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Estimating the effect of air pollution on road safety using atmospheric temperature inversions

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ABSTRACT

Does air quality influence road safety? We estimate the effect of increased air pollution on the number of road traffic accidents in the United Kingdom between 2009 and 2014. To address concerns of spurious correlation we exploit atmospheric temperature inversions as a source of plausibly exogenous variation in daily air pollution levels. We find an increase of 0.3–0.6% in the number of vehicles involved in accidents per day for each additional 1 μg/m^3 of $PM_{2.5}$. The finding suggests that less safe roads may present a large and previously overlooked cost of air pollution. The results are robust to a number of specifications and across various sub-samples.

1. Introduction

Road traffic accidents generate large costs in the form of material damages, loss of life and bodily harm. In the United Kingdom alone, the UK Department for Transport estimates the total cost of reported traffic accidents in 2014 at *GBP*16.3*bn* (Department for Transport, 2016). Any factor influencing the frequency of accidents is then of great relevance to social welfare. We ask if air pollution is one such factor that contributes to increases in the number of traffic accidents. This question is motivated by recent evidence indicating that short-term fluctuations in air pollution impair productivity and human behaviour in ways that could plausibly affect road safety.

Air pollution is known to be responsible for serious adverse health effects including respiratory illness and cardiovascular disease (Dockery and Pope, 1994; Seaton et al., 1995). Recently, evidence has accumulated that air pollution may also influence the behaviour, productivity and well-being of those exposed. Graff Zivin and Neidell (2012) find negative effects of pollution on the labour productivity of agricultural workers and Hanna and Oliva (2015) find a negative effect on hours worked. Productivity losses from air pollution, especially fine particulate matter below 2.5 μm ($PM_{2.5}$), have also been shown for less physically demanding work, such as in call centres (Chang et al., 2016a). Ebenstein et al. (2016) find that $PM_{2.5}$ and carbon monoxide (CO) impair cognitive performance and reduce standardised test scores of high school students. In addition to these productivity effects, air pollution has also been linked to changes in behaviour and well-being. In particular, elevated levels of pollution have been linked to criminal activity and unethical behaviour (Herrnstadt et al., 2016; Bondy et al., 2018; Lu et al., 2018).

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We hypothesise that air pollution may impair safe driving performance and consequently increase the number of traffic accidents. We are motivated by findings in the literature that link pollution exposure to lowered cognitive performance, heightened aggression, and higher levels of impatience. Driving safely is a complex task that relies on cognitive performance. It is well-established that cognitive performance is inversely related to the likelihood of crashes (Anstey et al., 2005, 2012). Similarly, aggressive or impulsive behaviour while in traffic may increase the likelihood of being involved in an accident. This potential link between air pollution and road safety has so far been overlooked in the literature. We estimate the effect of an increase in air pollution, measured as the daily average concentration of $PM_{2.5}$, on the number of vehicles involved in road traffic accidents within 153 NUTS3 regions in the United Kingdom between 2009 and 2014.

Estimating the effect of interest is complicated by the various ways in which the number of accidents and the concentration of air pollutants may co-vary with structural, seasonal, and weather-related phenomena. As road traffic itself is a major source of air pollution, endogeneity bias is a concern. In order to credibly identify the effect of interest, we rely on atmospheric temperature inversions as an instrument inducing plausibly exogenous variation in pollution levels. Temperature inversions are meteorological phenomena where temperature profiles in the atmosphere deviate from the norm. On most days, when temperature decreases with altitude, pollutants tend to rise and disperse. During inversion episodes, temperature profiles are inverted, and warmer air at higher altitudes traps pollutants close to the ground. As a well known example, the Great London Smog of 1952 has been linked to such an inversion episode. Assuming that these inversions occur randomly, after controlling for related weather patterns, they will introduce an exogenous shock to levels of air pollution. We follow previous work in the economics literature in using inversions as an instrument for air pollution (e.g. Jans et al., 2014; Arceo et al., 2016; He et al., 2019).

We find a positive and statistically significant effect of air pollution on the number of vehicles involved in traffic accidents. The estimate from our preferred specification is that an additional 1 μg/m^3 in the average concentration of $PM_{2.5}$ leads to a 0.4% increase in the number of vehicles involved in accidents. This corresponds to an elasticity of 0.06, which is slightly lower than elasticity estimates for labour productivity responses to air pollution (Neidell, 2017). The estimated effect is economically important considering the large number of accidents on UK roads every year. Simple extrapolation for London suggests that a one standard deviation reduction in $PM_{2.5}$ for a single day could lower accident costs by $GBP500k$.

To ensure robustness of the finding, we test a variety of alternative specifications and sub-samples. A main concern are unobserved weather conditions that may be correlated with inversion episodes and influence road safety. Our results are robust to additional analyses intended to control for those weather conditions. Estimates are similar across driver characteristics (gender, age) and vehicle types, with a slightly lower estimated increase in the number of two-wheel vehicles in accidents, and a larger effect for enclosed vehicles during warmer months. We find that the effect holds in urban as well as rural areas and may disproportionately raise the number of fatal and severe accidents. Importantly, we analyse a subset of days for which we obtain traffic count data and find no effect of pollution on traffic volume. This suggests that we are indeed identifying an effect of pollution on the likelihood of being involved in an accident while holding constant the volume of traffic.

Results are similar for alternative measures of air pollution, but we are not able to credibly identify the separate effects of different pollutants. We thus interpret our results as showing an effect of air pollution generally on road safety, without specifying the role of single pollutants. Compared to other measures of pollution, $PM_{2.5}$ appears to be a conservative choice as collective measure of air pollution. It is also in line with the medical literature and previous findings on productivity effects during less physically strenuous tasks (e.g. Chang et al., 2016a). We speculate that the observed effect of air pollution on road safety is driven by lowered safe driving performance, possibly via reduced cognitive performance (e.g. lower attention span or higher reaction time) or changed behaviour (e.g. more aggressive driving). However, we cannot exclude the possibility that air pollution affects drivers' performance through other channels, such as distraction due to irritated respiratory organs or impaired visibility.

Our finding that air pollution may lead to more accidents has a number of implications. Firstly, current estimates of the external cost of air pollution exposure, based largely on health outcomes, may underestimate the true cost of air pollution to society. Secondly, road vehicles constitute a major source of air pollutants and it is arguably while participating in road traffic that one is exposed to some of the highest concentrations of air pollution. However, the possibility that pollution may affect the frequency of traffic accidents has so far been overlooked. Finally, evidence that contemporaneous exposure to air pollution could impair driving performance may suggest further previously undiscovered costs of air pollution during similar high risk activities, such as operating heavy machinery.

This paper proceeds as follows. Section 2 discusses the relevant previous literature. Section 3 introduces the research design. Section 4 describes the data. Section 5 presents the main results. Section 6 discusses robustness and limitations. Section 7 concludes.

2. Previous literature

Air pollution refers to a variety of pollutants including carbon monoxide (CO), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), fine/small particulate matter ($PM_{2.5}$/PM_{10}), and ozone (O_3). A large literature exists exploring the adverse effects on health from exposure to air pollution (Currie et al., 2011; Graff Zivin and Neidell, 2013). Air pollution is linked to serious adverse health effects such as increased risk of cardiovascular disease, respiratory illness, and increased mortality in general (Dockery and Pope, 1994; Seaton et al., 1995; Heutel and Ruhm, 2016).

More recent work has found adverse effects of acute air pollution exposure on productivity (for a concise survey see Neidell, 2017), both outdoors (agricultural labourers in Graff Zivin and Neidell, 2012) and indoors (call-centre workers and pear-packers in Chang et al., 2016a,b). Pollution also appears to impair cognitive performance, such as lowering high-school student test scores (Ebenstein et al., 2016) and reducing the performance of investment professionals (Heyes et al., 2016). In addition to these productivity effects, acute exposure to air pollution has been linked to increased criminal activity (Herrnstadt et al., 2016; Bondy et al., 2018), unethical behaviour (Lu et al., 2018), and lower levels of reported happiness (Zhang et al., 2017).

The medical literature suggests multiple pathways for these observed effects on cognitive performance and behaviour. Pollution can impair respiratory function as well as blood flow and circulation (Dockery and Pope, 1994; Seaton et al., 1995). This may in turn limit the transport of oxygen to the brain, leading to lower concentration and slower reflexes[2] (Kampa and Castanas, 2008). In addition, some constituents of $PM_{2.5}$ may themselves reach the brain after crossing the blood brain barrier (Block and Calderon-Garciduenas, 2009; de Prado Bert et al., 2018). Beyond cognitive performance, pollution may also affect behaviour. Acute air pollution exposure, and in particular $PM_{2.5}$, has been linked to elevated levels of stress hormones such as cortisol, cortisone, and epinephrine (Li et al., 2017). Higher levels of stress hormones may then result in changed behaviour, in particular higher degrees of impatience (Riis-Vestergaard et al., 2018). Similarly, air pollution has been linked to elevated serotonin levels (Murphy et al., 2013), which may result in more aggressive behaviour and changes in risk appetites.

This paper adds to the literature by asking if air pollution may affect productivity in another dimension—namely the ability to safely participate in road traffic. It is well established that safely steering a vehicle and avoiding accidents is positively related to cognitive performance—in particular attention, reaction time, working memory, executive function, mental status, visual function, and physical function (Anstey et al., 2005, 2012). In addition, impatient and aggressive behaviour may lead to more accidents. Finally, other symptoms of air pollution exposure, such as irritation of the upper airways, may cause distractions and reduce driving performance.

