

Air pollution and mortality in European regions and cities: the effects of smart cities projects

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ABSTRACT

In recent years, urban sustainability initiatives have gained increasing attention as regions and cities seek to mitigate environmental degradation and improve public health. In this paper, we assess the potential impact of *Smart City* projects on the evolution of air pollutant concentration, such as particulate matter (PM 2.5), nitrogen dioxide (NO₂) and ozone (O₃), across European cities, and considering the existing connection between the concentration of these specific air pollutants and mortality. To do so, we build a rich panel dataset over the 2013–2022 period, merging information on air pollution and mortality at the level of 483 NUTS-3 regions and 597 large cities in Europe, with information on projects implemented across these cities. By comparing the differential evolution in cities where smart projects were implemented vs other cities, we identify whether the adoption of these projects led to measurable reductions in air pollution. Our findings aim to contribute to the growing dialogue on sustainable cities by i) studying the co-evolution on the concentration of air pollutants and mortality in European regions and cities over the last years, and ii) assessing the effectiveness of EU *Smart City* projects in reducing air pollution and enhancing public health.

1. Introduction

One important side effect of urban life is air pollution.¹ Exposure to fine particulate matter (PM 2.5), nitrogen dioxide (NO₂), and ozone (O₃) has been extensively documented as a leading cause of morbidity and premature mortality worldwide (Héroux et al., 2015; Khomenko et al., 2021; Kopas et al., 2020; Zhu et al., 2019). According to the World Health Organization, more than 4 million deaths every year worldwide are estimated to be directly related to outdoor air pollution. Pollution has also been shown to be associated with higher spread and mortality of contagious diseases, including COVID-19 (Austin et al., 2023; Ispording and Pestel, 2021),² and it is estimated that the health effects of air pollution create substantial fiscal burdens for governments worldwide (Mink, 2025).³ Human capital accumulation and productivity are also affected by exposure to air pollution (Anderson, 2019;

Annese-Maesano, 2017; Graff Zivin and Neidell, 2013; Lu and Deng, 2025). Other impacts are also felt on several individual decisions and markets, such as location choice (Banzhaf and Walsh, 2008; Pan, 2023) and housing prices (Chay and Greenstone, 2005; Gruhl et al., 2025; Molnár et al., 2012).

Urban areas, where the majority of the global population currently lives, are where pollutant sources such as road transport, heating, and industrial activity are concentrated. But cities are not only where exposure to air pollution is the highest, they are also key actors to fight environmental degradation and mitigate climate change. Thus, urban areas show valuable opportunities for mitigation (Aguilar-Gomez, 2025); their dense populations and infrastructure allow for the implementation of efficient public transportation (Borck, 2019), energy-efficient buildings, and innovative waste management systems (Shi and Zhang, 2023), all of which can significantly lower per capita

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¹ We refer to air pollution as exposure to main air pollutants, namely PM2.5, NO₂, and O₃.

² High air pollution not only reduces the capacity of the immune system to fight pathogens but also increases their contagion. Recent studies suggest that around 15% of global deaths due to COVID-19 were associated with high air pollution levels (see Pozzer et al., 2020).

³ According to Mink (2025), even pollution levels below EU standards are estimated to cost the French healthcare system billions annually through increased cardiology and pulmonology demands.

emissions of, and exposure to, air pollutants.

In Europe, air pollution has been declared as the largest environmental health risk, causing cardiovascular and respiratory diseases that lead to the loss of healthy years of life and, in the worst cases, to preventable deaths (European Environmental Agency, 2023). Recent European policy initiatives, such as the European Green Deal, the Zero Pollution Action Plan, and the revised Ambient Air Quality Directive (EU 2024/2881), aim to align EU air quality standards with WHO recommendations. These policies highlight the importance of integrated and localized actions to reduce pollutant concentrations, particularly in urban areas most exposed to traffic, heating, and industrial emissions (European Commission, 2022; Jakir, 2022). In recent years, European cities have implemented a variety of green and smart urban policies aimed at reducing emissions, improving air quality, and enhancing urban resilience. Among these initiatives, *Smart City* projects represent a key policy instrument that integrates technology, innovation, and citizen participation to support environmental and health goals (Borsboom-van Beurden et al., 2019; Kaiser et al., 2021).

In this paper, we re-examine the pollution-mortality connection and evaluate the impact of *Smart City* initiatives on air pollution across European regions and cities. To do so, we construct a unique panel dataset over the 2013–2022, covering 597 cities and 483 NUTS-3 regions, and integrate information on pollutant concentrations, mortality, and *Smart City* project implementation. By comparing the differential evolution in cities where smart projects were implemented vs other cities (via a *Difference-in-Differences* approach), our data allows us to investigate whether and how the adoption of *Smart City* projects has contributed to the reduction of harmful air pollutants and their related health effects.

We aim to contribute to the growing literature on urban sustainability and environmental health. In particular, we provide two main contributions. First, we document the evolving relationship between key pollutants (PM 2.5, NO₂, and O₃) and mortality across European regions and cities, using a significantly larger and longer panel dataset than previous papers studying the pollution-mortality connection. Second, exploiting our unique and comprehensive panel dataset that combines high-frequency information on multiple air pollutants, mortality indicators and *Smart City* project implementation, we provide, for the first time, to the best of our knowledge, an assessment of the environmental impacts of these initiatives in a comparative and policy-relevant framework.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature on pollution, mortality and *Smart City* projects. Section 3 describes the dataset and key variables. Section 4 outlines our empirical strategies and results. Section 5 offers a discussion and concluding remarks. Additional information and results are presented in Supplementary Material.

2. Pollution, mortality and *Smart City* projects: context and brief literature review

2.1. Air pollution in European cities

PM 2.5, NO₂ and O₃ are the most important air pollutants. PM 2.5 emissions are directly produced by combustion sources and remain one of the most harmful environmental risks in European cities. Long-term exposure to PM 2.5 is linked to higher mortality, cardiovascular and respiratory diseases, and reduced life expectancy (Ayudhya et al., 2026; Hoek et al., 2013). For Europe, Zhu and Shi (2023) show a lower and decreasing trend in PM 2.5 levels, compared to Asia and Africa. However, PM 2.5 levels remain high in many European regions, including some central European countries. Indeed, the EEA estimates that over 250,000 premature deaths annually in the EU are due to PM 2.5 emissions, highlighting the persistent challenge cities face in reducing exposure.

NO₂ emissions are primarily linked to road transport (36% of EU-27 emissions in 2021), followed by agriculture, energy supply, and

manufacturing sectors. In addition, NO₂ exposure has been associated with respiratory diseases, reduced lung function, and increased hospital admissions (Lelieveld et al., 2019; Hou et al., 2026).⁴ Some European policies (including the introduction of Euro vehicle standards, low-emission zones, and stricter controls on industrial and agricultural sources) may have helped to reduce NO_x emissions since 1990, with 66,000 estimated fewer annual deaths attributed to NO₂ exposure, according to the European Commission (2022). However, many European countries still face challenges in meeting ammonia reduction targets, underscoring the need for further action in agriculture and waste management.⁵

O₃ is a secondary pollutant formed through photochemical reactions involving NO_x and volatile organic compounds (VOCs), with significant contributions from intercontinental transport and Mediterranean shipping (European Commission, 2024). While long-term O₃ exposure causes around 81,000 annual deaths, mainly from respiratory diseases (Achebak et al., 2024), policy impacts are complex: reductions in NO_x emissions can sometimes increase ozone levels due to changes in atmospheric chemistry, particularly in industrial regions and in warm, sunlit environments.⁶

Integrated European policies have driven marked improvements in air quality and substantial reductions in mortality, particularly from PM 2.5 and NO₂, with O₃ impacts being more variable due to atmospheric complexities. According to the EEA, the most pronounced benefits are observed in regions with historically high emissions, such as Central and Eastern Europe, where renewable energy transitions and stricter vehicle standards have been implemented. Continued development of these cross-sectoral green policies has the potential to reduce air pollution-related deaths by up to 60% by 2030 (European Commission, 2021, 2022, 2024; Jakir, 2022).

Finally, greenhouse gas (GHG) emissions in Europe have declined over the past three decades, driven by improvements in energy efficiency and thanks to stricter EU climate policies. Between 1990 and 2020, total GHG emissions (excluding land use and forestry) fell by around 32%, mainly in the energy supply and industry sectors (EEA, 2020). Despite this progress, substantial cross-country heterogeneity remains: Eastern European countries tend to have higher emissions relative to population or GDP due to more carbon-intensive energy systems, while Northern and Western countries show higher transport emissions (Crippa et al., 2023). Buildings and road transport account for a large share of the remaining Europe's emissions, reflecting persistent challenges related to heating systems and mobility patterns (IEA, 2023).⁷

2.2. Air pollution and mortality

Air pollution is a well-established public health concern, with a direct relationship to morbidity and mortality (see Héroux et al., 2015). Several papers have also shown the association between pollution, (bad) health and mortality in cities (see for instance Vedal et al., 2003, for Vancouver, or Cao et al., 2011, for China).

⁴ Hou et al. (2026) show that long-term exposure to traffic-related air pollution (TRAP), including for instance NO₂, PM2.5, NO_x, is consistently associated with increased risks of all-cause mortality, with pooled risk ratios typically between 1.03 and 1.33 per 10 µg/m³ increase.

⁵ https://environment.ec.europa.eu/topics/air_en

⁶ Yao et al. (2025) highlight how photochemically consumed VOCs play a central role for O₃ formation, while meteorological factors represent about 50.8% of O₃ variability.

