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Urban NO_2-pollution and health outcomes: Evidence from a natural experiment in Italy on the simulated benefits of the EU zero-emission-vehicles resolution

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ABSTRACT

Background: The EU "Fit-For-55" resolution provisions the banning of fossil-fuel-vehicle sales beyond 2035, sparking a heated debate due to its uncertain effectiveness in reducing CO_2 emissions globally. Nevertheless, the EU shift towards zero-emission vehicles has the potential to decrease urban nitrogen dioxide (NO_2) pollution that is closely linked to respiratory and cardiovascular diseases and to increased mortality.
Objective: This paper aims to simulate the impact that the EU zero-emission-mobility policy is expected to have, post-transitional period, on urban NO_2 and health outcomes.
Methods: The analysis exploits some unique features of Northern-Italy air-pollution data and the Italian Covid-19 lockdown that is leveraged as a natural experiment to mimic the fossil-fuel traffic abatement expected by the policy. Our estimates are obtained by developing a novel intertemporal-statistical-matching approach specifically suited for quasi-experimental evaluations in the context of air-pollution multivariate time series.
Results: We find that the lockdown led to a mean NO_2 reduction of 13.62 μg/m^3 (53 % from a baseline of 25.8 μg/m^3), translating into a simulated reduction in the relative risk of total, cardiovascular, and respiratory mortality by 8.3, 7.5 and 3.8 percentage points, respectively. We also estimate impact heterogeneity, with log-linearly larger reductions in NO_2 and mortality risk at higher baseline-pollution levels.
Conclusions: These results imply that the EU zero-emission mobility policy is expected to improve air-quality and public health in urban areas with high traffic density, though benefits may vary across regions due to differences in meteorological conditions and urban/orographic characteristics, supporting a spatially differentiated policy implementation.

Research in context

What is already known about the topic?

The provisioned EU shift toward zero-emission mobility has the potential to decrease urban NO_2 pollution, achieving health benefits that are well established in the literature.

No empirical evidence however is yet available on expected NO_2 impacts and related health benefits of the EU zero-emission policy.

What does this study add to the literature?

We exploit data and natural-experiment condition that uniquely mimic the zero-emission policy to estimate its impact on NO_2 and simulated health outcomes.

We develop a novel quasi-experimental model suitable for policy evaluations involving multivariate time-series air-pollution data.

Results: NO_2 reduction of 13.62 μg/m^3 (53 % from the baseline); reduction in the relative risk (RR) of total, cardiovascular, and respiratory mortality by 8.3, 7.5 and 3.8 percentage points (pp); estimated health benefits steadily increase alongside the increase of baseline NO_2 pollution (maximum RR reduction of 32.8, 30 and 16.3 pp for total, cardiovascular and respiratory mortality, at the highest baseline).

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What are the policy implications?

In addition to CO_2-emissions, adequate considerations should be placed in the policy debate to the health benefits from urban NO_2 abatement.

High-pollution areas could be prioritized for intervention, through more aggressive timelines or additional support measures.

1. Background

In June 2021, the European Union approved the "Fit-For-55" resolution, aimed to cut emissions by 55 % by 2030 compared to 1990 levels (www.consilium.europa.eu/en/policies/fit-for-55). Among a variety of climate, energy, land-use and taxation policies, the resolution also provisions the banning of the sale of new diesel, gasoline, and hybrid internal-combustion engine (ICE)'s vehicles beyond 2035 which has sparked debate among policymakers and stakeholders, primarily due to uncertainties regarding the overall reduction of carbon dioxide (CO_2) emissions across the Union. Concerns include the potential offsetting of reduced vehicular emissions by increased emissions from electricity generation, as well as doubts about whether the full life-cycle climate footprint of zero-emission vehicles aligns with EU environmental goals.

In contrast, the local potential benefits of transitioning to zero-emission mobility are more promising, as this shift could potentially significantly enhance air-quality in EU densely populated urban areas, improving public health and quality of life. Indeed, as widely acknowledged, a large portion of Europe's population lives in urban areas that often have exceeded air-pollution limits. This leads to well documented adverse health effects [1,12,13,15,25,37,48,52,53,57,60,61,69], high mortality rates [5,29,39] and increased hospital admissions [18,36,42,54,55,63]. Poor air-quality conditions also negatively affect other socio-economic outcomes, such as school performances [14], human-capital [26], labour supply [31] and social welfare [62]. Among the different air pollutants, Particulate Matter ($PM_{2.5}$/PM_{10}), Ozone (O_3) and Nitrogen Dioxide (NO_2), the latter is primarily related to fossil-fuel vehicular traffic intensity [34], with NO_2 levels that are highest near major roads, especially in areas with unfavourable orography [9,64]. Moreover, NO_2 is closely linked to severe health impacts, such as respiratory and cardiovascular diseases [56], and to increased mortality (e.g., [21,76]), so that reducing NO_2-pollution in densely populated urban areas has the greatest potential for positive air-quality outcomes under fossil-fuel traffic reduction policies.

For these reasons, our paper aims at providing policy-relevant empirical evidence on the simulated impact, post-transitional period, of the EU zero-emission-mobility resolution on reducing local NO_2-pollution, and related health outcome improvements, in densely populated urban areas. In the analysis, we exploit data that were primarily collected from a large universe of selected urban measuring stations located in central urban areas of the Northern Italy's Po-river Valley, one of Europe's most polluted regions, with 14.8 million residents, and an average density of 252 inhabitants per square-kilometre. In order to record a sharp abatement of fossil-fuel vehicular traffic, comparable to that provisioned for the EU resolution, the data observation period is across the Italian Covid-19 lockdown of early 2020 that provisioned a draconian mandatory stay-at-home order that is uniquely posed to estimate causal impacts of the sharp fossil-fuel traffic abatement envisioned by the EU resolution.

