Public Transport Shocks: Locally Internalized Nitrogen Dioxide & Oxide Mitigation following the Electrification of Central London’s Busiest Bus Fleet

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Public Transport Shocks: Locally Internalized Nitrogen Dioxide & Oxide Mitigation following the Electrification of Central London’s Busiest Bus Fleet

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October 2018

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Abstract
This paper works to predict the marginal magnitude of mitigated nitrogen oxides pollution in the wake of the Transport for London’s electrified 507 and 521 bus routes. The study examines London Air’s atmospheric inventory across roadside and urban background monitoring sites throughout central London. The paper models panel data with individual and time fixed effects to theoretically predict the degree of an unambiguous decrease in public transport air pollution neighboring the Waterloo and London Bridge. Through difference in difference design, the paper uses a variety of hourly air monitoring controls and time fixed effects between January 2015 and September 2018 to analyze and fix average changes in local trends of nitrogen oxides, with respect to the rollout dates of the 26 electric buses onto route 521, where average hourly NO₂ and NOx concentrations during hours of operation were reduced during the treatment period. The study concludes that an electric bus fleet conversion, weather observations, and hourly parameters help to explain local, urban reductions in noxious pollution levels, but in this case, the mitigative magnitude remains uncertain. The paper supports public authorities to enact numerous, comprehensive enforcements on traffic-level sources of noxious pollution, each yielding an effect, to perform cumulatively to create important environmental and public benefits.

Introduction

Public buses play a valuable role in urban environments by reducing traffic and delivering sustainable, low-cost transportation to an ever-increasing commuting urban population. However, running conventional diesel city-buses presents costly public health externalities by generating outdoor urban air pollution through tailpipe emissions in the form of particulate matter and nitrogen oxides, for which local municipalities are directly responsible. Public concerns associated with air acidification (Sulphur dioxide, SO₂) from coal combustion have shifted to concerns regarding recently discovered problems pertaining to particulate pollution (PM) and nitrogen dioxide (NO₂) from condensed transport. Relatively new knowledge has found the greatest current impact on public health from outdoor air pollutants to be particulates (measured as PM10 and PM2.5) and nitrogen oxides (principally NO2) because these chemicals can endure local urban environments for days to even weeks at a time (Holgate...
Consequently, air pollution has evolved from being a local hazard to needing source controls at local, regional, and even macro-level scales.

**Motivation**

Every year in the United Kingdom, ~40,000 deaths and £20 billion in costs can be medically connected to exposure from transport pollution (Holgate et al., 2016). In the case of London, a 2015 press-released analysis from Kings College estimated 9,400 premature deaths in 2010 attributed to the public health impacts associated with the air pollutants nitrogen dioxide (NO₂) and particulate matter (PM_{2.5}) (London Gov’t, 2018). From an *Updated Analysis of Air Pollution Exposure in London* in 2017, 1.9 million people living in London in 2013 were found exposed to annual average NO₂ concentrations above the EU limit value of 40 µg/m³ while also modeling 72,000 people to be living in Greater London in 2020 exposed to NO₂ concentrations above the aforementioned limit (Brook & King, 2017). London’s Royal College of Physicians reports that inhaling nitrogen dioxide and fine particulates can cause inflammation and the worsening of heart and lung diseases, citing evidence coupling premature mortality, birth defects, and the impairment of childhood lung development with high levels of transport emission exposure (Holgate et al., 2016). The National Oceanic Atmospheric Administration reports high levels of NO₂ cause haze, irritation to the eyes, nose, throat, and lungs, acid rain, reduced plant growth, algal blooms, and corrosion on buildings (United States).

The City of London is progressively responding to these noxious public health threats by governing mitigation strategies through the EU Ambient Air Quality Directive, the Air Pollution Research in London Cooperative, and the UK Government’s Emission Reduction Plan ratified under the Paris Agreement, which have implemented regulatory standards on nitrogen oxides.
(NOx, NO2), particulate matter (PM2.5, PM10), ozone, benzene, and carbon dioxide (CO2) emissions (New Air Quality Directive, 2017). The Transport of London’s 2018 Bus Fleet - Emission Reductions report states that TfL buses contribute to 27% of NO2 in inner London while road transport explains 63% in London (Dipnarine, 2018). London is leading the public transit clean-energy transition through public motivations to improve their city’s air quality and produce positive public feedbacks regarding a healthier urban climate. Pedestrians feel safer breathing clean air, which incentivizes walking, cycling, and using public transportation—all of which reduce traffic volumes. According to Bloomberg New Energy Finance, the aggregate quantity of electric buses in public service is predicted to more than triple, from 386,000 in 2017 to about 1.2 million in 2025, leveling to approximately 47% of the future global public bus fleet (O’Donovan, 2018). Understanding the impacts electric bus fleets will have on improving air quality in urban corridors is essential.

Recent history from London’s air quality initiatives has focused on reducing emissions from mobile sources, improving fuel quality, and incentivizing and enacting environmental protection policies into the public transport and energy sector. Within London’s statutory air pollution objectives, these public management strategies on traffic emissions in highly-polluted urban areas are meant to promote positive alternatives in reducing pollutant emissions. The Mayor of London, Sadiq Khan, and Transport for London (TfL) have adopted significant research and development to appreciably cut concentrations of roadside nitrogen oxides and particulate matter by electrifying targeted bus routes. The following will analyze the effectiveness from the City of London’s implementation of the 2016-2017 BYD ADL Enviro200 electric bus routes in reducing local nitrogen oxides, by exploring relevant literature and imposing fixed effects models on nearby roadside air monitors. This report advises enacting
numerous public actions comprehensively, because compound enforcements, each yielding a small change, are more likely to perform cumulatively to create significant air quality benefits.

**Literature Review**

In order to create an eloquent and differentiated analysis, a robust literature review will serve to establish a knowledge base around studies relating to the effect on urban air quality from public action aiming to reduce transport emissions. Published empirical analyses reviewing the relationship between an alternative fuel public bus fleet conversion and the predicted average change in varying urban air emission trends (NO\textsubscript{x} & NO\textsubscript{2}) at local monitoring stations were non-existent; nonetheless, there exists a significant amount of empirical, economic research regarding the environmental costs and benefits of electrifying the transportation sector and governmental actions seeking to internalize the externality of transportation emissions in polluted metropolises.

