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The contemporaneous healthcare cost of particulate matter pollution for youth and older adult populations☆

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ABSTRACT

This paper estimates the impact of particulate matter pollutants, measured by $PM10$ levels, on public healthcare costs for youth and older adult populations using administrative data from two large UK hospitals and exploiting spatial and temporal variation in $PM10$ levels. We find that patient enrolment increases when their neighborhood experiences higher levels of $PM10$. Specifically, a standard deviation increase in $PM10$ levels increases the enrolment of patients aged 60 years and older by 6.2% and the enrolment of patients under 18 years of age by 3.1%. Using detailed costing information, we estimate that a standard deviation increase in $PM10$ increases public healthcare costs by £873, 985.20 per year in the municipality studied.

1. Introduction

The UK Government has identified poor air quality as the greatest environmental risk to public health (Smith, 2017). According to the Royal College of Physicians, 40,000 deaths annually are attributable to air pollution in the UK, costing more than £20 billion in 2016 (Holgate et al., 2016). It is well established that exposure of youths and older adults to air pollution can slow their development, decrease their lung function, increase their development of respiratory and coronary diseases, and even elevate their risk of diabetes and dementia (Brunekreef and Holgate, 2002; Margaryan, 2021; Mandal et al., 2023; Wilker et al., 2023). Particulate pollution has been specifically linked to various adverse short-run health outcomes, including increased infant mortality,

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increased hospital admissions for cardiovascular diseases, increased hospital admissions for chronic obstructive pulmonary disease, and increased severity of asthma attacks among youths. Longer-term exposure to particle pollution has been associated with asthma development and slower lung function growth in youths, and an increased risk of death from cardiovascular diseases, heart attacks, and strokes in adults (American Lung Association, 2021).

In this paper, we analyze the impact of particulate matter pollution on the contemporaneous use of public healthcare by youth and older adult populations, as well as the associated cost of public healthcare. Specifically, we examine how local emergency department (ED) visits, subsequent hospital admission, and corresponding public health costs vary with daily $PM10$ levels across a major UK city. In our preferred specification, we estimate that a standard deviation increase in $PM10$ increases local ED visits by 3.1% for youths and 6.2% for adults aged 60 years and older. We find that most of the youths are discharged from the ED, but about half of the older adults are admitted to hospital. Based on this, we find that a standard deviation increase in $PM10$ levels in the city will increase annual healthcare costs by almost £900,000 through this channel alone.

Our estimation is based on administrative data from several sources. We use administrative records reflecting the universe of ED visits at two large hospitals, covering the period from the start of 2006 to the end of 2011. We match these data with national tariff records that reflect the cost of each diagnosis, procedure, and hospitalization. Individual ED visits are aggregated to reflect daily ED use according to the neighborhood of residence in each record. We merge these aggregated hospitalization records with information reflecting daily $PM10$ levels by neighborhood. Neighborhood $PM10$ levels are calculated as a weighted average of reported $PM10$ levels for six monitors placed throughout the city, where weights account for distance, wind direction, and wind speed. In addition to this information, we include data reflecting neighborhood characteristics, weather, and levels of another pollutant ($N0_2$).

The literature contains several methodological challenges in quantifying the effects of pollution on health outcomes and their subsequent healthcare costs. To address challenges such as omitted variable bias, measurement error, and systematic changes in hospital attendance and admissions by day of the week, our primary estimation strategy controls for neighborhood fixed effects and systematic variation by day of the week and week of the year (see Neidell, 2006; Meacock et al., 2017; Deryugina et al., 2019; Green et al., 2020). As a result, our preferred estimates are based on variation in $PM10$ levels that reflect deviations from the average neighborhood and time patterns. This variation is plausibly exogenous (including controls for time-by-neighborhood varying characteristics), and we interpret our results as the causal effect of an increase in $PM10$ pollution on population hospital use and costs during the same day. Several robustness checks support this interpretation. For example, using lag or lead values of pollutants a week or more out rather than contemporaneous does not result in economically or statistically significant estimates.

Several previous studies have examined the relationship between air quality and human health outcomes. Knittel et al. (2016) found a large effect of $PM10$ levels on infant mortality in California, with a one-unit decrease in $PM10$ saving 18 infant lives per 100,000 live births. Chay and Greenstone (2003) found that dramatic reductions in pollution during a recession led to 2500 fewer infant deaths from 1980 to 1982 in the US. Similar child health and mortality outcomes have been found for exposure to CO (Currie and Neidell, 2005; Neidell, 2004), and O_3 (Coneus and Spiess, 2012). Samoli et al. (2006) found a positive relationship between NO_2 and mortality in European cities from 1990 to 1997. Related studies have examined the effects of policies aimed at reducing air pollution on child births (Currie and Walker, 2011), hospital visits for acute asthma attacks (Simeonova et al., 2018), and cardiovascular disease in older adults (Margaryan, 2021). Beatty and Shimshack (2011) found that a reduction in school bus emissions in the US reduced bronchitis, asthma, and pneumonia incidences among youths and adults with chronic conditions. A recent study found that short-term increases in $PM10$ concentrations increased COVID-19-related deaths among older adults (Isphording and Pestel, 2021).

Our study builds on the findings reported in two previous papers that explored the effect of pollution on healthcare costs. Schlenker and Walker (2016) used air travel network delays as a source of exogenous variation in ground-level airport congestion and corresponding increases in pollution levels to estimate the effect of pollution on health outcomes for residential populations close to airports. They found that a one standard deviation increase in daily pollution explained roughly one-third of the average daily hospital admissions of patients with asthma. They also found that a one standard deviation increase in daily pollution increased daily hospitalization costs by US$540 thousand for patients with respiratory and heart-related conditions residing within 10 km of a large airport. Deryugina et al. (2019) estimated the effect of fine particulate matter ($PM2.5$) exposure on older adults' mortality, healthcare use, and medical costs over a three-day window in the period 1999–2013 in the US. They found that increases in daily $PM2.5$ positively affected mortality, hospitalizations, and inpatient spending, mainly due to admissions originating in the ED.

This paper contributes to this previous literature in several ways. Firstly, we contribute to the pollution effects on health literature by documenting the concurrent effects of pollution on the population's health and the healthcare system's healthcare costs. Specifically, our paper expands on previous analyses by focusing on pollution's effects on youths (aged under 18 years) and older adults (aged over 60 years) and quantifying the economic costs of these effects for both groups. Youths are of interest because of their susceptibility to respiratory conditions, while older adults are of particular interest because of their susceptibility to cardiovascular conditions. Interestingly, we find that the total number of ED visits is very similar for discharged youths and older adults. However, the number of older adults admitted to hospital is significantly greater, and their admissions are considerably more expensive than those of youths (more than 15 times). Secondly, we contribute to the public policy literature by quantifying a direct benefit to policies targeted at reducing local particulate matter. Although our estimates are non-trivial in magnitude, they understate the total effect since we only quantify the contemporaneous effects of increasing particulate matter on population healthcare costs. We do not estimate potential longer-term outcomes, including changes in mortality, life expectancy, and long-term healthcare use and costs.

The remainder of this paper is structured as follows. In Section 2, we discuss the data and notation used. In Section 3, we present the empirical methodology. In Section 4 and Section 5, we present the results and robustness checks, respectively. In Section 6, we discuss our findings and provide concluding remarks.

Table 1
Summary statistics.

	Mean	SD	SDB	SDW	Min	Max	N
Hospital visits (Youth)	1.46	1.68	1.12	1.26	0.00	13.00	105 168
Hospital visits (Older Adults)	1.12	1.31	0.75	1.08	0.00	10.00	105 168
Daily $PM10$ (μg/m^3)	13.56	5.53	2.05	5.14	0.00	68.19	105 168
Daily NO_2 (μg/m^3)	43.21	16.64	3.00	16.37	4.86	165.91	105 168
Income score	0.20	0.16	0.16	0.02	0.00	0.83	105 168
Employment score	0.12	0.08	0.08	0.01	0.00	0.40	105 168
Health score	0.38	0.76	0.76	0.71	−1.08	1.92	105 168
Education score	27.04	17.79	17.83	1.40	0.00	76.87	105 168
Housing score	15.48	6.51	6.44	1.71	0.00	30.41	105 168
Crime score	0.37	0.61	0.61	0.12	−1.12	1.67	105 168
Environment score	22.04	14.72	14.74	1.30	0.00	60.04	105 168
Average temperature (C°)	10.18	5.56	0.00	5.56	−5.88	25.76	105 168
Daily Max temperature (C°)	14.26	6.57	0.00	6.57	−3.16	34.54	105 168
Daily Min temperature (C°)	6.38	5.10	0.00	5.10	−9.86	19.47	105 168
Rainfall	0.05	0.12	0.00	0.12	0.00	1.13	105 168

This table reports summary statistics for all variables used in the main analysis. The unit of observation is postcode by day. SD is the sample standard deviation, SDB and SDW are the between and within standard deviations.