This study also contributes to the literature on the environmental determinants of road safety (for a survey see Maze et al., 2006). This literature has largely focused on weather conditions (Koetse and Rietveld, 2009). Overall, findings suggest a strong positive effect of precipitation on accidents (Theofilatos and Yannis, 2014), while results are more mixed for wind speed, cloud coverage, temperature, and humidity (e.g. Edwards, 1999; Hermans et al., 2006). There also appears to be a link between weather and traffic volume, with snowfall, rainfall and wind speed diminishing traffic intensity, and higher temperatures raising it (Cools et al., 2010). However, the literature has so far overlooked the potential effect of air pollution on road safety. This is so despite the observation that individuals are exposed to particularly high concentrations of pollution while in traffic (e.g. Power et al., 2011; Knittel et al., 2016). For example, Riediker et al. (2004) find large effects of acute $PM_{2.5}$ exposure on levels of inflammation and cardiac rhythm among North Carolina State Highway Patrol Troopers while in traffic. Our analysis is thus motivated by the combination of high pollution exposure in traffic, the multiple potential ways in which pollution may lower safe driving performance, and the high cost associated with accidents.

3. Research design

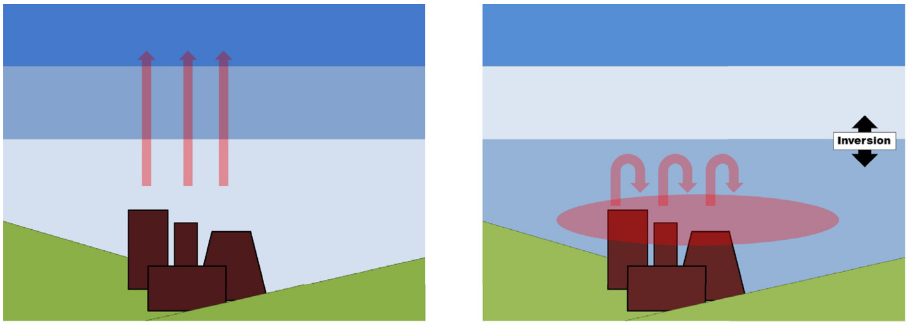
Identifying the effect of pollution on accidents from observed outcomes is challenging because air pollution is largely a product of human activity and we cannot reasonably assume that it is randomly assigned across locations. In the context of this paper, it is likely that both the number of accidents per day and the level of pollution in a certain region are related to unobserved confounding factors. These factors may be transitory, such as for example weather conditions affecting both accident frequencies and pollution levels, or structural, such as population density of regions, prevalence of road types, or speed regulations.

As we aim to identify a potential effect on drivers' performance, we are particularly interested in effects on the accident rate, the number of accidents holding the volume of traffic constant. A particular concern may then be that both pollution levels and the number of accidents are driven by changes in the volume of traffic. Green et al. (2016) have demonstrated in the context of the London congestion charge that traffic volume may affect accident counts and pollution levels at the same time. In this and a number of other plausible ways, endogeneity of pollution levels will result in biased estimates when applying simple regression analysis with OLS estimators.

Identification strategy: In order to overcome the problem posed by potential endogeneity of treatment, we adopt an instrumental variable (IV) approach to estimate the causal effect of air pollution on accidents. We use as an instrument a measure of atmospheric temperature inversions. While on most days, temperature decreases with altitude, inversion episodes are characterised by increasing temperature. During these inversion episodes, the warmer air at higher altitude prevents pollutants from rising and dispersing, but rather traps them close to the ground (see Fig. 1). We will argue that such inversion episodes present an exogenous source of variation in air pollution levels (after controlling for potentially related weather conditions).

Our method is related to that applied by Jans et al. (2014), who use a binary indicator of temperature inversions as an instrumental variable to estimate the effect of PM_{10} concentrations on children's respiratory health. Similarly, Arceo et al. (2016) use the number of temperature inversions per week to estimate effects of PM_{10} and CO on child mortality in Mexico City. We exploit inversion episodes to estimate the effect of air pollution on the number of road traffic accidents.

[2] In line with these pathways, there appears to be a link between acute $PM_{2.5}$ exposure and the occurrence of headaches and migraines (Szyszkowicz, 2008; Chen et al., 2015). Chen and Schwartz (2009) find a negative association between exposure to air pollution (O_3 and PM_{10}, yearly variation) and performance in neuro-behavioural tests designed to measure reaction time, attention, perceptual function, and short-term memory.



(a) Normal conditions: Temperature decreases with altitude, pollutants rise and disperse

(b) Inversion episode: Warmer layer above, pollutants remain trapped near ground

Fig. 1. Temperature inversions as instrument for air pollution.

We denote Z as an instrumental variable, which takes positive values on inversion days and negative values otherwise. The empirical specification that we implement for 2SLS estimation is represented by the following two equations:

$$D_{it} = \tau + \rho Z_{it} + \delta' \mathbf{x}_{it} + \eta_t + \theta_i + \upsilon_{it} \quad \text{(First Stage)} \tag{1}$$

$$Y_{it} = \mu + \alpha \widehat{D}_{it} + \beta' \mathbf{x}_{it} + \mu_t + \gamma_i + \epsilon_{it} \quad \text{(Second Stage)} \tag{2}$$

Here, Y_{it} is the natural logarithm of the number of vehicles involved in accidents in region i on day t (baseline), D_{it} is the average daily concentration of an air pollutant ($PM_{2.5}$ throughout most of this paper), Z_{it} is a measure of night-time inversion strength, $\mathbf{x}_{it}$ is a vector of controls for weather conditions, η_t and μ_t are time fixed effects, θ_i and γ_i are region fixed effects, τ and μ are constants, and υ_{it} and ϵ_{it} are error terms. Throughout much of this paper, we will rely on fine particulate matter ($PM_{2.5}$) as measure of air pollution. $PM_{2.5}$ describes a mixture of particles, which can include secondary particles derived from other pollutants such as SO_2 and NO_x. It is frequently used as key measure of air pollution. We discuss the role of specific pollutants further below (see Table 7).

We use the log-linear specification of the Second Stage as our baseline case, because we hypothesise that pollution D_{it} (and other explanatory variables $\mathbf{x}_{it}$) has proportionate effects on the number of daily accidents in a region by increasing the risk of each driver to be involved in an accident (for a given volume of traffic). In Appendix A.1, we provide a brief outline of why we assume that changes in the productivity of driving are most likely captured by such proportional effects. We also provide separate results for alternative functional forms, namely for a simple linear specification and an exponential conditional mean model akin to a Poisson model, which is often used to investigate factors influencing accident counts.

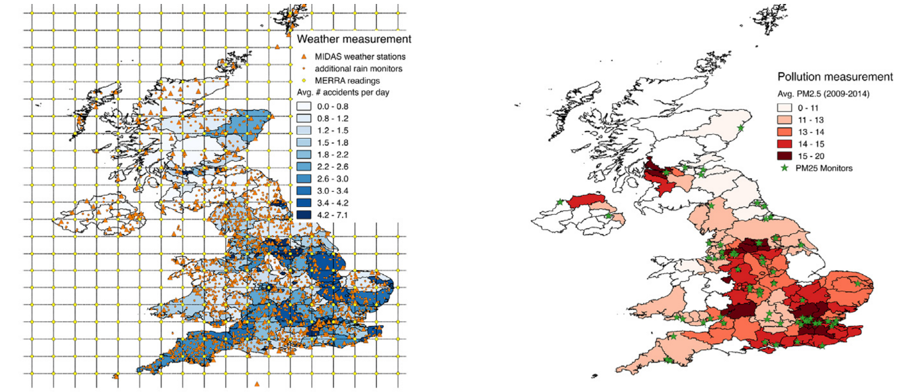
In order for our IV approach to yield an unbiased estimate of the suspected causal effect, the usual identifying assumptions of First Stage, Monotonicity, and Independence need to be met (see e.g. Imbens and Angrist, 1994). In essence, First Stage requires that inversion episodes significantly affect the concentration of air pollutants (instrument relevance). Independence requires inversion episodes to be randomly assigned. Crucially, it implies that inversions Z only affect accident frequency Y through their effect on pollution D (exclusion restriction). Monotonicity rules out the existence of regions where inversions systematically have the opposite effect on pollution than in general. If these assumptions hold and treatment effects are constant conditional on covariates $\mathbf{x}$, our approach will yield an unbiased estimate of the local average treatment effect (LATE) in the case without covariates. We will describe the choice of the inversion instrument in Section 4 and discuss the plausibility of these identifying assumptions alongside the results presented in Sections 5 and 6.

4. Data

We construct a panel data set on daily air quality, traffic accidents, and weather conditions in the United Kingdom between 2009 and 2014.

4.1. Data sources

Road accident statistics: Observations for road traffic performance are obtained from the Road Safety Data maintained by the UK [dataset] Department for Transport (2015). These publicly available data provide yearly lists of road traffic accidents in Great Britain involving personal injury which have been reported to the police and recorded using STATS19 forms. For the six years between 2009 and 2014, we have obtained details for a total of 899,995 individual accidents with exact timing and geo-coordinates (longitude to 6 digits after the comma, latitude to 5 digits). Each accident record is complemented by further



(a) Weather stations and NUTS3 regions (colouring according to daily mean of vehicles in accidents 2009-2014)

(b) Pollution $PM_{2.5}$ monitors and NUTS3 regions (colouring according to mean $PM_{2.5}$ concentration, inverse distance-weighted at max. 50km from region centroid)

Fig. 2. Geographic coverage of observational units.

details about the vehicles and drivers involved, which we exploit for further analyses in Section 6. We collapse these data to daily counts (including 0 counts) of vehicles in reported accidents within each of 171 NUTS3 regions[3] (see Fig. 2).

Atmospheric temperature data: As source for atmospheric temperature data, we use data extracts from NASA's MERRA-2 climate reanalysis product as described in Gelaro et al. (2017).[4] MERRA-2 is a reanalysis data product which combines a large range of observations from various sources—including from satellites, weather balloons, sondes, buoys, and other instruments[5]—with an atmospheric data assimilation algorithm to produce a 3-dimensional, gridded dataset containing atmospheric conditions for all of the planet since 1980.

We obtain data on 3-hourly atmospheric air temperature from MERRA ([dataset] Global Modeling and Assimilation Office (GMAO), 2015). We also obtain from MERRA data on surface-level air temperature, the amount of snowfall, and cloud coverage for all pressure levels combined.[6] MERRA data is provided at a spatial resolution of $0.5° \times 0.625°$ (ca. 45 km $\times$ 55 km). Our main units of observation are 171 NUTS3 regions which cover all of Great Britain, observed for the 2,191 days of the years 2009–2014. Each NUTS3 region is assigned the readings from the MERRA coordinate closest to the centroid of the region. Fig. 2a provides a visual representation of the geographic coverage of regions used in the final analysis.