For the causal-inference analysis, we develop a novel intertemporal-statistical-matching (SM) approach estimated with a Mahalanobis Distance (MAHD). This approach is best suited for the specific causal identification conditions posed by the air-pollution multivariate time series, such as those from our measurement stations, in which the major confounding factors (i.e. weather daily characteristics) are observable in the data and exogenous to the treatment status (lockdown/non-lockdown). Under these conditions, our intertemporal SM approach matches, separately for each air-pollution measurement station, the single lockdown (i.e. treated) days with the non-lockdown (i.e. untreated) ones sharing the same control variables in terms of the most relevant weather characteristics, as regards the influence on air-pollution concentration. Compared to panel-data multiple-regression (MR) models adopted elsewhere in the empirical literature on air-pollution outcomes [32,70,71,75], such an intertemporal matching approach shares the same well-known advantages (e.g. [17,66,72]) of the standard cross-sectional statistical matching (SM) approaches in strongly diminishing the sensibility of the estimated impacts to the choice of the functional form that links the effects of the controls on the outcome variable. Compared to RRD-in-time (e.g. [16]), our intertemporal matching approach is instead more efficient (granting larger external validity) and better suited to handle the potential of chance unbalancing due to the small sample size of treated units, because of arguments which build on Lee and Card [45], Lee and Lemieux [46], Bondonio [7] and are thoroughly discussed in Appendix A.1.

The results of our analysis show that the sharp traffic abatement of the lockdown produced a significant drop in daily average NO_2 levels, corresponding to a 53 % reduction from a baseline average value of about 25.80 $\mu g/m^3$. In terms of heterogeneous impacts, our results show that the magnitude of the estimated NO_2 reduction is higher the higher is the baseline NO_2-pollution. With reference to the findings from the pertaining medical literature [21], these estimated NO_2 reductions translate into an average decrease in the relative risk (RR) of mortality which is up to 32.8 (for all causes), 30 (for cardiovascular causes), and 16.3 (for respiratory causes) percentage points (pp) for the days with the highest baseline pollution.

These findings relate to the rapidly expanding studies on the effects of environmental policies on air quality. This strand of literature concentrates on regulations that specifically apply to local urban areas, such as traffic bans and low emission zones [23,30,65,74,77], road pricing policies [19,22,24,28], restrictions on gasoline content [3], as well as specifically targeted air quality policies [6,11] belong to this research area. In this context, compared to existing urban air-quality initiatives such as low-emission zones (LEZs) or temporary traffic bans, the simulated impact of the EU zero-emission vehicle resolution is expected to be substantially larger in magnitude and spatial extension. Empirical studies on LEZs – such as Wolff [77], Viard and Fu [74], Gehrsitz [23], Han et al. [30], Rivera [65], and Pestel and Wozny [57] – typically find modest reductions in air pollution and limited health effects, often constrained by weak enforcement, technological exemptions, or partial fleet turnover. Similarly, road pricing policies (e.g., [19,22,24,28]) tend to produce more localized improvements. In contrast, the EU 2035 resolution entails a radical and irreversible transition to zero tailpipe emissions for all new vehicles, leading to a structural transformation of the vehicle stock. By simulating the large-scale fossil-fuel traffic abatement analogous to a full zero-emission policy implementation, our findings suggest that the resolution could yield significantly greater NO_2 reductions and associated health benefits, particularly in high-density urban areas where LEZs have delivered only marginal gains. Thus, our study complements and expands the evidence on urban air-quality policies by estimating the highest benefits of a comprehensive and binding zero-emission mobility EU-level regulation.

Compared to the existing literature on the effect of the Covid-19 lockdown on NO_2 pollution, our findings uniquely provide evidence with greatest policy relevance due to both a rigorous causal-inference analysis on a comprehensive universe of measuring stations located in a densely-populated European area, and a well-defined operationalization of the severity of the lockdown and of the location of the NO_2 measuring station, which avoid capturing NO_2 variations due to non-vehicular-traffic sources (such as industrial production, power plants, airports and naval ports). These features enable the analysis to estimate the NO_2 reduction caused by traffic abatement comparable to that expected from EU resolution, providing insights into the environmental and health gains from the EU-2035 regulation, which can be compared

to the opportunity costs of implementing the green transition highlighted elsewhere in the literature (e.g. [33,40,58,73,79]). As discussed more in details in Appendix B, this is unlike the existing Covid-19 lockdown literature in which the results are difficult to compare with ours because they display an extremely wide range of estimated NO_2 reductions, bearing limited policy relevance. This is due to either an inadequate internal validity of the estimated casual effects (which are essentially produced by mere before-after-lockdown comparisons of NO_2 descriptive statistics); or the lacking of a precise information and a well-defined operationalization on the intensity of the lockdown and the distance of the measuring stations from non-vehicular-traffic sources of NO_2 pollution; or, finally, the extremely-low external validity of the findings which derive from simple case studies from data on one single measuring location (also in this case often with no metric on the distances from the different sources of pollution).

2. Method

2.1. Data

The NO_2 air-pollution data used in our analysis are collected from 77 different measurement stations of the Italian Regional Environmental Agencies (ARPA) of the regions of Piedmont, Lombardy, Emilia-Romagna, Veneto, and Friuli Venezia Giulia. These measurement stations are the universe of all ARPA stations (which are those deputed to providing officially-recognized air-pollution measurements in Italy) located in central urban areas in close proximity with vehicular traffic and residential/office buildings, and away from power plants, industrial sites, and airports. In particular, variations in pollution from power plants are likely not to be a significant biasing factor in our spatial context, because the central urban areas where all the ARPA measuring stations are located are away from these power plants, with an average minimum distance of 32 km (see Appendix C.1 for a detailed map of the measurement stations).