2. Data

We combined data from multiple sources to create a dataset that will allow us to exploit the relationship between random variation in $PM10$ levels and the quantity and cost of public healthcare use. Each of these data sources is discussed below. We provide basic summary statistics for all variables used in our main regression in Table 1 and additional detailed information, including data sources, in Appendix A.

2.1. Geography

The data reflects pollution and healthcare outcomes for the city of Leicester, England, which has a population of approximately 350 thousand and is covered by the University Hospitals of Leicester (UHL) National Health Service (NHS) Trust. It comprises three hospitals – the Leicester Royal Infirmary, Leicester General, and the Glenfield Hospital – and, with a current staff of over 17,500, it is the ninth largest of the 217 NHS trusts in England by employment (National Health Service, 2023b). The UHL NHS Trust hospitals serve a population of approximately one million across the county of Leicestershire and are the only facilities in the county offering emergency and acute care services. Our data are restricted to the Leicester Royal Infirmary and the Glenfield Hospital since they are the only facilities with an ED.

The primary geographic unit used in our analysis is the postcode sector, of which we use 48 that correspond to the city of Leicester. A postcode sector has an average population of 9,365 residents, or 3,534 households, based on the 2011 census data. We do not consider hospital visits of patients from the rural areas around the city or the other urban centers in Leicestershire since we restrict our analysis to the area where we can infer pollution levels. Individual patients are matched to the area of the city based on the postcode sector of their residence.

2.2. Health care background and data

Funding for the NHS comes mainly from central general taxation (80%), with smaller amounts coming from national insurance contributions (19%) and private healthcare services (1%). NHS day-to-day operations spending, such as medicine and staff salaries, was about £155.1 billion in 2022/23 (approximately 6% of UK GDP and 20% of total tax receipts).

The prices NHS hospitals charge for services are regulated and reported through the national tariff payment system. This system lays out the rules and prices through which payment for services, such as acute care, is made and accounts for 60% of hospital income (Timmins, 2023). While tariff prices and rules are negotiated annually, the timing of these negotiations means that tariff prices are usually based on the delivery costs from three years before. The finalized prices reported in the tariff are often adjusted to meet the budget allocated to healthcare services, which involves adjusting all prices so that relative pricing remains unchanged (National Health Service, 2023a). Therefore, within this system, budgeting drives the overall pricing rather than the other way around.

Unplanned budget strain within the NHS hospital system has consequences for population welfare. For example, in recent years, the UK has seen significant increases in waiting times, both for planned procedures and hospital emergency services (Timmins, 2023).[1] This increase may lead to less use of healthcare services overall, from which we expect to see spillovers to other public services. For example, focusing on assisting individuals at risk of or suffering from illness, disability, or poverty, it has been shown

[1] The NHS currently has a wait time target of four hours or less for patients seeking help through hospital EDs. In 2011, this target was met for 95% of patients. By 2023, this target was met for less than 60% of patients (Nuffield Trust, 2023).

that the healthcare and social care systems are closely linked (Dam, 2019). Previous cuts to spending on social care have been found to substantially increase hospital ED use by individuals aged 65 years and older (Crawford et al., 2020).

Our paper will focus solely on the effects of pollution on the healthcare system from 2006 to 2011. We aim to measure how pollution affects medical costs rather than looking at the broader issue of how individuals are impacted by pollution in their daily activities, which is the focus of the social care system.

2.2.1. Hospital use data

The UHL NHS Trust provided us with anonymized and confidential administrative records for all patients who attended the ED from January 1, 2006, to December 31, 2011. We count each record as a single visit and do not distinguish between different individuals visiting or the same individual visiting multiple times. For each record, we observe the date of attendance, the reason for visiting, and the resulting intervention and diagnosis, which are reported using a Healthcare Resource Group (HRG) code. We have HRG codes for 93% of the 254,203 ED attendants, which we will use to match with hospital cost information (see Appendix B).

The ED visits in the UHL NHS Trust exceed 150,000 in each studied year (2006–2011). These data reflect the universe of records for Leicester's two EDs over this period but do not capture patient visits to smaller neighborhood walk-in clinics or the remaining large hospital without an ED. Summary statistics for the final sample are presented in Table A.2.

For our analysis, the sample is restricted to records where the patient is aged less than 18 years or 60 years or older at ED attendance. We further restrict the sample to individuals with a home address in the city of Leicester. The final sample consists of 272,757 records, of which 56% (153,937) are youths, and 44% (118,820) are older adults (see Table A.2). Our sample consists of slightly more males (143,839 or 53%) than females (128,918 or 47%). Based on UK Census ethnic categories, most of the sample is White (168,036 or 62%), followed by Asian (64,576 or 24%), with Black being the smallest ethnic group (11,764 or 4%).

When an individual visits the ED, they may be admitted to the hospital for further treatment or monitoring. In our sample, 32% (87,400) of individuals were admitted to the hospital. Older adults were more likely to be admitted than youths (56% vs. 13%). For those admitted, the average length of stay is approximately two days for youths and nine days for older adults. We present a breakdown of these statistics by postcode districts in Table A.3.

For our principal analysis, individual records are aggregated to reflect the number of hospital visits by patients' postcode district of residence and day of visit. These data are matched to pollution data discussed in Section 2.3. For the studied period, there are 2,191 days for a total of 105,168 day/postcode pairs (2,191 × 48). On average, a postcode district has 1.46 youths and 1.12 older adults visiting the hospital (Table 1).

2.2.2. Hospital cost data

Each hospital record is associated with a diagnosis and its respective medical intervention. This information is captured in HRG codes in the obtained administrative records. In addition, each diagnosis and medical intervention has its own associated costs. The codification of these costs was retrieved from the national tariff data. Matching the HRG codes – related to diagnosis – to the corresponding national tariff and the patient's length of stay allows us to calculate the cost of each record (see Appendix B for calculation details). The national tariff data was obtained for the fiscal years 2005/06 to 2011/12 from The National Archives. For each HRG code, the national tariff data provide the tariff (in British pounds), the expected length of hospital stay, the incremental tariff for stays that exceed the expected length, and the price for short stays (<2 days). We matched 98% (248,572) of the diagnosed conditions in the hospital administrative data to cost information from the national tariff data. After calculating the cost of an individual record, we calculated the aggregates for each day/postcode totals.

2.3. Pollution data

The independent variable of interest for this study is the daily average levels of $PM10$ (in parts per million, or ppm hereafter). $PM10$ are particles 10 millionths of a meter or less in diameter. They have no fixed chemical composition and are derived from diverse natural and artificial sources (Evan, 2011).

Leicester City Council provided the pollution and meteorological data. The city collects $PM10$ data at six of the eight monitors in place. We use the additional two monitors that do not collect $PM10$ data for supplementary information, such as hourly data on climate variables – wind direction and speed, air pressure, rainfall, and temperature – and information on $N0_2$ levels. Regarding air pressure, we only have data for 2009–2011. Therefore, we exclude air pressure data from the principal analysis but include it as a robustness check in Section 5.

We use the pollution data for each of the six monitors to impute the $PM10$ (and $N0_2$) level of each postcode sector as the weighted average of pollution recorded at all of the monitors, according to the following equation:

$$PM10_{ct} = \sum_{k} w_{ckt} \times \overline{PM10}_{kt}, \tag{1}$$

where $\overline{PM10}_{kt}$ is the average pollution reading at monitor k on day t, and the weight w_{ckt} reflects the time-varying weight of monitor k's reading on neighborhood c pollution accounting for wind speed, wind direction, and the monitor's distance from the centroid of the postcode sector (following the insights presented in Smith et al., 2001).

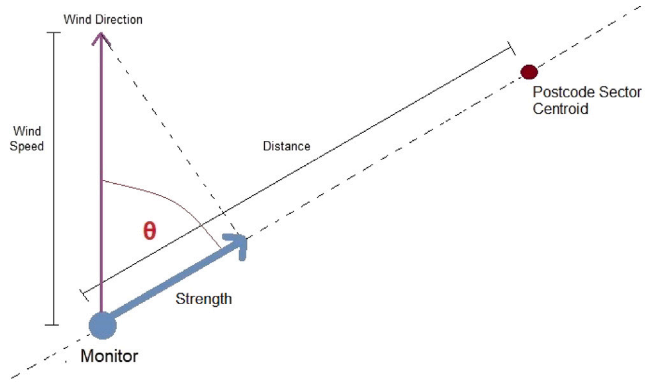


Fig. 1. Diagrammatic representation of wind strength. This figure is a diagrammatic representation of the calculation performed in Eq. (2).