In analyzing the environmental benefits from electrifying transportation, upstream emissions must first be considered. Holland et al. (2016) models electric vehicle (EV) purchases, electricity emissions from charging infrastructure, and overall air pollution to predict the geographic variation in air quality effects from driving EVs in the United States. Holland estimates ninety percent of local environmental externalities from driving an EV in one state are exported across state lines, and consequently, the upstream power plants responsible for powering electric vehicles often tend to export more air pollution across other states than conventional gasoline vehicles. However, it is important to consider the emission offsets from electrified transportation on local, urban areas, where approximately 58\% of all nitrogen oxides in urban air are attributed from traffic emissions, which is causing grave damage to public health at about $3$ trillion dollars per year, globally (Erickson, 2017). Tseng et al. (2013) uses economic analysis to exhibit that hybrid electric vehicles provide more than a 28\% reduction in GHG
tailpipe emissions and at least a 27% lower lifetime energy cost, and EVs produce a 43-69% lower lifetime energy consumption cost, when both were compared to CVs. Wang et al. (1990) analysis on the emission impacts of electrifying transportation concludes, unequivocally, that the substitution of EVs and hybrids for conventional vehicles significantly reduces carbon monoxide and hydrocarbons in California, but the magnitude of NOx, SOx, and particulate emission offsets are acutely sensitive to the deployment of effective emission controls and the use of cleaner fuels during electricity generation. Becker et al. (2009) models future California EV deployment, in the scenario of renewable electricity generation, to estimate a 20-69% decline in 2030 greenhouse gas (GHG) emissions from U.S. light-vehicles over 2005 levels. Emissions are estimated to be 8-47% lower when the same EVs are charged on the current electricity grid (Becker, 2009). Summarized in the Michalek et al. (2011) economic valuation of plug-in EV life-cycle air emissions and oil displacement benefits: electrifying the transportation sector definitively improves air quality in urban areas due to the reduction in local tailpipe emissions. Electrification also has the potential to release fewer overall GHG transportation emissions over diesel and gasoline, depending on the method of electricity generation (Michalek, 2011). In economies with higher urban population densities, costly petroleum prices, shorter driving distances, and lower emission electricity, electrifying transportation becomes more attractive to both emission externality reductions and ownership costs. There are ongoing research and development efforts related to electrifying the transportation sector and transitioning to renewable electricity generation. Currently, London’s electricity grid is powered by large power stations outside of London; however, the London government’s upstream clean energy transition has a target to supply 15% of London’s energy from local renewable sources by 2030 with public incentives provided through the London Energy Plan, the Decentralized Energy Project Delivery
Unit, and the Decentralised Energy Enabling Project (United Kingdom, London Assembly, London City Hall). The study will contribute to this literature by analyzing the air quality effects of electrifying the public transport sector in central London with the assumption that the change in upstream power generation emissions from charging these buses is being addressed through separate programs and is not affecting the localized environment on which this paper focuses.

In reviewing the changes in urban air quality from localized public regulation, which strives to internalize social costs from traffic emissions, existing literature finds significant welfare gains through programs that concentrate on the leading inefficiencies to existing urban transport markets. Proost et al. (2001) equates the welfare effects of alternative fuel efficiency and environmental policies for certain urban areas and quantifies the gap between price and the marginal social cost of air pollution associated with traffic congestion. This piece of literature finds that transport pricing policies yield significant welfare gains for urban areas, when compared to fuel taxes and car emission regulations. This is due to the substantial marginal abatement costs associated with regulating vehicle emission technology. De Borger et al. (2013) finds that tolls and low emission zones (LEZs) are most efficient in reducing emission externalities from traffic. The first economic analyses on LEZs have recently emerged in the literature: Anas and Lindsey (2011) report a 14–19% reduction in air pollution following the implementation of Milan’s Ecopass system, and another study, Wolff and Perry (2011) find that low emission zones in Germany produce an average pollution reduction of 8.7% in these zones. Carslaw (2002 & 2007 et. Al.) use Monte Carlo and traffic congestion simulation models to analyze the change in NOx from London’s Low Emission Traffic Zone tolls compared to the risks of exceeding hourly EU limits on road transport NO2 levels. The study shows that even ambitious LEZ scenarios will not alone significantly reduce NOx in Central London under EU
standards. Davis (2008) uses an air monitoring panel and linear probability model with a quadratic time trend to measures the effect of a 1989 Mexico City driving restriction policy on air quality by using high-frequency data from monitoring stations to highlight an unintended increase in total vehicle registrations from cheap, high-emission vehicles used to switch out on the day they were banned from driving their original car. Davis concludes that the shortage of evidence of an improvement in air quality is not caused by an offsetting increase in industrial activity because emissions in Mexico City are overpoweringly derived from transport. Furthermore, Davis’ large panel controls for heterogeneity across Mexico City’s industries; therefore, a number of industries would have needed to increase their emissions simultaneously—a highly improbably explanation. Davis also captured fixed effects on fuels prices and noticed his coefficients were largely unchanged when controlling for this variable.

The challenge of estimating the reduction of targeted emissions from these single governmental actions, while providing econometric significance, is an apparent challenge across the literature. The challenges in modelling statistically significant changes from environmental air regulations in urban transport is commonly attributed to the policy’s relatively small margin of emissions control enacted within heavily trafficked urban centers, where emitted pollution from high condensed mobile transport sources rapidly disperses. This study focuses on local nitrogen dioxide and oxides abatement through electrified bus routes; although, it is also important to know that the Transport for London authority is mitigating these emissions through congestion toll charges on vehicles entering London with pre-Euro IV emission standards, as well as with incoming low emission bus zones (hybrid-diesel fleets) ¹.

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Another action urban municipality is taking to improve urban air quality, and most closely related to the following research, is the topic of reducing public transportation emissions by adopting zero or low emission public bus fleets. Hydrogen fuel cell buses and battery electric buses do not produce any pollutant emissions from their operation—their emissions remain exclusively upstream, which is particularly beneficial considering the emission reduction capacities from buses idling in city centers with heavy traffic and poor air quality (Lajunen, 2016). A more recent focus in this literature exists life-cycle assessments of the net energy and CO₂ emissions of alternative bus powertrains: research results from Kaunas, Lithuania, indicate that, "biogas-powered buses and electric trolleybuses are the best alternatives in mitigating emissions from a public transport fleet", dependent on road grades (Kliucininkas, 2012). Electric buses are highlighted in Xu et al. 2015, in which pollutant emissions were computed for different bus technologies. The study emphasizes the geographic effects in terms of routes and operating conditions on the total tailpipe emissions of the buses. Lifecycle emissions from the deployment of hydrogen fuel cell buses have shown reductions in GHG of around 40 to 100% when compared with conventional fossil fuel buses, depending on the source of electricity production (Hwang, 2013). Many relevant analyses use adaptations of the “GREET (The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation)” model, developed by Argonne National Laboratory. For instance, GREET model results from the United States show emission reductions from hydrogen fuel cell engines at 40% when compared to gasoline engines and 33% when compared with Diesel (Lajunen, 2016). With this information, we presume a net emissions reduction in the case of London’s electric bus operation at the Waterloo station.