Being NO_2 a pollutant from fossil-fuel combustion with very little dispersion away from its source (e.g. [2,4,10,20]), these locational features of the measurement stations ensure that the possible recordable sources of NO_2-pollution in our data are solely vehicular traffic or fossil-fuel-combustion from heating systems and hot-water production in residential/office buildings. In this latter regard, however, data from the Ministry of the Environment and Energy Security in the National Energy Balance indicate that the Italian Covid-19 lockdown, in the central urban locations around the measurement stations, determined an increase in fossil-fuel consumption from the heating (and hot-water production) of residential buildings that was equally compensated by a decreased consumption from the heating (and hot-water production) of office buildings, with a net-zero effect of the lockdown in terms of fossil-fuel combustion unrelated to vehicular traffic (data sources and statistics: www.arera.it/dati-e-statistiche). For these reasons, a crucial feature of our data is the possibility to interpret the estimated causal effect of the Covid-19 lockdown in terms of the impact of the abrupt abatement of fossil-fuel vehicular traffic.

The central urban location of all 77 ARPA measuring stations is within municipalities characterized by elevated vehicular traffic density, with a pre-Covid-19 average of 237 registered vehicles per km of road (std. dev. 122, 10^{th} percentile 146, median 191, 90^{th} percentile 354; data source: Ministry of Infrastructures and Transportation and ISTAT – Public Register of motor-vehicles). Such a modestly–dispersed distribution of municipality-level traffic density translates into specific daily baseline NO_2-pollution levels, with a much larger variation based on both the daily meteorological characteristics and the micro-locational urban texture of the surroundings of the measuring stations (prevalence of major boulevards, average width of the streets, presence/absence of canyoning effects due to attached buildings of the same height, etc.).

Indeed, considering the 365 days preceding the start of 2020 lockdown (i.e. from March 10^{th}, 2019 to March 9^{th}, 2020), the average daily baseline NO_2-pollution recorded in the 77 measuring station is equal to 28.70 $\mu g/m^3$, with a std. dev of 18.60 $\mu g/m^3$, while the 10^{th} percentile, the median and the 90^{th} percentile are 9.00 $\mu g/m^3$, 25.10 $\mu g/m^3$ and 51.70 $\mu g/m^3$, respectively. Quite a similar distribution of the daily baseline NO_2-pollution is also recorded for the 69-days period of 2019 corresponding to the 2020 lockdown (i.e. from March 10^{th} to May 17^{th}, 2019): average 25.80 $\mu g/m^3$, std. dev. 16.40 $\mu g/m^3$, 10^{th} percentile 8.60 $\mu g/m^3$, median 22.20 $\mu g/m^3$, 90^{th} percentile 47.20 $\mu g/m^3$ (see Appendix C.2 for additional descriptive statistics).

The separate contributions from the two sources of heterogeneity (i.e. the different daily meteorological characteristics and micro-locational urban textures) in the distribution of the daily baseline NO_2 pollution are illustrated in the boxplots contained in Fig. 1. Boxplot A summarizes the distribution of the 365 daily NO_2 averages computed across the universe of all the 77 measuring stations during the one-year period preceding the lockdown. This distribution captures the degree of variability mainly deriving from the daily changing of meteorological conditions, which can be more or less prone to NO_2 accumulation. The distribution shows a minimum of 10.97 $\mu g/m^3$; a maximum of 61.67 $\mu g/m^3$, while the thresholds for the first and third quartile are 19.53 $\mu g/m^3$ and 35.45 $\mu g/m^3$, respectively.

Boxplot B illustrates instead the distribution of the 77 location-specific yearly averages (one for each measuring station) recorded for the same one-year period before the lockdown. This distribution captures the degree of variability mainly accounted for by the micro-locational urban textures that surround the measuring stations, and it shows a similar variability compared to boxplot A (with a minimum of 5.77 $\mu g/m^3$; a maximum of 69.90 $\mu g/m^3$, and the first and third quartile thresholds which are 20.99 $\mu g/m^3$ and 33.70 $\mu g/m^3$, respectively).

The extraordinary stringency of the mandatory-stay home provision of the Italian lockdown determined a fossil-fuel vehicular-traffic abatement which can be estimated to be around 77–90 % (see Appendix C for data sources and additional details) in the Po-river valley regions in which the measuring stations are located. Since in 2020 the percentage of non-fossil-fuel vehicles circulating in Northern Italy was negligible (with an estimated 2.2 % value; source: Ministry of Infrastructures and Transportation and ISTAT – Public Register of motor-vehicles), these circumstances entails that our impact evaluation analysis is adequately suited to empirically predict the local NO_2 air-quality gains that can be achieved by future policies, such as the 2035 EU Zero-Emission-Vehicles resolution, for which somehow similar reductions of fossil-fuel traffic are expected due to a significant quota of used and exempted fossil-fuel vehicles which are projected to still circulate well beyond 2035 [35]. Indeed, even assuming a 100 % zero-emission vehicles sales beyond 2035, projected estimates on the reduction in emissions achievable by 2050 imply that about 11 % of vehicular traffic is still expected to be equipped with fossil-fuel engines in the period 2035–2050 [59].

The period of observation for the analysis covers all the 69 days of the Italian nationwide Covid-19 lockdown (March 10^{th} - May 17^{th}, 2020), together with the 365 preceding days. The data also include a set of control variables that capture the main meteorological characteristics that are known in the literature to influence air-pollution [16,27,49,71,75]. In particular, the latter include the average daily temperature (TEMP), rainfall (RAIN), and maximum daily wind speed (WIND), together with their lagged terms capturing the same weather characteristics of the previous day. This is in line with the data operationalization choices adopted in most air-pollution causal inference analyses with observable weather controls (e.g. [16,49,75]). In addition, the adequacy of these observable controls is further validated by a placebo-test analysis (reported in Section 3) which indicates the absence of a secular or seasonal trend based on unobservable daily covariates. This finding is indicative that no other major confounders are left out in our intertemporal statistical matching estimation.