Table 2
Sensitivity analysis. Correlation between effective hourly PM10 and estimated hourly pollution using different PM10 interpolation methods at each monitor (2006–2011).

	(1) $IDW\,PM10$	(2) $IDW\,PM10$ (no Strength Weighting)	(3) $PM10$ from nearest monitor
Monitors			
Vaughan way	0.5074	0.4529	0.5042
Melton road	0.6257	0.5800	0.5719
Abbey lane	0.6467	0.5743	0.5586
Glenhills way	0.6667	0.6037	0.6159
Imperial Ave	0.6096	0.5368	0.5584
London road	0.5955	0.5446	0.5528

This table reports the correlation between imputed hourly pollution level at each monitor, based on pollution reported at other monitors, and actual hourly pollution level at each monitor. Imputed $PM10$ is measured using: (1) wind speed, wind direction and distance weighting following Eq. (1); (2) distance weighting only; (3) $PM10$ reported by nearest monitor only.

Specifically, we calculate w_{ckt} as the ratio of two variables. The first variable is the *wind strength* from a monitor to a neighborhood centroid. We calculate the wind strength of monitor k to centroid c as follows:

$$Strength_{ckt} = \text{abs}\,(\cos\theta_{ckt}) * WindSpeed_t \tag{2}$$

where θ_{ckt} is the angle difference between the wind direction and the projected line connecting the monitor k and the centroid c at time t, and $WindSpeed$ is the wind speed on day t. Therefore, the cosine of θ_{ckt} tells us how aligned the monitor and centroid are given the wind direction. When the wind is blowing along the straight line connecting the monitor and the centroid, then $\cos\theta = 1$; when the wind is blowing orthogonal to the straight line connecting the monitor and the centroid, then $\cos\theta = 0$. The absolute value of the cosine of the angle difference captures the case where a centroid is behind a monitor in terms of the wind direction. This use of wind speed and direction assumes two things. First, the higher the wind speed, the further away pollution particles travel. Second, if the monitor and centroid of the postcode sector are aligned along the wind direction, then the exposure of that centroid relative to that monitor is high. Fig. 1 provides a diagrammatic representation of this calculation.

The second variable in the calculation of w_{ckt} is the *distance* from each monitor to each centroid, reflecting that the closer a monitor is to a centroid, the more accurately its reading will reflect the centroid, all else being equal. Of the 48 centroids in our data, 37 are less than three kilometers from the nearest monitor, and all are less than five kilometers (see Table A.5 in the appendix). Where $Distance_{ck}$ is the Euclidean distance (in kilometers) between the monitor and the centroid, we write the weight of monitor k on centroid c at time t as:

$$w_{ckt} = \frac{\frac{Strength_{ckt}}{Distance_{ck}}}{\sum_k \frac{Strength_{ckt}}{Distance_{ck}}}. \tag{3}$$

To evaluate how well this measure predicts $PM10$ levels, we use Eq. (1) to predict hourly pollution levels for each of the six monitors in our data based on information from the other five monitors. The correlation between predicted and actual values at each monitor is reported in Table 2. The correlations between predicted and actual values are high, between 0.5074 and 0.6667 (column 1). Furthermore, the correlations are stronger than what we observe using simpler measures such as simple inverse distance weighting or the nearest monitor readings (columns 2 and 3).

Postcode districts in our data have an average $PM10$ measure of 13.56 parts per million, with a standard deviation of 5.53 parts per million (41% of the mean; Table 1). The variation in these data largely arises from changes over time within a postcode district; the within-postcode standard deviation is 5.14 parts per million. Additional summary statistics for hourly pollution and climate measures at each monitor in the period 2006–2011 are provided in Tables A.6 and A.7, which show temporal and spatial variation. Furthermore, the locations of Leicester's air monitors are shown in Map 1, and more information on pollution and meteorological variation across space and time is provided in Appendix C.2.[2]

2.4. Control variables

To control for socioeconomic characteristics in our analysis, we use official deprivation scores provided by the UK Ministry of Housing, Communities & Local Government. These scores are used to build a relative ranking of the 32,482 neighborhoods in England and Wales based on seven categories: household income, employment, health and disabilities, education and training, barriers to housing, crime, and living environment. The *neighborhood* level at which deprivation scores are calculated is the *lower super output area*, containing a population of approximately 3,000 residents. The deprivation scores were updated in 2004, 2007, 2010, and 2015; therefore, we interpolate those for which we do not have a directly reported score (2006, 2008, 2009, and 2011) using a weighted average of the previous and subsequent reported values.[3] Additionally, since a postcode sector contains many neighborhoods, we calculate a postcode sector score for each of the seven categories, reflecting the average score of all its neighborhoods. Including the postcode sector score in our analysis allows us to control for broad postcode sector characteristics that may change over time.

The numerical value of the different deprivation score categories does not have a consistent interpretation. While the income scores roughly reflect the proportion of the population living in low-income households, and the employment score reflects the proportion of the working-age population excluded from the workforce, the other scores are generated using factor analysis applied to several different measures of deprivation. However, all measures are qualitatively the same in that a larger value means increased deprivation under that domain.[4]

In addition, we use information collected from each monitor to control for daily fluctuations in weather and other pollutants. Specifically, we include information on the average, maximum, and minimum daily temperatures, rainfall levels, and NO_2 levels.

3. Estimation specification

The main estimation specification is summarized in the following regression equation:

$$Y_{ct} = \gamma_0 + \gamma_1 \ PM10_{ct} + X'_{ct}\Gamma + \zeta_d + \delta_{wy} + \omega_c + \epsilon_{ct}. \tag{4}$$

The outcome, Y_{ct}, is the total number of hospital visits on day t by patients who live in neighborhood c. In addition to the total number, we stratify this outcome by visits that result in ED discharges and hospital admissions (mode of disposal) and by the type of diagnosis. The independent variable of interest is $PM10_{ct}$, reflecting particulate matter pollution as calculated in Eq. (1). X_{ct} is a vector of control variables, including weather, nitrogen dioxide (NO_2) levels, and postcode deprivation indices (described in Section 2). The parameters ζ_d, δ_{wy}, and ω_c capture day of the week, week-by-year, and postcode district fixed effects, which we estimate using dummy variables. Week-by-year fixed effects account for seasonal effects that can vary across years, such as influenza, asthma, and urinary tract infection prevalence (see Johnston et al., 1996; Rosello et al., 2018; BBC, 2018). All other unobservable time and neighborhood-varying factors that affect population hospitalization are captured by ϵ_{ct}.

We interpret the parameter of interest, γ_1, as the effect of $PM10$ on the hospital admission outcome, Y_{ct}. For this to be a valid interpretation, it must be the case that, once we control for variables in X and our fixed effects, $PM10$ is uncorrelated with ϵ_{ct}. We believe that this assumption is reasonable; controls for postcode sector, weekly, and seasonal fixed effects ensure that γ_1 is estimated by exploiting idiosyncratic variation in $PM10$ across day and location. This identifying assumption will be violated if there are factors that change over time within a postcode district that both affect hospital visits and are correlated with pollution. For example, one possible violation would be if increased neighborhood traffic led to greater traffic accidents and, thus, hospital admissions. We believe this is unlikely to be the case in a city of the size we are examining; an increase in traffic that leads to increased hospital admissions is unlikely to be large enough to be measurable. Furthermore, we can show significant increases in hospital visits specifically for pollution-related complications. As an additional check on this, in Section 5, we discuss results using an alternative instrumental variable (IV) identification strategy following Deryugina et al. (2019) and Isphording and Pestel (2021).

In the second part of our analysis, we estimate the effect of pollution on healthcare costs. We estimate two equations to distinguish how much of any change in total healthcare costs is due to changes in the average cost of healthcare per visit as opposed to changes in the number of visits. First, we estimate the effect of pollution on the average cost of hospital visits:

$$Cost_{ict} = \beta_0 + \beta_1 \ PM10_{ct} + X'_{ct}\Omega + \phi_d + \theta_{wy} + \pi_c + \mu_{ct}. \tag{5}$$

[2] In Appendix C.2, we provide several depictions of the temporal and spatial variations in pollution. In particular, Figure C.1 shows the temporary variation in pollution recorded at each monitor, while Maps 2 and 3 visually represent the spatial variation in pollution on January 1 and July 1 for each studied year.

