



# London congestion charge: the impact on air pollution and school attendance by socioeconomic status

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## Abstract

Air pollution negatively affects individuals' health and human capital accumulation. For example, students' school performance is hampered by air pollution as it decreases cognitive abilities and increases absences. Moreover, low-income students are the most exposed and vulnerable to the negative effects of air pollution as they lack protective resources and suffer from pre-existing health conditions. Here, we inquire how more stringent traffic regulations implemented in Central London from late 2015 affected pollution levels and school absences. First, we observe a substantive decrease in pollution in the area affected by the regulations from 2016 onwards. Secondly, we use a difference in differences approach to estimate the causal effect of the policy on school absences. For all schools combined, findings do not show any substantive improvement in attendance. However, when looking at the heterogeneous effects of the policy, we observe a significant decrease in absences for schools with a high share of students with low socioeconomic status (SES). Consequently, the findings highlight the efficacy of environmental policy in diminishing pollution levels and to benefit the poor.

**Keywords** Air pollution · Children · Socioeconomic inequalities · Environmental policy

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## Introduction

Exposure to air pollution has been linked to negative health and behavioural outcomes (Alexander & Schwandt, 2022; Currie, 2013; Jans et al., 2018; Khreis et al., 2017; Kravitz-Wirtz et al., 2018; Loftus et al., 2020; Thygesen et al., 2020) but also to educational performance of children (Amanzadeh et al., 2020; Buka et al., 2006; Heissel et al., 2020; Persico, 2020). Recent research shows, for instance, that early-life exposure to industrial emissions can cause long-lasting educational disadvantages (Colmer & Voorheis, 2020). One pathway of the negative effect of air pollution on educational performance is an increase in school absences. Exposure to air pollution has been shown to increase absences due to poor health, or protective behaviours skipping classes during polluted days (Currie et al., 2009). This pathway of educational consequences might also reinforce more general inequalities in society, as some individuals are more exposed and more vulnerable to air pollution and its negative effect on human capital accumulation and later life outcomes (Manduca & Sampson, 2019, 2021).

Socioeconomic status is a main characteristic affecting disparities in exposure and vulnerability to air pollution. Inequalities in exposure are well known in the literature and show that air pollution is more concentrated in areas inhabited by minorities and low-income individuals (Colmer et al., 2020; Grineski & Collins, 2018; Rüttenauer, 2018). Moreover, Kravitz-Wirtz et al. (2018) have documented disparities in vulnerability to air pollution, showing that mainly inhabitants of poor neighbourhoods experience detrimental health effects when exposed to nitrogen dioxides and particulate matter. Similarly, exposure to PM10 has been linked with excess mortality particularly for low-SES individuals in Latium, Italy (Forastiere et al., 2007) and to more severe health effects in low-SES children in Sweden (Jans et al., 2018). It is thus important to assess the efficacy of policies aiming at reducing exposure to pollution, and to investigate their implications for inequalities in educational outcomes.

In this study, we use the case of Greater London to investigate three main research questions. First, we explore the effect of environmental policies targeting urban traffic on air quality. Secondly, we inquire about the health benefits of decreased air pollution, focusing on children's school absences. Finally, we ask if school SES stratifies decrease in air pollution and the effect on school absences inspired by previous work showing disparities in exposure and vulnerabilities.

London's poor air quality is a risk to citizen's health and wellbeing.<sup>1</sup> Most notably, several schools are still exposed to pollution levels well above the World Health Organization (WHO) guidelines<sup>2</sup> and children continue to suffer from negative

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<sup>1</sup> Extensive evidence on exposure to air pollution has been collected by a report promoted by the Mayor of London and can be found at <https://www.london.gov.uk/press-releases/mayoral/hundreds-of-schools-exceed-air-quality-limits>.

<sup>2</sup> However, current WHO guidelines are particularly stringent and 99% of the world population lives in areas that exceed the limit of PM2.5 set at 5 µg/m<sup>3</sup> (Carvalho, 2021). Nevertheless, schools in London exceed also the previous less stringent guidelines set at 10 µg/m<sup>3</sup> (Krzyzanowski & Cohen, 2008).

health effects, despite the introduction of traffic regulations in 2003 (Green et al., 2020; Mudway et al., 2019; Wood et al., 2015). However, starting in September 2015, tighter rules have been implemented in the London Congestion Charge Zone (CCZ), ultimately leading to the implementation of an Ultra-Low Emission Zone (ULEZ) in 2019 that has been further expanded in 2021. The set of policies implemented from 2015 in the CCZ remarkably improved air quality in several neighbourhoods, raising questions about possible health benefits for school children. Consequently, we combined precise information on air pollution and school absences in the Greater London area from 2012 to 2019. To answer our research question, we use a difference in differences approach to estimate the causal effect of more stringent regulation on air quality and school absences.

Our paper contributes to the literature on the link between air pollution, children's health and socioeconomic disparities in three main ways. First, best to our knowledge, this is the first study inquiring how environmental policies targeted at reducing traffic-related pollution affect school absences. Secondly, we provide novel evidence of SES disparities in vulnerability and responsiveness to policies targeting air pollution. Finally, we discover positive spillover effects of the CCZ on air pollution, thereby showing that also inhabitants adjacent to the actual zone profited from the policy in terms of cleaner air.

The article is structured as follows. In the next section, we describe how air pollution affects school absences and why it is more critical for low-socioeconomic groups. Moreover, we illustrate why the regulations implemented in London's CCZ from late 2015 and not before improved air quality. We then proceed with outlining the data, variables and identification strategy. In the results section, we report the findings on the pooled sample, stratified effects on air pollution, absences and supplementary analysis. Lastly, we discuss the relevance of the results, limitations and further venues of research.