⁷ The connection between air pollutants has been highlighted in the literature (Lin et al., 2022; Song et al., 2026). As described by Song et al. (2026), in most OECD countries, peak emissions of air pollutants and greenhouse gases follow a clear sequential temporal pattern, generally occurring in the following order: SO₂ first, followed by CO, NO_x, NMVOCs, PM10, PM2.5, and lastly GHGs. This highlights the relevance of synergistic pollution-reducing strategies.

In a European context, several studies indicate that cities investing in green initiatives not only improve local air quality but also provide significant public health benefits (Stump and Szabó-Morvai, 2025). For example, Lelieveld et al. (2019), using data from 2015, highlight the connection between air pollution and cardiovascular disease, showing that cities prioritizing smart projects may diminish health risks linked to air quality. In addition, higher air pollution levels often exhibited elevated COVID-19 mortality rates, reinforcing the critical nexus between environmental quality and public health during pandemics (Bourdrel et al., 2021).

Air pollution exposure and its health impacts vary considerably across geographic and socioeconomic dimensions. Achebak et al. (2024) analysed O₃ contributions and related mortality across European regions. Khomenko et al. (2021) assessed premature mortality due to air pollution in almost 1000 European cities in 2015, identifying clear patterns of inequality, with urban areas in Northern Europe, such as Stockholm or Helsinki, successfully reducing particulate matter levels with its associated health benefits. We aim to contribute with a comprehensive longitudinal analysis of the pollution-mortality connection across a large balanced sample of European cities and regions, over the 2013–2022 period.

2.3. Smart City projects

Close to 80% of the total global population is expected to be living in urban areas by 2050. In this context, cities are expected to deliver adequate facilities, secure energy, economic and social opportunities, as well as guarantee a livable environment. The role of urban areas is recognised by UN Sustainable Development Goal 11 on “sustainable cities”. To fight environmental challenges, cities worldwide have been implementing an array of legislation, projects and innovations, recognising that effective governmental policies can play a crucial role in ensuring improvements in air quality. The central role of cities in fighting air pollution has been widely recognised (see for instance Guo and Zhou, 2025). In Europe, the EU has established clear climate targets and set the framework for the implementation of *Smart City* initiatives aiming at solving pressing issues, including congestion and pollution, with already visible improvements in many urban areas (EEA, 2023). However, it is also recognised that several cities still exceed recommended pollutant limits established by the World Health Organization.

European cities have been recently implementing a variety of green and smart urban policies aimed at reducing emissions and improving air quality. EU *Smart City Projects* are now at the forefront of transforming urban environments to be more sustainable and efficient, leveraging digital innovation and cross-sector collaboration.^{8,9,10,11} Supported by major EU initiatives such as the Horizon 2020 and Horizon Europe programs, these projects bring together cities, industry, and citizens to develop and demonstrate scalable solutions in areas like energy efficiency, smart mobility, and digital infrastructure.⁶ Like other EU urban initiatives, an explicit aim of these projects is to reduce air pollution.

In this line, recent research has focused on analysing the impact of some EU urban initiatives. Turnock et al. (2016) quantified the effects of EU legislative measures and technological upgrades, finding a 29% decrease in PM 2.5 levels across Europe between 2000 and 2015. Some other studies have argued for the integration of green infrastructure with digital monitoring systems to manage urban pollution and enhance health equity (see for instance Nieuwenhuijsen et al., 2017;

Nieuwenhuijsen, 2021). However, despite the growing body of research on air pollution and the role of public policies in mitigating its effects, empirical evidence on the causal impact of *Smart City* projects on air quality remains limited. To the best of our knowledge, there is no systematic empirical analysis assessing whether and to what extent the *Smart City* projects implementation leads to measurable changes in air pollutant concentrations over time. We contribute to this literature by providing the first large-scale empirical investigation of the impact of *Smart City* projects on air pollution outcomes across European cities.

3. Data and stylised facts

We build a novel and unique panel dataset including data on air pollution, mortality and *Smart City Projects*, for a large balanced sample of cities and NUTS-3 regions in Europe. We look at both cities and regions to capture and describe as much as possible the spatial reality of the co-evolution of air pollution and mortality in Europe. Our final panel dataset includes 5970 observations spanning from 2013 to 2022 across 597 unique cities and 483 NUTS-3 regions.¹² Fig. A.1 in Appendix A (in Supplementary Material) displays the number of cities included in our sample for each country. Our 597 cities are located in 26 European countries.¹³

For our key variables, we extract information from different sources, including: i) Air quality data from the European Environment Agency (EEA), ii) Mortality statistics from Eurostat, and iii) City-level projects data from the *Smart Cities Marketplace*. The European Environment Agency and the related ETC HE Report (Soares et al., 2023; Soares et al., 2024), provides information on air quality and evaluates the Environmental Burden of Disease (EBD) caused by exposure to three major air pollutants (PM 2.5, NO₂, and O₃) in Europe. Our work focuses on all-cause mortality.¹⁴ The methodology follows a robust framework incorporating data on environment air concentrations, population demographics, baseline health data, and concentration-response functions (CRF). This section presents a data description to investigate the evolution over time of key pollutants (PM 2.5, NO₂, and O₃), mortality indicators, and *Smart City* projects, across European regions and cities.

3.1. Air pollution

We consider air quality using the population-weighted concentrations for three key pollutants (see Table A.1 and A.3 in the Appendix A): PM 2.5 (Particulate Matter $\leq 2.5 \mu\text{m}$), NO₂ (Nitrogen Dioxide), both represented by annual mean concentrations and used to capture long-

¹² From Eurostat, the total number of NUTS 3 is 1165 that is lower compared to the number in our dataset due to the match with the city-level data available in our study. Following Eurostat's Degree of Urbanisation methodology, a city is defined as a Local Administrative Unit (LAU) in which the majority of the population lives in an urban centre with at least 50,000 inhabitants. Importantly, this threshold applies to the underlying urban centre rather than to the administrative municipality itself. As a result, municipalities with resident populations below 50,000 inhabitants may still be classified as cities if they are part of a larger contiguous densely populated urban area exceeding this threshold. In addition, we removed from the sample all cities where *Smart City* projects started before 2013 (our first observation year) and either ended in 2013 or were still ongoing during our study period.

¹³ The distribution is unbalanced: a few countries account for a very large share of observations. In particular, Germany (103), Italy (80), Spain (89), and France (62) represent the largest contributors, together covering a substantial proportion of the dataset. By contrast, smaller countries such as Malta (1), Slovenia (2), Cyprus (2), and Estonia (3) have only minimal representation. Several medium-sized contributors, including Poland (58), Portugal (13), and Romania (29), provide intermediate levels of coverage.

¹⁴ Additional analyses were conducted considering the total number of deaths under 65 (overall) and due to cardiovascular and respiratory diseases. Results are available upon request.

⁸ <https://digital-strategy.ec.europa.eu/en/policies/smart-city-digital-ecosystem>

⁹ <https://smart-cities-marketplace.ec.europa.eu/projects-and-sites>

¹⁰ <https://oascities.org/projects/>

¹¹ <https://cordis.europa.eu/article/id/450538-making-europe-s-cities-smarter-and-greener>

term exposure, and O₃ (Ozone), using the SOMO35 indicator (Sum of Ozone Means Over 35 ppb), defined as the annual sum of daily maximum 8-h ozone concentrations exceeding 35 ppb. SOMO35 is a cumulative exposure metric rather than an ambient concentration measure and therefore reflects the intensity and persistence of short-term ozone exceedances rather than average atmospheric levels. SOMO35 measure is considered reliable for comparative analysis over time, which is what we do here working with panel data.¹⁵

Table A.1 in the Appendix A shows notable levels of exposure to O₃, NO₂ and PM 2.5 in European cities. For instance, the mean SOMO35 for O₃ is 4622.6 µg/m³, with a population-weighted average of 4275.1 µg/m³. Regarding NO₂, the average concentration is 14.6 µg/m³, with a higher rate of 18.8 per 100,000 people. At NUTS 3 level (Table A.3), concentrations mirror the city-level data.

Table A.2 in the Appendix A shows aggregated GHG indicators that we have considered as complementary analysis: the GHG indicator of emissions from energy sectors (including power, manufacturing and industry emissions) displays the highest levels and variability, with an average of 0.9 and a maximum above 19 t, highlighting substantial cross-city differences in energy production and consumption; the GHG indicator of emission from transport sector (road and other) is smaller in magnitude but still shows notable variation; and the GHG indicator of emissions from buildings is the lowest on average (0.2) and ranging up to 10.8 t, suggesting significant heterogeneity in building efficiency and heating systems.

Fig. 1, and Table A.4 in the Appendix A, present a detailed overview of the annual evolution of pollutants indicators from 2013 to 2022. The results are very similar at both city and NUTS3 regional levels. The data reveal significant year-to-year fluctuations, with O₃ (SOMO35) generally exhibiting the highest variability. Notably, the concentrations of NO₂ and PM 2.5 show a decreasing trend over the period, particularly during 2020, likely reflecting the impact of mobility restrictions during the COVID-19 pandemic. In Table A.4 in the Appendix A, the standardized changes further highlight the dynamic behaviour of air quality indicators, with the “*max_std_change*” column identifying the pollutant with the most pronounced deviation annually. For instance, at city level, PM 2.5 frequently exhibits the largest standardized fluctuations, especially in years like 2019 and 2021, suggesting a higher sensitivity to local emissions and meteorological variability. In contrast, O₃ (SOMO35) shows dominant fluctuations in several years, possibly reflecting sensitivity to broader atmospheric conditions.