The MERRA data is provided at various atmospheric pressure levels which correspond to different altitudes. The standard interval between pressure levels is 25 hPa, starting from the lowest 1000 hPa pressure level (ca. 30 m above sea-level). To construct the measure of inversion strength (the instrument), we use the continuous difference in temperature between the 925 hPa pressure level (ca. 600 m above sea level) and air temperature at the surface as provided by MERRA. This approach follows recent contributions, for example He et al. (2019), who argue that continuous temperature differences may better instrument for vertical ventilation conditions than a binary inversion indicator. Using surface-level air temperature is motivated by the larger number of missing values at the 1000 hPa pressure level. It may also be more robust to any potential co-variation between atmospheric pressure and temperature which could introduce endogeneity bias (further discussed below). To be clear, to calculate inversion strength we use surface-level temperature as provided by MERRA, not temperature data from ground-level monitoring stations. We use data at 3am local time to construct our instrument of night-time inversion strength. We focus on night-time inversions to counter concerns that daytime inversions may be perceivable for road traffic participants (inversions during daylight can occasionally be seen with the naked eye) and because these inversions occur before the bulk of recorded traffic accidents on a given day. Furthermore, inversions are more frequent at night.

However, it is important to note that the results throughout this paper are stable across various ways of constructing the inversion instrument. In Table A.8 in Appendix, we replicate the main result of this paper (Table 3, Column 6) using a range

[3] NUTS3 regions are congruent with administrative boundaries, in particular counties, unitary authorities and districts. Out of the 179 NUTS3 regions in the United Kingdom (January 2018 version), at least one accident is listed for 171 regions.

[4] In a previous working paper version of this paper, we relied on satellite readings from NASA's Atmospheric Infrared Sounder (AIRS), which has a less fine spatial resolution and more frequent missing values ([dataset] AIRS Science Team/Joao Texeira, 2015).

[5] In 2014, around 88% of the over 5 million 6-hourly observations in the MERRA-2 global observing system are measured from space, i.e. using satellites. Other sources include ships, buoys and land surface stations at the surface level; and sondes, weather balloons and ground-based radars, and wind profilers.

[6] Specifically, we use air temperature at different atmospheric pressure levels from the M2T3NVASM file, surface air temperature from the M2I1NXLFO file; bias corrected snowfall from the M2T1NXLFO file; and total cloud area fraction from the M2T1NXRAD file.

of inversion measures. The results are highly similar when using a binary indicator for inversion episodes (as used by Jans et al., 2014), multiple temperature differences between different atmospheric layers (as used by He et al., 2019), and inversion strength at 3pm in the afternoon.

Air pollution data: Air pollution data come from the United Kingdom Automatic Urban and Rural Network (AURN), which includes automatic air quality monitoring stations measuring a variety of air pollutants. The data is provided by the [dataset] Department for Environment, Food and Rural Affairs (2016). The network comprises a total of 198 monitoring sites with data available at different degrees since 22 February 1973. For the 2, 191 days in the period between 2009 and 2014, we obtain daily readings from 161 sites, reporting at varying levels of coverage the concentrations of NO_2, PM_{10}, $PM_{2.5}$, SO_2, and O_3, with the lowest coverage for $PM_{2.5}$ (77 stations, see Fig. 2b). We further calculate the corresponding value of the air quality index (AQI) according to UK guidelines by COMEAP (2011). To assign daily pollution levels to NUTS3 regions, we use the three pollution monitors that are closest to the region centroid but not further than 50 km away and calculate the distance-weighted average pollution level (as proposed by e.g. Currie and Neidell, 2005).[7] Using this approach, we obtain daily $PM_{2.5}$ levels for 153 of the 171 NUTS3 regions. However, the results are robust to more local ways of constructing pollution measures as shown in Table 4.

We use $PM_{2.5}$ as our primary measure of pollution in baseline specifications. $PM_{2.5}$ is known to cause irritation of respiratory organs (throat, nose, lungs) and headaches as well as affect blood pressure (World Health Organization, 2013). In addition, $PM_{2.5}$ was found to affect student test scores (Ebenstein et al., 2016), either through one of these aforementioned channels or as a separate effect on cognitive performance. However, the fact that many pollutants are emitted by the same source, and certain pollutants play a role in the formation of others (e.g. NO_x in the formation of Ozone), complicates attributing observed outcomes to individual pollutants. In Table 7, we replicate our main results using different measures of pollution.

Additional weather data: Finally, we complement atmospheric climate data with ground-level observations on weather conditions from the United Kingdom Met Office Integrated Data Archive System (MIDAS) Land and Marine Surface Stations ([dataset] Met Office, 2012). We use hourly measures of wind speed (in knots), air temperature (in degrees Celsius) and calculated relative humidity. These come from 338 weather monitors and are averaged for each day (00:00–00:00) and NUTS3 region (using only stations within the bounds of each region). We also obtain rainfall over a 24-h period in mm/m^2 (usually 09:00–09:00) from 1, 521 monitors, which are again averaged for each NUTS3 region.

4.2. Descriptive statistics

The final sample used in the analysis consists of 374, 661 observations, each representing one day in one NUTS3 region (2, 191 days, 171 regions). Summary statistics for key variables are presented in Panel A of Table 1. On average the number of accidents per region per day is 2.40, involving 4.39 vehicles. The average $PM_{2.5}$ concentration is 13.32 μg/m^3. The average temperature difference between the lower atmosphere (925 hPa pressure level) and the surface is $-1.81°C$ and inversion episodes occur 16% of the time (i.e. the difference is positive for 16% of observations). Data availability may introduce a sample bias, as less populated and more rural areas more likely suffer from missing values in pollution levels. In our preferred model—which includes $PM_{2.5}$ readings and weather controls—our sample accounts for 765, 714 accidents, i.e. 85% of the total 899, 995 accidents reported between 2009 and 2014. Further accident statistics are provided in Panel B of Table 1.

5. Results

This section presents results of the empirical model detailed in Section 3. The reliability and economic significance of estimates is assessed, and threats to internal validity are discussed. Section 6 provides further robustness tests and discusses limitations.

5.1. Baseline results

This paper aims to estimate the effect of increased concentrations of air pollution on the number of road traffic accidents in the United Kingdom between 2009 and 2014.

First stage estimates: Table 2 presents results from the first stage regression, Eq. (1), assessing the effect of inversion strength on daily $PM_{2.5}$ pollution levels. Column 1 shows that each additional degree of night-time temperature difference between the 925 hPa pressure level and the surface level is associated with a concentration of $PM_{2.5}$ which is 1.830 μg/m^3 higher. This amounts to an increase of 14% relative to the sample average of 13.32. However, one concern for the analysis presented is that inversion episodes may be correlated with other weather conditions that affect pollution and accidents. For example, inversion episodes are more frequent in West London (e.g. 21% of days in Brent and Ealing), which also has higher structural pollution levels and accident numbers.

[7] We construct averages where monitor readings are weighted by the inverse distance from the centroid of a given region. Distances are calculated using the Haversine formula to find the great-circle distance in kilometres between two coordinate-points.

Table 1
Descriptive statistics.

Panel A: Descriptive statistics of main variables					
Variable	N	mean	sd	min	max
Accidents (# accidents)	374,661	2.40	2.21	0	27
Accidents (# vehicles)	374,661	4.39	4.22	0	69
$PM_{2.5}$	317,168	13.32	9.30	0	130
PM_{10}	368,127	19.10	10.62	1	142
NO_2	370,763	29.63	18.43	0	325
SO_2	371,086	3.12	3.27	0	119
O_3	371,104	43.75	18.46	0	127
AQI	374,536	2.50	0.83	1	10
Temperature (^oC) [MIDAS monitor]	367,094	9.97	5.42	−15.02	29.74
Inversion strength (^oC) [MERRA data]	374,654	−1.81	2.11	−8.45	10.96
Humidity	366,830	81.64	9.80	4.31	100
Rainfall	363,443	2.58	5.42	0	586.16
Snowfall	374,661	0.87	6.37	0	261.10
Cloud coverage	369,057	0.57	0.27	0	1
Wind speed	362,290	8.00	4.65	0	71.56
Panel B: Accident statistics					
# vehicles	899,995	1.826	0.71	1	67
# cars	899,995	1.32	0.854	0	48
# bicycles	899,995	0.13	0.342	0	7
# motorcycles	899,995	0.137	0.354	0	15
# casualties	899,995	1.343	0.827	1	93
# female drivers	899,995	0.525	0.658	0	22
# male drivers	899,995	1.193	0.791	0	45

Note: The unit of observation is a NUTS3 region on a given day (Panel A) and individual accidents (Panel B). Data sources are the UK Department for Transport for the number of accidents; UK DEFRA/AURN for NO_2, $PM_{2.5}$, SO_2, Ozone, PM_{10} data ($\mu g/m^3$, distance-weighted average of 3 monitors closest to NUTS3 centroid, but not further than 50 km); *AQI* is calculated according to UK guidelines by COMEAP (2011); NASA MERRA for surface-level and atmospheric temperature (Celsius, 925 hPa pressure layer) and Cloud coverage (fraction); and UK MIDAS for Rainfall (mm, daily total), Wind speed (Knots, daily average of hourly readings), Snowfall (mg) and Humidity (percentage, relative to equilibrium).

Table 2
First stage - effect of inversion on pollution.