## **Air pollution, socioeconomic status and educational inequalities**

Air pollution is a major threat to children's health, having direct consequences on their school performance. On the one hand, pollution has been found to negatively affect short-term cognitive abilities and thus to decrease test performance (Amanzadeh et al., 2020; Berman et al., 2018; Ebenstein et al., 2016; Grineski et al., 2020). On the other hand, several studies have found that air pollution increases school absences (Hales et al., 2016; Liu & Salvo, 2018; MacNaughton et al., 2017; Marcon et al., 2014; Zhang et al., 2018), thereby imposing indirect consequences on the educational outcomes of children (Berman et al., 2018). For example, Currie et al. (2009) have shown that higher levels of pollution increased school absences in Texas, which is partly explained by the aggravation of cardio-respiratory conditions in children. In particular, individuals suffering from chronic obstructive pulmonary disease, allergic symptoms, asthma or rhinitis are ill prepared to face high levels of air pollutants (Alotaibi et al., 2019; Jiang et al., 2016; Mudway et al., 2019; Wood et al., 2015). A competing explanation is based on behavioural responses to air pollution: individuals prefer to avoid exposure by staying at home when air pollution is high (Yoo, 2021). Additionally, studies

have linked air pollution with sleeplessness and suggested poor sleep to be a potential mechanism explaining the increase in school absences among children (Heyes & Zhu, 2019).

However, the consequences of air pollution are not uniformly distributed, and socioeconomic status is likely to stratify the effects on health. The pathways explaining these differences are related to disparities in exposure and vulnerability. Previous studies have found low-SES neighbourhoods and ethnic minorities to be more exposed to air pollutants (Colmer et al., 2020; Rüttenauer, 2018). A similar pattern has been found when inquiring about exposure at school premises in the USA (Grineski & Collins, 2018). In addition, parents could proactively reduce children's exposure to air pollutants during highly polluted days, keeping them home as they are more wary of air quality (Currie et al., 2009; Guo et al., 2016; Yoo, 2021). Similarly, high-SES households are likely to have better means to shield themselves from high levels of outdoor emissions due to better window quality or more expensive flats pointing into less polluted directions of a building (Diekmann et al., 2022). Consequently, low-SES households experience higher exposure to air pollution and are less protected when exposed to the same level of outdoor traffic pollution, thus experiencing higher inhalation risks of outdoor pollution.

Even when exposed to the same amount of air pollution, individuals differ in their vulnerability to these pollutants (Cakmak et al., 2016; Forastiere et al., 2007; Hajat et al., 2015). There are two possible mechanisms explaining the differences according to SES. Firstly, the prevalence of cardio-respiratory conditions is more common among poor children. For example, low-SES children have a higher prevalence of asthma (Gong et al., 2014), and existing health conditions are a major driver of the link between respiratory illness hospitalizations and air pollution among children (Jans et al., 2018). Secondly, high-SES parents are better able to compensate for negative events that might affect their children (Bernardi, 2014; Torche, 2018), or seek primary care related to respiratory diseases (Cope et al., 2008; Stingone & Claudio, 2006). Consequently, children of high-SES parents are more likely to receive critical support when they are exposed to high levels of air pollution, thus limiting the negative impact on health conditions and school absences.

## London, traffic regulation and air pollution

Traffic is the main contributor to air pollution in London and several policies have been implemented to improve air quality. In 2003, the first Congestion Charge Zone (CCZ) was established, requiring a fee of 5£ to access the area of Central London. Ever since, authorities have increased financial charges and tightened rules for access to affected regions. For instance, fees were increased from 5£ in 2003 to 10£ in 2011. Moreover, in 2007, authorities enlarged the original charging zone by an additional area in Central West London (Western Extension). This Western

Extension, however, led to large opposition among affected residents and was abolished again in 2011.<sup>3</sup>

Several studies have investigated the impacts of these early phases of the CCZ. However, results on improvements in air quality are mixed. For instance, Green et al. (2020) have explored the effectiveness of the establishment of the CCZ in 2003, showing only a slight decrease in PM10 and carbon oxide (CO) but an increase in nitrogen dioxide (NO<sub>2</sub>). Authors explain contrasting evidence by a potential substitution effect: the enhanced presence of public transportation or diesel engine cars might have replaced previous petrol vehicles, thereby increasing the level of NO<sub>2</sub> in the targeted area. Also, a reduction in traffic volume and air pollutants CO and nitrogen oxide (NO<sub>x</sub>) has been found when inquiring about the Western Extension of the congestion charge from 2007 to 2011 (Ding et al., 2021). Considering health benefits derived from the policy, two studies inquired how children's respiratory health responded to the implementation of the CCZ (Mudway et al., 2019; Wood et al., 2015). Both studies do not show any improvement in children's respiratory health. Given these mixed results, studies on London's CCZ argued for stricter traffic rules to enhance air quality and public health.

Tighter rules regulating emissions of vehicles in this area have been implemented from September 2015 on. These rules heightened the standards of diesel cars entering the area to Euro 6 level. At the same time, cleaner public transport vehicles have been introduced. These policies thereby explicitly targeted a reduction in hazardous pollution from traffic rather than targeting a mere reduction in traffic volume. Early results of a report commissioned by the Mayor of London showed major improvements in air quality from 2016 to 2020 in several neighbourhoods of the city.<sup>4</sup> Since then, additional restrictions have been imposed, such as a Toxicity Charge ("T-Charge") in 2017 and the Ultra-Low Emission Zone (ULEZ) with even higher emission standards and fees in 2019. Although these measures should have additional effects on air pollution, recent results (Ma et al., 2021) indicate that the policy measures in 2015 had the strongest relative effect on air pollution in 2016, with only slight improvements due to subsequent adjustments.

In this study, we will focus on the onset of tightening restrictions in late 2015, thus using the transition from 2015 to 2016 as our main treatment. Nonetheless, we will perform additional analyses that explicitly account for heterogeneous effects over time. Thus, we will also test gradual improvements and the possibility of additional effects due to later policy adjustments.

<sup>3</sup> A summative list of the policies is present in the Online Supplementary Materials in Table A1.

<sup>4</sup> The full report is available on the following website: [https://www.london.gov.uk/sites/default/files/air\\_quality\\_in\\_london\\_2016-2020\\_october2020final.pdf](https://www.london.gov.uk/sites/default/files/air_quality_in_london_2016-2020_october2020final.pdf).