Overall, while air pollution levels have declined in Europe, there are important heterogeneities across regions. Fig. 2 shows maps of the change from 2013 to 2022 of air pollution across NUTS-3 European regions in the full sample.¹⁶ NO₂ shows significant and consistent declines across most European regions (with few exceptions in the Eastern Europe), PM 2.5 also declines in most regions, with localized increases in parts of Spain, and O₃ (SOMO35) exhibits a more heterogeneous pattern, with declines concentrated in the Northern and Southern Europe, and increases observed in Central and Eastern Europe.

¹⁵ The recent EBD assessment (Soares et al., 2024) introduced the measurement of the long-term O₃ exposure using the peak season approach. The peak season is the average of the daily maximum 8-h mean concentration in the six consecutive months with the highest six-month running-average O₃ concentration. Thus, the period defining the peak season may vary across the stations. Also note that SOMO35 is not directly comparable in magnitude to annual mean concentrations of PM2.5 and NO₂, as it captures threshold-weighted exposure over time rather than average pollutant levels.

¹⁶ For these data, the full sample includes 514 NUTS 3 and 637 cities: 597 with information about *Smart City* project and 40 without.

3.2. Air-pollution-related mortality and overall mortality in European regions

Health data sources used by EEA includes Eurostat mortality statistics (i.e., deaths) from natural causes (excluding external causes like accidents or poisoning per ICD10). Additional mortality data come from the statistics released by Eurostat. The main health indicator used by EEA to estimate the burden of disease due to air pollution is the Attributable Deaths (AD), including deaths statistically linked to exposure to a pollutant, based on epidemiological risk estimates. We use its normalized value per 100,000 inhabitants considering the population at risk (e.g., aged >30 for PM 2.5 and NO₂, aged >0 for O₃) for all the main results.

The burden of disease is estimated using Concentration-Response Functions (CRFs), which quantify the change in risk per pollutant concentration increase. These CRFs are primarily based on meta-analyses and WHO-endorsed guidelines.¹⁷ Tables A.1 to A.3 in the Appendix A present descriptive statistics for our mortality variables. In particular, Table A.1 displays city-level data with the annual mean number of deaths attributable to long-term O₃ exposure equal to 10.9, with a rate of 4.6 per 100,000 people per year. Regarding NO₂, the mean number of attributable deaths is 55.6, with a rate of 25.3 per 100,000 people. PM 2.5 is associated with the highest average mortality: 165.6 deaths and a rate of 96.8 per 100,000 people. At NUTS-3 level, O₃ exposure leads to about 30 deaths on average, NO₂ to about 92 deaths, and PM 2.5 to approximately 373 deaths. The attributable death rate per 100,000 population is the highest for PM 2.5 (94.8), followed by NO₂ (20.4) and O₃ (4.8).

Fig. 3 illustrates trends in total deaths attributed to air pollution over the 2013–2022 period. The trends point to divergent dynamics across pollutants with the same distributions at both NUTS-3 and city level. Deaths due to NO₂ and PM 2.5 exhibit a clear and constant decline, particularly after 2017. This is in line with observed reductions in the concentrations of these pollutants and may reflect the effectiveness of emissions regulations, improvements in air quality, and cleaner transportation technologies. In contrast, O₃-related mortality shows greater volatility and a slight upward trend over the same period. This pattern likely reflects the complex and non-linear formation of ozone, which can increase even as precursor pollutants like NO₂ decline, especially under certain meteorological conditions.

Fig. A.2 in the Appendix A presents trends in overall mortality. At both city and regional levels, total deaths show a general upward trend, with a notable spike around 2020, likely reflecting the impact of the COVID-19 pandemic. At the city level, while total deaths under 65 appear relatively stable, deaths under 65 due to respiratory and cardiovascular problems show greater volatility, with an average of 97 deaths per year in affected cities and sharp increase in 2022, potentially due to post-pandemic effects. In the regional data, deaths under 65 decline steadily until 2019, followed by an increase in 2020–2021 and a slight reduction in 2022, suggesting a temporary pandemic-related shock. The trends highlight both long-term demographic pressures and acute public health events, with possible links to environmental or epidemiological factors deserving further investigation.

3.3. Smart City projects

As highlighted, the European Commission has promoted *Smart City* projects as a core strategy to encourage cities to adopt integrated solutions in energy efficiency, low-carbon mobility, digital infrastructure,

¹⁷ PM2.5: 8% increase in mortality per 10 µg/m³; NO₂: 2% increase per 10 µg/m³; O₃: 0.43% increase per 10 µg/m³. The baseline counterfactual concentrations (levels below which no adverse health effects are assumed) are 5 µg/m³ for PM2.5, 10 µg/m³ for NO₂ and 35 ppb for O₃. For additional information on how to compute the excess mortality see Soares et al. (2023, 2024).

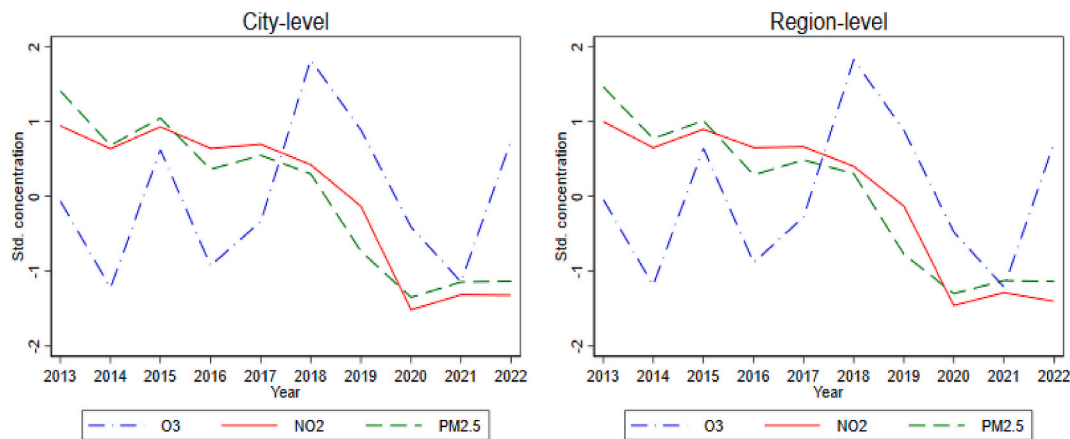


Fig. 1. Evolution of main air pollutants: average across European regions and cities.
Note: Authors' computation. The graph shows standardized trends in population weighted average concentrations of O₃, NO₂, and PM 2.5 from 2013 to 2022 at both city and region levels. While NO₂ and PM 2.5 show a clear decline, especially after 2017, O₃ remains volatile. The sharp drop around 2020 aligns with expected effects of pandemic-related activity reductions.