To measure the effect of an electric bus fleet conversion on air quality, urban-air relationships must be considered. From 1996-2006, an eleven-year study was conducted to
compare hourly NO\textsubscript{x} readings at urban roadside and urban background monitors in Seoul. The paper finds average nitrogen oxide and dioxide levels at the urban background to be nearly the same. The roadside site displayed significantly higher levels of nitrogen oxides than nitrogen dioxide due to the direct impact of vehicular emissions, which confirms that traffic activities are the primary determinant of NO\textsubscript{x} concentrations at urban roadside environments (Pandey et al., 2008). Another empirical study examining the relationship between urban NO\textsubscript{x}, NO\textsubscript{2}, and PM\textsubscript{10} and meteorological variance at an urban background site in Gothenburg, Sweden finds a strong dependence between temperature inversions, wind speed, and NO\textsubscript{x} concentrations using the Lamb Weather Type classification method. The study concludes that NO\textsubscript{x} is a good proxy for predicting particulate number concentrations (Grundström et al., 2015).

Gilbert et al. (2003) measured the variation of ambient nitrogen dioxide concentration with increasing distance from major highways and found that concentrations decreased significantly with increasing logarithmic distance from the highway but were still significant up to a 1310-meter distance. The following analysis will use on-route, curbside NO\textsubscript{x} and NO\textsubscript{2} monitors as the primary treatment for the electric bus fleet conversion. The analysis will control for wind speed and temperature—urban backgrounds will be controlled for in separate regressions as they are located less than a kilometer off route.

In the case of London, a piece from the *Environmental Modeling and Software* journal presents air quality assessments for distinctive scenarios to predict concentrations of nitrogen dioxide. The model uses scenarios with different traffic and industrial emissions, types of roads, and meteorological parameters to derive nitrogen dioxide from nitrogen oxides generated from the tailpipe. The results clearly convey that industrial sources account for a comparatively lesser contribution to ground level NO\textsubscript{2} intensities per unit of emission with higher concentrations of
nitrogen oxides in urban meteorological conditions than rural (Leksmon et al., 2006). In 1997, a study based on ordinary least squares and first-order autocorrelation models used hourly NO\textsubscript{x}, NO\textsubscript{2}, O\textsubscript{3}, and meteorological data from 1991 to predict NO\textsubscript{x} and NO\textsubscript{2} in London. The study found high correlation coefficients between NO\textsubscript{x} and NO\textsubscript{2} (R>0.95), as well as primary emissions and wind speed being the most important factors influencing NO\textsubscript{x} levels in London (Shi et al., 1997). The analysis will use the results of these relevant studies in its analysis while providing updated interpretations.

Drawing from a September 2016 press release from the Transport for London announcing the Mayor's plan to introduce central London’s first fully electric bus fleet at the Waterloo Garage, TfL broadcasted the elimination of NO\textsubscript{x} emissions on routes 521 and 507, noting the buses should reduce harmful nitrogen oxides by 10 tons of NO\textsubscript{x} per year\textsuperscript{2}. This paper will strive to contribute to the aforementioned literature by presenting an econometric analysis on the effect of nitrogen oxides and nitrogen dioxide measurements on route 521’s curbside air monitors. The study uses a panel fixed effects model to account for changes in these pollutant air emissions while controlling for meteorological variables and nitrogen oxides and nitrogen dioxide emissions trends across relevant central London air monitors. This public-transport bus fleet conversion study on emission effects is unique in its econometric analysis, as this particular government action does not require incentivized consumer response to marginally improve urban air quality. This public transport strategy instead focuses on a physical, publicly funded reduction in NO\textsubscript{x} emissions in the context of a bus fleet conversion; yet, the significance of this

action on its targeted local environment, within the multifaceted urban emissions background of central London, is not yet explained.

Data

This analysis uses cross-sectional time-series data and will depend on hourly, air measurements on Nitric Oxides (NO\textsubscript{x}) and Nitrogen dioxide (NO\textsubscript{2}) in Micrograms per Cubic Meter of Air (\(\mu g/m^3\)), while controlling for meteorological parameters: ambient air temperature (\(^\circ C\)), wind direction (azimuth degrees) and speed (m/s), relative humidity (%), and barometric pressure (millibars). Air monitoring stations are distributed throughout London under the London Air Quality Network; although, each monitor appears online and offline across different time intervals, measures different emissions and sources, and is managed by different municipalities (Environmental Research Group & King’s College). To obtain a balanced panel, hourly measurements from January 2015 through September 2018 were extracted from every air monitor in central London that provided consistent hourly weather, NO\textsubscript{x} and NO\textsubscript{2} observations across from January to 2015 to September 2018, using Dr. David Carslaw’s OpenAir Project, an R package managed by the Environmental Research Group within King’s College London, which combines air pollutant data and meteorological variables at roadside and background air monitors (Carslaw & Ropkins, 2012). With zero observations at the sample treatment sites, particulate matter and ozone must be omitted from the analysis.

Following the September 9, 2016 press release reporting fifty-one BYD D9UR / ADL Enviro 200 buses electrifying TfL routes 507 and 521, 2017 Transport for London Bus fleet audits and an email from the former Transport Commissioner of London, Leon Daniels, confirmed the exact dates the 51 electric buses were phased onto routes 507 and 521: six buses
for route 507 & four buses for route 521 on September 24, 2016, seven buses for route 507 & 11 buses for route 521 on November 11, 2016, eleven buses for route 507 & ten buses for route 521 on January 14, 2017, and one bus for each route, 507 & 521, on January 28, 2017 (Daniels, 2018; United Kingdom, TfL, 2017). On a daily average, the 507 travels 1282 km and the 521 travels 2202 km and operate from 6:00 a.m. to midnight with just five buses running on the weekends (Thomas, 2018). By setting time parameters on these precise dates and holding panel fixed effects to nearby monitors, the study expects to regress a significant drop in NO\textsubscript{x} and NO\textsubscript{2} emissions at the Camden Holborn (Bee Midtown) and Westminster Strand North Bank BID roadside monitors, located curbside on electrified Route 521, from the 26 electric buses added on September 24 and November 12, 2016 and January 14 and 28, 2017.
Summary Statistics

In order to better understand the context of the following analysis, a set of descriptive statistics and maps are used to inform on the urban landscape and relativity of the sample’s nitrogen oxides and nitrogen dioxide emission monitors throughout central London’s air.

It is most important to see the location of the electrified Transport for London 521 & 507 bus routes in relation to the locations of the air monitors used.