## Data, variables and method

### Data

We use pollution estimates based on Defra's modelled background pollution data (Ricardo Energy & Environment, 2021). Defra's pollution estimates incorporate industrial point sources of emissions, household combustion estimates and road traffic emissions to estimate annual average pollution for a 1 km × 1 km grid across the UK. The modelled estimates are calculated by pollutant diffusion models, which incorporate a range of different data sources, such as the official Pollution Inventory, data on energy use, travelled vehicle kilometres or regional housing data. Most of the data sources are updated annually. These data sources are then used in dispersion kernel models to calculate area-wide estimates of pollution. Subsequently, the estimates are calibrated against measured pollution values from ground-based pollution monitors. The data include annual averages of particulate matter of different sizes (PM10, PM2.5), nitrogen dioxide (NO<sub>2</sub>) and benzene, which are all measured in µg/m<sup>3</sup>. To allocate the pollution estimates to each school, we created a 500 m radius buffer around each school and assigned pollution estimates of the 1 km × 1 km grid to each school weighted by the proportionate overlap between buffers and pollution grids.

For additional analysis, we also added raw traffic counts from official road traffic statistics of the Department for Transport.<sup>5</sup> We first restricted the data to a balanced subset of count points and subsequently calculated the average annual traffic count within 1 km of each school.<sup>6</sup> Moreover, we used official geographical outlines of the Congestion Charge Zone (CCZ) to construct (1) a binary indicator of whether a school lies within the CCZ and (2) the distance of each outside-located school to the CCZ.

Information on schools' absences is for students in the age range 5–15 and provided by the British Department of Education for all state-funded schools in the Greater London Area.<sup>7</sup> We combined data on school absences with the pupils' and institutional characteristics for the entire period.<sup>8</sup> However, due to missing information, the dataset results in an un-balanced panel as information is not provided for all schools in the period of analysis.<sup>9</sup>

<sup>5</sup> The data is available at the following website: <https://roadtraffic.dft.gov.uk/downloads>.

<sup>6</sup> We chose 1 km rather than 500 m here to avoid losing many schools which do not have a traffic count station within 500 m distance.

<sup>7</sup> The dataset is accessible online: <https://explore-education-statistics.service.gov.uk/find-statistics/pupil-absence-in-schools-in-england#dataDownloads-1> and comprises detailed information on the data.

<sup>8</sup> More precisely, the state-funded schools are primary, secondary and special. Moreover, information on the school characteristics is available at the following website: <https://www.gov.uk/government/statistics/schools-pupils-and-their-characteristics-january-2019>.

<sup>9</sup> Information for the whole period of 8 years is present for 80% of the total sample of schools.

## Variables

We focus on two sets of dependent variables. First, we investigated the log value of the pollution estimates (PM10, PM2.5, NO2 and benzene) and the traffic count. Secondly, we focus on school absences, computed as percentage of total sessions lost over the total number of school sessions. We introduce control variables using % of students eligible to free meals, % of students with English as a first language, % of students of white and British origin and % of boys in the school, which are all measured annually and available from the British Department of Education (see above). We further add the Index of Multiple Deprivation (IMD)<sup>10</sup> rank of the neighbourhood where the school is settled. As the deprivation indices are only available in 2010, 2015 and 2019, we used linear interpolation between those years.

## Method

In the main analysis, we apply a difference-in-differences (DID) estimator to capture the causal effect of the stricter CCZ on air pollution and school absences. In the analysis, we include schools observed from 2012 to 2019 and use the CCZ policy to separate schools into treated and control groups. Treated are schools within the CCZ area from 2016 onwards as policies were implemented in late 2015. The control group is composed of schools outside the CCZ area. We estimate the DID parameters using linear models with year and school fixed effects, borough-specific linear time trends and the control variables discussed above. The borough-specific time trends account for heterogeneous temporal developments across London and significantly reduce differences between treatment and control areas in pre-treatment periods (for a more detailed discussion see e.g. Rüttenauer & Ludwig, 2020). Moreover, we apply frequency weights<sup>11</sup> to account for yearly variations in the number of pupils in the schools. We use cluster standard errors at the school level. Formally, we estimate the following model:

$$Y_{st} = \beta_1 Z_s + \beta_2 T_t + \beta_3 Z_s \times T_t + \beta_4 \mathbf{X}_{st}^T + \alpha_s + \alpha_t + \alpha_{bt} + \varepsilon_{st} \quad (1)$$

The outcome  $Y_{st}$  represents air pollution/absences in school  $s$  at year  $t$ .  $Z_s$  is a binary indicator taking the value one for all schools within CCZ, zero otherwise.  $T_t$  is a binary indicator separating schools before and after the year of implementation of the stricter policy (one since 2016). The interaction between  $Z_s$  and  $T_t$  represents the DiD estimator.  $\alpha_s$  captures school fixed effects,  $\alpha_t$  year fixed effects,  $\alpha_{bt}$  borough-specific linear time trends, and  $\mathbf{X}_{st}^T$  is a row-vector of time varying control variables. Throughout the paper, we will estimate this model with varying control

<sup>10</sup> The IMD ranks are available online at <https://www.gov.uk/government/collections/english-indices-of-deprivation>.

<sup>11</sup> We use frequency weights only in the analysis with absences as our main dependent variable, but not in the analysis of air pollution. Results are, however, similar with applied weights.