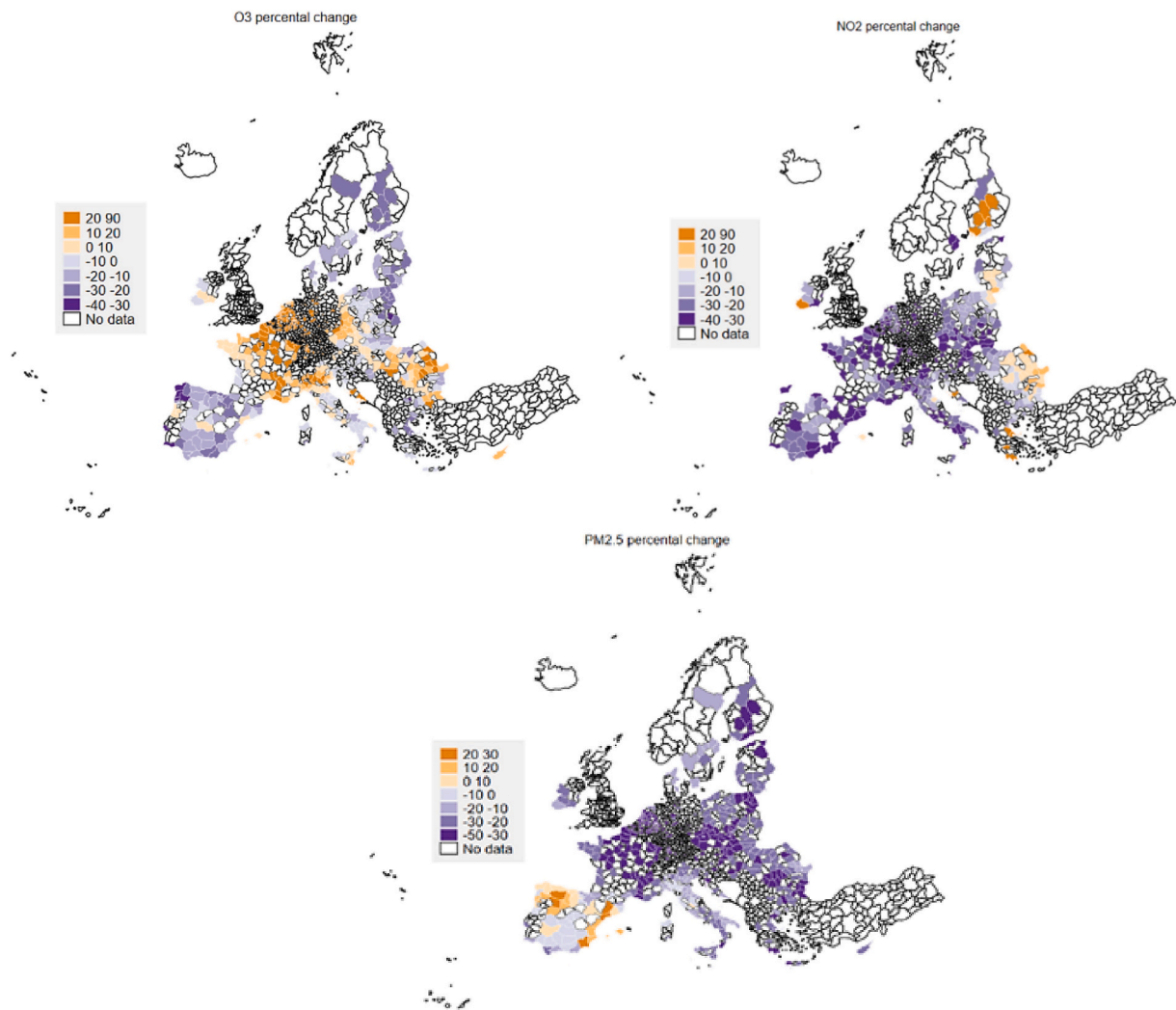


Fig. 2. Air pollution in European regions: changes from 2013 to 2022.
Note: Authors' computation. Regions are NUTS-3 level. Each range of the scale represents a discrete interval of percentage change. The scale emphasizes larger increases in pollution (orange scale), which are more dispersed, while reductions are concentrated within narrower bands (purple scale).

and urban sustainability. Target cities are typically medium and large urban areas facing challenges related to air pollution, congestion and

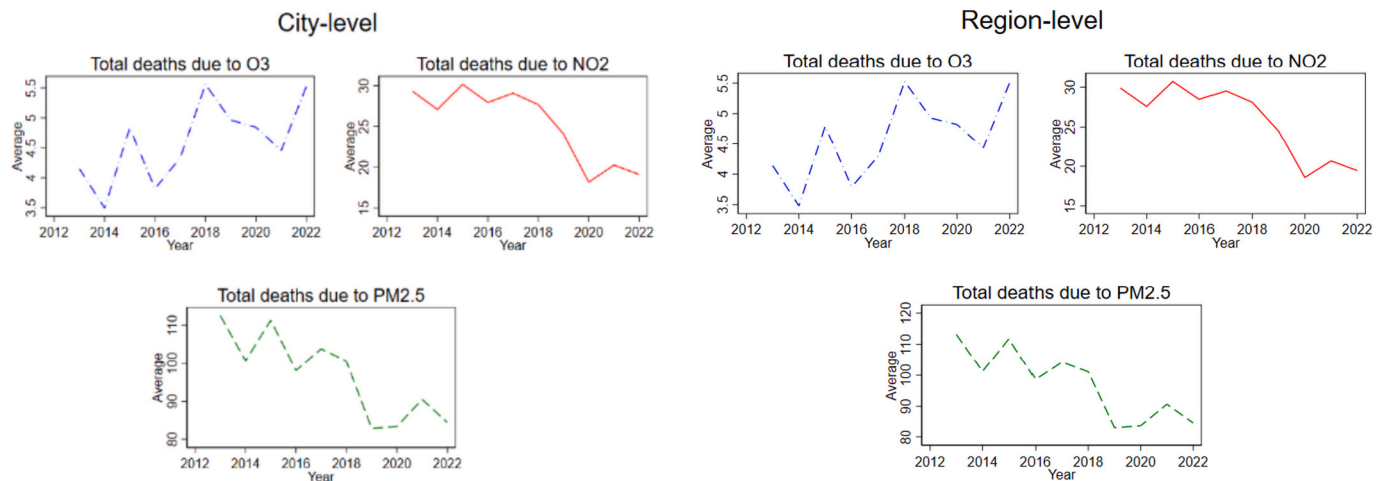


Fig. 3. Evolution of deaths due to air pollution: average across European regions and cities.

Note: Authors' computation. The Attributable Deaths (AD), that includes deaths statistically linked to exposure to a pollutant, is based on epidemiological risk estimates and its value is normalized per 100,000 inhabitants considering the population at risk (e.g., aged >30 for PM 2.5 and NO₂, aged >0 for O₃) for a better comparison. The data at NUTS 3 level refers to the full sample with 514 NUTS 3.

climate mitigation. Remarkable examples of projects include the *SmartEnCity* project, which renovated thousands of homes, introduced renewable energy systems, and developed public transport in cities like Vitoria-Gasteiz (Spain), Tartu (Estonia), and Sønderborg (Denmark).¹⁸ Other innovative projects, such as *GrowSmarter* and *mySMARTLife*, focus on integrating smart solutions in energy, infrastructure, and transport, while also supporting knowledge transfer and replication across EU cities. The EU's approach emphasizes interoperability, standardization, and citizen engagement, ensuring that digital and green transitions are mutually reinforcing and accessible to all urban areas, including those at the early stages of digital transformation.^{19,20} A key feature of *Smart City* projects is their emphasis on demonstrating economic viability to facilitate replication and scalability in other urban contexts. Indeed, these projects often involve pilot implementations of smart technologies (e.g., smart grids, intelligent transport systems, energy-positive districts) that are typically part of *Lighthouse Projects*, where innovative solutions are tested in selected *Lighthouse Cities* and replicated in *Fellow Cities*.

The *Smart Cities Marketplace* platform currently includes 100 successful projects implemented in 194 cities. In terms of type of cities, there are 54 Lighthouse cities that act as demo sites and 140 fellow cities. The total combined budget of projects is equal to €1,441,151,514, while the total contribution received by the European Union is €923,905,377. The distribution of smart cities over Europe is displayed in Fig. 4. There is a clear concentration of smart cities in Western and Central countries, notably Germany, France, and Belgium. These countries benefit from strong institutional capacity and access to EU innovation funding, which supports a high number of initiatives. Southern Europe, particularly Portugal, Spain and Italy, also shows substantial involvement. In Northern Europe, Nordic and Baltic countries such as Sweden and Finland, are engaged in fewer but high-quality projects, often focused on digital innovation and clean energy. Eastern European countries show emerging participation, suggesting progress toward more balanced geographic inclusion. However, South-Eastern Europe and the Balkans remain underrepresented, pointing to ongoing disparities in access to funding and technical capacity. Despite this, the overall trend suggests increasing diffusion of smart cities practices across



Fig. 4. Smart Cities in number.

Note: This figure comes from the *Smart Cities Marketplace* website (Kaiser et al., 2021) and refers to the full set of 194 smart cities that implemented projects in Europe, not those included in our sample.

Europe.

The implementation of projects in the *Smart Cities Marketplace* reflects a strategic European-level response to fragmentation and limited flexibility of urban innovation initiatives. One explicit aim is to foster collaboration among cities, industry, and academia, as well as promoting shared standards and practices.²¹ In this line, the *Smart Cities Marketplace* also aims to accelerate the spread of solutions that promote digitalisation, social cohesion and decarbonisation. Several large cities demonstrate this dynamic. In Amsterdam and Bilbao, the *ATELIER* project is developing Positive Energy Districts aiming for an energy surplus of approximately 1340 MWh of primary energy, CO₂ reductions

¹⁸ <https://cordis.europa.eu/project/id/691883/reporting>

¹⁹ <https://smart-cities-marketplace.ec.europa.eu/projects-and-sites>

²⁰ Efforts explicitly mention ambitious climate targets, as well as improving quality of life, create new economic opportunities, and serve as blueprints for urban innovation across Europe (<https://oascities.org/projects/>)

²¹ <https://smart-cities-marketplace.ec.europa.eu/>

of 1.7 kt, and NO_x emissions savings of 23 tons. In Barcelona, the *GrowSmarter* initiative achieved reductions of about 30–70% in final energy consumption in its demonstration phase, alongside significant retrofitting of public and private buildings.

Table A.2 in the Appendix A lists some key variables for a selection of *Smart City* projects in our sample. Table A.5 in the Appendix A provides an overview of the four main categories of *Smart City* projects considered in the analysis: ICT and mobility, building, energy system and integrated projects.²²

Fig. 5 shows the distribution of cities in our sample across European countries by treatment status over the period 2013–2022.²³ The bars report the percentage of cities that implemented a project (in blue) and those that have not (in red). The evidence highlights substantial cross-country heterogeneity. In several countries (e.g., Austria, Denmark, Estonia, Slovenia and Latvia) a large fraction of cities had implemented a project. By contrast, in most countries (such as Belgium, Bulgaria, Croatia, France, and Portugal) most cities are without project implementation. In Cyprus, there are no cities that implemented *Smart City* projects.

Fig. A.3 in Appendix A reports the share of treated years for cities across European countries between 2013 and 2022. Adoption rates vary substantially: some countries exhibit relatively high implementation of projects, such as Malta (80%), Austria (45%), Estonia (63.3%), Denmark (47.5%), Finland (51.2%), and Slovenia (50%), while others show limited diffusion over time, including Greece (5%), France (4.7%), and Poland (6.4%). In many countries, only a minority of cities implemented projects during the observation window, with values often below 20%. Overall, Northern and smaller countries generally show higher adoption rates compared to southern and larger countries.