	(1) OLS	(2) OLS	(3) OLS
Inversion strength (^oC)	1.830***	1.725***	1.394***
	(0.0967)	(0.0831)	(0.0771)
Observations	265,723	265,723	247,106
Number of Clusters	153/2191	153/2191	153/2161
F test (K–P)	358.5	430.8	327.3
Partial R^2 of instrument	0.17	0.16	0.12
Region-Year FE		YES	YES
Day-of-Week FE		YES	YES
Month FE		YES	YES
Weather Covariates			YES

Note: This table provides estimates of the effect of inversion strength (continuous difference between atmospheric temperature at the 925 hPa pressure level and surface-level temperature as provided in MERRA) on the average daily $PM_{2.5}$ concentration in a NUTS3 region. Weather covariates included are rainfall, rainfall squared, humidity, cloud coverage, wind speed, and dummies for 5 temperature bins (< 0, 0–5, 5–10, 10–15, $> 15°C$). Cluster-robust standard errors are reported in parentheses, allowing for two-way clustering over NUTS3 regions (153 clusters) and days (2161–2191 clusters). $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Column 2 thus reports results for the first stage regression, when introducing region-by-year fixed effects (to account for structural differences over time) and further controlling for month fixed effects (as both inversion frequency and pollution levels vary by season) and day of the week. An additional degree in inversion strength is then estimated to relate to an increase of 1.725 μg/m^3 in daily average $PM_{2.5}$ concentrations (13% relative to the mean). Finally, Column 3 shows that when additionally controlling for weather conditions (ground-level temperature, humidity, cloud coverage, wind speed, and rainfall), the coefficient is 1.394 μg/m^3. The reduction in coefficient when accounting for weather conditions is plausible, as inversion episodes can be associated with anticyclones, which tend to be characterised by fair weather (gentle winds and little rainfall) that often brings with it higher concentrations of air pollutants. In all specifications, coefficients of night-time inversion strength are statistically significant at the 1% level and the smallest value of the Kleibergen-Paap F-tests is 327. While there is an apparent correlation between inversions and other weather conditions, we conclude that the First Stage assumption holds and night-time inversions are a relevant instrument for daily $PM_{2.5}$ concentrations.

Estimates of the effect of pollution on accidents: Table 3 reports the main results of this paper—estimates of the effect of $PM_{2.5}$ pollution on the daily number of vehicles involved in traffic accidents in a region. Columns 1 to 3 display results from an OLS estimation. Column 1 shows the simple regression coefficient, which suggest that each additional 1 μg/m^3 of $PM_{2.5}$ is associated with 0.3% more vehicles involved in accidents in a given region on a given day. Column 2 includes the fixed effects discussed above, and Column 3 further includes weather covariates. All specifications result in a positive coefficient estimate between 0.2and0.3%. However, these OLS estimates may well suffer from a range of biases. For example, an omitted variable bias from traffic volume being positively associated with both pollution and accidents would result in over-estimation. The set of fixed effects included from Column 2 onwards arguably captures a large share of such omitted variable bias by accounting for the structural (region-by-year fixed effects) and seasonal (day-of-week and month fixed effects) association between traffic and pollution. However, a more complex relationship between traffic volume and accidents is also possible, since strong congestion might actually reduce accidents (at least those involving injury). Finally, the different plausible channels of co-determination of accidents and pollution can result in a simultaneity bias in either direction.

Columns 4 to 9 of Table 3 thus report 2SLS estimates using inversion strength as an instrument for the concentration of $PM_{2.5}$. Column 4 reports the 2SLS estimate from an IV specification without covariates. The interpretation of the estimate is as follows: An increase of 1 μg/m^3 in the daily average concentration of $PM_{2.5}$ in a NUTS3 region, is associated with an increase of 0.8% (more precisely $e^{0.008} - 1$) in the number of vehicles involved in road accidents in that region on that day, given that at least one accident occurs (zero counts are excluded in this log-linear specification). The estimate is statistically significant at the 1% level allowing for serial correlation in errors by clustering standard errors in two dimensions at the level of regions and days. Under the assumptions outlined above, the 2SLS estimate without covariates has a direct causal interpretation as the local average treatment effect (LATE). This interpretation rests on the internal validity of the estimates and the corresponding identifying assumptions.

Internal validity: We have already demonstrated, both in theory (Fig. 1) and empirically (Table 2), that the First Stage assumption likely holds and the inversion instrument is relevant in driving $PM_{2.5}$ concentrations. Monotonicity is not a testable assumption. However, we would like to argue that, given the nature of the instrument as a weather phenomenon, it is likely to hold that night-time inversions are associated with higher pollution levels across all regions and there is no region where this relationship is systematically reversed. However, we have argued above that the estimate in Column 4 of Table 3 may plausibly be biased due to confounding from structural differences between regions, seasonal effects, and weather patterns. This would constitute a violation of the independence assumption.

The independence assumption is crucial to the causal interpretation and unbiasedness of the reported estimates. Independence requires that inversions do not affect road safety, except through their effect on pollution levels (exclusion restriction). Specifically, we require that the inversion instrument Z is not correlated with the error term ϵ_{it} in Eq. (2). This might be violated if inversion episodes themselves affect the performance of traffic participants. We are not aware of any evidence showing adverse effects of inversion episodes on well-being or cognitive performance. However, it is possible that inversions are associated with other weather patterns that affect road safety or that inversions are more frequent in regions or at times with a higher number of accidents. While Independence cannot be tested formally, results from additional model specifications strengthen our confidence in the assumption. Below, we report a range of results which are supportive of our claim that we are indeed identifying an effect of pollution on road safety.

5.2. Alternative specifications

Structural differences, seasonality, time trends: Regions systematically differ in terms of weather patterns (including inversions) as well as structural characteristics affecting accident rates (e.g. different road network densities between coastal and mountainous regions). Column 5 of Table 3 presents 2SLS results from a specification with added region and time fixed effects. These are intended to control for unobserved heterogeneity (due to structural traffic/accident patterns) and confounding over time, especially by including month fixed effects to control for seasonality of inversions (inversion frequency ranges from 5% in August to 26% in March) which may correlate with seasonality in pollution and traffic. Further fixed effects control for variation by day of the week and for possible time trends in both accidents and inversions (inversion frequency ranges from 14% in 2014 to 19% in 2011) by allowing for region-by-year fixed effects.[8] The estimated effect of $PM_{2.5}$ is now 0.4%, but remains significantly different from 0. The reduction in coefficient is consistent with a previous upward bias due to structural covariation of accidents and inversions across regions. For example, both accidents and inversions are more frequent in London.

Weather confounding: A further threat to independence might be that inversion episodes are related to other weather phenomena that also affect road safety. For example, inversion episodes can be associated with anticyclones with gentle winds and less rain, which both may be related to less accidents. To control as much as possible for these threats to independence, Column 6 of Table 3 reports results from our preferred specification, which includes the following weather controls: Rainfall, rainfall

[8] In Appendix Table A.9, we report additional results based on alternative strategies to account for seasonality, in particular taking into account the possibility of recurring events such as holidays. The consistency of coefficient estimates using varying techniques to account for potential seasonality suggest that our results are not primarily driven by cyclicality of pollution and accidents.

Table 3
Main results - effect of pollution on accidents.

Regressor	(1) OLS (Log-lin)	(2) OLS (Log-lin)	(3) OLS (Log-lin)	(4) 2SLS (Log-lin)	(5) 2SLS (Log-lin)	(6) 2SLS (Log-lin)	(7) 2SLS (Expontl)	(8) 2SLS (Linear)	(9) 2SLS (Quadratic)
$\boldsymbol{PM_{2.5}}$	**0.003*****	**0.003*****	**0.002**	**0.008*****	**0.004*****	**0.004*****	**0.005*****	**0.024*****	**0.005*****
	(0.0009)	(0.0009)	(0.0011)	(0.0022)	(0.0008)	(0.0010)	(0.0005)	(0.0058)	(0.0016)
[relative effect]								**[0.005]**	
$PM_{2.5}$ (squared)									−0.000
									(0.0000)
Temperature									
(0–5)			0.092***			0.093***	0.119***	0.531***	0.092***
			(0.0212)			(0.0215)	(0.0094)	(0.1232)	(0.0215)
(5–10)			0.138***			0.103***	0.117***	0.536***	0.102***
			(0.0286)			(0.0226)	(0.0100)	(0.1297)	(0.0226)
(10–15)			0.203***			0.117***	0.135***	0.631***	0.116***
			(0.0381)			(0.0232)	(0.0104)	(0.1337)	(0.0232)
(>15)			0.258***			0.126***	0.141***	0.684***	0.125***
			(0.0491)			(0.0238)	(0.0106)	(0.1365)	(0.0241)
Humidity			−0.005***			−0.002***	−0.00263***	−0.013***	−0.003***
			(0.0012)			(0.0003)	(0.0002)	(0.0019)	(0.0003)
Cloud coverage			−0.053***			−0.041***	−0.0499***	−0.267***	−0.041***
			(0.0191)			(0.0099)	(0.0059)	(0.0546)	(0.0088)
Rainfall			4.503***			6.162***	8.014***	37.408***	6.172***
			(1.4147)			(0.6894)	(0.604)	(4.4307)	(0.6408)
Rainfall (squared)			−70.105***			−75.072***	−99.51***	−464.432***	−74.043***
			(20.2184)			(13.2360)	(19.59)	(101.5635)	(11.8342)
Wind speed			−0.009***			−0.001	−0.001	−0.004	−0.001
			(0.0032)			(0.0009)	(0.0006)	(0.0047)	(0.0008)
Observations	265,723	265,723	247,106	265,723	265,723	247,106	293,122	293,122	247,106
Number of Clusters	153/2191	153/2191	153/2161	153/2191	153/2191	153/2161	153/−	153/2161	153/2161
Region-Year FE		YES	YES		YES	YES	YES	YES	YES
Day-of-Week FE		YES	YES		YES	YES	YES	YES	YES
Month FE		YES	YES		YES	YES	YES	YES	YES
Weather Covariates			YES			YES	YES	YES	YES

Note: This table provides estimates of the effect of an increase in $PM_{2.5}$ concentration on the (log) number of vehicles involved in accidents per NUTS3 region per day. Estimates in Columns 1–3 are from OLS estimation. Estimates in Columns 4–9 are from 2SLS estimators using the inversion strength (continuous difference between atmospheric temperature at the 925 hPa pressure level and surface-level temperature as provided in MERRA) on a given day as instrumental variable for pollution. Cluster-robust standard errors are reported in parentheses, allowing for two-way clustering over NUTS3 regions (153 clusters) and days (2161–2191 clusters), except in the conditional exponential mean specification, where clustering is only over regions. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