Route 521 (Left), Route 507 (Right)
Exercising London grid coordinate data and ArcGIS, the point locations of the 521 and 507 bus stops are overlaid with the sampled air monitors, to best visualize the context of this analysis given the public data provided (TfL Digital, 2015; London Air). ArcGIS 1 conveys the varying distances of the monitors from the electrified routes—with some controls being independently variant considering their proximity to the treatment sites and the type of land zoning present. NO₂ data from Westminster Covent Garden and Camden Bloomsbury urban background are experimented with as the two monitors are located two blocks and a half mile off Route 521 respectively (ArcGIS 2). Kensington and Chelsea—Cromwell Road is dropped to avoid possible unobservable heterogeneity assumed by its obscure distance from the rest of the panel. The Lambeth-Bondway Interchange Industrial air monitor and the Lambeth Brixton Road curbside monitors are also dropped as they reside within an industrial corridor that is much more susceptible to volatile nitrogen oxides and dioxide than the rest of the sites located in commercial or residential downtown. In support, the monitors reside in one of London’s ‘most heavily polluted areas’, where a Transport for London bus route from Brixton to Streatham exceeded hourly legal levels of nitrogen dioxide on 539 occasions in 2016 (United Kingdom, Mayor of London, 2017).

The Transport for London’s *Bus Fleet – Emission Reductions* 2018 report provides a contextualized visual of average nitrogen dioxide concentrations within the scope of this study (below)—the treatment monitors along route 521 lie within the red shading and the entire sample draws from locations within either the yellow or red shading (Dipnarine, 2018).
Modelled annual mean NO2 air pollution, based on measurements made during 2013.

This map was used with permission from The Greater London Authority and Transport for London, who fund, develop and maintain the London Atmospheric Emissions Inventory. For more information please visit data.london.gov.uk

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3 Dipnarine 2018
4 Greater London Authority 2013
The maps lead the study to predict that the Camden Euston roadside, the Westminster Marylebone roadside, the City of London Beech Street roadside, Kensington & Chelsea Knightsbridge roadside, and the City of London Sir John Cass urban background are the sample’s best control sites geographically because these monitors are all located one to three miles off route from 521 and 507 but still lie within similar shaded areas within the TFL NO₂ and London Air NO₂ maps. We predict urban NOₓ and NO₂ variables at these controls to be most analogous to the treatments—without being too close to the electrified route. The study chooses Camden Holborn (Bee Midtown) and Westminster Strand Northbank BID as the treatment sites because the two are located on route 521. Because the Westminster Horseferry Road monitor, located beside route 507 and mapped on ArcGIS image 1, was offline during the time of the fleet conversion, the site is omitted from the analysis to avoid inaccurate treatment effects.

Before conducting the analysis, it is important to check for a visual discontinuity in NO₂ or NOₓ levels at the treatment sites in retrospect to control site patterns. The week following November 12, 2016 experienced the addition of eleven electric buses on route 521, the largest change in buses within the sample. Two scatter plots below display nitrogen oxides and dioxide levels during the four weeks before and after the treatment date, November 12—a time interval that allows visual comparability between emissions trends at control versus treatment sites while excluding the possibility of a visual discontinuity from the September or January rollout dates. EU law requires that average hourly levels of toxic NO₂ must not surpass 200 µg/m³ more than 18 times in a whole year (Holder and Carrington 2018).
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**Treatment v. Control Hourly NO2**

- Westminster Strand Northbank Treatment
- Westminster Marylebone Treatment
- Camden Holborn (Bee Midtown) Treatment
- Camden Euston Road Control
- Treatment Fitted values
- Control Fitted values

Quadratic Fitted Trend Lines, Horizontal EU Hourly Legal NO2 Limit Line, Vertical Line for Beginning of EBus Rollouts

**Treatment v. Control Hourly NOx**

- Westminster Strand Northbank Treatment
- Westminster Marylebone Treatment
- Camden Holborn (Bee Midtown) Treatment
- Camden Euston Control
- Treatment Fitted values
- Control Fitted values

Quadratic Fitted Trend Lines, Horizontal EU Legal NOx Limit Line, Vertical Line for Beginning of EBus Rollouts
From the scatter plots, rapid changes over the hours of day indicate that air quality in London responds quickly to changes in emissions—it may be possible to analyze changes in emissions by equating air pollution levels within a relatively narrow time interval. It appears that the green treatment points display a downward drop in both NO$_x$ and NO$_2$ levels following the addition of the eleven buses on November 12, 2016; however, the following weeks display random noise within the data where treatment levels are both above and below the controls at different periods in time.

Next, summary statistics will check for significant statistical differences by organizing pre- and post-rollout summary tables for the treatment monitors and control variables. The tables summarize treatment site data from Camden Holborn and Westminster Strand Northbank and control site data from Camden Euston, the Westminster Marylebone, Kensington & Chelsea—Knightsbridge, Tower Hamlets Mile End Road, City of London John Cass, Southwark A2 Kent Road and the City of London Beech Street monitors from January 1, 2016 to September 23, 2016 and September 24, 2016 through September 2018.

<table>
<thead>
<tr>
<th>2 Treatment Road Monitors Before</th>
<th>Obs.</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO$_x$ (µg/m$^3$)</td>
<td>25,477</td>
<td>267.84</td>
<td>210.50</td>
<td>196.92</td>
<td>5.48</td>
<td>1651.29</td>
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<tr>
<td>NO$_2$ (µg/m$^3$)</td>
<td>25,477</td>
<td>92.08</td>
<td>82.87</td>
<td>45.37</td>
<td>4.45</td>
<td>351.36</td>
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<tr>
<td>Wind Speed (meters/second)</td>
<td>25,477</td>
<td>1.77</td>
<td>1.55</td>
<td>1.32</td>
<td>0.088</td>
<td>8.79</td>
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<tr>
<td>Wind Direction (azimuth degrees)</td>
<td>25,477</td>
<td>207.02</td>
<td>234.93</td>
<td>86.86</td>
<td>0.099</td>
<td>359.99</td>
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<tr>
<td>Rain (cm)</td>
<td>25,102</td>
<td>0.02</td>
<td>0.00</td>
<td>0.10</td>
<td>0.00</td>
<td>5.55</td>
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<tr>
<td>Ambient Air Temperature (°C)</td>
<td>25,477</td>
<td>13.38</td>
<td>13.20</td>
<td>6.07</td>
<td>-2.43</td>
<td>36.45</td>
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<td>Barometric Pressure (millibars)</td>
<td>25,477</td>
<td>1009.46</td>
<td>1010.61</td>
<td>9.68</td>
<td>969.26</td>
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<td>Relative Humidity (%)</td>
<td>25,468</td>
<td>73.69</td>
<td>76.50</td>
<td>16.28</td>
<td>23.37</td>
<td>99.92</td>
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### Control Road Monitors Before

