandie), Nantes, Rennes, Tours, and Orléans. See the map in Figure 3 for a reference of the spatial extent of these treated zones.
**: Actions labelled as "urban planning" can refer to two types of actions: a) including air quality considerations into urban planning schemes (PLU) and asking *ex ante* air quality impact evaluations before authorising new construction projects and b) ask main construction firms to sign a clean-worksite charter (*charte chantier propre*) which includes all types of procedures aiming at reducing the impact of construction works on the environment, and in particular, regarding air pollution, measures such as putting tarpaulins on skips, or soil watering.
***: Actions that are labelled as "all sectors" are broad measures in terms of raising awareness, both in the long run ("Making the general public aware of issues related to air quality", "General smart city project"), or in the short run in case of pollution peaks (official decree, local media broadcasting).