[3] The deprivation scores for 2006 were interpolated as one-third of the 2004 deprivation scores and two-thirds of the 2007 deprivation scores. Similarly, the deprivation scores for 2008 were interpolated as two-thirds of the 2007 deprivation scores and one-third of the 2010 deprivation scores, and the deprivation scores for 2009 were interpolated using the same data but with opposite weights. Lastly, the deprivation scores for 2011 were interpolated as four-fifths of the 2010 deprivation scores and one-fifth of the 2015 deprivation scores.

[4] A detailed description of the procedure for calculating each deprivation score is provide in Office of the Deputy Prime Minister (2004).

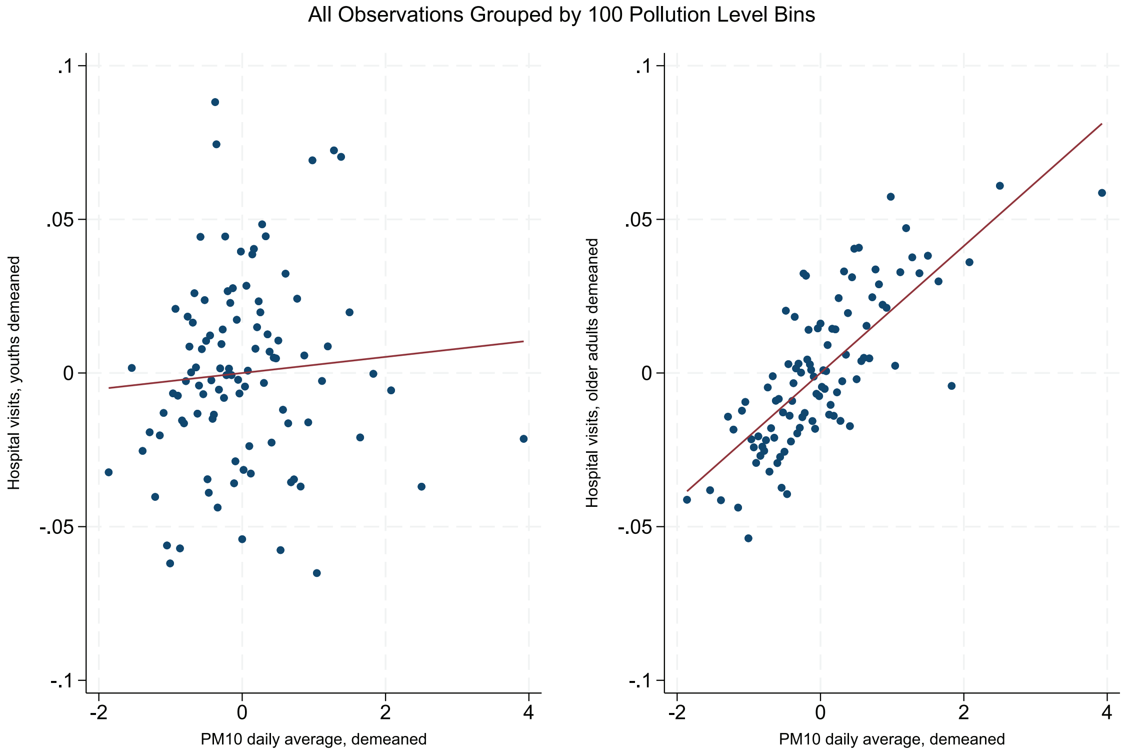


Fig. 2. Pollution on hospital visits by age group, 2006 to 2011. These figures are created using a binscatter plot, in which the variable $PM10$ (demeaned) is grouped into 100 equal-sized bins. Markers plot the average number of hospital visits (demeaned) for each bin. The red line shows the best linear fit from an OLS regression of the demeaned hospital visits on $PM10$ bins. The left figure includes only hospital visits by youths (age 18 and under) and the right figure includes only hospital visits by older adults (age 60 and older).

where $Cost_{ict}$ is the cost of a hospital visit (in British pounds) for an individual i residing in postcode sector c at time t, X_{ct} is a vector of control variables, as specified for Eq. (4), and ϕ_d, θ_{wy}, and π_c capture day of the week, week-by-year, and postcode sector fixed effects. The coefficient of interest, β_1, reflects the effect of a one standard deviation increase in $PM10$ on the *average* cost of a patient visit.

Secondly, we estimate the change in the total costs by mode of disposal due to spatial and daily changes in pollution as follows:

$$TotalCost_{ct} = \hat{\beta}_0 + \hat{\beta}_1 \; PM10_{ct} + X'_{ct}\hat{\Omega} + \hat{\phi}_d + \hat{\theta}_{wy} + \hat{\pi}_c + \hat{\mu}_{ct}, \tag{6}$$

where $TotalCost$ is the aggregate cost of all hospital visits at time t for patients residing in postcode sector c. We interpret $\hat{\beta}_1$ as the incremental effect of a standard deviation change in $PM10$ on total daily healthcare costs for the population residing in postcode sector c.

Eqs. (4), (5), and (6) are all estimated using linear regression. We consider several alternative specifications in Section 5.

4. Results

Fig. 2 shows the relationship between $PM10$ daily demeaned average grouped by 100 pollution level bins and the hospital visits' count demeaned average by age group – youths and older adults – during the six years from 2006 to 2011. We observe a positive relationship between the $PM10$ daily demeaned average and daily hospital visits demeaned average for youths and older adults. However, this relationship is more pronounced for older adults. These graphs show a relationship in the raw variation between $PM10$ and hospital visits. We now focus on testing whether these relationships persist when we control for the relevant characteristics described in Section 3.

4.1. Total number of hospital visits

We report estimates for Eq. (4) in Table 3. We stratified all results according to patients' age: youths aged under 18 years (columns 1 to 3) and older adults aged 60 years and older (columns 4 to 6).

Table 3
Pollution on hospital visits with deprivation and weather controls, and time and geographical fixed effects.

	Youths			Older adults		
	(1) Visits	(2) Admitted	(3) Discharged	(4) Visits	(5) Admitted	(6) Discharged
Daily $PM10$	0.045***	0.006**	0.039***	0.070***	0.034***	0.036***
	(0.007)	(0.002)	(0.007)	(0.006)	(0.005)	(0.004)
Postcode sector controls						
Income score	3.439***	0.639***	2.800***	−2.132***	−1.482***	−0.649***
	(0.182)	(0.061)	(0.166)	(0.139)	(0.101)	(0.089)
Employment score	−5.679***	−1.213***	−4.467***	6.820***	4.013***	2.808***
	(0.408)	(0.135)	(0.373)	(0.319)	(0.232)	(0.203)
Health score	0.419***	0.054***	0.365***	0.137***	0.048***	0.089***
	(0.020)	(0.007)	(0.018)	(0.016)	(0.012)	(0.010)
Education score	0.028***	0.004***	0.024***	0.005***	0.004***	0.001***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Housing score	−0.023***	−0.003***	−0.020***	−0.014***	−0.007***	−0.007***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Crime score	0.263***	0.059***	0.204***	−0.051***	0.034***	−0.085***
	(0.023)	(0.007)	(0.021)	(0.018)	(0.013)	(0.012)
Environmental score	−0.046***	−0.006***	−0.040***	−0.019***	−0.010***	−0.009***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Weather controls						
Average temperature	0.007	−0.001	0.008	0.021***	0.013***	0.008*
	(0.008)	(0.003)	(0.007)	(0.007)	(0.005)	(0.004)
Daily Max temperature	0.012**	0.001	0.011**	−0.009**	−0.005*	−0.004
	(0.005)	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)
Daily Min temperature	−0.011**	−0.000	−0.011***	−0.008**	−0.005**	−0.003
	(0.004)	(0.001)	(0.004)	(0.004)	(0.003)	(0.002)
Rainfall	−0.132***	−0.010	−0.122***	0.076**	0.052**	0.024
	(0.040)	(0.014)	(0.037)	(0.035)	(0.025)	(0.022)
Pollution controls						
Daily NO_2	−0.064***	−0.011***	−0.053***	−0.007	−0.003	−0.004
	(0.009)	(0.003)	(0.008)	(0.008)	(0.006)	(0.005)
Observations	105 168	105 168	105 168	105 168	105 168	105 168
Adjusted R^2	0.3568	0.0888	0.33	0.2382	0.1661	0.1259
Dep. var. mean	1.463	0.193	1.270	1.123	0.638	0.485
Dep. var. st. dev.	1.678	0.472	1.512	1.314	0.915	0.779
Day of the week FE	✓	✓	✓	✓	✓	✓
Week × Year FE	✓	✓	✓	✓	✓	✓
Post District FE	✓	✓	✓	✓	✓	✓

This table reports linear regression estimates corresponding to Eq. (4). Dependent variables are, for each day/postcode sector, the total number of hospital visits (*Visits*), the total number of hospital visits that are admitted (*Admitted*), and the total number of hospital visits that are discharged from the Emergency Department (*Discharged*). All outcomes are stratified by youths (age < 18) and older adults (age ≥ 60). $PM10$ and $N0_2$ are in daily standard deviations. Our postcode sector controls are the interpolation of deprivation scores for the years 2004, 2007, 2010 and 2015 corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average, minimum, and maximum daily temperature, and daily rainfall. Standard errors in parentheses, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

For youths (columns 1 to 3), we find that a one standard deviation increase in exposure to $PM10$ increases the number of daily hospital visits by 0.045 ($p \leq 0.001$), or a 3.1% increase relative to the mean. Of this, 0.006 patients are admitted to the hospital ($p = 0.033$), and 0.039 patients are discharged from the ED ($p \leq 0.001$).