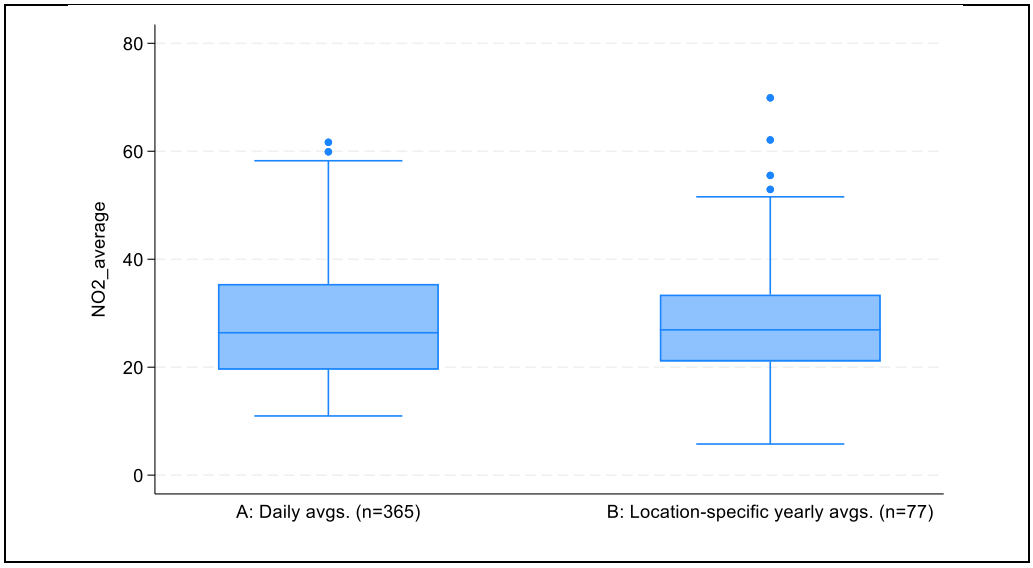

Fig. 1. Boxplots of NO_2 baseline distributions across the one-year period before the lockdown
Notes: Boxplot A summarizes the distribution of the 365 daily NO_2 averages computed across the universe of all the 77 measuring stations during the one-year period preceding the lockdown. This distribution captures the degree of variability mainly deriving from the daily changing of meteorological conditions, which can be more or less prone to NO_2 accumulation. Boxplot B illustrates the distribution of the 77 location-specific yearly averages (one for each measuring station) recorded for the same one-year period before the lockdown. This distribution captures the degree of variability mainly accounted for by the micro-locational urban textures that surround the measuring stations.

2.2. Intertemporal statistical matching estimation

The impact identification conditions for estimating the causal effect of the Italian lockdown are in terms of the availability of multiple multivariate time-series, one for each air-pollution measurement station, with units of observations represented by the calendar days in which NO_2 air pollution and weather characteristic are measured. Within these multivariate time-series, the abrupt change in the secular trend of NO_2 pollution brought by the lockdown-induced sharp decrease in traffic is the treatment of interest, while the major (observable and unobservable) weather (or seasonal related) confounding factors, are exogenous to the treatment status (lockdown/non-lockdown). This is because the latter was determined by the severity of the Covid-19 pandemic trend, and it was not based on weather forecasting/seasonal factors which predicts favorable/unfavorable conditions for NO_2 accumulation. For this reason, the Covid-19 pandemic acted as an exogenous traffic-abatement factor which determined quasi natural-experiment conditions.

Under these conditions, building on Bondonio and Chirico [8], the implementation of our novel intertemporal Mahalanobis Distance (MAHD) matching approach is composed by the following steps (see also Appendix A.1 for a more formalized and detailed description of the estimation process and related statistical properties).

First, separately considering the multivariate time series of daily NO_2 and weather observations from the 77 air-pollution measuring stations, each treated (i.e. lockdown) day is matched with the untreated (i.e. pre-lockdown) day(s) from the same measuring station that share(s) the most similar values of the weather controls and related lagged values. Besides the balancing of the weather controls, such conditioning on the same measuring station is also crucial to achieve a perfect correspondence between the treated and matched untreated days of the micro-characteristics of the location in which NO_2 pollution is measured. Second, for each lockdown day on common support, a counterfactual NO_2 outcome is estimated as the mean of the $N0_2$ values of the corresponding matched untreated day(s). Third, a local intertemporal ATT is estimated for each multivariate time series in terms of the difference between the average daily $N0_2$ values of treated and untreated days. Finally, a global ATT estimate is obtained by averaging-out the series of

Table 1
Balancing of control variables in intertemporal MAHD matching ($c = 1$).

Variables		Unmatched/ Matched	Mean Treated	Mean Control	% bias	% reduction |bias|
WIND	(m/s)	U	2.13	1.88	19.60	
		M	1.89	1.86	2.00	89.60
RAIN	(m/m)	U	1.35	2.43	−17.20	
		M	0.39	0.40	−0.10	99.20
TEMP	(c°)	U	13.79	15.05	−20.40	
		M	14.24	14.14	1.60	92.10
WIND-1	(m/s)	U	2.14	1.88	20.30	
		M	1.93	1.90	2.10	89.80
RAIN-1	(m/m)	U	1.34	2.58	−18.90	
		M	0.39	0.41	−0.20	98.70
TEMP-1	(c°)	U	13.71	15.01	−21.10	
		M	13.81	13.70	1.80	91.60

Notes: the Table illustrates the balancing of the control variables (namely the weather controls and related lagged values) achieved by the intertemporal MAHD SM for ATT estimation across all the daily NO_2 baseline levels. This is in terms of percentage bias and reduction of percentage bias of the pooled distribution (across all the ARPA-stations time series) of the L_1 days and the matched L_0 day(s).