Fig. A.4 shows the evolution over time of the (approximate) number of cities implementing projects each year. A year-by-year description of the percentage of projects implemented in each country is displayed in Fig. A.5. Initially, early adoption was concentrated in a small set of countries (e.g., Latvia, Slovenia, Estonia, Denmark and Finland), with a gradual diffusion in other countries over the following years. By 2022 other countries, such as Malta, Latvia, and Finland, report more than half of cities treated, while others (including Czechia, Greece, and Portugal) exhibit very limited adoption.

Fig. A.6 reports the distribution of treated city-years across the four *Smart City* project categories reported in Table A.5. Integrated projects, namely projects that have an impact on at least two sectors, out of energy, ICT, mobility and building, clearly dominate, accounting for more than half of all observations treated (359 out of 642). Energy projects represent the second most common treatment (168 city-years), while Building projects (70) and ICT & Mobility interventions (45) are substantially less frequent. This imbalance in treatment composition highlights that the *Smart City* initiatives in our sample are primarily implemented through multi-domain integrated projects.

Fig. A.7 breaks down Integrated *Smart City* projects, the dominant category in our dataset, by country, displaying a high heterogeneity among countries. Germany and Spain lead with 54 Integrated projects each, followed closely by Italy (48), Sweden (32) and Poland (28). Other countries such as Austria, Czechia and Romania show moderate uptake (12–18 projects). Finally, several countries like Hungary, Belgium, Croatia, Finland and Portugal, implemented fewer than 8 Integrated

projects over the period.

Finally, Fig. A.8 displays the trends of each pollutant across project types. Air pollutant levels generally decline over 2013–2022, although with notable differences in magnitude and volatility. Integrated projects consistently display the lowest and most stable levels of PM 2.5, NO₂ and O₃, and their trends show a smoother reduction relative to other categories. ICT & Mobility and Building projects exhibit more fluctuation, especially around 2018–2020, while Energy projects follow an intermediate pattern. For GHG emissions, Integrated projects again show the steepest decline and remain the lowest over time. Overall, cities implementing Integrated *Smart City* projects tend to have cleaner and more stable patterns over time.

4. Econometric analysis

In this section, we benefit from our rich dataset to apply a range of econometric techniques tailored for panel data analysis. *Smart City* initiatives are designed to act directly on environmental conditions and, in turn, to shape health outcomes over longer time horizons. Consequently, we structure the empirical analysis in two steps. Our main analysis is on whether *Smart City* projects contribute to reduce the concentration of air pollutants. But first, we estimate pollution-mortality elasticities to i) confirm the relevance of pollution dynamics on health outcomes across our large sample of European regions and cities, and ii) have a benchmark to calculate potential indirect impacts on pollution-driven mortality.

4.1. Pollution and mortality in European cities

We begin by examining the simple relationship between the evolution of air pollutants and mortality in EU cities. To do so, we follow a simple econometric specification:

$$\log(M_{it}) = \gamma \log(\text{AirPollution}_{it}) + \alpha_i + \delta_t + \epsilon_{it} \quad (1)$$

where M_{it} is one of our indicators of mortality in city i , in time t . AirPollution_{it} measures one of the air pollutants considered (i.e., PM 2.5, NO₂, and O₃), or GHG emissions for complementary analysis. α_i controls for idiosyncratic time-invariant characteristics of cities, like geographical location, while δ_t controls for time-specific shock affecting all cities. This all means that our estimates are based on within city variation over time.

Looking at the simple correlations between air pollution and mortality, the scatter plots in Fig. A.9 show a strong positive relationship between the average concentrations of PM 2.5, NO₂, and O₃, and the mean number of attributable deaths (AD). At city level, the relationships remain linear and statistically strong (see also Table 1, Model 1), with a higher variability in exposure and vulnerability across urban areas. Across pollutants, we see the highest elasticity for PM 2.5, in line with the exponentially increasing health risks of exposure to higher levels of particulate matter concentration. In particular, results suggest that a 1% increase in concentration of PM 2.5 is associated with a 1.95% increase in attributable deaths.

In Table 1, Model 2, we also test the robustness of our pollution-mortality results to the inclusion of some controls (at the expense of losing observations), including climatic variables (i.e., average temperature, heat stress and urban heat island effect) and total population. Results remain highly significant, and coefficients hardly change in magnitude.²⁴ To tackle the fact that attributable deaths are themselves derived from pollutant exposure using the EEA concentration-response framework, in Table B.1 in Appendix B (in Supplementary Material), we consider total, rather than attributable, deaths. Including the same

²² The original classification includes six main groups of projects: energy, ICT, building, refurbish, PED, mobility. However, considering that a lot of projects belong to several types of projects, we identify three main groups of projects: energy, ICT and mobility and building. A cluster analysis was conducted as robustness check, confirming these three main groups.

²³ A city is considered treated from the year in which its first *Smart City* project starts and remains treated for the entire duration of the project. When multiple projects are implemented in the same city, treatment timing is defined by the start date of the earliest project.

²⁴ As expected, higher temperatures and heat stress are positive and significantly associated with higher mortality.

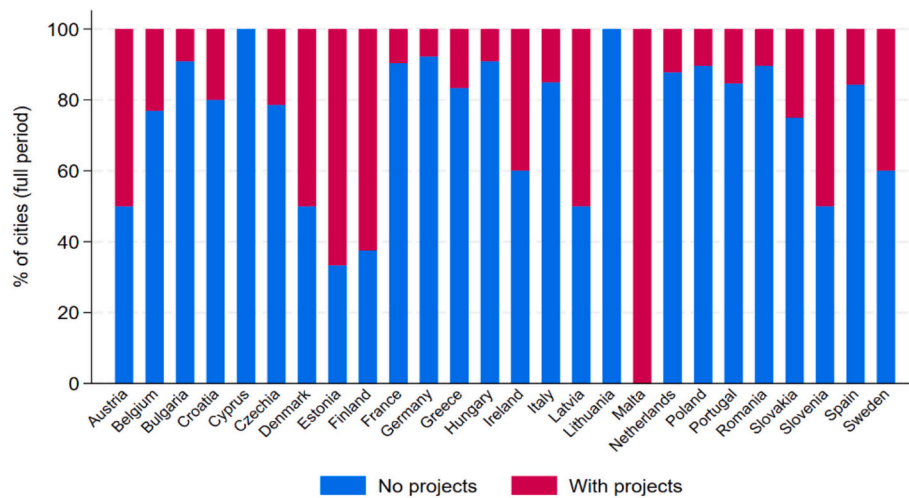


Fig. 5. Cities with vs without projects by country (2013–2022).

Note: Authors' computation. Distribution of cities in our sample across European countries by treatment status over the period 2013–2022.

Table 1
Pollution and mortality in European cities.

	PM 2.5		NO ₂		O ₃	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Dependent variable:	Log(AD)					
Log(AirPollution)	1.95*** (0.061)	2.05*** (0.08)	1.88*** (0.074)	1.72*** (0.105)	0.96*** (0.022)	1.02*** (0.018)
City FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Controls	NO	YES	NO	YES	NO	YES
Observations	5970	4051	5970	4051	5970	4051
Cities	597	478	597	478	597	478

Note: Obtained using “xtreg, fe” command. This table reports results of the relationship between the evolution of air pollutants and mortality (i.e., attributable deaths) in EU cities applying the formula in Eq. (1). Variables are log-log highlighting the impact of a 1% change in pollutant on 1% change in mortality. In Model 2, controls include heat_stress urban_heat_island AIR_TEMP and the lagged value of the total population in January of each year. Robust standard errors (clustered by city) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

controls as in Table 1, coefficients are much smaller, as expected, but remain significant. In particular, results suggest that a 1% increase in concentration of PM 2.5, NO₂, O₃ or GHG emission is associated with a 0.037%, 0.077%, 0.020% or 0.022% increase in total deaths, respectively. These results are in line with previous findings in the literature using smaller samples, and reinforce the evidence on the connection between air pollution and mortality across European cities and regions. However, they should not be interpreted in fully causal terms.²⁵

Finally, if we look at the pollution-mortality relationship distinguishing between cities that implemented smart-city projects vs. those that did not (see Table B.2 in Appendix B), we tend to find smaller associations in the former group of cities (i.e., those that implemented smart-city projects). This suggests a potential role of projects in reducing pollution and pollution-induced mortality, something that we explore next.²⁶

²⁵ Establishing a proper causal link between pollution and mortality would require the use of microdata (probably scarifying the wide and long scope of the current paper looking at large sample of regions over several years). We leave this for further research.

²⁶ However, the stronger association observed for ozone in cities with a project likely reflects the fact that cities participating in smart-city programs are systematically different from other cities in terms of urban structure, environmental conditions, and baseline exposure profiles. These pre-existing differences further justify the use of a Difference-in-Differences framework to identify the causal impact of smart-city interventions.