For older adults (columns 4 to 6), we find that a one standard deviation increase in exposure to $PM10$ increases the number of hospital visits by 0.070 ($p \leq 0.001$), or 6.2% relative to the mean. Almost half of these incremental visits – 0.034 ($p \leq 0.001$) – resulted in admission to the hospital, with the remaining 0.036 ($p \leq 0.001$) being discharged from the ED.

Note that while neighborhood characteristics are significant determinants of hospital visits, the direction of their effect is not always the same for youths and older adults. A one standard deviation increase in income deprivation (0.16, Table 1) is associated with a 0.55 increase in daily hospital visits for youths but a 0.34 decrease for older adults. Similarly, a one standard deviation decrease in employment deprivation (0.08; implying an increase in working-age employment) is associated with a 0.45 decrease in hospital visits for youths but a 0.55 increase for older adults. The other measures are similar across both groups; for example, a one standard deviation increase in housing deprivation (6.51) is associated with a decrease in hospital visits of 0.15 for youths and 0.09 for older adults.

Table 4
Pollution and hospital visits by diagnosis (Admitted Patients Only).

	Youths				Older adults			
	(1) All	(2) Respiratory	(3) Cardiovascular	(4) Cerebrovascular	(5) All	(6) Respiratory	(7) Cardiovascular	(8) Cerebrovascular
Daily $PM10$	0.002	0.002	0.000	0.001**	0.029***	0.011***	0.024***	0.006***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.004)	(0.003)	(0.004)	(0.002)
Postcode sector controls								
Income score	0.278***	0.264***	0.031**	0.005	−1.217***	−0.763***	−0.975***	−0.196***
	(0.038)	(0.033)	(0.013)	(0.017)	(0.092)	(0.063)	(0.083)	(0.033)
Employment score	−0.527***	−0.478***	−0.046	−0.027	3.303***	1.811***	2.825***	0.498***
	(0.085)	(0.074)	(0.028)	(0.039)	(0.210)	(0.144)	(0.190)	(0.076)
Health score	0.022***	0.021***	0.003**	−0.000	0.040***	0.005	0.049***	−0.001
	(0.004)	(0.003)	(0.001)	(0.002)	(0.010)	(0.007)	(0.010)	(0.004)
Education score	0.002***	0.001***	0.000	0.001***	0.003***	0.003***	0.002***	−0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Housing score	−0.001***	−0.001***	−0.000	−0.000***	−0.006***	−0.003***	−0.006***	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Crime score	0.029***	0.026***	0.002	0.005**	0.026**	0.019**	−0.006	0.026***
	(0.005)	(0.004)	(0.001)	(0.002)	(0.012)	(0.008)	(0.011)	(0.004)
Environmental score	−0.003***	−0.003***	−0.000***	−0.000***	−0.008***	−0.003***	−0.007***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Weather controls								
Average temperature	−0.000	0.000	−0.000	−0.000	0.008*	0.003	0.005	0.002
	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.004)	(0.002)
Daily Max temperature	0.000	−0.000	0.000	0.000	−0.003	−0.002	−0.002	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.003)	(0.002)	(0.002)	(0.001)
Daily Min temperature	0.000	0.000	0.000	−0.000	−0.003	0.000	−0.003	−0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)	(0.002)	(0.001)
Rainfall	−0.003	−0.005	−0.000	−0.001	0.047**	0.036**	0.042**	0.008
	(0.009)	(0.008)	(0.003)	(0.004)	(0.023)	(0.016)	(0.021)	(0.008)
Pollution controls								
Daily NO_2	−0.004**	−0.002	−0.001	−0.002*	−0.004	0.000	−0.005	−0.004**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.004)	(0.005)	(0.002)
Observations	105 168	105 168	105 168	105 168	105 168	105 168	105 168	105 168
Adjusted R^2	0.0447	0.0373	0.0037	0.01	0.1449	0.0862	0.1241	0.027
Dep. var. mean	0.081	0.062	0.008	0.018	0.532	0.258	0.445	0.078
Dep. var. st. dev.	0.295	0.255	0.087	0.134	0.817	0.543	0.734	0.287
Day of the week FE	✓	✓	✓	✓	✓	✓	✓	✓
Week × Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Post District FE	✓	✓	✓	✓	✓	✓	✓	✓

This table reports the linear regression estimates obtained from performing Eq. (4). Our dependent variables are, for each day/postcode sector, the total number of admitted patients that have been diagnosed with respiratory illnesses (*Respiratory*), cardiovascular illnesses (*Cardiovascular*), cerebrovascular illness (*Cerebrovascular*), as well as any of these illnesses (*All*). All outcomes are stratified by youths (age < 18) and older adults (age ≥ 60). $PM10$ and NO_2 are in daily standard deviations. Our postcode sector controls are the interpolation of deprivation scores for the years 2004, 2007, 2010 and 2015 corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average, minimum, and maximum daily temperature, and daily rainfall. Standard errors in parentheses, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

We report the results for specific diseases in Table 4. We focus specifically on three broad categories of diagnoses: (1) respiratory conditions, (2) cardiovascular conditions, and (3) cerebrovascular conditions.[5] In the case of youths, we find a significant increase in hospital visits for cerebrovascular but not other conditions. In the case of older adults, diagnosis of all three types of conditions increased significantly. These results are consistent with a previous study that found short-term increases in particle pollution to be associated with increased mortality in infants and increased hospital admissions for cardiovascular disease, and year-round exposure to be associated with increased risk of death from cardiovascular disease and increased risk of heart attacks and strokes (American Lung Association, 2021).

4.2. Cost of hospital visits

We did not find a significant increase in the per-patient average healthcare cost for either youths or older adults (see Table 5). While the per-patient healthcare cost is decreasing, the change is economically small (less than 1% relative to their respective means) and statistically nonsignificant.

[5] In Table A.4 in the appendix, we provide a breakdown of some of the major specific diagnoses within these categories. Note that for a single patient, co-morbidity across these different diagnoses is common.

Table 5
Pollution and individual cost with deprivation and weather controls, and time and geographical fixed effects.

	Youths		Older adults	
	(1) Admitted	(2) Discharged	(3) Admitted	(4) Discharged
Daily $PM10$	−7.424	−0.205*	−18.042	−0.241
	(21.333)	(0.117)	(14.996)	(0.191)
Postcode sector controls				
Income score	332.755	−5.347*	−1448.457***	−21.531***
	(347.690)	(2.969)	(403.383)	(5.214)
Employment score	−807.525	18.127**	2395.845**	34.210***
	(830.521)	(7.702)	(986.607)	(13.075)
Health score	26.896	−1.084**	32.510	0.403
	(50.272)	(0.440)	(49.146)	(0.714)
Education score	−0.452	0.027***	−1.585	0.055***
	(1.216)	(0.010)	(1.277)	(0.018)
Housing score	−2.703	−0.080***	−0.718	0.031
	(3.956)	(0.027)	(2.684)	(0.036)
Crime score	1.217	−0.338	47.660	−0.287
	(35.999)	(0.326)	(42.068)	(0.549)
Environmental score	−2.301	−0.111***	−0.707	0.030
	(1.995)	(0.017)	(1.939)	(0.030)
Weather controls				
Average temperature	16.834	−0.076	2.052	0.028
	(14.134)	(0.123)	(15.922)	(0.203)
Daily Max temperature	−12.108	0.129*	−2.706	−0.001
	(7.862)	(0.070)	(9.435)	(0.116)
Daily Min temperature	−5.542	0.013	4.274	0.013
	(6.665)	(0.066)	(8.309)	(0.108)
Rainfall	61.633	−1.191*	−174.857**	0.347
	(98.936)	(0.662)	(76.484)	(1.062)
Pollution controls				
daily NO_2	2.866	0.146	1.766	0.665***
	(30.803)	(0.150)	(16.451)	(0.245)
Observations	12 449	133 534	50 948	51 039
Adjusted R^2	0.0616	0.0695	0.2821	0.0909
Dep. var. mean	845.257	75.029	1836.828	76.407
Dep. var. st. dev.	930.974	25.260	2077.935	25.562
Day of the week FE	✓	✓	✓	✓
Week × Year FE	✓	✓	✓	✓
Post District FE	✓	✓	✓	✓