**Table 1** Summary statistics within 10 km before and from 2016

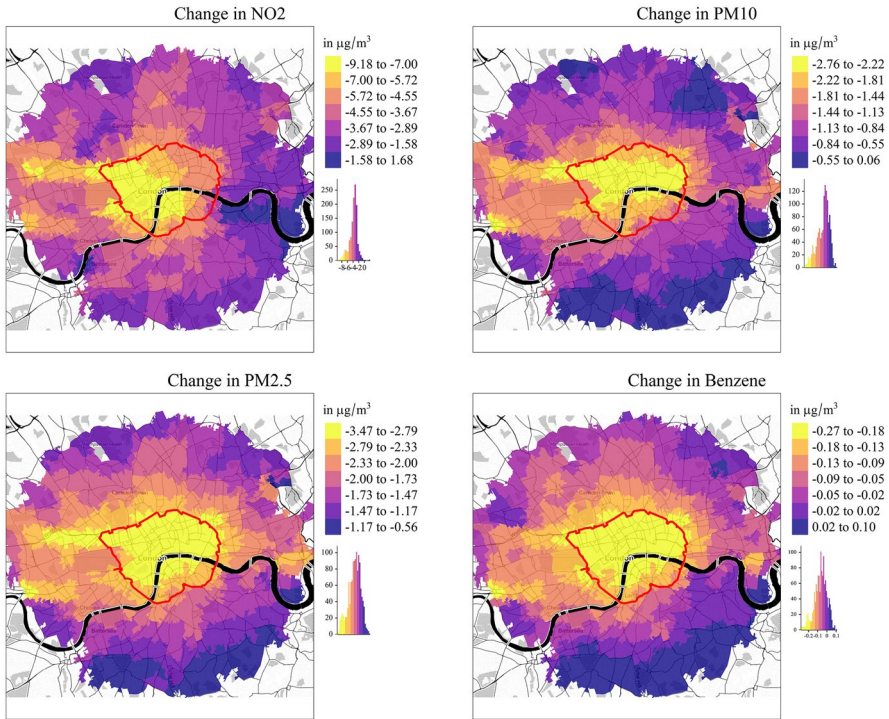
	CCZ			Not CCZ		
	Before	After	Difference	Before	After	Difference
Absences	4.33 (0.08)	4.3 (0.09)	-0.03 (0.06)	4.57 (0.03)	4.45 (0.03)	-0.12 (0.04)
% eligible to free meal	29.46 (0.98)	23.05 (0.90)	-6.41 (1.33)	28.61 (0.22)	21.71 (0.18)	-6.89 (0.29)
% English first language	45.17 (1.33)	50.08 (1.28)	4.91 (1.81)	48.11 (0.62)	48.19 (0.59)	-0.08 (0.44)
% White British	19.81 (0.91)	19.03 (0.81)	-0.78 (1.21)	20.09 (0.25)	19.2 (0.47)	-0.92 (0.04)
% boys	50.39 (1.52)	49.51 (1.25)	-0.88 (2.15)	51.05 (0.39)	51.10 (0.37)	-0.04 (0.27)
IMD rank	10,009.96 (355.60)	11,678.97 (425.72)	1669.01 (555.58)	10,132.27 (101.74)	11,485.57 (199.61)	1353.3 (144.85)
No. pupils	358.97 (19.82)	376.06 (20.55)	17.09 (28.57)	469.81 (4.77)	483.95 (4.96)	14.13 (6.89)
PM10	22.2 (0.07)	20.15 (0.04)	-2.05 (0.08)	19.51 (0.02)	18.91 (0.01)	-0.6 (0.03)
PM2.5	15.77 (0.11)	12.95 (0.02)	-2.82 (0.09)	13.7 (0.02)	12.44 (0.01)	-1.31 (0.02)
NO2	46.72 (0.32)	40.35 (0.28)	-6.3 (0.27)	31.09 (0.15)	28.34 (0.12)	-2.85 (0.10)
Benzene	0.91 (0.01)	0.72 (0.00)	-0.19 (0.01)	0.7 (0.00)	0.7 (0.00)	0 (0.00)
No. schools	44	45	1	1072	1133	61
Total schoolyears	175	178	3	4288	4530	242

The table represents the descriptive statistics of the main variables used in the analysis. We report the mean values in the CCZ and outside the CCZ and from 2012 to 2015 and from 2016 to 2019. In parenthesis we report the standard error. Moreover, we compute the absolute difference for schools in the CCZ and outside

groups using three boundaries of respectively 3 km, 5 km and 10 km from the CCZ (Tang, 2021).

This approach assumes a clear-cut boundary that is affected by the policy change. It is, however, likely that the policy also affected proximate regions by reducing traffic and pollution around the CCZ. Thus, we will also test potential spillover effects on adjacent schools and perform supplementary robustness checks of the DiD approach in which we hollow out adjacent regions. Moreover, the conventional DiD estimator as described above relies on the parallel trends assumption given the included covariates, and furthermore assumes the absence of heterogeneous treatment effects. To overcome these potential problems, we also apply the more flexible DiD version as proposed by Callaway and Sant'Anna (2021). In our setting, this estimator calculates a series of  $2 \times 2$  DiD estimators for each year before and after



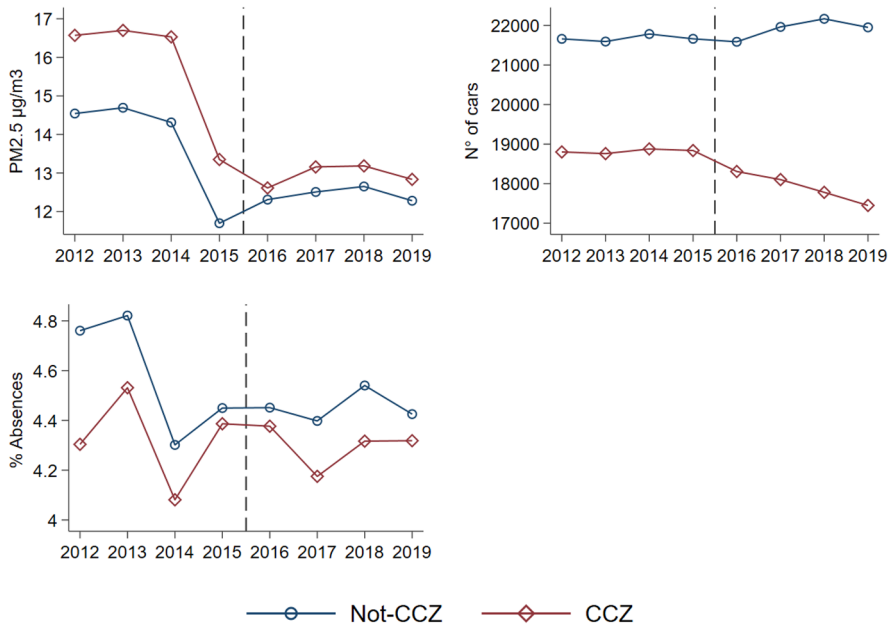


**Fig. 1** Change in pollution in the CCZ and not-CCZ before and after tighter regulations. Note: the figure depicts the difference in air pollution in the Greater London before (2012–2015) and after (2016–2019) tighter regulations. Lighter colours indicate stronger reductions in pollution. The red polygon marks the outline of the CCZ

the actual treatment. This allows us (1) to inspect the validity of parallel trends and the absence of a significant “treatment effect” before the actual treatment and (2) to investigate potential heterogeneity in treatment effects. For instance, the actual policy might unfold its effect on school outcomes only after a time lag.