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<td>58,107</td>
<td>270.59</td>
<td>199.96</td>
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<td><strong>NO₂ (µg/m³)</strong></td>
<td>58,107</td>
<td>83.62</td>
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<td>58,520</td>
<td>1.78</td>
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<td>0.09</td>
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### Treatment Road Monitors After

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<td>190.70</td>
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<td><strong>NO₂ (µg/m³)</strong></td>
<td>29,776</td>
<td>83.94</td>
<td>79.35</td>
<td>35.11</td>
<td>9.19</td>
<td>289.18</td>
</tr>
<tr>
<td><strong>Wind Speed (meters/second)</strong></td>
<td>25,210</td>
<td>1.03</td>
<td>0.64</td>
<td>1.05</td>
<td>0.00</td>
<td>7.61</td>
</tr>
<tr>
<td><strong>Wind Direction (azimuth degrees)</strong></td>
<td>25,210</td>
<td>203.04</td>
<td>229.93</td>
<td>88.18</td>
<td>0.00</td>
<td>359.97</td>
</tr>
<tr>
<td><strong>Rain (cm)</strong></td>
<td>25,734</td>
<td>0.01</td>
<td>0.00</td>
<td>0.08</td>
<td>0.00</td>
<td>3.15</td>
</tr>
<tr>
<td><strong>Ambient Air Temperature (°C)</strong></td>
<td>29,055</td>
<td>12.34</td>
<td>11.66</td>
<td>6.57</td>
<td>-4.26</td>
<td>107.88</td>
</tr>
<tr>
<td><strong>Barometric Pressure (millibars)</strong></td>
<td>28,128</td>
<td>1010.46</td>
<td>1011.69</td>
<td>10.02</td>
<td>966.29</td>
<td>1037.85</td>
</tr>
<tr>
<td><strong>Relative Humidity (%)</strong></td>
<td>29,721</td>
<td>75.82</td>
<td>79.00</td>
<td>16.08</td>
<td>18.67</td>
<td>99.92</td>
</tr>
</tbody>
</table>
## 4 Control Road Monitors After Obs. Mean Median Std. Dev. Min Max

<table>
<thead>
<tr>
<th></th>
<th>Observations</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>NO\textsubscript{x} (µg/m\textsuperscript{3})</strong></td>
<td>58,945</td>
<td>260.09</td>
<td>195.76</td>
<td>225.82</td>
<td>1.90</td>
<td>3252.55</td>
</tr>
<tr>
<td><strong>NO\textsubscript{2} (µg/m\textsuperscript{3})</strong></td>
<td>58,945</td>
<td>81.31</td>
<td>76.27</td>
<td>39.65</td>
<td>0.67</td>
<td>414.82</td>
</tr>
<tr>
<td><strong>Wind Speed (meters/second)</strong></td>
<td>51,358</td>
<td>1.05</td>
<td>0.68</td>
<td>1.06</td>
<td>0.00</td>
<td>7.61</td>
</tr>
<tr>
<td><strong>Wind Direction (azimuth degrees)</strong></td>
<td>51,358</td>
<td>204.25</td>
<td>231.26</td>
<td>86.66</td>
<td>0.00</td>
<td>359.97</td>
</tr>
<tr>
<td><strong>Rain (cm)</strong></td>
<td>52,041</td>
<td>0.01</td>
<td>0.00</td>
<td>0.08</td>
<td>0.00</td>
<td>3.15</td>
</tr>
<tr>
<td><strong>Ambient Air Temperature (°C)</strong></td>
<td>58,190</td>
<td>12.50</td>
<td>11.95</td>
<td>6.60</td>
<td>-4.26</td>
<td>107.88</td>
</tr>
<tr>
<td><strong>Barometric Pressure (millibars)</strong></td>
<td>56,770</td>
<td>1010.40</td>
<td>1011.62</td>
<td>10.03</td>
<td>966.29</td>
<td>1037.85</td>
</tr>
<tr>
<td><strong>Relative Humidity (%)</strong></td>
<td>59,398</td>
<td>75.91</td>
<td>79.12</td>
<td>16.13</td>
<td>18.67</td>
<td>99.92</td>
</tr>
</tbody>
</table>

The summary tables convey nearly constant weather effects between the control and treatment monitors following electrification: wind speed, rain, ambient air temperature, barometric pressure, and relative humidity, all of which affect air pollution concentrations, have similar mean, median, and standard deviations across the treatment and control panels. It should also be noted that the NO\textsubscript{x} and NO\textsubscript{2} sample measurements share a correlation of 0.89, which indicates a strong positive linear relationship and precedent to run separate regressions to avoid endogeneity.

Prior to the first electric bus fleet conversion date, NO\textsubscript{x} volumes at the treatment sites had an average of 267.84 µg/m\textsuperscript{3}, a median of 210.50 µg/m\textsuperscript{3}, and a standard deviation of 196.92 µg/m\textsuperscript{3}. At the control sites, NO\textsubscript{x} volumes average of 270.59 µg/m\textsuperscript{3}, have a median of 199.96 µg/m\textsuperscript{3}, and a standard deviation of 239.13 µg/m\textsuperscript{3}. Following the electric bus fleet conversion, NO\textsubscript{x} volumes at the treatment sites decreased to an average of 233.55 µg/m\textsuperscript{3}, a median of 190.70 µg/m\textsuperscript{3}, and a standard deviation of 162.65 µg/m\textsuperscript{3}. During this same time period, NO\textsubscript{x} volumes at
Before the bus route’s electrification, NO$_2$ volumes at the treatment sites averaged 92.08 µg/m³ with a median of 82.87 µg/m³ and standard deviation of 45.37 µg/m³, while control site NO$_2$ volumes averaged 83.62 µg/m³ with a median of 77.29 µg/m³ and a standard deviation of 43.03 µg/m³. After the conversion date, NO$_2$ volumes at the treatment sites averaged 83.94 µg/m³ with a median of 79.35 µg/m³ and a standard deviation of 35.11 µg/m³. At the control sites, NO$_2$ averaged 81.31 µg/m³ with a median of 76.27 µg/m³ and standard deviation of 39.65 µg/m³.

Between the two time periods, the average and median reductions in volume of NO$_x$ and NO$_2$ at the treatment sites each equate to be approximately three to four times the amount of decline in NO$_x$ and NO$_2$ at the control sites, respectively. However, the high standard deviations for both NO$_x$ and NO$_2$ indicate that these data points are spread out across a much larger range of values, leading the study to expect statistically insignificant results, as the differences in average and median pollutant decline between the treatment and control sites for before and after the electric buses find values at small fractions to their corresponding standard deviations.