Table 2
Rubin's *R* and *B* indices for MAHD matching.

Sample	Ps R^2	LR chi^2	$p > chi^2$	Mean Bias	Med Bias	*B*	*R*
Unmatched	0.03	659.42	0	19.60	19.90	40.10*	0.77
Matched - MDM	0	3.14	0.79	1.30	1.70	4.10	1.01

Notes: the Table summarizes Rubin's *R* and *B* balancing indices, assuming the standard thresholds for acceptance posed in terms of $B < 25$ and $0.5 < R < 2$.

local ATTs.

The specific operationalization of the MAHD caliper (*c*) used in our intertemporal statistical matching analysis is $c = 1$, which is the value that maximize the statistical efficiency of the analysis under the constrain of satisfying the balancing of the control variables between the intervention days L_1 and the matched controlled days L_0. This latter testing is implemented by means of the Rubin's *R* and *B* indices [47,68], with the standard thresholds for acceptance posed in terms of $B < 25$ and $0.5 < R < 2$. Tables 1 and 2 illustrate the balancing of the control variables achieved by the intertemporal MAHD SM for ATT estimation across all the daily NO_2 baseline levels. This is in terms of percentage bias and reduction of percentage bias of the pooled distribution (across all the ARPA-stations time series) of the L_1 days and the matched L_0 days. For all the control variables, the intertemporal MAHD SM drastically reduces the initial percentage bias between the intervention period L_1 and the control period L_0. Such reduction in the percentage bias ranges from 89.6 % to 99.2 %, with a negligible after-matching remaining % bias which ranges from −0.10 % to 2.10 %.

The Rubin's *R* and *B* balancing indices are summarized in Table 2. The after-matching value of the *B* index is 4.1, while that of the *R* index is 1.01. These values are well within the limits ($B < 25$ and $0.5 < R < 2$) that indicate a fully acceptable overall balancing of the control variables between the intervention days L_1 and the matched controlled days L_0.

2.3. Heterogeneous-impacts estimation

These ATT estimates can be conceptualized in terms of the difference between a baseline NO_2-pollution in existence under standard pre-lockdown conditions and the NO_2-pollution that is recordable in the same identical measuring station, holding everything else constant, except for the lockdown-induced abatement of fossil-fuel traffic. In this regard, for each single baseline day, it is important to notice that the estimated NO_2 reduction has the potential of being different based on the severity of the daily NO_2. Days with unfavorable meteorological conditions, or with NO_2 pollution recorded in unfavorable micro-locational urban texture conditions, leading to a buildup of high baseline NO_2-pollution, have a larger potential to greatly benefit from a fossil-fuel traffic abatement than days with favorable conditions (e.g. windy or rainy conditions, and/or with NO_2 pollution measured in more favorable micro-locational urban settings). The Po-river-valley and the central-urban-area location of the measuring stations in our data ensures that the estimated impacts are representative of the average air-quality gain achievable where it matters the most: the places with elevated traffic density and very high average air pollution. In order to further enlarge the external validity of the findings, however, it is also relevant to estimate the NO_2 reduction that may be expected at large in a variety of other urban EU locations. Indeed, outside of the Po-river valley, central urban areas with high traffic-density experience heterogeneous average baseline pollutions due to a different prevalence of favorable/unfavorable meteorological conditions and/or variations in the orographic characteristics and features of the urban texture.

For this reason, we further exploited the whole distribution of the baseline NO_2-pollution recorded in our data (including some low NO_2 levels from the days with heavy precipitations and strong sustained wind and/or with NO_2 recordings from favorable micro-locational unban contexts) to estimate heterogeneous impacts based on categories of the baseline NO_2-pollution. This is achieved by implementing a categorical-treatment version of our intertemporal SM estimation which can summarized as follows. First, holding constant a same measuring station, each lockdown day is matched with the pre-lockdown day(s) with the most similar control variables, based on MAHD. Likewise for the global ATT estimation, the procedure is repeated for each measuring station, and the value of the caliper ($c = 1$) is determined as the one that maximize the statistical efficiency of the analysis under the constrain of satisfying the balancing of the controls between the lockdown and the pre-lockdown days. The paired matched days are sorted into categories based on the recorded baseline NO_2 pollution level. For the main specification of the model, the number and span of these categories are determined with the criteria of covering the entire distribution of the baseline NO_2 pollution, ensuring a strong policy relevance of the results, while maintaining also an adequate statistical efficiency of the estimates. This translates into the following eleven categories: 0–10 $\mu g/m^3$; 10–20 $\mu g/m^3$; […]; 90–100 $\mu g/m^3$; 100–150 $\mu g/m^3$.

To further test the robustness of the estimated heterogeneous impacts (as part of the sensitivity analysis reported in detail in Appendix E), the estimation of the MAHD model is also replicated with two different operationalization of the categories of baseline NO_2 pollution. The first is in terms of four categories based on the quartiles of the same overall distribution of the baseline NO_2. The second is instead in terms of grouping the matched pairs of treated (i.e. lockdown) and untreated (i.e. pre-lockdown) day(s) from the different 77 measuring stations, based on location-specific baseline pollution levels. This is in terms of the station-specific yearly average of the NO_2 baseline pollution recorded in the one-year period before the lockdown. In this latter case the resulting treatment categories, determined by the threshold of the quartiles of this station-specific distribution of baseline NO_2, capture the heterogeneity in the baseline NO_2 pollution stemming primarily from the different micro-locational urban texture characteristics of the sites where NO_2 levels are measured (e.g., proximity/distance to major boulevards, traffic arteries, parks or green areas; urban texture with prevailing attached buildings of the same heights which determine the presence of street canyoning effects that favour high NO_2 concentrations).