## Empirical results

In Table 1, we report the summary statistics of main variables used in the analysis, separated by schools within the CCZ and outside, but within the 10 km boundary of the CCZ. Moreover, we report statistics for these areas before and after 2015—when the stricter policy was implemented. Descriptively, air pollution shows a stronger decrease in the CCZ. In addition, school absences decreased only slightly in both areas before and after 2015 with a 0.03%-points decrease in the CCZ and a 0.12%-points decrease outside the CCZ. Overall, there is no significant change in the composition of schools in the CCZ compared to those outside, with the only



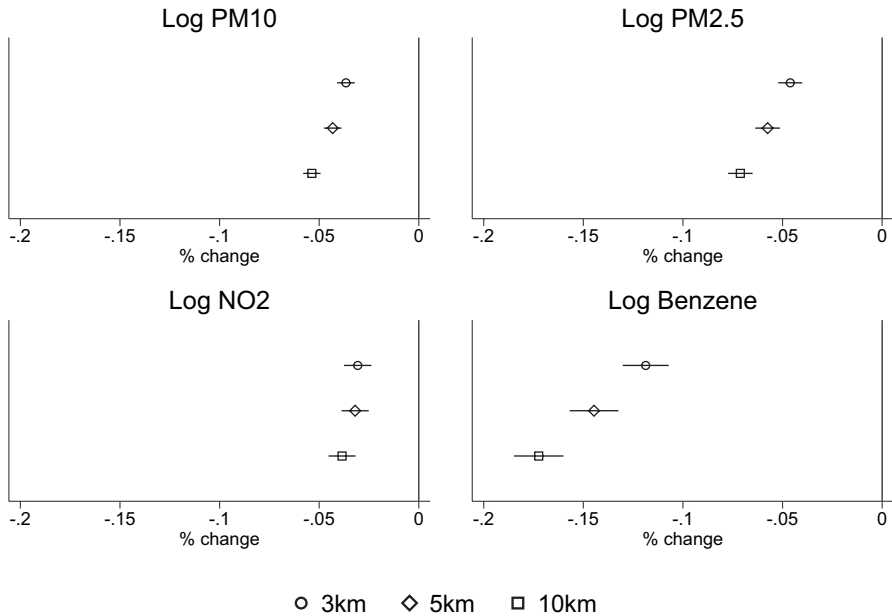
**Fig. 2** Air pollution, absences and cars over time in the CCZ and not-CCZ. Note: the figure displays the average level of air pollutant PM2.5, no. of cars and absences in the CCZ and 10 km outside from 2012 to 2019. A dashed line between the years 2015 and 2016 demarcates the start of tighter measures

exception of the percentage of students with English as first language showing an increase in the CCZ.

Figure 1 provides a descriptive map of the change in nitrogen dioxide (NO<sub>2</sub>), particulate matter 10 (PM<sub>10</sub>), particulate matter 2.5 (PM<sub>2.5</sub>) and benzene across London between pre- and post-treatment periods. Across all pollutants, we observe a substantial decrease in pollution over time and this decrease is stronger within the CCZ area than outside of the CCZ. This decrease is critical as toxic pollution started at much higher levels within the CCZ area. Especially for PM<sub>2.5</sub> and benzene, there is a strong decrease from 2015 onwards. Therefore, several schools in the CCZ, which largely exceeded the recommended WHO threshold in the earlier years, currently are closer to complying with the targets.

These improvements are also visible in Fig. 2, where we plot the annual trends in PM<sub>2.5</sub>, car counts and absences from 2012 to 2019. The trend shows a decline in PM<sub>2.5</sub> in all areas, but the improvement is more substantial in the CCZ. Similarly, average car counts remained relatively stable outside the CCZ, but started to decline after 2015 inside the targeted areas. For absences, we observe a slightly larger decrease in the CCZ after 2016. Moreover, the trends in absences between 2013 and 2015 largely follow parallel trends. However, we will discuss this assumption further in our main analysis.

The main results of our DiD analysis for all four pollutants as outcomes are presented in Fig. 3 (Online Supplementary Materials: Table A2). We vary the selection of the control group according to the distance of schools to the CCZ.



**Fig. 3** DiD estimator for air pollution at different km distance. Note: the figure displays the DiD estimates of Eq. (1) on the log value of the air pollutants PM10, PM2.5, NO2 and benzene, using as control group schools at 3 km, 5 km and 10 km from the CCZ. Standard errors are clustered at the school level. All models include year, school fixed effects and borough linear time trends. Other control variables are % students eligible to free meal, % of students with English as first language, % of native British students, % of boys and the IMD rank of the school neighbourhood. 95% confidence intervals are displayed

Coefficients thus tell us how much more air pollution has changed in the CCZ as compared to schools outside the CCZ but within the respective distance. Results reveal that decreases in all pollutants were stronger within the CCZ. Moreover, the differences become more pronounced at a larger distance from the CCZ. For instance, PM2.5 decreased by 4.6 percentage points more inside the CCZ as compared to schools within 3 km distance and by 7.1 percentage points more relative to schools within 10 km distance to the CCZ. Across all pollutants, benzene shows the largest decrease. Furthermore, we run the same analysis using the log count of cars as outcome variable (Online Supplementary Materials: Table A3). Findings highlight a decline in cars travelling inside the CCZ after 2015, in this case without differences according to distance. However, these results could be influenced by a lower number of available count points with increasing distance to the CCZ. Overall, our results indicate that the tightening of the regulation was effective in reducing air pollution and traffic at the targeted schools.