Before imposing the methodological parameters onto the panel, a simple linear regression model dependent on NO$_2$ and NO$_x$ and controlling for hour of day and the corresponding hourly weather runs on the following page. The downward non-linearity and skewed error variance of the residual plots showcase the intertwined erraticism in working within emissions inventories. The model is aware of the long-term downward trend of emissions in the sample and its ability to bias the treatment coefficients.
Predicted NO2 Residuals with Bus Variable Omitted

Ticks denote EBus rollout dates

Predicted NOx Residuals with Bus Variable Omitted

Ticks denote EBus rollout dates
Methodology

A panel fixed effects model with individual and time fixed effects is deployed to test the designed research hypothesis that the twenty-six total electric buses rolled out onto Route 521 across four separate events, caused a significant, exogenous reduction in average hourly nitrogen dioxide and oxide emissions at local route-side and urban background air monitors. If the model proves effective, we can accurately estimate the marginal and cumulative magnitudes of air pollutant mitigation funded from the electric buses. The analysis utilizes a variety of air-monitoring control sites and copious amounts of restrictive time dummies. The model is as follows:

\[ Y_{it} = \beta b_{it} + \delta w_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \]

The fixed effects regression model relies on the statistical properties of OLS to explore the exogenous relationships between the experimentally defined electric bus difference in difference estimator, \(\beta b_{it}\), and hourly weather predictors, \(\delta w_{it}\), with the endogenous \(\text{NO}_x\) and \(\text{NO}_2\) outcome variables, \(Y_{it}\). The model symbolizes \(Y_{it}\) as predicted \(\text{NO}_2\) or \(\text{NO}_x\) (\(\mu g/m^3\)) at air monitoring site, \(i\) and at hour, \(t\), which denote the cumulative number of hours since the sample’s beginning date, January 1, 2015. The coefficients of interest, \(\beta b_{it}\) at independent route-side and urban background treatments, control for individual changes in average hourly \(\text{NO}_2\) and \(\text{NO}_x\) variation attributed to the time-specific electric bus values. With respect to the aforementioned rollout events, \(\beta b_{it}\) is measured by the specified treatments: number of electric buses in operation, \(b\), during the cumulative hour, hour of day, and day of week \(t\), at roadside and urban background sites, \(i\). The treatment parameter measures cross-sectional variation in \(\text{NO}_x\) and \(\text{NO}_2\) at the individual treatment sites caused from an electric bus addition of four on September 24, eleven on November 11, 2016 and ten on January 14 and one on January 28, 2017. Parameters
checking for variation from just three buses operating route 521 and zero buses running from midnight to six a.m. are treated within $\beta_i$ in separate regressions. The weather covariate, $\delta w_{it}$, uses the panel’s hourly meteorological observations to predict the strength between hourly and seasonal meteorological cycles and NO$_2$ and NO$_x$ concentrations at hour, $t$, caused from the variables: wind direction (azimuth degrees), wind speed (m/s), rainfall (cm), ambient air temperature ($^\circ$C), relative humidity (%), and barometric pressure (millibars). The estimator, $\propto_i$, employs both panel fixed effects estimation to account for unobserved time-constant heterogeneity and cluster-adjusted standard error to account for within-group correlation or heteroscedasticity across the regression’s air monitoring sites, $i$. The time fixed effects variable, $\lambda_t$, controls for time-variant, omitted variables, by capturing average group trends across the panels and demeaning the uncorrelated regressors at their respective time restrictive dummy.

With a three- and a half-year hourly time series, we can reasonably assume its ability to balance the average cyclical patterns across seasons as well as short term variations happening during, say, weekends or rush hours. The idiosyncratic error term, $\varepsilon_{it}$, represents the differences between the predicted and observed values of $Y_{it}$ in correspondence to the $i^{th}$ air monitoring site in the $t^{th}$ hour. The error term is made up of three components: one site specific, one time specific, and a remainder which is both time and site specific. The error term is expressed as: $\varepsilon_{it} = f_i + \mu_t + \nu_{it}$. These three components are assumed to be uncorrelated with one other and with the variables in the equation. The error component, $f_i$, represents individual effects from unobserved characteristics at each monitoring control site, which are likely correlated with the observed exogenous variables in the model. Because it is likely that these individual characteristics, i.e. traffic congestion, vehicle fleet, and changes in emission regulations, are non-random and
consequently correlated with the observed exogenous variables, this is why the study is led inexorably to the fixed effects model.

The fixed effects model implicitly assists in controlling for unobserved heterogeneity of NO$_2$ and NO$_x$ by utilizing thirteen hourly urban-air monitoring panels for the duration of ~1.5 years before and after the four-month electrification period. Because it is impossible to measure the individual causal-effects at the counterfactual level, the model relies on the parallel trends assumption to discount the average causal effects happening at the treatment site during the time of treatment. By netting out common differences in average NO$_2$ and NO$_x$ time trends across the sample’s air monitors, the model assumes these trends to have an equal effect at the control and treatment sites. To better explain, let $Y_{1it}$ imply the potential hourly NOx or NO2 reduction at the treatment monitoring site $i$ if the electric bus fleet conversion were to happen at $t$ and let $Y_{0it}$ denote the average NO$_x$ or NO$_2$ reduction during $t$ at treatment monitoring site $i$ if not. Denote electric bus status by a dummy variable, $\beta_{bit}$. For each monitoring site, we observe $Y_{i} = Y_{0it} + \beta_{bit} (Y_{1it} - Y_{0it})$, or that is, we perceive $Y_{1it}$ for the electric bus fleet conversion and $Y_{0it}$ for every other site. Now let $E[Y_i]$ express the population average for the continuous random variable. With a large enough observation, sample averages converge to population averages and the average treatment effect on the treated monitor is contextualized as $E[Y_{1it} - Y_{0it} | \beta_{bit} = 1] = E[Y_{1it} | \beta_{bit} = 1] - E[Y_{0it} | \beta_{bit} = 1]$. This equation explains the counter-factual behavior of a causal effect. The leading term is the average change in NO$_2$ or NO$_x$ concentrations within the population of electric buses—a hypothetically observable quantity. The following term is the average change in NO$_2$ or NO$_x$ volumes had the electrification been cancelled. Although this is untestable, the model utilizes an alternative control group strategy to provide a consistent
econometric estimate. Through this methodology, the goal is to detrend the unobserved, time-
constant effects on NO₂ & NOₓ trending across the sample site group, such as constantly higher
traffic densities during weekday rush hours, the average change in alternative fuel use across
London’s vehicle fleet, higher pollutant combustions during periods of hot or cold weather, or
changes from London’s congestion toll or emission standards. If the panel data’s heterogeneity is
constant over time, then the model will enable us to acquire coefficients on the exogenous
variables with theoretically no selection bias by excluding the related individual properties of
each monitoring site. However, unpredictability and random noise are fundamental problems in
this field of study.
Method 1: Treating Route-side Monitors with Progressive Electric Bus Parameters

\[ NO_{2it}, NO_{xit} = \beta b_{it} + \delta_1 \text{windspeed}_{it} + \delta_2 \text{winddirection}_{it} + \delta_3 \text{rain}_{it} + \delta_4 \text{temp}_{it} + \delta_5 \text{bp}_{it} + \]
\[ \delta_6 \text{rhum}_{it} + \alpha_i + \lambda_1 \text{hour of day}_{t} + \lambda_2 \text{hour of weekend}_{t} + \lambda_3 \text{day of week}_{t} + \lambda_4 \text{month}_{t} + \]
\[ \lambda_5 \text{hour insample}_{t} + \lambda_6 \text{hour insample}^2_{t} + \varepsilon_{it} \]