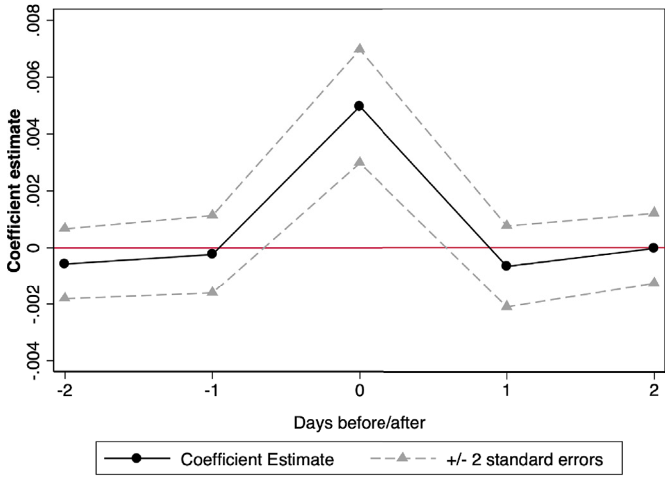


Fig. 3. Lead/lag analysis; coefficient estimates from full specification (equivalent to Table 3, Column 6), including predicted $PM_{2.5}$ on the two previous and two following days (fitted from the first-stage regression in Table 2, Column 3). Confidence intervals based on standard errors that are two-way clustered on both NUTS3 region and date.

squared, relative humidity, cloud coverage, wind speed, and temperature. These are the key weather characteristics that were previously found to be relevant for road safety[9] (Koetse and Rietveld, 2009; Theofilatos and Yannis, 2014). The estimated effect of $PM_{2.5}$ on vehicles in accidents is unchanged at 0.4% and again significantly different from 0. We interpret the stability of the coefficient estimate when including a range of weather covariates as supportive of the exclusion restriction and Independence assumption for the instrument.

Alternative functional forms for the assumed Second Stage relation yield similar results. The estimate from an exponential mean specification with multiplicative error akin to a Poisson model is provided in Column 7. The estimated effect is slightly higher at 0.5%, but remains statistically significant. Notably, the exponential/Poisson specification can make use of observations with 0 accidents reported on a given day, resulting in a slightly larger number of observations[10] (16% of the 293,122 observations are 0s). Estimates for a linear specification, with the number of vehicles in accidents as outcome variable, are provided in Column 8. We do not favour this specification, as we believe that it is unlikely that effects are additive in nature and similar in size between diverse regions such as London or Cornwall. However, the estimated effect remains positive (0.24) and amounts to 0.5% of the sample mean. We note that all specifications yield similar and statistically significant estimates and continue below to make use of the log-linear specification.

Finally, the effect of pollution exposure may well be non-linear and could potentially occur with a delay. We do not find evidence of either. In Column 9 of Table 3, we report estimates when including in the second stage a quadratic term for $PM_{2.5}$ (as fitted from Table 2, Column 3). We do not find evidence of a non-linear effect. In Fig. 3, we show coefficient estimates of the effects of air pollution on a given day as well as the two previous/following days. It appears that only contemporaneous $PM_{2.5}$ is associated with an increase in accidents.

6. Robustness and limitations

We have estimated a positive and significant effect of air pollution (measured by $PM_{2.5}$) on the number of vehicles in traffic accidents in the United Kingdom between 2009 and 2014. Below we present additional results intended to ensure the robustness of the results as well as improve the understanding of the underlying mechanisms responsible for the observed association between air pollution and road traffic accidents.

6.1. Subset analysis: weather conditions - fog, rain and snow

A major concern is that there may be weather patterns which are associated with inversions and also affect road safety. We have attempted above to control for such weather patterns, in particular those that were previously found to be relevant for road safety (temperature, wind speed, rainfall, cloud coverage, and relative surface humidity). Nevertheless, it is possible that the exclusion restriction fails to hold and temperature inversions are associated with accidents through weather patterns that we do not control for. In Table 3, we relied on temperature bins as covariates. However, the relationship between temperature

[9] Edwards (1999) shows that between 1981 and 1994, around 16% accidents in England and Wales occurred during rainy conditions, 4% during high winds, and around 1% each during fog and snow.

[10] In addition, the estimated model allows for overdispersion by not restricting the conditional variance to be equal to the conditional mean. This allows us to avoid a negative binomial model with the accompanying restrictive assumptions.

and accidents may well be complex. To ensure that our results are not due to spurious correlation with temperature, we replicate the main specification (Table 3, Column 6), but this time control for ground-level temperature through a 7-degree polynomial. As can be seen in Column 1 of Table 4, the results are unchanged.

Fog and freezing rain are two further weather phenomena that are known to be associated with inversion episodes and that might affect the number of accidents. Fog occurs when the relative humidity of the air close to the ground approaches 100% (e.g. Gultepe et al., 2007). Accordingly, we report in Column 2 of Table 4 the results for the subset of days on which such weather confounding is unlikely. We only include days on which relative humidity is below 80% and total precipitation is below 0.5 mm/m^2, which means that both fog and freezing rain are much less likely to drive a change in accident numbers. We also exclude days with any snowfall. The estimated coefficient is slightly higher (1.0%), suggesting that, if anything, weather confounding might result in underestimation of the effect of pollution on road safety.

In Column 3 of Table 4, we make use of additional controls for fog. In addition to the other weather covariates, we include controls for the station-level air pressure (hPa) and the ratio of relative humidity to air pressure. This accounts for the possibility that fog may form when high humidity is paired with low pressure. We also include the station-level dewpoint depression (C^o), which describes the difference between the air temperature and the dewpoint temperature. When the dewpoint depression is close to 0, the water vapour pressure approaches saturation—that is when fog (and clouds) is commonly formed. Finally, a major link between fog and road safety may be via impaired visibility. Hence, we control for the daily average station-level visibility (decametres). These covariates are available for a subset of MIDAS stations. Adding these additional fog controls does not significantly alter the results.

Finally, we not only exploit weather conditions as measured by monitors, but also those reported by police officers attending the scene of individual accidents. These reported conditions provide an alternative source for weather and road conditions that is much more localised and specific to each accident, albeit the classification is arguably somewhat subjective. Column 4 reports results when only those vehicles in accidents are counted where a police officer attended the scene and reported good or no unusual conditions.[11] Again, the coefficient estimate is similar (0.7%) and significantly different from 0 at the 1% level. We interpret this as reassuring evidence that previous estimates were not due to correlation of the instrument with unobserved weather patterns in the error term[12] (such as localised and short duration fog or freezing rain).

6.2. Pollution measurement

A recurring problem when estimating adverse effects of air pollution is potential imprecision in attributing pollution levels to regions. In addition, drivers may be moving between regions throughout the day. We believe this is less of a concern in this paper since we focus on large geographic areas and our source of exogenous variation is based on large-scale weather patterns (thermal inversions). While we cannot control for all types of avoidance behaviour (such as rolling up car windows), we believe that it is reasonable to assume that there is no systematic shift of population or traffic between regions in response to weather fluctuations. However, since pollution is a highly localised phenomenon, the method of assigning pollution levels to NUTS3 regions may influence the results. We thus report results based on alternative methods for assigning pollution levels to observations. In our main specification (Table 3), we use the distance-weighted average pollution of the 3 monitors that are closest, but not further than 50 km from the region centroid. Here, we limit ourselves to monitors not further than 10 km from the centroid (Table 4, Column 5) or monitors that are strictly within a NUTS3 region (Column 6). This exercise has the additional advantage that we are re-estimating the model on two different subsets of regions that are more likely to be densely populated and urban (see Fig. A.4 in Appendix). For both subsets, the estimated coefficient for $PM_{2.5}$ is unchanged at 0.4%.

6.3. Traffic volume

Our findings suggest that higher levels of air pollution result in more traffic accidents. However, the number of accidents can be thought of as a function of both the traffic volume and the accident rate (see Appendix A.1). The motivating hypothesis of this paper—that air pollution impedes road safety via safe driving performance—would suggest an effect on the accident rate, but not on the volume of traffic. We obtain traffic count data for a subset of our sample from the UK Department for Transport, which we use to calculate the daily mean traffic volume in each region.[13] We then re-estimate our main specification on the subset of region-days for which at least one traffic count is available, once using traffic volume as outcome variable, once using accident counts as outcome. We find no effect of $PM_{2.5}$ on traffic volume (Table 4, Column 7), but again estimate a positive effect (0.7%) on traffic accidents (Column 8). This analysis suggests that we are observing an effect on the likelihood of being involved

[11] This refers to a subset of accidents where a police officer attended the scene and reported weather conditions as “Fine no high winds”, road surface conditions as “Dry”, “No” special conditions at site, and “No” carriageway hazards. This excludes accidents where police officers characterised weather conditions as “Rain”, “Snow”, “Fog or mist”, “Other”, and “Unknown”.

[12] We note that there may also be a danger of multicollinearity if inversions were equivalent to a linear combination of the weather covariates. However, the large F-statistic in the first stage regressions strongly suggests that this is not the case.

[13] We obtain raw manual traffic counts by trained enumerators for a number of “count points” on both major and minor roads. The data includes repeated counts for each “count point” over multiple years. We de-mean traffic counts for each “count point” and then calculate the daily mean for each NUTS3 region. The data is available at https://www.dft.gov.uk/traffic-counts/.

Table 4
Robustness - weather conditions, pollution measurement, and traffic volume.