Nonetheless, did the policy also reduce school absences in targeted areas? The DiD estimates on absences indicate a reduction in absences due to the policy when compared to schools within 3, 5 and 10 km distance from the CCZ (Online Supplementary Materials: Table A4). The estimates are small in magnitude and

**Table 2** DiD estimator for air pollution and interaction with school SES

Variables	(1)	(2)	(3)	(4)
	Log PM2.5	Log PM10	Log NO2	Log benzene
DiD	-0.058* (0.005)	-0.050* (0.003)	-0.049* (0.004)	-0.152* (0.011)
DiD*medium SES	-0.019* (0.007)	-0.006 (0.005)	0.010 (0.007)	-0.029 (0.016)
DiD*low SES	-0.014 (0.008)	0.001 (0.007)	0.022* (0.008)	-0.019 (0.014)
No. schoolyears	9171	9171	9171	9171
No. schools	1.234	1.234	1.234	1.234

The table displays the DiD estimates of Eq. (1) on the log value of the air pollutants PM10, PM2.5, NO2 and benzene, and an interaction term with school SES using as control group schools 10 km from the CCZ. The SES measure is a categorical variable that classifies a school with more than 35% of students eligible for free school meal as “low SES”, 20 to 35% as “medium SES” and lower than 20% as “high SES”. Standard errors are clustered at the school level. All the models include year, school fixed effects and borough linear time trends. Other control variables are % of students with English as first language, % of native British students, % of boys and the IMD rank of the school neighbourhood. Constant present but not reported

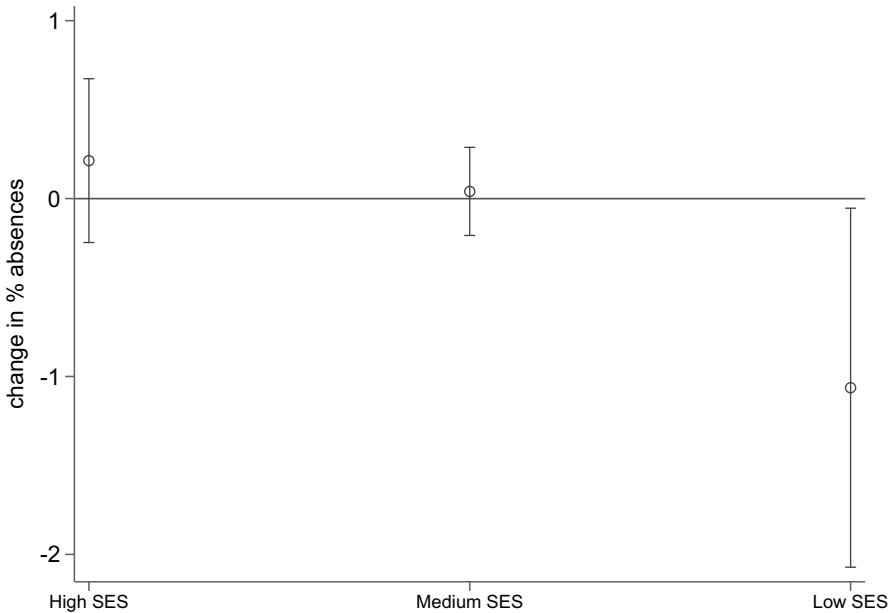
\* $p < 0.05$

not significantly different from zero. These overall estimates thus lead us to conclude that the CCZ policy did not substantially affect school absences. However, as we have argued earlier, the policy may have benefited some individuals more as different socioeconomic groups could react differently to improvements in air pollution.

### SES differences, air pollution and absences

We first inquire how SES stratifies the improvements in air quality in Table 2 by adding an interaction term between the DiD estimator and a categorical variable that classifies a school with more than 35% of students eligible for free school meals as “low SES”, 20 to 35% as “medium SES” and lower than 20% as “high SES”. This follows the official categorization by the Ministry of Education. We use the average percentage of students eligible for free school meals over the whole period of analysis to have a more stable indicator of school SES which is less susceptible to yearly variations. If there are differences in the reduction in air pollution at the school premises, this would suggest a different intensity of treatment.<sup>12</sup> However, the results do not reveal substantive differences in the improvements for most pollutants. Only for NO2, we observe slightly lower reductions in air pollution for low-SES schools. PM2.5 improves slightly more across medium-SES schools.

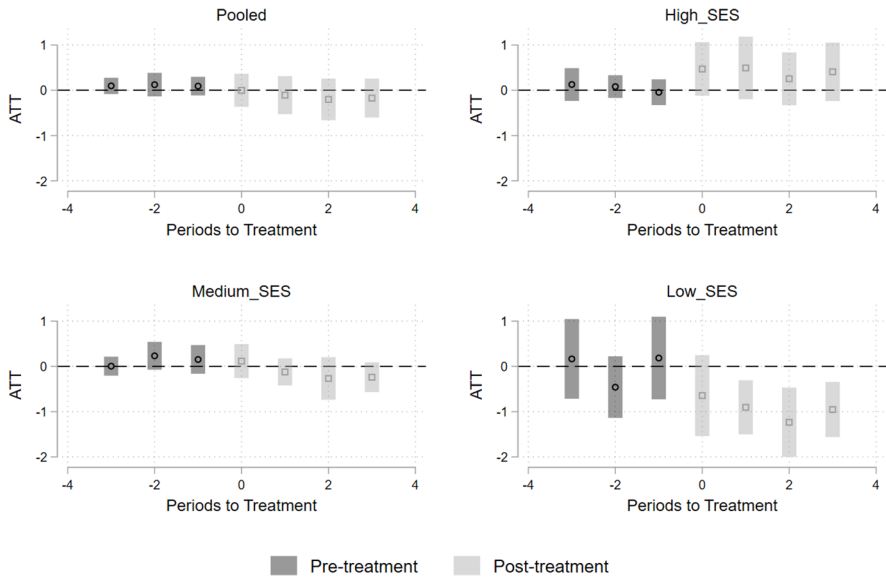
<sup>12</sup> In this analysis, we use schools at 10 km as our control group.