The first method runs eight regressions to establish a baseline significance by
incrementally treating route-side hourly NO₂ and NOₓ concentrations upon the case’s
electrification events. We explain \( \beta b_{it} \) to signify the marginal reduction in cubic micrograms of
nitrogen dioxide attributed from an electric bus brought online, by adding treatment parameters
to the route-side sites, Westminster Northbank Strand and Camden Holborn Bee Midtown. To
control for the hourly intervals of electric bus operation by the number of electric buses rolled
out, the following regressions redefine \( \beta b_{it} \) by adding more concise time parameters within, to
demonstrate the treatment’s increased accuracy in predicting marginal route-side changes in NO₂
and NOₓ. \( \delta_{1-6} \text{w}_{it} \) strive to control for weather effects while \( \alpha_i \) imposes panel fixed effects and
cluster-adjusted standard errors across twelve individual panels. \( \lambda_{1-6} \) are imposed to demean commonly unobserved, cross-sectional, cyclical trends in \( NO_2 \) & \( NO_x \) across hours of the day, weekend hours, weekends, days of the week, and months. To fix long term trends, \( \lambda_6 \) & \( \lambda_7 \) employ two continuous linear and quadratic parameters on the across the sample’s cumulative hours to differentiate time-constant \( NO_x \) or \( NO_2 \) trends between January 2015 and September 2018.

Method 1: Regression 1 & 2

\[
NO_2_{it} = \beta_1 h_{osrdEB_{it}} + \delta_{1-6} w_{it} + \alpha_i + \lambda_{1-7} t + \epsilon_{it}
\]

\[
NO_x_{it} = \beta_2 h_{osrdEB_{it}} + \delta_{1-6} w_{it} + \alpha_i + \lambda_{1-7} t + \epsilon_{it}
\]

Before testing the effect of bus electrification on \( NO_2 \) and \( NO_x \) at the two, individual route-side monitors, we start by defining \( \beta_{bt} = \beta_{hosrdEB_{it}} \) and analyze the common difference in effects shared between Camden Holborn and Westminster Strand. Each electric bus variable, \( \beta_{hosrdEB_{it}} \) is simply defined by setting four parameters on the cumulative hour of sample (\( hos \)) to treat for the time of increase in total electric buses online following the four aforementioned rollout dates.

Method 1: Regression 3 & 4

\[
NO_2_{it} = \beta_3 w_{hosrdEB_{it}} + \delta_{1-6} w_{it} + \alpha_i + \lambda_{1-7} t + \epsilon_{it}
\]

\[
NO_x_{it} = \beta_4 w_{hosrdEB_{it}} + \delta_{1-6} w_{it} + \alpha_i + \lambda_{1-7} t + \epsilon_{it}
\]

Next, we support the previous bus variable and create \( \beta_{bt} = \beta_{dowhosroadEBus_{it}} \), to account for just three electric buses operating Route 521 on weekends (\( dow \)), following September 24, 2016. \( \beta_{dowhosrdEB_{it}} \) maintains the marginal rollout numbers according to the respective dates (\( hos \)) and recycles Method 1 parameters.

Method 1: Route side Regression 5 & 6
\[\text{NO}_2_{it} = \beta_5 hrwdhosrdEB_{it} + \delta_1 \text{ six } w_{it} + \alpha_i + \lambda_{1-7t} + \varepsilon_{it}\]

\[\text{NO}_x_{it} = \beta_6 hrwdhosrdEB_{it} + \delta_1 \text{ six } w_{it} + \alpha_i + \lambda_{1-7t} + \varepsilon_{it}\]

The sequence continues to fix the model’s bus variable by adding parameters to control for Route 521 hours of operation (hr), six a.m. to midnight, which will exclude the coefficient’s effect on NO₂ and NOₓ during definitive hours outside of TfL operation, 1:00 a.m. to 4:59 a.m.

Method 1: Route side Regression 7 & 8

\[\text{NO}_2_{it} = \beta_7 hrwdhosCHEB_{it} + \beta_8 hrwdhosNBEB_{it} + \delta_1 \text{ six } w_{it} + \alpha_i + \lambda_{1-7t} + \varepsilon_{it}\]

\[\text{NO}_x_{it} = \beta_9 hrwdhosCHEB_{it} + \beta_{10} hrwdhosNBEB_{it} + \delta_1 \text{ six } w_{it} + \alpha_i + \lambda_{1-7t} + \varepsilon_{it}\]

Now that the comprehensive time parameters have been identified within \(\beta_{bt}\), Method 1 concludes by verifying the electric bus coefficient’s significance in predicting marginal bus pollution abatement at each individual route-side monitor. The completed set of parameters define \(\beta_{bt}\) for the remainder of the analysis.

Method 2: Urban Background & Roadside Bus Treatments with interactive & continuous Fixed Effects

Regression 1 & 2

\[\text{NO}_2_{it} \& \text{NO}_x_{it} = \beta_1 NBrEB_{it} + \beta_2 CHrEB_{it} + \beta_3 \text{ubEB}_{it} + \delta_1 \text{ six } w_{it} + \delta_7 \text{ windspeed}_{it} \ast \text{hour}_{it} + \delta_8 \text{ Temp}_{it} \ast \text{month}_{it} + \alpha_i + \lambda_{1-7t} + \lambda_8 \text{Hour}_{t} \ast \text{Month}_{t} + \lambda_9 \text{Month}_{t} \ast \text{Year}_{t} + \lambda_{10} \text{Year}_{t} + \varepsilon_{it}\]