4.2. The role of Smart City projects in reducing air pollution

To explore the role of *Smart City* projects, we benefit from the fact that project implementation differs by cities and years. This allows us to implement a staggered *Difference-in-Differences* (DiD) approach to identify the causal impact of *Smart City* initiatives on air pollution. Our DiD strategy is specified in Eq. (2):

$$AirPollution_{it} = \beta_1(Project_{it}) + \beta_2(Project_{it} * Year) + \theta_c d + \alpha_i + \delta_t + \epsilon_{it} \quad (2)$$

where $AirPollution_{it}$ measures one of each specific air pollutant (PM 2.5, NO₂, and O₃) or the greenhouse gas emissions for the i cities at time t , $Project_{it}$ is our “treatment”, indicating the implementation of a *Smart City* project in a given city i -year t . As in Eq. (1), here we also control for time-invariant specific characteristics of cities and time-specific shocks affecting all cities. This allows us to compare trends between cities that implemented *Smart City* projects in a given year and a control group of other cities that did not (conditional on fixed effects). For air pollution concentration, we also include $\theta_c d$, where d is $country_c \times (t - t_1)$, to control for country-specific linear trends.²⁷ Our main estimation of Eq. (2) relies on the methodology proposed by Callaway and Sant’Anna (2021) for staggered treatment. As robustness, we check our DiD specification to alternative estimation techniques like the Synthetic DiD,

²⁷ We do not include the country-specific linear trend parameter for the GHG emissions analysis.

proposed by Arkhangelsky et al. (2021). The aim of our model is to estimate the heterogeneous average treatment effects on the treated (ATT) as follows:

$$ATT(g, t) = [EY(g)_t - EY(C)_t] - [EY(g)_{g-1} - EY(C)_{g-1}] \quad (3)$$

where $EY(g)$ is the expected value of the outcome at time t (post-treatment) and $g-1$ (pre-treatment) for group g , while $EY(C)$ is the expected value of the outcome for the group of not-yet treated.

Table 2 displays the results of the static ATT obtained from the DiD implementation following Callaway and Sant'Anna (2021). The results highlight a significant reduction only in terms of O_3 after the implementation of smart projects. The magnitude of the average impact of a project is a reduction of $215 \mu\text{g}/\text{m}^3$ in O_3 , which is around a 5% of the mean in our sample, a non-negligible impact.

Finally, static treatment effects may mask longer-term or cumulative effects that emerge over time. We estimate heterogeneous treatment effects on the treated considering a dynamic context, as displayed in Fig. 6. We find no significant differences between treated and control cities pre-treatment (reinforcing the parallel trends assumption). Post-treatment trends show reductions over time in concentration of O_3 in treated cities, compared to control ones, consistent with expectations from long-term smart project implementations. Results are clearer for O_3 than for the other pollutants. Post-treatment effects in terms of PM 2.5 are not significant, possibly due to specificities of PM 2.5 concentration (including climatic drivers, warming, and others). Overall, the results suggest partial effectiveness of *Smart City* projects in reducing air pollution, especially in terms of long-run concentrations of O_3 .

Table 2
The role of *Smart City* projects: DiD results.

	(1) PM 2.5	(2) NO ₂	(3) O ₃
Dependent variable:	Concentration (Population weighted average)		
ATT (Total)	0.18 (0.183)	-0.22 (0.253)	-215.71*** (64.87)
ATT (by group)			
2014	-0.61** (0.31)	-0.17 (0.49)	-339.62*** (119.37)
2015	0.07 (0.28)	-0.34 (0.47)	-369.76*** (133.16)
2016	-1.22* (0.65)	-1.39 (0.88)	49.23 (155.94)
2017	0.63* (0.35)	0.51 (0.32)	-81.93 (119.36)
2018	0.65 (0.58)	1.26** (0.59)	58.53 (160.83)
2019	0.59 (0.67)	0.07 (0.46)	-327.92** (131.92)
2020	0.62** (0.24)	-0.52 (0.42)	382.50 (498.04)
2021	-0.80 (0.54)	-0.24 (0.29)	-101.90 (370.81)
2022	1.15*** (0.22)	-0.05 (0.26)	-490.90*** (169.50)
City FE	YES	YES	YES
Time FE	YES	YES	YES
Country-specific time trends	YES	YES	YES
Mean Dep. variable	13.60	18.82	4248
Parallel trend test (p-value)	0.1292	0.0527	0.1135
Observations	5810	5810	5810

Note: This table reports results of Difference-in-Differences specification, as in Eq. (2). We use the *csdid*, (method reg) command in Stata, where the control group is cities not yet treated and never treated. The parallel trend test is conducted considering a minimum of one and a maximum of three years before treatment, as environmental outcomes are usually persistent with limited changes over time and very distant periods could be affected by unrelated shocks. Robust standard errors (clustered city) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Our sample includes European cities with over 40 thousand inhabitants, as well as larger cities over millions of residents, and projects are implemented in cities of all sizes. Fig. B.1 shows the composition of cities by size category (small and medium vs large) across countries, both considering as threshold the median value (118,992) or 250,000 inhabitants. The distribution of cities by population size varies substantially across countries. In most countries, most cities fall into the smaller population class. This pattern is particularly pronounced in Germany, Italy and Spain, where the number of small cities is very high and dominates the sample. In contrast, a few countries such as France, Poland and the Netherlands have a more balanced composition, although smaller cities remain the largest group. When using a higher population threshold (250,000 inhabitants), the dominance of smaller cities becomes even more evident. Overall, the dataset is strongly skewed toward smaller urban areas, reflecting the typical size structure of European cities.

Investigating the change of ozone by city size, we find the strongest impact of projects in reducing O_3 in cities below 250 thousand inhabitants. The coefficient for O_3 is in fact almost 3 times higher in these cities (see Table B.3 and Fig. B.2). This suggests higher efficacy of smart-city projects in medium-sized cities (as the smallest city in our sample is around 40 thousand inhabitants) and is in line with recent literature showing evidence of better performance of medium-sized cities (McCann and Ortega-Argilés, 2011).

4.3. The impact of Smart City projects by project type

Our main analysis focuses on integrated projects rather than individual intervention domains, as *Smart City* initiatives are increasingly interconnected and implemented as bundles of complementary investments spanning energy, ICT, mobility, and buildings. Evaluating these dimensions separately risks overlooking the synergies and spill-over effects generated by their interaction. Indeed, the benefits of investments in one domain often depend on the presence of complementary infrastructures and technologies in others. By treating integrated projects as the relevant unit of analysis, we capture the systemic nature of urban innovation and provide a more comprehensive assessment of its impact. This approach is also consistent with the policy design of contemporary *Smart City* programs, which increasingly prioritize cross-sectoral solutions to address complex urban challenges.

Table 3 displays the results of the treatment effects obtained from the DiD implementation, considering only *Integrated Projects* (namely projects that have an impact on at least two main sectors, out of energy, ICT, mobility and building). Again, the results highlight a significant reduction only in terms of O_3 .

Fig. 7 suggests a relatively different dynamic impact of integrated projects on each pollutant. While pre-treatment trends confirm parallel trend assumption, post-treatment responses vary by pollutants: integrated projects seem to reduce O_3 over the short and medium term (i.e., 1–4 years), and PM 2.5 and NO₂ slightly, but after longer terms (i.e., after 6 years).²⁸ This delayed pattern is broadly suggestive of the multi-year NO₂ response. More generally, the literature notes that the effects of structural urban interventions on air quality can unfold over several years (Liu et al., 2022) and are often difficult to detect in the short run because of atmospheric, behavioural and systemic adjustment (Lewis et al., 2020).

Table B.4 in Appendix B displays the results of the treatment effects obtained from the DiD implementation by independent project type. The results highlight a significant reduction of almost $235 \mu\text{g}/\text{m}^3$ only in terms of O_3 (i.e., SOMO35) after the implementation of building and

²⁸ For GHG emissions, as complementary analysis, we find no significant post-treatment differences between city implementing projects vs those that do not (if anything a slight increase in total GHG emissions – see Table B.5 in Appendix B). Given the complexity of GHG emissions, this result calls for further research.

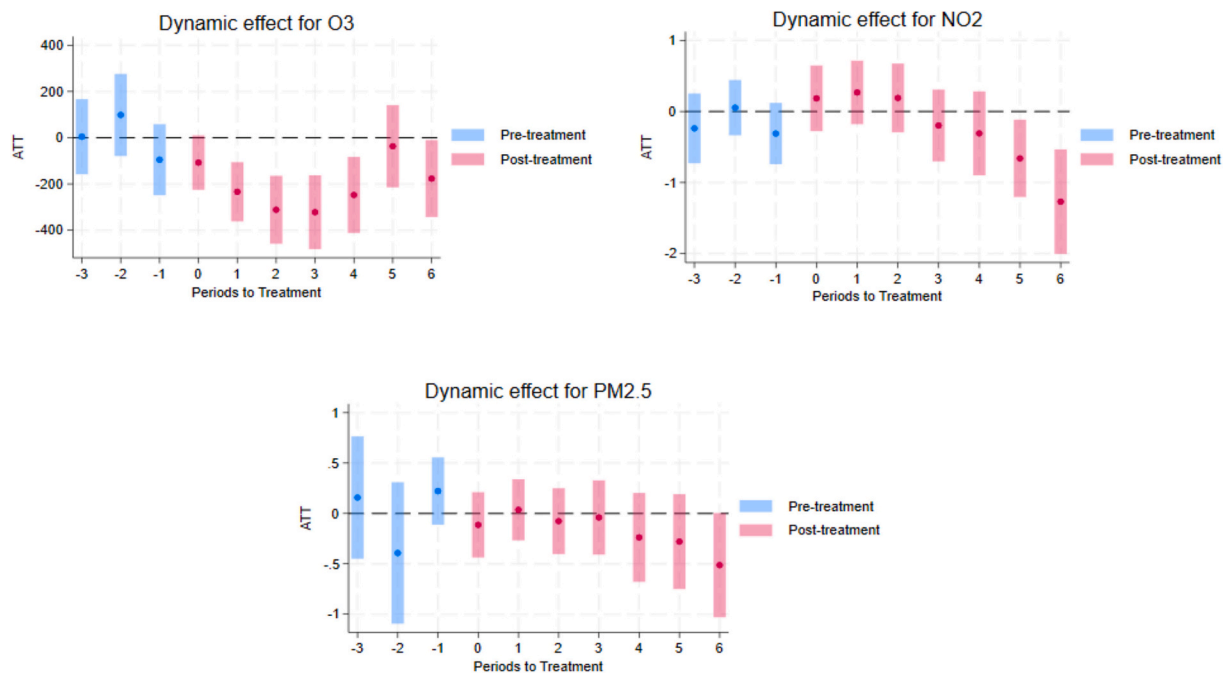


Fig. 6. Dynamic effects, by air pollutant.