This table reports the linear regression estimates obtained from performing Eq. (5) at the individual level. Our dependent variables are for each day/postcode sector, the individual cost of hospital visits for those who are admitted (*Admitted*), and the individual cost of hospital visits for those who are discharged from the Emergency Department (*Discharged*). All outcomes are stratified by youths (age < 18) and older adults (age ≥ 60). $PM10$ and $N0_2$ are in daily standard deviations. Our postcode sector controls are the interpolation of deprivation scores for the years 2004, 2007, 2010 and 2015 corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average, minimum, and maximum daily temperature, and daily rainfall. Standard errors in parentheses, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Together with the nonsignificant decrease in average per-patient costs, we find an increase in total costs, which is statistically significant for all groups except admitted youth (see Table 6). For discharged youths (column 2), we find that a one standard deviation increase in exposure to $PM10$ increases the daily total cost per postcode sector by £2.88 ($p \leq 0.001$) or 2.87% relative to the daily total mean cost per postcode sector. For admitted older adults (column 3), we find that a one standard deviation increase in exposure to $PM10$ increases the daily total cost per postcode sector by £49.11 ($p \leq 0.001$), or 5.52% relative to the daily total mean cost per postcode sector. For discharged older adults (column 4), a one standard deviation increase in exposure to $PM10$ increases their total daily cost per postcode sector by £2.72 ($p \leq 0.001$), or 7.32% relative to the daily total mean cost per postcode sector.

Altogether, these results suggest that higher exposure to $PM10$ increases healthcare costs because it leads to more ED visits and, in the case of older adults, more hospital admissions. As indicated above, a one standard deviation increase in exposure to $PM10$ increases the total costs for youths discharged from the ED by £2.88 on average per day per postcode sector, which translates to £46,252.80 for the 44 postcode sectors that comprise the studied city – for which we have their local characteristics (deprivation indices) – per year. Similarly, a one standard deviation increase in exposure to $PM10$ increases the daily cost for admitted and discharged older adults by £49.11 and £2.72, respectively, which translate to £788,706.60 and £43,683.20 per year. In total, a Leicester city-wide one standard deviation increase in exposure to $PM10$ would cost the UHL NHS Trust an additional £41,595.40 in treating youths and £832,389.80 in treating older adults annually, equating to a total cost of £873,985.20.

Table 6
Pollution and total cost with deprivation and weather controls, and time and geographical fixed effects.

	Youths		Older adults	
	(1) Admitted	(2) Discharged	(3) Admitted	(4) Discharged
Daily $PM10$	3.269	2.880***	49.113***	2.715***
	(2.945)	(0.519)	(11.375)	(0.312)
Postcode sector controls				
Income score	454.871***	196.518***	−4008.791***	−47.879***
	(59.028)	(12.671)	(242.186)	(6.965)
Employment score	−833.163***	−282.880***	9361.010***	218.705***
	(128.509)	(28.507)	(561.926)	(15.931)
Health score	38.820***	28.018***	−79.288***	7.647***
	(6.450)	(1.410)	(26.138)	(0.810)
Education score	1.382***	1.775***	9.607***	0.048*
	(0.232)	(0.049)	(1.011)	(0.028)
Housing score	−2.038***	−1.739***	−1.372	−0.615***
	(0.321)	(0.066)	(1.442)	(0.044)
Crime score	33.265***	16.119***	−12.419	−5.060***
	(7.008)	(1.611)	(31.448)	(0.919)
Environmental score	−3.884***	−3.229***	−5.567***	−0.823***
	(0.328)	(0.071)	(1.329)	(0.041)
Weather controls				
Average temperature	0.625	0.549	21.085*	0.667**
	(2.325)	(0.572)	(12.605)	(0.338)
Daily Max temperature	−0.666	0.946***	−8.820	−0.288
	(1.351)	(0.322)	(7.328)	(0.193)
Daily Min temperature	−0.556	−0.821***	−6.731	−0.262
	(1.219)	(0.307)	(6.503)	(0.182)
Rainfall	1.136	−10.502***	−32.464	2.269
	(14.339)	(2.852)	(59.531)	(1.772)
Pollution controls				
Daily NO_2	−6.637*	−3.858***	−17.327	−0.094
	(3.581)	(0.651)	(12.829)	(0.397)
Observations	105 168	105 168	105 168	105 168
Adjusted R^2	0.0252	0.3181	0.1111	0.1221
Dep. var. mean	100.055	95.266	889.840	37.081
Dep. var. st. dev.	440.538	117.230	2115.218	62.389
Day of the week FE	✓	✓	✓	✓
Week × Year FE	✓	✓	✓	✓
Post District FE	✓	✓	✓	✓

This table reports the linear regression estimates obtained from performing Eq. (6) at the postcode sector level. Our dependent variables are for each day/postcode sector, the total cost of hospital visits for those who are admitted (*Admitted*), and the total cost of hospital visits for those who are discharged from the Emergency Department (*Discharged*). All outcomes are stratified by youths (age < 18) and older adults (age ≥ 60). $PM10$ and $N0_2$ are in daily standard deviations. Our postcode sector controls are the interpolation of deprivation scores for the years 2004, 2007, 2010 and 2015 corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average, minimum, and maximum daily temperature, and daily rainfall. Standard errors in parentheses, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

It is important to note that these estimates should be interpreted as a lower bound on pollution-related healthcare costs since there are many factors that our focus on the cost of hospital visits will not capture. For example, increased pollution levels may increase ongoing medical expenses for affected patients. Similarly, we only capture the cost for those individuals who immediately attend the hospital in response to the elevated pollution. We will miss individuals who seek help from other sources (e.g., a local general practitioner or pharmacist) or forgo seeking help in the short run. We also do not capture costs for patients and their families associated with extreme outcomes such as mortality due to higher pollution levels.

5. Robustness and additional results

5.1. Robustness of main results

We provide the results of several other robustness checks in Appendix D. First, for transparency, we repeated our main analysis using $PM10$ levels recorded by the nearest monitor to each postcode sector weighted by their *strength* as our pollution measure rather than a weighted average of all monitors. We find the results reported in Section 4 remain largely unaltered by the change in the pollution measure (see Table D.1). Second, we excluded air pressure as a weather control in our main analysis since we only

Table 7
Placebo regression for pollution on total number of hospital visits (7- and 10-Day Lags and Leads).

	(1) Youths	(2) Youths	(3) Youths	(4) Older adults	(5) Older adults	(6) Older adults
(A) 10 day differences						
$t = 0$	0.045***			0.070***		
	(0.007)			(0.006)		
$t = -10$		−0.001			0.009	
		(0.007)			(0.006)	
$t = 10$			−0.004			0.005
			(0.007)			(0.006)
Observations	105 168	105 158	105 158	105 168	105 158	105 158
Adjusted R^2	0.3568	0.3564	0.3564	0.2382	0.2371	0.237
Dep. var. mean	1.463	1.463	1.463	1.123	1.123	1.123
Dep. var. st. dev.	1.678	1.678	1.678	1.314	1.314	1.314
(B) 7 day differences						
$t = 0$	0.045***			0.070***		
	(0.007)			(0.006)		
$t = -7$		−0.000			0.005	
		(0.007)			(0.006)	
$t = 7$			−0.009			−0.002
			(0.007)			(0.006)
Observations	105 168	105 161	105 161	105 168	105 161	105 161
Adjusted R^2	0.3568	0.3564	0.3565	0.2382	0.2371	0.237
Dep. var. mean	1.463	1.463	1.463	1.123	1.123	1.123
Dep. var. st. dev.	1.678	1.678	1.678	1.314	1.314	1.314
Pollution control	✓	✓	✓	✓	✓	✓
Postcode sector controls	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓
Day of the week FE	✓	✓	✓	✓	✓	✓
Week × Year FE	✓	✓	✓	✓	✓	✓

This table reports linear regression estimates corresponding to Eq. (4) where we replace $Pollution$ with its lagged and lead versions for 10 days in Panel A and 7 days in Panel B. Dependent variables are, for each day/postcode sector, the total number of hospital visits (*Visits*), the total number of hospital visits that are admitted (*Admitted*), and the total number of hospital visits that are discharged from the Emergency Department (*Discharged*). All outcomes are stratified by youths (age < 18) and older adults (age ≥ 60). $PM10$ and NO_2 are in daily standard deviations. Our postcode sector controls are the interpolation of deprivation scores for the years 2004, 2007, 2010 and 2015 corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average, minimum, and maximum daily temperature, and daily rainfall. Standard errors in parentheses, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

have average daily air pressure data for 2009–2011. When we include air pressure as a control and restrict the sample to 2009–2011, the results from the main analysis still hold (see Table D.2). Third, we address a potential concern that weekdays may have very different pollution patterns and hospital admissions than weekends. Most of our main results hold when we restrict the sample to weekdays. The exception is the effect of a daily increase in $PM10$ on youth hospital admissions, which became nonsignificant albeit of a similar magnitude (see Table D.3). Fourth, we address another potential concern that our measure may not capture pollution in postcode sectors further away from all monitors appropriately. We present the distance of each postcode sector to a monitor in Table A.5. The results of our main analysis remain largely unaltered when we restrict it to postcode sectors within three kilometers of a monitor (Table D.4).