3. Results

Table 3 reports the global ATT impact estimates of the analysis, obtained across all the baseline NO_2-pollution levels. The average reduction in local NO_2-pollution caused by the traffic abatement of the lockdown is estimated as -13.62 $\mu g/m^3$, with a confidence interval of (-14.15 $\mu g/m^3$, -13.09 $\mu g/m^3$) and a significance level well within the 5 % level. Considering that the average daily baseline NO_2-pollution recorded in 2019 during the same corresponding period of the 2020 lockdown is about 25.80 $\mu g/m^3$ (see Table C.2 in Appendix C.2), the estimated ATT impact translate into an average NO_2 reduction of about 53 %.

Table 3 also shows results from a placebo test aimed to assess the robustness of the aforementioned ATT estimate and to rule out the influence of potential unobserved secular changes (or unobservable seasonal trends that are not captured by our observable controls) unrelated to the lockdown's traffic abatement. The test involves replicating the intertemporal MAHD SM estimation four times, each using a different *false* lockdown period of identical duration but shifted backward from the actual lockdown. In this setting, we should not observe any significant effect of these *false* treatments on pollution levels. Indeed, for the

Table 3
Causal effect of the lockdown on local NO_2 pollution: global ATT estimates (intertemporal MAHD matching, $c = 1$).

Period (dd/mm/yy)	Duration (days)	Treated obs. on common support	$\widehat{ATT}$ μg/m³	S.E.	95 % Conf. Interval	
Actual lockdown [10/03/20 – 17/05/20]	69	3815	−13.62	0.27	−14.15	−13.09
False lockdown 1 [01/01/20 – 09/03/20]	69	3232	−0.58	0.36	−1.28	0.12
False lockdown 2 [24/10/19 – 31/12/19]	69	2474	−2.71	0.37	−3.43	−1.98
False lockdown 3 [16/08/19 – 23/10/19]	69	3431	−0.70	0.25	−1.18	−0.22
False lockdown 4 [08/06/19 – 15/08/19]	69	3215	−1.38	0.21	−1.80	−0.97

Sample	Ps R^2	LR chi^2	$p > chi^2$	Mean Bias	Med Bias	*B*	*R*
Unmatched	0.03	659.42	0	19.60	19.90	40.10*	0.77
Matched MDM	0	3.14	0.79	1.30	1.70	4.10	1.01

Notes: global ATT estimates of the impact of the Covid-19 lockdown on local NO_2 pollution. Estimates are based on our novel intertemporal MAHD SM approach described in Section 2 and Appendix A, with caliper $c = 1$. The Rubin's *R* and *B* balancing indices are summarized in Table 2. The estimated impact is in terms of the difference between the baseline NO_2 recorded in the standard working days in the pre-Covid period and the NO_2 recorded in the same exact identical measurement location, holding everything else constant (including all relevant meteorological characteristics), except for the lockdown fossil-fuel traffic abatement. The placebo test is performed by replicating four different times the estimation of our intertemporal MAHD SM estimation, each time assuming as a treatment a different *false* lockdown period of the same exact duration but shifted backward from the date of the actual lockdown.

first *false* period, which immediately precedes the actual lockdown, the estimated impact is very close to zero (−0.58 μg/m³) and not statistically significant (at the 5 % level), while for the remaining three *false* periods, the ATT point estimates show only a very minimal negative deviation from zero, ranging from −0.70 μg/m³ for the third period, to −2.71 μg/m³ for the second period.

The categorical ATT estimates for the heterogeneous impacts are reported in both Fig. 2 and Table D.1 (in Appendix D). For the days in which the meteorological conditions determine the lowest baseline NO_2-pollution (i.e. between 0 and 10 μg/m³), the causal effect of the traffic abatement brought by the lockdown is close to zero (−0.18 μg/m³) and not statistically significant (at the 5 % confidence). For the next categories, the magnitude of the reduction of NO_2-pollution caused by the lockdown traffic abatement is linearly increasing with the increase of the baseline-pollution. These categorical ATT estimates are always statistical significant and range from −4.97 μg/m³, for the 10–20 μg/m³ baseline NO_2-pollution, to a maximum of −62.16 μg/m³ for the highest baseline-pollution (100–150 μg/m³).

3.1. Sensitivity analysis

As described in detail in Appendix E, all of these results are robust to a wide array of further sensitivity analyses (besides the placebo test described above). In particular, the latter are implemented by replicating the estimation using, in turn, Intertemporal Propensity Score Matching and Random Forest Regression (RFR) models, different specifications of intertemporal MAHD matching, and alternative specifications of the categories of baseline NO_2-pollution. All the results from this sensitivity analysis entirely support the findings from our main specifications, highlighting an adequate robustness of the estimated causal effects for both the ATT and the heterogeneous impacts (see Appendix E for a complete summary of all the results).

4. Discussion

The estimated NO_2 reductions caused by the lockdown fossil-fuel traffic abatement can be translated into simulated health benefits based on established meta-analysis findings, such as those from Faustini et al. [21], which reviewed 23 epidemiological European cohort studies published between 2004 and 2013 to evaluate the link between NO_2 and relative risk of total, cardiovascular and respiratory mortality. These findings indicate that, for Europe, the pooled estimates of the NO_2 effect, per 10 μg/m³, translate into a relative risk (RR) of total mortality of 1.066 (95 % CI: 1.029–1.104), and a RR of cardiovascular and respiratory mortality of 1.059 (95 % CI: 1.032–1.086) and 1.029 (95 % CI: 1.013–1.045), respectively (see Appendix F for a detailed discussion on the strengths and limitations of translating these RR estimates to the specific Italian context).