Note: Authors' computation using *csdid_plot* command in Stata. For Eq. (2) plots we use pollutants in their population-weighted value, and not in logs like for the Eq. (1).

Table 3

The role of Smart City projects: DiD results for integrated projects.

Integrated projects			
Dependent variable:	PM 2.5	NO ₂	O ₃
ATT (Total)	-0.29 (0.218)	-0.14 (0.30)	-173.28** (79.59)
City FE	YES	YES	YES
Time FE	YES	YES	YES
Country-specific time trends	YES	YES	YES
Controls	NO	NO	NO
Parallel trend test (p-value)	0.5268	0.3117	0.7820
Observations	5970	5970	5970

Note: This table reports results of Difference-in-Differences specification, as in Eq. (2). We use the *csdid*, (method reg) command in Stata, where the control group is cities not yet treated and never treated. The parallel trend test is conducted considering a maximum of three years before treatment. The parallel trend holds also without considering the country-specific time trend, results are available upon request. Robust standard errors (clustered by city) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

energy projects (with parallel trends assumption holding only for building projects). O₃ is a secondary pollutant formed by photochemical reactions involving both NO_x and VOCs. The direction of the response of O₃ to emission reductions depends on the local atmospheric regime. In VOCs-limited (i.e., NO_x saturated) regimes, typical of urban areas, lower ozone levels are mainly achieved by reducing VOCs.²⁹ Sarmiento et al.

²⁹ During daytime, NO₂ is broken down into NO and a single oxygen atom (O), which attaches to an oxygen molecule (O₂) to create O₃. During nighttime, the reaction reverses. In this way, NO “destroys” ozone at nighttime. This is why lower NO can lead to less ozone destruction and thus the inverse relationship: less NO - > more O₃. But here is where Volatile Organic Compounds (VOCs) play a role, converting NO into NO₂ without consuming O₃. This breaks the cycle and leads to a harmful buildup of ground-level ozone. Liu et al. (2025) show how photochemical consumption of VOCs plays a critical role in regulating ozone formation by enhancing radical sink reactions that limit net O₃ production.

(2023), analysing LEZs in German cities, find increase in ozone coming from reductions in traffic-related NO_x. In our case, the reduction in ozone is likely to come, at least partially, from reductions in artificial VOCs. Smart City building and energy interventions (district heating, retrofits, efficiency and electrification, and fuel substitution) reduce combustion- and solvent-related VOCs. Improvements such as better insulation, improved windows, and optimized heating systems reduce building energy demand. Lower fuel consumption leads to reduced combustion emissions from heating systems, including VOCs emitted during fossil fuel combustion. Retrofits may also improve indoor and outdoor air exchange dynamics, reducing reliance on inefficient heating or ventilation practices. A representative example is the R2CITIES Smart City project, based on improved building envelopes, efficient heating systems, renewable energy integration, and smart energy management, all lowering VOC emissions.³⁰

As before, static treatment effects may mask longer-term or cumulative effects that emerge over time. We therefore estimate heterogeneous treatment effects on the treatment considering a dynamic context, as displayed in Fig. B.3 in Appendix B. Fig. B.3 shows clear heterogeneity across project types. While pre-treatment trends are mostly flat, confirming comparable baseline dynamics, post-treatment effects materialize only with a lag, becoming more pronounced approximately five to six years after implementation, particularly for Energy projects, while ICT and Mobility projects display more moderate effects, and Building projects yield smaller improvements. Such delayed dynamics are consistent with the nature of Smart City projects considered. Many interventions (e.g., district energy systems, large-scale building retrofits, and integrated urban infrastructure projects such as CELSIUS, SPARCS

³⁰ However, the final effect on ozone is not warranted and may change according to local precursor and meteorological conditions. Also, our outcome is SOMO35, a threshold-accumulated peak-exposure metric: it sums daily 8 h ozone maxima above the WHO health threshold (~70 µg/m³), capturing the intensity of high-ozone episodes rather than the annual mean (as in Sarmiento et al. (2023)). SOMO35 can therefore fall even where annual-mean ozone is stable or rising.

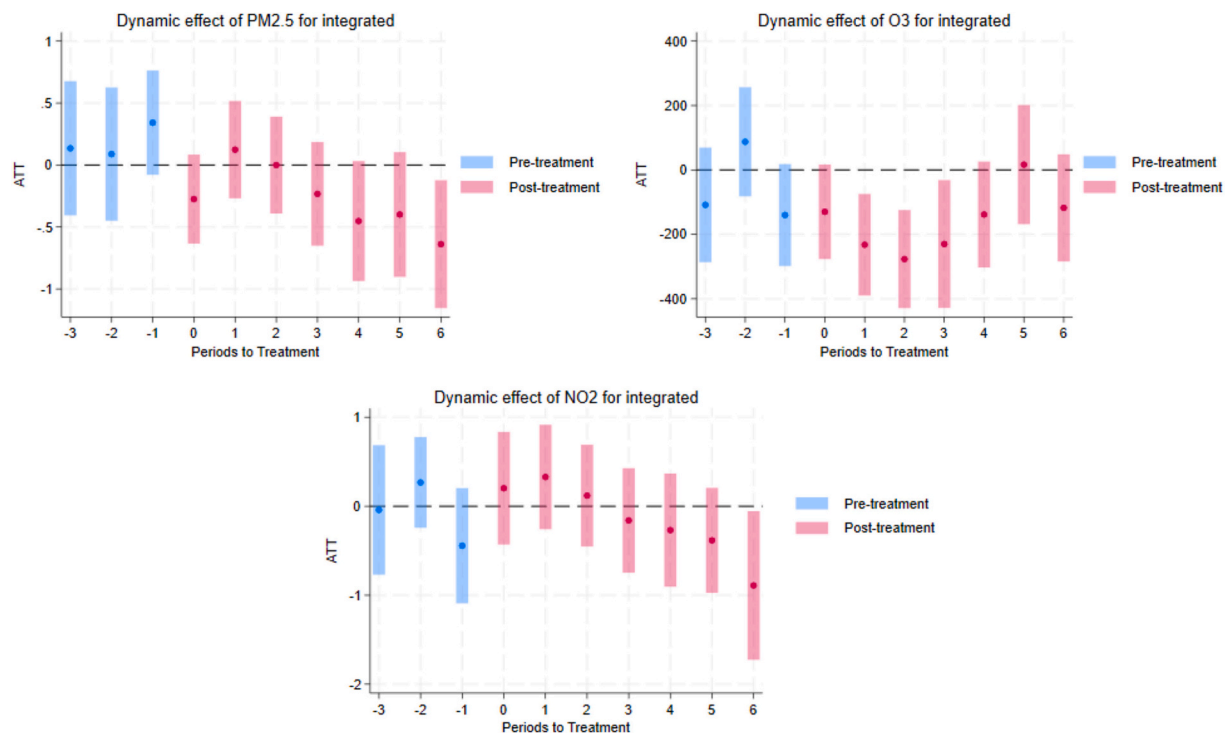


Fig. 7. Dynamic effects, all air pollutants for integrated projects.

Note: Authors' computation using *csdid* plot command in Stata. For Eq. (2) plots we use pollutants in their population-weighted value and not in logs like for the Eq. (1).

and GrowSmarter) involve lengthy planning, construction, and deployment phases, followed by gradual uptake and optimization. As a result, measurable environmental impacts, for instance for pollutants tied to transport and heating systems, are unlikely to emerge in the short period.

4.4. Robustness and sensitivity analysis

A main threat to identification is that cities adopting projects may differ from untreated cities in many aspects (including institutional capacity, access to EU funding, environmental preferences, and underlying pollution trends). We have checked for this analysing pre-trends. However, as a robustness check, we also implement the Synthetic Difference-in-Differences (SDID) estimator proposed by Arkhangelsky et al. (2021). The SDID method combines the advantages of traditional Difference-in-Differences and Synthetic Control approaches, improving robustness to parallel trends assumption violations by reweighting control units and time periods to match pre-treatment outcomes of treated units. Formally, the estimator minimizes discrepancies in pre-treatment trends while preserving a Difference-in-Differences identification structure. We implement the estimator using placebo-based inference with 100 replications. The results, reported in Appendix B (Table B.6 and Fig. B.4), confirm the robustness of the main findings, showing significant reductions in O_3 following the implementation of *Smart City* projects. Fig. B.4 indicates a close pre-treatment correspondence between treated and synthetic control cities, suggesting that the SDID procedure achieves a good match prior to treatment and providing additional support for the validity of the estimated effects.

Most treated cities (approximately 74%) receive only one *Smart City* project during the observation period, while a smaller share receives two (20%) or three projects (6%). This distribution suggests that treatment assignment is generally driven by a single intervention rather than by repeated exposure to multiple projects. Accordingly, defining treatment timing based on the implementation year of the first project appears to be a reasonable approximation. Nevertheless, we further assess the

sensitivity of our results by conducting robustness checks that account for variation in project intensity across cities. In particular, we removed from our sample the cities with multiple projects, and we re-estimate our main specification to validate our results (see Table B.7 and Fig. B.5).