One concern is that we may simply be picking up spurious correlations in the data. To test for this, we ran a falsification test in which we replaced $PM10_{ct}$ in Eq. (4) with its corresponding ten-day and seven-day lags and leads. A significant result using lags and leads would cast doubt on our empirical strategy and causal interpretation of γ_1 in Eq. (4). The results of this exercise are reported in Table 7. The estimated coefficients corresponding to lags and leads are all very small – the largest coefficients are less than one-quarter the size of our main estimates – and statistically nonsignificant at conventional levels, supporting the argument that our identification strategy is based on idiosyncratic variation in daily $PM10$ levels.

We also apply an IV estimation strategy similar that of Isphording and Pestel (2021) and Deryugina et al. (2019), in which $PM10$ measures are instrumented using a postcode region dummies interacted with the interaction of wind speed and wind direction.[6] This approach ensures we only identify pollution using variations in daily wind patterns while remaining agnostic about how wind patterns affect pollution in different areas. We apply this IV strategy using two measures of $PM10$: the strength-weighted measure calculated using Eq. (1) and a simple nearest monitor measure (Table D.9). The first stage F-statistics suggest that the instruments are strong, and the resulting estimates suggest that the effects of $PM10$ on hospital visits are large. When we instrument the nearest monitor measure of $PM10$, we find a one standard deviation increase in $PM10$ increases daily hospital visits by 0.153 for youths

6 As in Isphording and Pestel (2021), wind direction is captured using four dummy variables denoting north-west, north-east, south-west, and south-east. In each equation, we estimate both $PM10$ and NO_2 measures.

Table 8
Pollution on total number of hospital visits with 7-Day Lags (Robustness Check).

	(1) Youths	(2) Youths	(3) Older adults	(4) Older adults
$t = 0$	0.045***	0.138***	0.070***	0.190***
	(0.007)	(0.012)	(0.006)	(0.011)
$t = -1$		−0.022**		−0.046***
		(0.010)		(0.009)
$t = -2$		−0.049***		−0.026***
		(0.011)		(0.009)
$t = -3$		−0.016		−0.026***
		(0.011)		(0.009)
$t = -4$		−0.021*		−0.025***
		(0.011)		(0.009)
$t = -5$		−0.004		−0.031***
		(0.010)		(0.009)
$t = -6$		0.002		−0.010
		(0.010)		(0.009)
$t = -7$		−0.018*		−0.002
		(0.010)		(0.009)
7-day cumulative		0.012		0.025**
		(0.008)		(0.007)
Observations	105 168	105 161	105 168	105 161
Adjusted R^2	0.3568	0.3576	0.2382	0.2397
Dep. var. mean	1.463	1.463	1.123	1.123
Dep. var. st. dev.	1.678	1.678	1.314	1.314
Pollution control	✓	✓	✓	✓
Postcode sector controls	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Day of the week FE	✓	✓	✓	✓
Week × Year FE	✓	✓	✓	✓

This table reports the linear regression estimates corresponding to Eq. (4) where we add 10 days lagged versions of $Pollution$ as controls. Dependent variables are, for each day/postcode sector, the total number of hospital visits (*Visits*), the total number of hospital visits that are admitted (*Admitted*), and the total number of hospital visits that are discharged from the Emergency Department (*Discharged*). All outcomes are stratified by youths (age < 18) and older adults (age ≥ 60). $PM10$ and NO_2 are in daily standard deviations. Our postcode sector controls are the interpolation of deprivation scores for the years 2004, 2007, 2010 and 2015 corresponding to the following categories: income, employment, health and disabilities, education and training, barriers to housing, crime, and living environments. Our weather controls are average, minimum, and maximum daily temperature, and daily rainfall. Standard errors in parentheses, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

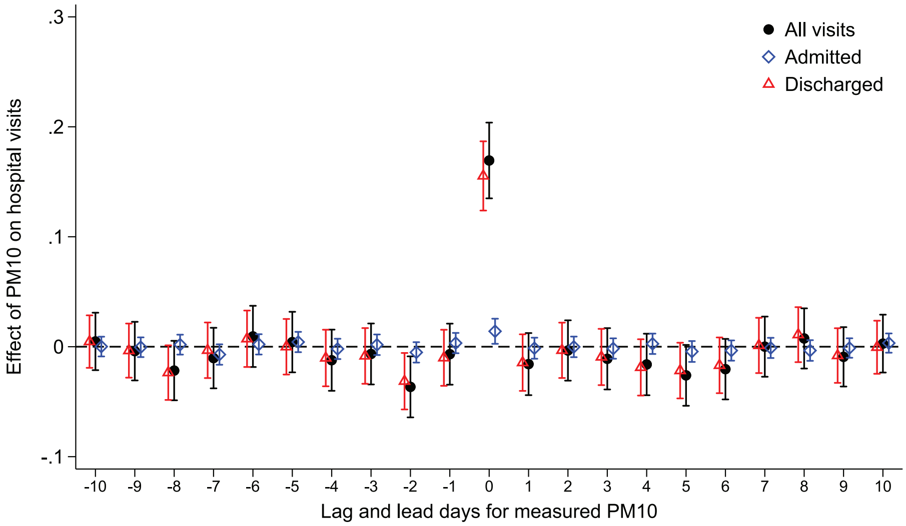
and 0.190 for older adults, corresponding to roughly a 10% and 17% increase (columns 3 and 4, *Panel A*). These results are robust to instrumenting only $PM10$ (*Panel A*) or simultaneously instrumenting $PM10$ and NO_2 (*Panel B*). Overall, the IV estimates are consistent with ordinary least squares regression (OLS), providing a conservative underestimation of the true effect of pollution on hospital use.

We repeat our estimates while allowing for different functional form assumptions in our main estimating equation. First, we allow for non-linearities in the effect of $PM10$ on hospital use and costs by including dummy variables for $PM10$ quartiles and $PM10$ as a quadratic. Unsurprisingly, the higher quartile bins have larger positive coefficients for hospital visits for both youths and older adults (Table D.5). For example, exposure to the highest quartile of $PM10$ levels leads to 0.166 ($p \leq 0.00$) more hospital visits for older adults than exposure to the lowest quartile. However, $PM10$ levels do not increase linearly across these bins; moving from the second to third quartile reflects an average change of 1.139 standard deviations, while moving from the third to the fourth quartile reflects an average change of 2.361 standard deviations. Therefore, the marginal effect of $PM10$ appears to be decreasing, consistent with what we find when we instead include a quadratic term for $PM10$ (Table D.6). This finding is consistent with the possibility that individuals with potential health risks act to mitigate exposure at high pollution levels, offsetting some of the potential effects of hospitalization.