	Weather Conditions				PM2.5 Measurement		Traffic Volume	
	(1) Flexible temperature (polynomial)	(2) Low humidity, rain, snow (subset)	(3) Fog indicators (controls)	(4) Police: "Good conditions" (subset)	(5) Max. 10 km (subset)	(6) Inside NUTS3 (subset)	(7) Traffic volume (outcome)	(8) Traffic accidents (outcome)
$PM_{2.5}$	0.004***	0.010***	0.006***	0.007***	0.004***	0.004***	−0.000	0.007***
	(0.0010)	(0.0017)	(0.0014)	(0.0010)	(0.0013)	(0.0013)	(0.0004)	(0.0017)
Observations	247,106	65,346	151,717	182,231	95,918	85,332	25,071	25,071
Number of Clusters	153/2161	151/1607	98/2161	152/2160	62/2161	56/2161	150/—	150/—
Region-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Weather Covariates	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table provides estimates of the effect of an increase in $PM_{2.5}$ concentration on the (log) number of vehicles involved in accidents per NUTS3 region per day using different model specifications and sub-samples. Column 1 shows results equivalent to Table 3, Column 6, but with a 7-degree polynomial control for temperature; Column 2 shows results for a sub-sample of days with rainfall below 0.5 mm, relative humidity below 80% and no snowfall; Column 3 shows results equivalent to Table 3, Column 6, but with additional covariates intended to control for fog formation (air pressure, the ratio of relative humidity to air pressure, the dewpoint depression, and average station-level visibility); Column 4 shows results for a sub-sample of accidents based on police-reported "good conditions", which refers to accidents where a police officer attended the scene and reported weather conditions as "Fine no high winds", road surface conditions as "Dry", "No" special conditions at site, and "No" carriageway hazards; Column 5 uses the inverse-distance weighted average of $PM_{2.5}$ only from monitors max. 10 km away; Column 6 uses the simple average of $PM_{2.5}$ only from monitors within the boundaries of a NUTS3 region; Column 7 is equivalent to the specification in Table 3, Column 6, but using traffic volume (daily average of normalised traffic counts) as outcome variable; Column 8 is equivalent to Table 3, Column 6, but using only the subset from Column 7. Weather covariates included are rainfall, rainfall squared, humidity, cloud coverage, wind speed, and dummies for 5 temperature bins (<0, 0–5, 5–10, 10–15, $>15°C$). Cluster-robust standard errors are reported in parentheses, allowing for two-way clustering over NUTS3 regions and days. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5
Heterogeneous treatment - vehicle types and driver characteristics.

	Panel A: Vehicles						Panel B: Regions	
	(1) Two-wheel	(2) Other	(3) Two-wheel (cold)	(4) Two-wheel (warm)	(5) Other (cold)	(6) Other (warm)	(7) Urban	(8) Other
$PM_{2.5}$	0.002***	0.004***	0.002***	0.003*	0.002**	0.011***	0.004***	0.005***
	(0.0006)	(0.0006)	(0.0009)	(0.0014)	(0.0010)	(0.0022)	(0.0012)	(0.0010)
Observations	126,051	244,457	77,181	48,864	160,028	84,418	93,120	153,986
Number of Clusters	152/2161	153/2161	151/1429	150/732	152/1429	152/732	52/2159	101/2161
Region-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Weather Covariates	YES	YES	YES	YES	YES	YES	YES	YES

	Panel C: Drivers					Panel D: Accidents	
	(9) Male	(10) Female	(11) Age (<=25)	(12) Age (26–45)	(13) Age (>=46)	(14) Hit-and-Run (Share)	(15) Fatal/severe (Share)
$PM_{2.5}$	0.004***	0.003***	0.001*	0.003***	0.003***	0.000	0.047**
	(0.0009)	(0.0007)	(0.0006)	(0.0008)	(0.0007)	(0.0001)	(0.0218)
Observations	233,485	181,409	159,152	200,770	184,222	247,106	247,106
Number of Clusters	152/2161	152/2161	152/2161	152/2161	153/2161	153/2161	153/2161
Region-Year FE	YES	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES
Weather Covariates	YES	YES	YES	YES	YES	YES	YES

Note: This table provides estimates of the effect of an increase in $PM_{2.5}$ concentration on the (log) number of vehicles involved in accidents per region per day using different sub-samples and counts of different vehicle types (Panel A), subsets of NUTS3 regions (Panel B); subsets of drivers involved in accidents by driver gender and age (Panel C); and shares of accident characteristics (Panel D). The "warm" sub-sample covers the four months from June through September, and the "cold" sub-sample the other eight months. "Urban" areas are NUTS3 regions with codes "UKI" (London), "UKD" (North West England, including Manchester and Liverpool), and "UKD" (Yorkshire and the Humber, including York and Leeds). Estimates are from 2SLS estimators using the inversion strength (continuous difference between atmospheric temperature at the 925 hPa pressure level and surface-level temperature as provided in MERRA) on a given day as instrumental variable for pollution. Weather covariates include rainfall, rainfall squared, humidity, cloud coverage, wind speed, and dummies for 5 temperature bins (< 0, 0–5, 5–10, 10–15, > 15°C). Cluster-robust standard errors are reported in parentheses, allowing for two-way clustering over NUTS3 regions and days. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

in an accident rather than a change in the volume of traffic.[14]

6.4. Heterogenous treatment effect

The accident data provided by the UK Department for Transport include information about the vehicles and drivers involved in each accident. This makes it possible to split the number of total vehicles involved in accidents by vehicle types. In the context of air pollution, it is particularly interesting to differentiate between vehicles with two wheels and other types of vehicles. We report separately in Table 5 (Panel A) estimates for the number of two-wheel vehicles (bicycles, scooters, and motorcycles) involved in accidents, as well as the number of other vehicles. The motivation for this distinction is the idea that drivers of two-wheel vehicles are arguably exposed to air pollution in a different manner than drivers of other vehicles (cars, vans, trucks, etc.). Interestingly, the estimates in Columns 1 and 2 of Table 5 suggest that the estimated effects for these two categories are similar, with the effect on two-wheel vehicles (0.2%) somewhat smaller than that on closed vehicles (0.4%).[15] The difference is statistically significant at the 1% level.

We further split the sample between what we call "warm months" (June through September) and other months. Interestingly, there is no difference between these periods in the estimated effect of $PM_{2.5}$ on the number of two-wheel vehicles involved in accidents (0.3% and 0.2% respectively, not statistically different).[16] The estimated effect of pollution on other vehicles involved in accidents is much higher in the warm period than in the colder period (1.1% and 0.2%, difference statistically significant at the 1% level). One interpretation may be that drivers of other vehicles may be exposed to higher levels of pollution in warm months when they are more likely to drive with open windows while drivers of two-wheel vehicles face a more constant exposure. While this interpretation is speculative, and there may be other plausible reasons for these estimates, including

[14] It also shows that independence of the inversion instrument is not threatened by any omitted factor that may be related to traffic volume.

[15] It should be noted that vehicles of one type can be involved in accidents with vehicles of another type. There may be some spillovers when, for example, cars are involved in more accidents, some of which with motorcycles.

[16] Estimates in Table 5 are from log-linear specifications and represent proportionate changes independent of volume. For example, there are on average over 30% more two-wheel vehicles involved in accidents during warmer months (0.76 per region per day) than during colder months (0.58). The relative effects of 0.3% and 0.2% apply to these different bases respectively. The difference in estimates is more pronounced when interpreted in levels.

Table 6
Pollutants - pairwise correlation.

	$PM_{2.5}$	PM_{10}	AQI	NO_2	SO_2	O_3
$PM_{2.5}$	1					
PM_{10}	0.91	1				
AQI	0.63	0.62	1			
NO_2	0.50	0.50	0.11	1		
SO_2	0.22	0.24	0.13	0.26	1	
O_3	−0.41	−0.35	0.14	−0.55	−0.12	1

Note: This table provides pairwise correlation coefficient between the of $PM_{2.5}$, PM_{10}, the AQI, NO_2, SO_2, and Ozone per region per day (residuals relative to region-month means).

coincidence, it is certainly not inconsistent with a pollution induced increase in accident rates.

In Panel B of Table 5, we further estimate the model separately for highly urbanised areas[17] (Column 7) and other areas (Column 8). The results are very similar (0.4% and 0.5%, not statistically different), suggesting that we are not solely capturing an effect in urban areas.[18]

As we have noted above, adverse health effects of air pollution are often found to disproportionally affect more vulnerable groups in the population, such as those with previous health problems (e.g. asthma), infants, or the elderly. In Panel C of Table 5, we report results of our preferred specification applied to alternative outcome variables, which are counts of drivers from different groups that are involved in accidents on a given day. While estimated effects are larger for men and older drivers, we do not interpret these as strong evidence in favour of differential treatment effects between genders or age groups. We note, however, that a lower effect on two-wheel vehicles is also consistent with a lower effect on younger drivers, who may be more likely to use those.

Finally, we exploit information from police reports on accident characteristics. One of the potential pathways through which pollution may affect road safety is via increased aggressive driving in line with the evidence on violent crime and unethical behaviour (Herrnstadt et al., 2016; Lu et al., 2018). In Panel D of Table 5, we report coefficient estimates of the preferred specification where the outcome variable is replaced with the share of "hit and run" vehicles among all vehicles involved in accidents (Column 14). We do not find evidence of an effect on the share of "hit and run" activity within accidents. We also test for an effect on the share of accidents involving a "fatality" or "serious" injury (Column 15) on a given day. Possibly, these more severe accidents may become more likely with a heightened degree of impatience and risk appetites of drivers. The results suggest an increase in the share of severe accidents (in addition to the overall increase in accidents) on polluted days. This effect is statistically significant at the 5% level, but its magnitude appears rather small (an increase in 0.05 percentage points in the share of such accidents, which on average occur 16% of times).

6.5. Pollutant co-emission

A further challenge for the estimation of adverse effects from air pollution comes from the fact that multiple air pollutants, such as NO_2, SO_2, or $PM_{2.5}$, are often emitted from the same source and are highly correlated. Observed adverse effects from pollution may then be due to any one or several of these pollutants.