Applying the parameters from Faustini et al. [21] to our estimated average reduction of −13.6 μg/m³ in daily NO_2-pollution entails a simulated decrease in the RR of total mortality by about 8.3 pp, and RR reductions of 7.5 and 3.8 pp for cardiovascular mortality and respiratory mortality, respectively. This is estimated assuming a log-linear relationship between $N0_2$ exposure and health outcomes, which is in accordance with the vast majority of the epidemiological literature that investigate the shape of the NO_2-concentration-response functions [43,50,67,78]. Indeed, all of these studies indicate that no deviation from log-linearity does exist, especially within the most commonly observed ranges of NO_2 exposure distribution, as in Kasdagli et al. [38].

When considering instead our estimated heterogeneous NO_2 impacts, the application of the meta-analysis RR results from Faustini et al. [21] – based again on a log-linear relationship assumption – suggests that the expected health benefits are likely to vary across EU urban areas due to differences in baseline NO_2-pollution levels driven by meteorological conditions and micro-location urban texture characteristics. Indeed, as shown in Table 4, negligible health benefits are to be expected in urban areas with prevailing meteorological conditions leading to extremely low baseline NO_2 levels (0–10 μg/m³). For areas with the next higher baseline-pollution of 10–20 μg/m³, the simulated health benefits are instead in terms of −3.1 pp for total mortality, −2.8 and −1.4 pp for cardiovascular and respiratory mortality, respectively. Such estimated health benefits further steadily increase for all the subsequent categories of higher baseline pollutions, reaching a maximum RR reduction of 32.8, 30 and 16.3 pp for total, cardiovascular and respiratory mortality, respectively, at the highest baseline of 100–150 μg/m³.

It is worth noting, however, that some strands of epidemiological literature support a convex/accelerated positively-sloped dose-response function linking NO_2 exposure to health outcomes (e.g., [41]). Unfortunately, no NO_2-specific robustly-tested dose-response functions can be promptly used for computing RR reductions so as to account for

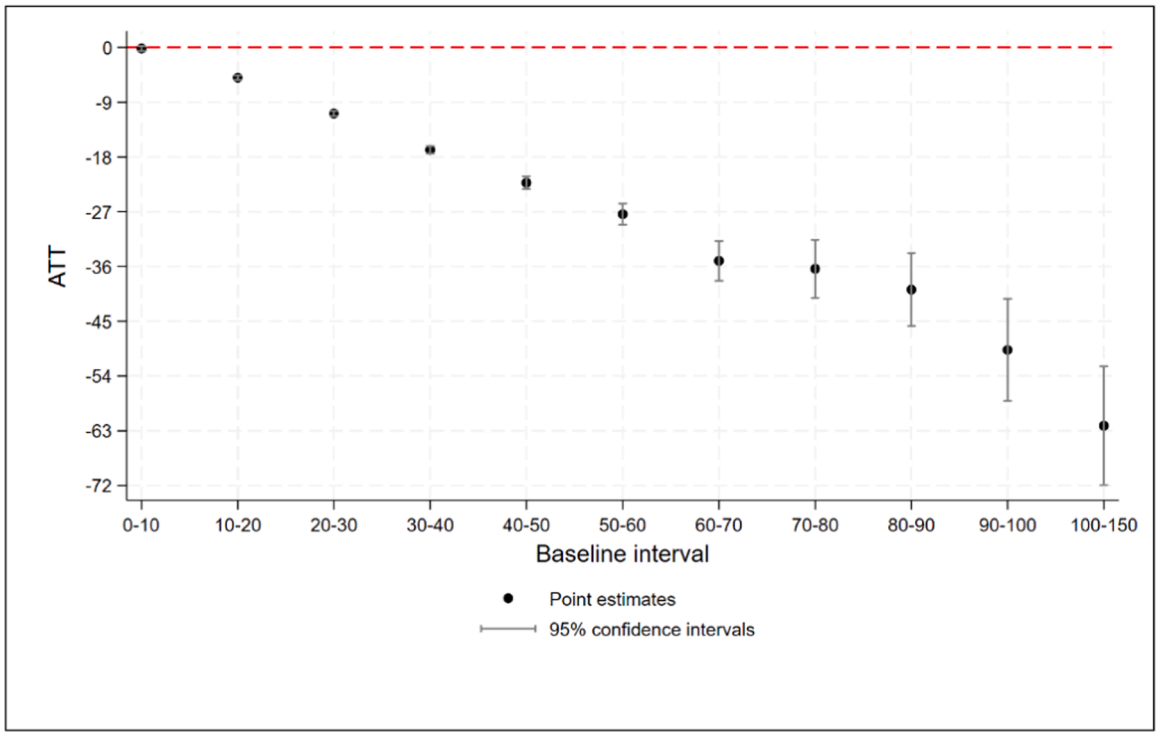

Fig. 2. Causal effect of the lockdown by baseline pollution levels (μg/m^3)
Notes: the Figure provides categorical ATT estimates for the heterogeneous impacts. See Appendix A.2 for methodological details.

Table 4
Simulated reductions in the relative risk of mortality associated with estimated NO_2 impacts (ATT): log-linear relationship.