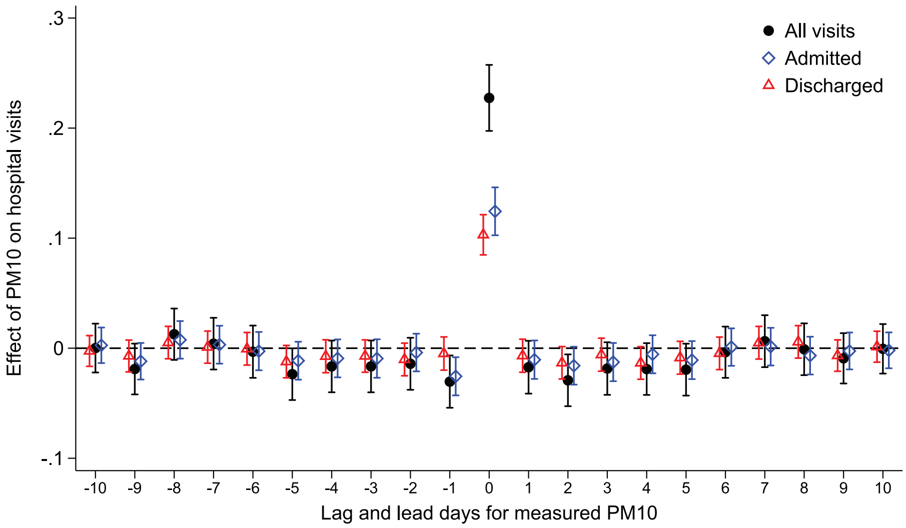
Second, we repeat our main estimates using a Poisson model to account for the fact that approximately 40% of hospital visit outcomes are equal to 0 (see Table D.8). The results are very similar to those with linear OLS. Specifically, a one standard deviation increase in daily $PM10$ increases hospital visits by 4.3% (compared to a 3.1% increase using OLS) for youths and 6.3% (compared to a 6.2% increase using OLS) for older adults. Similarly, Poisson estimates imply a one standard deviation increase in daily $PM10$ increases hospital admissions by 4.7% for youths and 5.1% for older adults (compared to 3.1% and 7.4% increases using OLS). Therefore, we believe that the simpler linear specification is not significantly miss-specified.

5.2. Dynamic analysis

There may also be concern that our main results are confounded by the cumulative effect of pollution over a (short) period of time. The effect this may have on our estimates is ambiguous. If prolonged pollution exposure worsens health outcomes, our



(a) Hospital visits by youth



(b) Hospital visits by older adults

Fig. 3. The effect of lag and lead $PM10$ on hospital visits. These figures plot the coefficients of a regression of hospital visits for youth 3(a) and older adults 3(a) on $PM10$ values on the day of the hospital visit ($t = 0$) and ten days before and ten days after. Estimates are based on a version of Eq. (4) which includes the 10-day lags and leads of $PM10$. Bars indicate 99% confidence intervals.

estimates may reflect the cumulative effect of $PM10$ over several days rather than the strictly contemporaneous effect. Alternatively, pollution exposure in the days leading up to a day of interest ($t = 0$) may lead individuals to seek medical attention earlier or take precautions to mitigate high $PM10$ levels (e.g., remaining indoors). In this case, the lagged $PM10$ exposure will lead us to underestimate the contemporaneous effect of pollution. The overall effect on our estimate will depend on which one of these two effects dominates and how strong the correlation is between daily $PM10$ levels over time.[7]

To address this concern, we estimated Eq. (4), including lagged values of $PM10$ for each day of the previous seven days (see Table 8). We find that adding the $PM10$ lags increases the magnitude of the effect on the day of interest ($t = 0$) by a factor of

[7] It is straightforward to show that the estimated value for γ_1 in Eq. (4) can be written as $\hat{\gamma}_1 = \gamma_1 + \Sigma_{d=1}^{7} \alpha_d \frac{Cov(PM10_t, PM10_{t-d})}{Var(PM10_t)}$, where α_d is the effect of $PM10$ d days earlier on the current day's hospital visits.

three for youths and just over two for older adults. A one standard deviation increase in $PM10$ on day $t = 0$ increases hospital visits by 0.138 ($p \leq 0.001$) for youths and 0.190 ($p \leq 0.001$) for older adults. We also find relatively small negative effects for the lagged $PM10$, concentrated in the days just before $t = 0$. For example, a one standard deviation increase in $PM10$ on day $t = -1$ is associated with a 0.022 ($p = 0.027$) fewer youth patients on day $t = 0$. This has implications for how we interpret our coefficients. First, the $t = 0$ estimates reported in Table 8 reflect the effect of an increase in $PM10$ levels on day $t = 0$ only. If we see a one standard deviation increase in $PM10$ over the previous days and $t = 0$, the effect on hospital visits will equal the sum of all the coefficients. A one standard deviation increase in $PM10$ over seven days will increase hospital visits by 0.012 ($p = 0.165$) for youths and 0.025 ($p \leq 0.001$) for older adults.

We expand the dynamic analysis to examine the effect of $PM10$ levels for a 10-day window around the hospital visits ($t = 0$). The results of this exercise are shown in Fig. 3, which makes several things clear. First, for both youths and older adults, the magnitude of the effects at $t = 0$ is significantly larger than for any day in the window. Second, most point estimates for days $t \neq 0$ are statistically nonsignificant at 99%, suggesting that the lagged-pollution effects reported in Table 8 are sensitive to specification. Third, point estimates for $t = 0$ are qualitatively the same, although larger in magnitude, as those reported in Table 3.

Altogether, these estimates suggest that dynamic factors may influence the relationship between hospital use and pollution. These dynamic effects appear to lead to our main static estimates understating the contemporaneous effect of $PM10$. However, when we consider the effect of a change in $PM10$ levels over several days, our main estimates may overestimate the effect on daily hospital use.

6. Discussion and concluding remarks

This paper analyzed the contemporaneous impact of pollution on public healthcare costs for youths and older adults. To do so, we quantified the effect of $PM10$ on the economic costs of ED visits and their consequent outcomes (hospital discharge or admission). It is important to note that our estimates reflect population-level outcomes, not the effect of the exposure to $PM10$ on individual healthcare use. However, population-level outcomes are of interest for policy purposes, such as considering the wider benefits of reductions in particulate matter.

One way population-level outcomes may deviate from individual-level outcomes is through avoidance behavior, where individuals change their behavior to avoid exposure to excessive pollution. For example, Janke (2014), Neidell (2009), and Moretti and Neidell (2011) found that pre-emptive pollution warnings significantly reduced hospitalization among youths and older adults than would be experienced without them. We do not believe that avoidance behavior plays a significant role in our study setting because our estimation strategy exploits differential variation over time in air quality across neighborhoods rather than for the entire city. While individuals are likely to have pre-emptive information on pollution levels for the city, they are less likely to have this information at a more disaggregated level. That said, if avoidance behavior is common in our population, this will likely reduce the healthcare costs we estimated compared to a no-avoidance scenario. This may be important when considering the total social cost of pollution if these behavior changes reflect increased costs to individuals.

Our estimates come with three other important limitations. Firstly, this paper does not aim to address any non-concurrent or long-term effects of pollution on the targeted population's health, life expectancy, or healthcare costs. For example, if increased exposure to $PM10$ over a short period leads to long-term health complications, our estimates will understate the total effect of $PM10$ on healthcare costs. Secondly, this paper does not address specific mechanisms that lead to variations in pollution, such as transport modes, increased traffic across different hours of the day, or air pollutants and dust from demolition or construction. Knowing the contribution of these different sources to overall pollution is important for considering how to structure a pollution reduction policy. Finally, our ability to examine how pollution impacts healthcare use for different populations within the city is limited. In the appendix, we provide results when examining hospital visits according to self-identified ethnic groups: White, Black, Asian, and Other (Table D.7). We find effects similar to our main results for all groups except patients self-identifying as Black, whose results are negative and only marginally significant. The interpretation of these results poses a challenge as we cannot distinguish whether Black communities in Leicester are less exposed to neighborhood pollution levels or are less likely to respond to adverse pollution-related health effects by visiting the ED. Interestingly, the R^2 for hospital visits for patients self-identifying as Black are much lower than for the other ethnicities (for example, 0.058 for Black youths vs. 0.4099 for white youths), suggesting our equations do a much worse job overall at explaining hospital use for this ethnic group.

While many studies have established that chronic exposure of youths and older adults to air pollution can slow their development, decrease their lung function, and increase their development of respiratory and coronary conditions, diabetes, and dementia, there is little empirical evidence evaluating the immediate effects of $PM10$ on healthcare costs for these potentially most vulnerable groups.

We have attempted to address this gap in the literature by exploiting spatial and temporal variation in population exposure to $PM10$. We found that a one standard deviation increase in $PM10$ exposure was associated with an annual increase in public healthcare costs of £46,252.80 for treating youths and £832,389.80 for treating older adults, totaling £873,985.20, for Leicester, a city in England with about 350,000 residents. This cost represents 0.14% of the average total expenditure of the UHL NHS Trust based on its total £667.4 million expenditure for the fiscal period 2007/08 to 2011/12 (Leicester Hospitals Annual Reports, 2007-2012).

Our findings quantify the resources that could be reallocated from national healthcare services to treat the immediate consequences of pollution, particularly $PM10$, through pollution reduction programs.

CRediT authorship contribution statement

Barbara Boggiano: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Melisa Williams Higgins:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jesse Matheson:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Investigation, Conceptualization. **David Jenkins:** Validation, Supervision, Project administration. **Marco R. Oggioni:** Validation, Supervision, Project administration, Conceptualization.

Supplementary Material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2024.102994.

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