Table 6 shows correlation coefficients between pairs of air pollutants (residuals relative to region-month means). It makes clear that there is a relatively strong correlation between certain sets of pollutants. Fine particle concentrations ($PM_{2.5}$) are highly correlated with small particles (PM_{10}), the AQI index, and NO_2 concentrations. As a matter of fact, higher values of the AQI index are largely driven by the concentration of $PM_{2.5}$. Both NO_2 and SO_2 are precursors to $PM_{2.5}$ and as such show a positive correlation with it. The correlation is particularly strong for NO_2, a main source of which is fuel combustion by road vehicles, especially those reliant on Diesel. Ozone is negatively correlated with the other pollutants, in particular with NO_2, which is one of its precursors. It shall be noted that the sources for $PM_{2.5}$ are more diverse than those for the other (gaseous) pollutants. They include not only the combustion of fossil fuels from industry and road vehicles, but also non-exhaust related sources such as tyre, break, and road wear.

Such pollutant correlation poses a challenge to the causal interpretation of our results, because it seems likely that inversion episodes also affect concentrations of pollutants other than $PM_{2.5}$. Table 7 reports estimates from our preferred specification measuring air pollution as the concentration of NO_2, SO_2, O_3, and AQI. The estimated effect on the number of vehicles in accidents is again positive, except for ozone, and significantly different from 0 at the 1% level. However, $PM_{2.5}$ estimates result in the highest first stage F-test and the lowest elasticity estimate (0.06).

We believe that the use of $PM_{2.5}$ as default measure for air pollution is justified as a conservative approach.[19] $PM_{2.5}$ describes a mixture of particles, which can include secondary particles derived from other pollutants such as SO_2 and NO_x. Further argu-

[17] Here, the sample is restricted to the NUTS3 regions with codes "UKI" (London), "UKD" (North West England, including Manchester and Liverpool), and "UKD" (Yorkshire and the Humber, including York and Leeds).

[18] It should be noted that the whole of Great Britain is relatively densely populated. Eurostat categorises 70% of the 153 NUTS3 regions in our sample as "predominantly urban". The results in Table 5, Columns 7 and 8 are very similar when splitting the sample along this more generous definition of urban areas.

[19] In a previous working paper version of this article, we relied on NO_2 as the primary measure of air pollution due to better data availability.

Table 7
Pollutants - comparison of estimates.

	(1) $PM_{2.5}$ 2SLS (LL)	(2) NO_2 2SLS (LL)	(3) SO_2 2SLS (LL)	(4) O_3 2SLS (LL)	(5) AQI 2SLS (LL)	(6) $PM_{2.5}$ 2SLS (LL)
$PM_{2.5}$	0.004***					0.004***
	(0.0010)					(0.0012)
NO_2		0.006***				0.001***
		(0.0012)				(0.0004)
SO_2			0.051***			−0.001
			(0.0114)			(0.0008)
O_3				−0.011***		0.000
				(0.0030)		(0.0002)
AQI					0.070***	
					(0.0169)	
Avg. concentration	13.38	30.49	3.048	42.70	2.474	13.37
[Implied elasticity]	**[0.06]**	**[0.17]**	**[0.15]**	**[-0.46]**	**[0.17]**	**[0.05]**
FIRST STAGE						
	$PM_{2.5}$	NO_2	SO_2	O_3	AQI	$PM_{2.5}$
Inversion strength (^oC)	1.394***	1.025***	0.117***	−0.552***	0.085***	1.109***
	(0.0771)	(0.0617)	(0.0114)	(0.1010)	(0.0083)	(0.0700)
First stage F test (K–P)	327.3	276.3	105.5	29.87	104.6	250.9
Observations	247,106	275,013	275,214	275,239	277,707	244,425
Number of Clusters	153/2161	171/2161	171/2161	171/2161	171/2161	153/2161
Region-Year FE	YES	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Weather Covariates	YES	YES	YES	YES	YES	YES

Note: This table provides estimates of the effect of an increase in $PM_{2.5}$ (Column 1), AQI (Column 2), NO_2 (Column 3), SO_2 (Column 4), and Ozone (Column 5) concentration on the (log) number of vehicles involved in accidents per region per day. Estimates are from 2SLS estimators using the inversion strength (continuous difference between atmospheric temperature at the 925 hPa pressure level and surface-level temperature as provided in MERRA) on a given day as instrumental variable for pollution. Weather covariates included are rainfall, rainfall squared, humidity, cloud coverage, wind speed, and dummies for 5 temperature bins (< 0, 0–5, 5–10, 10–15, > 15°C). Cluster-robust standard errors are reported in parentheses, allowing for two-way clustering over NUTS3 regions and days. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

ments in favour of using $PM_{2.5}$ as pollution measure come from the consensus in the medical literature in combination with the spatial and temporal dimension of this analysis. This paper analyses the effects of short-term variation (24-h) in pollution concentrations. There is a consensus on the short-term adverse health-effects of $PM_{2.5}$ and Ozone (on both respiratory and cardiovascular health). The evidence is less clear on short-term effects of NO_2, and more so for respiratory consequences than cardiovascular ones (World Health Organization, 2013). Finally, units of observation are fairly large geographic regions, while pollutant concentrations vary greatly over much smaller distances. Still, particulate matter (including $PM_{2.5}$) appears to have a lower distance-decay gradient and be more uniformly distributed over space (Karner et al., 2010; World Health Organization, 2013). In sum, $PM_{2.5}$ is plausibly related to the relevant physiological pathways driving accidents as discussed in Section 2 and may generally provide an adequate measure of daily fluctuations in background pollution concentrations.

As an additional exercise, Column 6 of Table 7 reports coefficient estimates of the effect of $PM_{2.5}$ (instrumented by inversion strength) when NO_2, SO_2 and O_3 are included as covariates in the 2SLS estimation procedure. The coefficient estimate of the effect of $PM_{2.5}$ on (the logarithm of) accident vehicles remains at 0.4% and statistically significant at the 1% level. Nevertheless, we cannot conclusively disprove the possibility that a pollutant other than those included in $PM_{2.5}$ is driving the observed effect. Following Schlenker and Walker (2015) and Knittel et al. (2016), we have attempted to use multiple instruments to disentangle effects of pollutants with different physical properties (e.g. lags of inversions, interactions with weather patterns, and structural differences between regions). These attempts have not yielded credible and statistically trustworthy results. We thus interpret our results as strong evidence for an effect of air pollution on road safety, but refrain from separately identifying which pollutant is responsible for what portion of the effect. This is an important topic to pursue in future research.

6.6. Discussion

Internal validity: As discussed above, our estimates of the effect of pollution on road safety rely in the independence of the inversion instrument. In particular, we may obtain biased estimates if the inversion instrument is correlated with the error term in Eq. (2). The question is then if there may be an unobserved factor that is correlated both with traffic accidents and with inversion strength (in its various forms in Appendix Table A.8). As with any instrumental variable approach, there is no conclusive test for the absence of such a factor. However, the results presented throughout this section significantly reduce the possible set of such factors. We have shown that such an unobserved factor cannot be systematically related to the observed weather covariates, which constitute the known determinants of traffic accidents (same coefficient estimate in Columns 5 and 6 of Table 3). We have also shown that fog, snow and freezing rain—key weather phenomena that may covary with inversions—are unlikely this factor (Table 4, Columns 2 through 4). Finally, we have shown that such an unobserved factor would have to drive the accident rate, but not traffic volume (Table 4, Column 7). We are not aware of any such factor.

External validity: While we believe that our results show strong evidence for an effect of air pollution (measured as $PM_{2.5}$) on road safety, external validity is limited in some ways. Firstly, our period of observation is limited to 2009–2014 and any extrapolation to other time periods needs to take into account likely time trends in air quality, automotive technology, road networks and traffic policies. Data availability has likely introduced a certain sampling bias away from regions with missing data on air quality and weather conditions. The observed causal effect is thus likely more representative of more densely populated areas. Nevertheless, our sample accounts for 85% of reported accidents between 2009 and 2014 in much of the United Kingdom.

Extrapolation to other countries is subject to further limitations. We believe that the biological effects of air pollution on humans, including their ability to drive a car, are likely similar across the world. We estimate a similar effect for highly urbanised and other regions of the United Kingdom (Table 5, Panel B). However, differences in road networks, traffic policies, automotive technologies, and weather conditions may result in different effects in other countries. Furthermore, different levels of air quality, in particular in emerging economies, might result in different magnitudes if one suspects a non-linear dose-response function (for which we do not find evidence in Table 3, Column 9). Finally, our units of observation are administrative NUTS3 regions. Extrapolation to other units, such as specific road segments or individual traffic participants, is likely to be erroneous, as both air pollution and road safety vary significantly within regions. For example, we would expect very different effects when comparing a major intersection and a recreational park without accessible roads. Still, we believe that the robust finding of an average effect for larger geographic areas is highly relevant, as such areas can be subject to policies affecting both air quality and road safety.

In our analysis, we focus on daily variation in pollution levels and thus estimate relatively short-term effects. We can neither draw conclusions about long-term exposure effects from living permanently in a polluted area, nor can we infer whether or not the observed effects occur immediately or are of a cumulative nature, resulting from continued exposure to pollution over the span of multiple hours. We do not find evidence of lags over multiple days (Fig. 3).

7. Conclusion

This paper assesses the link between air pollution and road safety using data from multiple sources, including atmospheric climate data from NASA. The initiating hypothesis was that acute air pollution exposure may reduce safe driving performance, resulting in an increase in the number of accidents at any given traffic volume. In order to credibly identify the effect of pollution on accident frequency, we have adopted an instrumental variable approach, which relies on plausibly exogenous variation in pollution levels arising from atmospheric temperature inversions. Our findings indicate a positive and likely causal effect of air pollution on the number of road traffic accidents. Given the identifying assumptions, a 1 $\mu g/m^3$ increase in the average daily concentration of $PM_{2.5}$ is estimated to be associated with an increase of 0.3–0.6% in the number of vehicles involved in traffic accidents in the average NUTS3 region. This corresponds to elasticity estimates of 0.04–0.08, similar in magnitude to elasticity estimates for effects on the productivity of call-centre workers (Chang et al., 2016a) and pear packers (Chang et al., 2016b). These estimates are robust to different model specifications and subset analyses.