**Fig. 4** Absences and DiD estimator by SES. Note: the point estimate represents the average marginal effect for the three SES groups based on the interaction between the DID estimator of Eq. (1) with three school SES categories. The SES measure is a categorical variable that classifies a school with more than 35% of students eligible for free school meal as “low SES”, 20 to 35% as “medium SES” and lower than 20% as “high SES”. Standard errors are clustered at the school level. All models include year, school fixed effects and borough linear time trends. Other control variables are % of students with English as first language, % of native British students, % of boys and the IMD rank of the school neighbourhood. Moreover, we introduce frequency weights for the number of pupils in the school. 95% confidence intervals are displayed.

We repeat our main analysis on the absences, adding an additional interaction with the school SES classifier. In Fig. 4 (Online Supplementary Materials: Table A5), when compared with schools at 10 km from the CCZ, the differentiated models reveal a significant effect only for low-SES schools: the tightening of the congestion charge led to a 1.1 percentage points reduction in absences among low-SES schools. This effect is 1.28 percentage points larger than among high-SES schools and this difference is statistically significant. Moreover, we observe a similar pattern when schools within the CCZ are compared with schools at 3 km and 5 km distance.

Additionally, we used an instrumental variable (IV) approach to instrument  $\text{PM}_{2.5}$   $\mu\text{g}/\text{m}^3$  with the implementation of the new regulations in the CCZ after 2015. With this strategy, we take advantage of the sharp variation in air quality in the CCZ and outside the CCZ after 2015 to estimate the causal effect of air pollution on school absences. Moreover, we ran the analysis separately by schools SES to observe if the results match the stratified effect mentioned above. Results (Online Supplementary Materials: Table A11) exhibit that  $\text{PM}_{2.5}$  increases absences



**Fig. 5** Callaway and Sant’Anna event study plot of absences by SES. Note: the figure reports results of the Callaway Sant’Anna event study plot for the pooled and high-, medium- and low-SES schools. Standard errors are clustered at the school level. All models include year, school fixed effects and borough-specific predicted time trends. Other control variables are % of students eligible to free meal at school (not in the stratified analysis), % of students with English as first language, % of native British students, % of boys and the IMD rank of the school neighbourhood. Moreover, we introduce frequency weights for the number of pupils in the school. 95% confidence intervals are displayed

for low-SES schools but not for the other SES groups or the pooled sample. The elasticity observed suggests an increase of absences by 1.27 percentage points per  $1 \mu\text{g}/\text{m}^3$  increase in  $\text{PM}_{2.5}$  air pollution.

In summary, our DiD results suggest a decrease in particulate matter,  $\text{NO}_2$  and benzene within the CCZ after 2015 for all students. Still, we observe a stratified effect of the congestion charge policy on school absences: tightening the restriction in inner London has mostly benefitted low-SES students.

## Dynamic effects

Our main DiD estimator depends on two crucial assumptions: first the parallel trends assumption, and second, treatment homogeneity. To inspect these assumptions, we employ the flexible DiD extension proposed by Callaway and Sant’Anna (2021). First, we ran the event study plot for the pooled sample with  $\text{PM}_{2.5}$ ,  $\text{PM}_{10}$  and car counts as the outcome variables. We observe some significant estimates up to 2015 for  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$ , but differences are of minor size. Nevertheless, a substantial decrease in all pollutants occurred after 2015 and subsequently remains at a lower level (Online Supplementary Materials: Figure A1). Second, in Fig. 5, we calculated dynamic effects of the CCZ on

absences for the pooled sample and separated by SES. Across all groups, we do not find significant effects in the pre-treatment periods. This adds support to the parallel trends assumption before 2016. We observe a significant post-treatment effect only in low-SES schools, while medium- and high-SES schools do not experience a substantial change in absences. Low-SES schools indicate an initial decrease in 2016 that becomes larger and statistically significant from 2017 onwards. This gradual decrease in absences is theoretically plausible as the reductions in air pollution are likely to unfold their impact on health outcomes only after some time.

## Spillovers

Policies targeting air pollution may determine positive and negative spillover effects (Fang et al., 2019; Feng et al., 2020). In the case of the CCZ in London, we would expect benefits for neighbouring areas as lower traffic and air pollution in the central area might also benefit adjacent areas. Descriptive maps of air pollution (Fig. 1) seem to support the idea of spillover effects, as areas adjacent to the CCZ show a larger reduction in air pollution compared to more distant areas. We tested the existence of spillover effects by running a DiD analysis using the schools settled within 1 km, 2 km and 3 km from the CCZ as the treated group and the schools within 10 km from the CCZ as the control group. Importantly, schools within the CCZ are excluded from this analysis. We used different specifications of our treated group to test if there is a decrease of the spillover effect when we extended our sample to schools more distant from the CCZ.

The results for air pollution (Online Supplementary Materials: Table A6) show a reduction in all pollutants at 1 km, 2 km and 3 km from the CCZ. The reduction is slightly larger for the areas at 1 km from the CCZ for all pollutants, but the differences are not substantive. As expected, the decrease is smaller compared to the estimates we found for the CCZ area as seen in Fig. 3. Supplementary analyses further show no differences in reductions across SES categories. The spillover effect on pooled school absences shows a reduction at 1 km and 2 km, but the results are not statistically significant (Online Supplementary Materials: Table A7). Similarly, we do not find significant spillover effects for low-SES schools (Online Supplementary Materials: Table A8). Overall, results document positive spillover effects on air quality, but improvements are not enough to observe a substantial decrease in absences across adjacent schools.

The reduction in air pollution in neighbouring areas could bias our results as the control group could also be considered as treated. Consequently, we ran further analyses excluding the area within 1 km, 2 km and 3 km from the CCZ to observe how results change when the control group includes only the schools outside this range. Results (Online Supplementary Materials: Tables A9 and A10) corroborate our previous findings. The effects of pollution become slightly stronger when excluding adjacent areas. The effects on absences, however, remain widely unchanged, which is in line with the null finding of spillover effects on absences.