Considering that the COVID-19 accelerated the adoption of digital and *Smart City* tools, with municipalities attempted to improve resilience, ensure service continuity, and support new modes of mobility and remote work (OECD, 2020), as additional robustness check, we re-estimate our baseline specifications excluding the COVID-19 period (2020–2022) and main results hold (see Table B.8. and Fig. B.6 in Appendix B).

We also evaluate how robust estimated treatment effects are to potential pre-trend differences of DiD results. Following the sensitivity-based framework developed by Rambachan and Roth (2023), we use a parameter M as a measure of bounded deviations from the strict parallel trend assumption, and construct “honest” confidence intervals that remain valid under such violations. Figs. B.7 and B.8 in Appendix B display this sensitivity analysis, (with and without country-specific linear trends). For integrated projects, the Honest DiD results are similar with and without country-specific linear trends. In both specifications, the original estimates (red) remain within the 90% robust confidence intervals for all values of the sensitivity parameter. However, the confidence intervals widen rapidly with deviations from the parallel trends assumption. As a result, statistical significance fades quickly, particularly for PM 2.5, NO_2 , and GHG emissions. For O_3 , the original estimate is negative but remains within all robustness intervals. Overall, these results suggest that the estimated effects are qualitatively stable in sign and magnitude, but the statistical significance of the findings is sensitive to departures from the standard parallel trends assumption.

We further consider the implementation of Low-Emission Zones (LEZ) across our sample of cities (building on Delgado-Lindeman et al., 2025). We find 84 cities implementing LEZs, and where this may have contributed to reducing air pollution. Excluding these cities does not change the representation of treatment in the estimation sample, and the timing of *Smart City* project adoption remains broadly distributed across

cohorts, while a large pool of never-treated cities continues to be available as controls. Removing cities that have implemented LEZ does not change our main results on the impacts of smart-city projects (see Fig. B.9 in Appendix B).

Finally, we check for the potential confounding effects of Clean Air Action Plans (CAAPs) required by EU legislation in cities exceeding pollution limit values. We do not observe plan-adoption dates for every EU city; we therefore proxy plan obligation with baseline (pre-treatment) pollution pressure. Because average concentrations in our EU sample are moderate (mean baseline NO₂ 18.8 µg/m³), very few cities exceed the absolute EU limit values, so a strict legal proxy has limited power to discriminate. Our main proxy is therefore a relative one: a standardized index combining baseline NO₂ and PM_{2.5}, with cities in its upper portion (top half, tercile, or quartile) treated as plausibly plan-bound. Table B.9 provides EU air-quality thresholds. Table B.10 reports the balance of these indicators across treated and control cities; while Table B.11 reports the staggered difference-in-differences estimates when high-pollution cities are excluded. Figs. B.10 show the exceedance share by treatment status over calendar and event time. Excluding the high-pollution (plausibly plan-bound) cities - in the spirit of the CAAP-control design of [Sarmiento et al. \(2023\)](#) - leaves the O₃ (SOMO35) effect essentially unchanged, while average NO₂ effects become marginally significant.³¹

5. Discussion and conclusions

In this paper we first explored the relationship between air pollution and mortality across European regions and cities, to then focus on the effects of *Smart City* projects implemented between 2013 and 2022. To do so, we built a unique panel dataset over the 2013–2022 period, covering 597 cities and 483 NUTS-3 regions, and integrated information on pollutant concentrations, mortality, and *Smart City* project implementation.

Our empirical analysis provides several contributions to the literature. First, we have documented the evolving relationship between key pollutants, namely PM 2.5, NO₂, and O₃, and mortality across European regions and cities, expanding previous limited results in the literature. Second, applying advanced econometric techniques, we have estimated the causal impact of *Smart City* projects on air pollution at the city level, and explored heterogeneity across pollutants, types of projects, and city sizes.

Our findings confirm that higher concentrations of air pollutants are significantly correlated with higher rates of mortality. But more importantly, our analysis shows that *Smart City* initiatives have (partially) contributed to reducing pollution levels in participating cities. Particularly, our *staggered DiD* approach suggests long-term reductions for O₃ related mainly to the implementation of integrated projects, namely projects that have an impact on at least two main

sectors, out of energy, ICT, mobility and building. Indeed, our results highlight the relevance of integrated *Smart City* projects in promoting environmental health, particularly when supported by sustained investment and policy implementation in the long-term. While O₃ results show clearer improvement trends, PM 2.5 reductions seem to require more targeted efforts due to its source diversification, such as heating, agriculture and traffic.

Together, and as a back-of-the-envelope calculation, our results suggest that, by reducing air pollution, the implementation of *Smart City* projects could potentially reduce, on average, O₃-attributable deaths by around 5%. While this should not be interpreted in fully causal terms, but in any case, indicates a non-negligible potential impact.

By city size, we find the strongest impact of projects in medium-size cities (i.e., between 40 thousand and 250 thousand inhabitants). Eindhoven, one of the three Lighthouse Cities of the Triangulum project (within the EU *Smart Cities* Marketplace), may be a good example to understand our results. Interventions there focused on building renovation, renewable heating, and smart energy management in the districts of Strijp-S and Eckart-Vaartbroek. In Eckart-Vaartbroek, around 11,200 m² of social housing were renovated, leading to an estimated 20% reduction in greenhouse gas emissions and energy bill savings of about 55% by 2019, compared with the baseline. In Strijp-S, a shift to 100% renewable heating, mainly from the Sanergy biomass system, resulted in roughly 14% of all energy generated from renewable sources within the district. These measures, combined with smart control systems, are included in a broader goal to decarbonize the city's building stock. The reduction in overall energy demand was expected. The observed reduction in O₃ following the implementation of *Smart City* initiatives targeting buildings and energy projects can be attributed to a systemic decrease in ozone precursor emissions, mainly artificial volatile organic compounds (VOCs). Building-focused interventions reduce final energy demand, consequently lowering combustions from both on-site heating systems and centralized power generation. On the other hand, energy related projects contribute to reducing precursor emissions through measures such as increased energy efficiency, electrification and the adoption of renewable energy sources, alongside partial substitution of fossil fuels with lower-emissions sources.

To assess the robustness of our findings, we re-estimated our models excluding the cities with multiple *Smart City* projects, those with the most stringent policies such as Low Emission Zones (LEZs), cities exceeding pollution limits, and the COVID-19 period. Across all these specifications, our results remained stable.

From a policy perspective, our results highlight the importance of aligning urban innovation strategies with broader environmental and public health goals. The higher performance of integrated projects suggests that funding mechanisms could prioritize cross-sectoral interventions (e.g., linking building renovation with smart grids) over isolated technological pilots. Prioritizing these interventions is also crucial for maintaining the “smart” economy itself; research shows that high pollution levels stifle corporate innovation and drive the migration of high-skilled human capital away from urban centers ([Cavalcanti et al., 2025](#)). Second, while smart mobility and energy management can curb NO₂ and O₃, the persistence of PM 2.5 demands complementary regulatory approaches. Policymakers must pair digital innovation with targeted policies addressing diverse sources such as residential heating and regional background pollution, which “smart” technologies alone cannot eliminate. The need for localized urban policy is further underscored by the role of microclimates. In this line, recent research using small-scale data shows that neighbourhood-level variations in temperature and pollution, often overlooked by broader regional models, are key determinants of local pollution as well as health outcomes ([Bian,](#)

³¹ [Sarmiento et al. \(2023\)](#) address the analogous concern for German LEZs by restricting controls to clean-air-plan cities without an LEZ. Table B.12 in Appendix B reports normalized differences in baseline concentrations between treated and control cities across progressively restrictive sub-samples; values below 0.25 indicate adequate balance. In Panel C, excluding both LEZ cities and cities bound by an air-quality plan under the legal proxy, treated and control cities are balanced on all three pollutants (0.14, -0.18 and -0.04). Treated cities are therefore not systematically more polluted at baseline, and no more likely to have been subject to the exceedance-triggered obligations of Article 23 of Directive 2008/50/EC. A residual imbalance appears only in PM_{2.5} under the relative proxies, and to a lesser extent in O₃ at the top-half cut, but it runs opposite to the confounding channel of concern, treated cities are the less polluted group and attenuates monotonically as the sample widens (-0.60 to -0.33 excluding LEZ cities), indicating it is driven by the few treated units surviving the most restrictive cuts. Since the estimator identifies effects from within-city changes under parallel trends rather than from baseline levels, these level differences do not threaten identification.

2025).³²

While we have provided valuable insights on the role of smart-city projects on curbing pollution, and thus reducing mortality, future research is essential to increase our understanding of the transition mechanics between project implementation and outcomes. Further research could investigate in more depth the specific effects of different project types, explore their long-term sustainability, their cost-benefit, and examine interactions with complementary policies in housing, energy, and mobility, that are also implemented in recent initiatives like *Smart Village* projects.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material to this article can be found online at <https://doi.org/10.1016/j.eiar.2026.108671>.

Data availability

Data will be made available on request.

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³² Smart projects can increase the desirability and health-profile of specific areas, leading to “residential sorting.” As argued by Basu et al. (2025), environmental improvements can inadvertently lead to higher housing prices that displace vulnerable populations into remaining high-pollution areas. Future research should therefore study distributional impacts of the health benefits of *Smart City* projects.

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