To illustrate the magnitude of this effect, we consider the example of the region with the most accidents, containing a large portion of Greater London (the 21 NUTS3 regions with codes beginning "UKI"). London registered on average 151 vehicles involved in 84 accidents per day in 2014, and had a mean level of $PM_{2.5}$ of 15.0 with a standard deviation of 9.5. Our estimates suggest that a one standard deviation reduction in $PM_{2.5}$ for one day (from 25 to 15 $\mu g/m^3$) may prevent about 6 vehicles from being involved in accidents in that area alone. Multiplied by the average accident cost involving at least one casualty estimated at GBP 78 k (Department for Transport, 2016), this translates into an approximate cost saving of GBP 500 k. Using a similar extrapolation, we estimate the yearly benefit (due to foregone accidents) of a permanent 1 $\mu g/m^3$ reduction in $PM_{2.5}$ in that same area as approximately GBP 10 m (or about 125 avoided accidents involving injury).

The relationship between air pollution and road safety has been surprisingly overlooked in the literature. We believe that our analysis identifies a causal effect of pollution on road safety, but can only speculate about the mechanisms involved. We provide additional analysis using traffic count data which suggests that this effect is not due to changes in traffic volume, but instead linked to a higher accident rate on polluted days. This is compatible with our initial hypothesis that pollution may reduce safe driving performance either by impairing the cognitive performance of drivers or by rendering them more aggressive or impatient. However, we cannot exclude other possible explanations, such as pollution causing physical distractions (e.g. from inflammation of airways).

Further research will be necessary to corroborate (or refute) the relationship found to hold in our sample. Exploiting alternative empirical strategies might increase confidence in the causal interpretation of the results based here on an instrumental variable approach. Other areas for further research are the transmission channel through which pollution affects road safety, as well as the role played by individual pollutants. Whichever the exact mechanism involved, the finding of a significant effect of air quality on road safety points to another benefit of reducing air pollution levels in addition to those identified by previous research.

Declaration of interest

None.

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Appendix A.1. Motivating model of accident counts

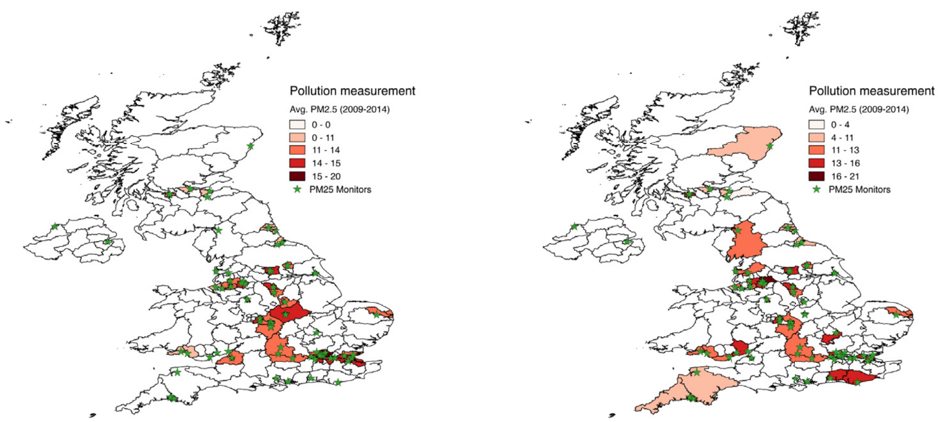
We are interested in the effect of the level of air pollution (as measured by $PM_{2.5}$) on road traffic accidents. We hypothesise that the total number of vehicles involved in accidents in region *i* on day *t* is the result of a stochastic process, in the sense that:

$$E[Vehicles_{it}] = P(Accident)_{it} \cdot TrafficVolume_{it}$$

Here, $TrafficVolume_{it}$ might for example refer to the number of vehicle miles driven in region *i* on day *t*. $P(Accident)_{it}$ will accordingly be interpreted as the probability of being involved in an accident per average mile driven. This measure is closely aligned with the *accident rate* used by Green et al. (2016) in their analysis of the impact of the London congestion charge on traffic accidents. We hypothesise that air pollution exposure may raise the accident probability. By using the total number of vehicles involved rather than the number of accidents, we leave room for the possibility that multiple drivers involved in a particular accident may be at fault. For our empirical specification, we assume a log-linear relationship between the number of vehicles involved in traffic accidents and the relevant explanatory variables including the level of air pollution D_{it}:

$$\begin{aligned} ln[Vehicles_{it}] &= ln[P(Accident)_{it}] + ln[TrafficVolume_{it}] \\ &= ln[\exp(\mu^P + \alpha^P D_{it} + \beta^P X_{it} + \epsilon^P_{it}] + ln[\Gamma_i \cdot \Psi_{it}] \\ &= \mu^P + \alpha^P + \beta^P X_{it} + \epsilon^P_{it} + log[\Gamma_i] + ln[\exp(\mu^V + \alpha^V D_{it} + \beta^V X_{it} + \epsilon^V_{it})] \\ &= (\mu^P + \mu^V) + (\alpha^P + \alpha^V) D_{it} + (\beta^P + \beta^V) X_{it} + ln[\Gamma_i] + (\epsilon^P_{it} + \epsilon^V_{it}) \end{aligned}$$

The interpretation of the determinants of $TrafficVolume_{it}$ is as follows: Γ_i stands for potential volume in a given region, while Ψ_{it} refers to the realised utilisation of that potential in region *i* on day *t*. To estimate the effect of pollution on $P(Accident)_{it}$, we then rely on the additional assumption that pollution does not drive traffic volume via Ψ_{it} ($\alpha^V = 0$). The results in Table 4, Columns 7 and 8 support this assumption.



(a) Pollution $PM_{2.5}$ monitors and NUTS3 regions (colouring according to mean $PM_{2.5}$ concentration, inverse distance-weighted at max. 10km from region centroid)

(b) Pollution $PM_{2.5}$ monitors and NUTS3 regions (colouring according to mean $PM_{2.5}$ concentration, only monitors within region)

Fig. A.4 Geographic coverage with alternative pollution measurement.

Table A.8
Alternative inversion instruments.

	(1) 2SLS (Surface diff.)	(2) 2SLS (Surface bin.)	(3) 2SLS (Monitor diff.)	(4) 2SLS (4 Layers)	(5) 2SLS (Afternoon)
$PM_{2.5}$	0.004***	0.004***	0.005***	0.005***	0.006***
	(0.0010)	(0.0009)	(0.0010)	(0.0014)	(0.0011)
Observations	247,106	247,106	247,106	116,792	246,990
Number of Clusters	153/2161	153/2161	153/2070	153/2070	153/2070
First stage F test (K–P)	327.3	324.9	296.6	52.59	265.7
First stage partial R^2	0.12	0.10	0.09	0.11	0.13
Region-Year FE	YES	YES	YES	YES	YES
Day-of-Week FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
Weather Covariates	YES	YES	YES	YES	YES

Note: This table provides estimates of the effect of an increase in $PM_{2.5}$ concentration on the number of vehicles involved in accidents per region per day. Estimates are from 2SLS estimators using different measures of temperature inversions on a given day as instrumental variable for pollution. Column 1 uses the continuous difference between the atmospheric temperature at 925 hPa and the surface-level air temperature (both provided by MERRA and measured at 3am). It is identical to the main results in Table 3, Column 6. Column 2 uses as instrument a binary indicator when this difference is positive. Column 3 uses the temperature difference between 925 hPa (MERRA) and ground-level temperature as measured by weather stations. Column 4 uses as instrument the combination of 4 temperature differences (between 1000 and 925 hPa; 925-850 hPa; 850-700 hPa; 700-500 hPa), all from MERRA. Lower sample size due to missing values at 1000 hPa (missing when surface pressure is below 1000 hPa). Column 5 uses the instrument identical to the main instrument in the paper (Column 1), but measured instead at 3pm in the afternoon. Weather covariates included are rainfall, rainfall squared, humidity, cloud coverage, wind speed, and dummies for 5 temperature bins (< 0, 0–5, 5–10, 10–15, $> 15°C$). Cluster-robust standard errors are reported in parentheses, allowing for two-way clustering over regions and days. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.9
Alternative controls for seasonality.

	(1) 2SLS (Log-lin)	(2) 2SLS (Log-lin)	(3) 2SLS (Log-lin)	(4) 2SLS (Log-lin)
$PM_{2.5}$	0.004***	0.004***	0.004***	0.006***
	(0.0010)	(0.0010)	(0.0009)	(0.0009)
Observations	247,106	246,925	237,823	238,179
Number of Clusters	153/2161	152/2161	150/2070	153/2070
Region-Year FE	YES	NO	YES	YES
Day-of-Week FE	YES	YES	NO	NO
Month FE	YES	NO	NO	NO
Region-Year-Month FE	NO	YES	NO	NO
Day FE	NO	NO	YES	NO
Daily region avg.	NO	NO	NO	YES
Weather Covariates	YES	YES	YES	YES

Note: This table provides estimates of the effect of an increase in $PM_{2.5}$ concentration on the number of vehicles involved in accidents per region per day. Estimates are from 2SLS estimators using the inversion strength (continuous difference between atmospheric temperature at the 925 hPa pressure level and surface-level temperature as provided in MERRA) on a given day as instrumental variable for pollution. Column 1 replicates the results from Table 3, Column 6. Column 2 allows for region-year-month fixed effects. Column 3 then reports results from a specification including fixed effects for 350 artificial year-days, starting on the first Monday of January and ending the last Sunday before Christmas (e.g. Monday, 6 January 2014 through Sunday, 21 December 2014). This approach also excludes the days around the Christmas holidays and New Year's celebrations. Column 4 include as control variable the regional averages in accident vehicle totals for each of the 350 year-days, each time excluding the current year. Weather covariates included are rainfall, rainfall squared, humidity, cloud coverage, wind speed, and dummies for 5 temperature bins (< 0, 0–5, 5–10, 10–15, $> 15°C$). Cluster-robust standard errors are reported in parentheses, allowing for two-way clustering over NUTS3 regions and days. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2019.102250.

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