Category γ of baseline NO_2 (μg/m^3)	$\widehat{ATT}_\gamma$ μg/m^3	RR total mortality (pp)	RR cardiovascular mortality (pp)	RR respiratory mortality (pp)
0 - 10	−0.18	−0.11	−0.10	−0.05
10 - 20	−4.97	−3.13	−2.81	−1.41
20 - 30	−10.83	−6.69	−6.02	−3.05
30 - 40	−16.83	−10.20	−9.20	−4.70
40 - 50	−22.24	−13.25	−11.97	−6.16
50 - 60	−27.40	−16.06	−14.54	−7.53
60 - 70	−35.08	−20.09	−18.22	−9.54
70 - 80	−36.38	−20.75	−18.82	−9.88
80 - 90	−39.79	−22.45	−20.40	−10.75
90 - 100	−49.71	−27.22	−24.80	−13.25
100 - 150	−62.16	−32.79	−29.98	−16.28

Notes: the Table provides the simulated reductions in the relative risk of mortality associated with estimated NO_2 heterogeneous impacts (ATT), assuming a log-linear relationship. Authors' computations based on parameters from Faustini et al. [21].

nonlinear reactions where negative health impacts accelerate at higher NO_2 concentrations. Therefore, based on a well-known practice in radiation biology and physics (see, e.g., [51]), as part of the sensitivity analysis (see details in Appendix E), we have re-estimated RR gains based on a linear-quadratic model, which reflects a more than proportional increase in health benefits as pollution reduction increases. This functional form is consistent with the approach proposed in previous analyses on air pollution where the dose-effect response is convex (e.g., [41,44]), namely contexts with high baseline exposure, such as the Po-river area in northern Italy, where each μg/m^3 reduction can result amplified. Table E.4 in Appendix E shows the results of this alternative computation, which indicates a more pronounced heterogeneous impact than those in Table 4, with areas with the highest baseline pollution levels expected to benefit the most, with RR reductions of up to −91.54, −89.08, and −66.87 pp for total, cardiovascular, and respiratory mortality, respectively.

These latter findings highlight that the magnitude of the simulated health benefits vary non-negligibly based on the choice of the functional form which maps NO_2 reductions into RR decreases, with a differentiated pattern which holds across all mortality categories (total, cardiovascular, respiratory) and becomes much more pronounced at higher pollution baselines. In this regard, on the one hand, a linear-quadratic model, although more speculative, could indeed align well with biological plausibility in highly polluted urban areas, such as the Po-river Valley, in which incorporating an accelerated specification might better capture the health co-benefits of large-scale NO_2 abatements. Nonetheless, on the other hand, assuming a log-linearity link between NO_2 exposure and health outcomes can be usefully regarded as a robust lower-bound estimate of the health impacts associated with reductions in NO_2 exposure. For this latter reason, we prefer to consider the log-linear results as a benchmark for our analysis, enabling the dose-specific RR findings of Table 4 to represent safe conservative estimates to inform public health officials and policymakers about the minimum certain health benefits that are locally achievable in central urban areas

from NO_2 air-quality improvements due to a sharp abatement of fossil-fuel vehicular traffic.

5. Conclusion

As well established in the literature, long-lasting air-quality improvements may have long-term health and socio-economic benefits and make citizens more sensitive to the presence of chronic air-pollution, especially in highly-congested urban areas, thus increasing political pressure for effective environmental reforms. For this reason, empirical evaluations of policies aimed at improving urban air-quality will increasingly gain importance. In this regard, the first contribution offered by this study is the development of a novel counterfactual impact evaluation tool, in terms of an intertemporal statistical matching (SM) approach which is specifically suited for the unique causal identification conditions posed by the air-pollution multivariate time-series data related to these policies.

By applying our novel intertemporal SM approach and leveraging unique data specificities and conditions of the Italian Covid-19 lockdown as a natural-experiment for an exogenous fossil-fuel traffic abatement, the second contribution of this study is to offer evidence on the reduction in urban NO_2-pollution and related health outcomes gains that might be expected from the implementation of the EU 2035 zero-emission-mobility resolution. Exploiting data from a large sample of air-pollution measuring stations, which provides a widespread distribution of the baseline NO_2-pollution determined by varying daily meteorological conditions and local urban texture features, our analysis also estimates heterogeneous NO_2 impacts based on different baseline pollution levels. This is a critical aspect often overlooked in other studies, for which our results clearly indicate that the NO_2 reductions caused by fossil-fuel traffic abatement increase (almost linearly) along with increments of the baseline NO_2 concentration.

These local air-quality gains translate into significant health benefits which can be estimated in terms of a 8.3 percentage points average decrease in the relative risk of total mortality, with even more pronounced health benefits when considering the NO_2 reduction for the highest baseline pollution conditions. These latter results indicate that regions with meteorological conditions and typical urban texture features that exacerbate NO_2 baseline accumulation stand to benefit disproportionately from stringent vehicular emission controls, suggesting the need for tailored policy approaches in which high-pollution areas could be prioritized for intervention, potentially through more aggressive timelines or additional support measures to accelerate the transition. Less polluted areas could be instead considered for more generous fossil-fuel traffic phasing-out periods and allowances.

Because the estimated health benefits from local pollution gains in urban areas are a significant element which is very often neglected in the policy debates, our findings, finally, also importantly complements the other factors that are usually discussed and weighted in the literature when assessing zero-emission-mobility proposals. As discussed in more details in Appendix G, these factors are noticeably in terms of the need to examine: the entire lifecycle emissions of zero-emission vehicles, including electricity generation; the welfare loss due to drastic changes in the European automotive industry and its supply chain; the opportunity cost of taxpayers' money needed to implement the infrastructures for the zero-emission-mobility transition; the risk of displacing resources available to public transit system improvements for the promotion of private electric vehicles usage; and the loss of welfare, particularly for the groups of less affluent citizens, related to the higher purchasing cost of electric vehicles.

Data statement

The data used in the paper were primarily collected from the validated records of the network of air-pollution measuring stations in five Northern Italian regions. Data, program codes, data documentations and readme files suitable to permit full replication of the analysis are available upon request.

CRediT authorship contribution statement

Daniele Bondonio: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Paolo Chirico:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Massimiliano Piacenza:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Simone Robbiano:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None.

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Supplementary materials

Supplementary material (Appendices from A to G) associated with this article can be found, in the online version, at doi:10.1016/j.healthpol.2025.105376.

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