## Sensitivity analysis

We ran further tests to check robustness of our results. A common challenge of the DiD approach is related to compositional changes in the unit of analysis. In our case, student's composition of schools might vary year-to-year or during the time of the treatment. To further explore compositional changes and possible differences by SES of schools (that might explain the stratified effect we found) we run Eq. (1) separately by school SES categories on the following outcomes: % of students eligible for free school meals, % of students with English as first language and % of native British students. Results (Online Supplementary Materials: Table A12) suggest no substantive compositional changes in the % of students eligible for free school meal but an increase in the % of native British students and the % of students with English as their first language in medium-SES schools. Conversely, for the high- and low-SES schools, we do not observe any substantive results. The absence of changes in low-SES schools adds confidence that our main findings are unrelated to compositional changes. A possible explanation for the pattern observed in medium-SES schools is likely the increase in birth rates within the cohorts between 2002 and 2013, which was higher among non-UK born individuals. Combined with a high immigrant share in Central London, this may have caused a disproportionate increase in children from non-UK born parents in schools within the CCZ area. However, given the changes are only substantive among medium-SES schools, this is unlikely to affect our main finding. It could still partly explain the lack of an effect in medium-SES schools.

We tested three alternative SES measures to replicate our main results. First, we used a time varying categorical variable for SES based on the yearly variation in the % of students eligible for free school meals. Secondly, we used a continuous variable capturing the average % of students in the period of analysis eligible for free school meals. Thirdly, we used the average reversed percentile rank in the IMD of the school's neighbourhood over the period of analysis. All three measures replicate the main findings, but we lack some statistical power for the continuous measure of the % of students eligible for free meals and the IMD rank (Online Supplementary Materials: Table A13).

We further inquired which kind of absences has been reduced through the policy. More precisely, we used absences by the following classification: authorized, unauthorized, illness related, late arrivals and medical appointments. Although all types of absences decreased for low-SES schools, we only observe significant results for medical appointments (Online Supplementary Materials: Table A14).

An alternative factor which might explain our results is commuting time. Possibly, decreased traffic could reduce the time spent on reaching the school and diminish the perceived cost of attending school. For example, research has found that the introduction of the CCZ in 2003 reduced car accidents (Green et al., 2016). To rule out this potential hypothesis, we collected data on the median distance of pupils



from schools by SES from 2011 to 2016.<sup>13</sup> On average, the median distance of pupils attending a high-SES school is 0.93 km, 0.83 km in medium-SES schools and 0.97 km in low-SES schools. The low median distance from schools makes it unlikely that changes in commuting time drive our results for low-SES students. Moreover, we do observe a null finding on late arrival related absences in our previous robustness check (Online Supplementary Materials: Table A14).

## Discussion and conclusions

Air pollution is a major threat to pupils' school performance and cardio-respiratory health. Here, we analysed the effectiveness of tightening traffic regulations for improving air quality at schools and its benefits for pupils captured by school absences in London. We highlighted four main findings. First, the stricter policies have been effective in reducing schools' exposure to toxic pollutants and traffic volume. Secondly, in the pooled sample of schools, there is no substantive decline in school absences. Thirdly, we found that the policy decreased school absences for low-SES schools, i.e. schools with the highest percentage of pupils eligible for free school meals. Fourthly, we identified positive spillover effects on air quality for schools proximate to but outside of the CCZ. Consequently, the tightening of CCZ rules has been effective in tackling air pollution and benefitted the poor by reducing school absences. These findings corroborate previous findings acknowledging the existence of disparities in vulnerability to air pollution between high- and low-SES individuals (Jans et al., 2018).

Presumably, low-SES children already suffer from respiratory conditions (e.g. asthma, allergies or rhinitis), which can be aggravated by higher levels of air pollution (Wood et al., 2015), and thus explain SES differences. Moreover, low-SES parents might have lower means to shield their children from perilous outdoor conditions and keep them at home during days of high air pollution. Similarly, the observed increase in absences related to medical appointments in high-SES schools could be determined by behavioural responses. In fact, parents of high-SES children are more likely to enact compensatory behaviours to protect their children from suffering exposure to negative events in life (Bernardi, 2014; Torche, 2018). When the new mayor, Sadiq Khan, took office in 2016 and started to stress the risks of air quality in Central London, high-SES parents might have started to take actions to protect their children by keeping them at home during polluted days. Overall, SES differences in vulnerability and avoidance behaviour are both likely to partially explain our results.

Still, this study has several limitations. First, we cannot test mechanisms and the only suggestive mechanism that we observe is related to the decrease in medical appointments for low-SES schools. However, other mechanisms such as safer travel to school determined by less traffic and car accidents could be competing

<sup>13</sup> Data on distance from school and other metrics is present in the UK Datastore: <https://data.london.gov.uk/dataset/london-schools-atlas>. Unfortunately, the information is provided only until 2016.

explanations (Green et al., 2016). Secondly, we use annual school level instead of individual level information. This comes with limitations regarding our ability to robustly capture heterogeneous effects among individuals of different groups within the same school and hinders more fine-grained analyses of the daily variation in pollution and absences. Additionally, individual level data could have allowed the use of student fixed effects controlling critical confounding factors such as compositional changes in schools. Also, we are not able to test the short-term and long-term benefits of the policy on the same individual. Thirdly, we do not have information on the exact address of residence of children and we cannot infer if the exposure to air pollution driving our results mostly happens at home, on the way to school or on the school premises.

We conclude by suggesting possible venues for further research. First, inquiring about the specific mechanisms that determine an SES gradient in the effect of environmental policies is vital to target the most vulnerable. For example, studies inquiring into SES differences in avoidance behaviour could shed new light on parental responses to air pollution. Secondly, the use of repeated observations at the individual level could allow us to observe short-term and long-term improvements in children's health determined by lower air pollution. Thirdly, future research should aim to compile daily data on absences and air pollution to better capture their elasticity and how they relate to specific air pollutants or traffic volumes. Finally, our study is focused on London—a wealthy city in a developed country—which likely makes our estimates a lower bound. This raises important questions about the role such environmental policies could play in countries with higher pollution and lower economic development.

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## Declarations

**Conflict of interest** The authors declare no competing interests.

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