Method 2 equations recycle the electrification parameters from the final pairs of regressions in Method 1, as expressed by the number of online electric buses during the cumulative hour of sample, weekend, and hour of day. The analysis also resumes the baseline weather covariates, panel fixed effects, and clustering methods. Moreover, Method 2 strengthens
the model’s dummies with 336 additional time-trending fixed compared to Method 1’s 93, by interacting the previously used indicator variables on the panel’s twenty-four-clock and the twelve-month indicators, the average yearly trends between 2015-2018, and a robust, forty-five term control on common monthly trends by year. Since we have now chosen to group the local background monitors as relatively equal, distant treatments, the model must undercut wind and temperature interactions. Continuous hourly wind speeds are interacted with the continuous hour of day parameter to allow for continuous changes as wind fluctuates momentously—we expect this to have an immediate effect on predicting average hourly emissions concentrations. Method 2 also considers how outlying high and low temperatures typically inhibit abnormally high concentrations of toxic pollution. In accordance, the model adds a coefficient to help control for the non-linear hourly averages varying by month, but most likely uniform within the panel. With more considerate site treatment and control over hourly pollutant trends, Method 2 assesses the Transport for London’s affirmative emission offsets traveling throughout the square kilometer ranges of two local urban background monitors measuring diffuse transport, commercial, and residential emissions 50 meters from the road, Westminster Covent Garden and Camden Bloomsbury. This ideology derives from the secondary livelihood of NO\textsubscript{2} and the sample’s urban street canyons and infamous temperature inversions. Regressions 1 and 2 start by grouping the background treatment sites under a single coefficient, to first see if their pooled variance can explain a significant difference across the treatment period.

\textbf{Method 2: Regression 3 & 4}

\[ NO_2_{it}, NOx_{it} \]
\[
\beta_1 NBrEB_{it} + \beta_2 CHrEB_{it} + \beta_3 WCGubEB_{it} + \\
\beta_4 CBubEB_{it} + \delta_{1-6} w_t + \delta_7 (\text{Hour}_t \times \text{Month}_t \times \text{Windspeed}_{it}) + \\
\delta_8 (\text{Month}_t \times \text{Windspeed}_{it}) + \delta_9 (\text{Hour}_t \times \text{Windspeed}_{it}) + \delta_{10} (\text{Temp}_{it} \times \text{Month}_t) + \delta_{11} (\text{Hour}_t \times \text{windir}_{it}) \\
+ \alpha + \lambda_1 \text{hour of day}_t + \lambda_2 \text{hour of weekend}_t + \lambda_3 \text{weekend}_t + \lambda_4 \text{day of week}_t + \\
\lambda_5 (\text{day of week}_t \times \text{year}_t) + \lambda_6 (\text{hour}_t \times \text{month}_t) + \lambda_7 \text{month}_t + \lambda_8 \text{year}_t + \lambda_9 (\text{hour} \times \text{day of week})_t + \epsilon_{it}
\]

With signs of grouped significance at the urban background sites, this next step in regressions separates Camden Bloomsbury and Westminster Covent Garden urban backgrounds to test each of the four treatment sites separately. With careful review, a variety of controls are removed and replaced. We first implement a three-factorial interaction, \( \delta_{7-9} \), to control for the varying trends in continual hourly windspeeds by its monthly indicator. The term condenses itself to interact for common emission variations across continuous hours of the day by month and continuous average wind speeds by month. Continual average hourly temperature trends across the sample, by month, \( \delta_{10} \), are brought forth to explain outlying pollutant variations from extreme weather events. \( \lambda_5 \) adds 18 dummies to control for weekday by year effects and \( \lambda_9 \) fixes for continuous time effects for hourly emissions patterns happening across hours of the week. \( \delta_{11}, \alpha \), \( \lambda_{1-4} \), and \( \lambda_{6-8} \) showed constant significance and are recycled. Method 2 regression 3 and 4 utilize 527 fixed effects.

Method 3: Natural Logs & Robust Standard Error Check

Regression 1 & 2

\[
\ln(N02_{it}), \ln(\text{NOx}_{it}) = \\
\ln(\text{NO2}_t), \ln(\text{NOx}_t) = \\
= \beta_1 NBrEB_{it} + \beta_2 CHrEB_{it} + \beta_3 WCGubEB_{it} + \beta_4 CBubEB_{it} + \delta_{1-12} w_t + \alpha + \lambda_{1-9}_t + \\
\epsilon_{it}
\]
Regression 3 & 4

\[ \begin{align*}
&= \beta_1 NBrEB_{it} + \beta_2 CHrEB_{it} + \beta_3 WCGubEB_{it} \\
&+ \beta_4 CBubEB_{it} + \delta_{1-12} w_t + \alpha i(month*year) + \lambda_{1-9_t} + \lambda_{10 site} + \epsilon_{it}
\end{align*} \]

With vigorous fixed effects and high statistical significance founded at each treatment monitor, the final method concludes with a log-level model and a check on potentially missed spatial correlations across the few clusters. By applying the same individual electric bus parameters and 527 fixed effects as the last pair of regressions onto a log-level model, the model better interprets the estimated roadside and background magnitudes of NO\textsubscript{2} and NO\textsubscript{x} emissions prospectively attributed to the electrified transport corridors. The natural logarithmic model is also attractive in its properties as it will smooth out the fluctuative nature of urban air quality data and more accurately predict the Transport for London’s local pollution mitigation. To check for uncontrolled influential observations at the treatment sites and possibly results conveying underestimated standard errors, regressions 3 and 4 are ran as a standard log-level regression with site fixed effects, \( \lambda_{10} \), and a cluster at the month-year level, which allows for cross-site correlations that may have previously underestimated the standard errors of the electric bus coefficients. As the final step of the methodology, a residual versus fitted plot will visualize the preciseness of the targeted roadside and urban background pairs.
Results

This section begins by analyzing the three method’s regression equations. Next, discussion and robustness checks over the model’s predictions in NO$_x$ and NO$_2$ will explore alternative specifications and controls on input choices. Finally, the paper concludes with a discussion of additional extensions and limitations that were considered during the research. In the succeeding results, each table value denotes the subsequent Method used.

Table 1: Route side Bus Treatments

<table>
<thead>
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<th>VARIABLES</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.0893)</td>
<td>(0.605)</td>
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<td></td>
<td></td>
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<tr>
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<td>-0.985**</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>(0.0686)</td>
<td>(0.389)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>BP (millibars)</td>
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<td>-0.886</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>(0.0932)</td>
<td>(0.547)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Wind (m/s)</td>
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<td>-34.95***</td>
<td>-8.909***</td>
<td>-35.88***</td>
<td>-8.918***</td>
<td>-35.92***</td>
<td>-7.890***</td>
<td>-31.15***</td>
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<td>(0.781)</td>
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<td>(0.806)</td>
<td>(7.124)</td>
<td>(0.807)</td>
<td>(7.137)</td>
<td>(0.880)</td>
<td>(6.419)</td>
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<tr>
<td>Wind Direction</td>
<td>-0.0451**</td>
<td>-0.153</td>
<td>-0.0476**</td>
<td>-0.160</td>
<td>-0.0476**</td>
<td>-0.160</td>
<td>-0.0434*</td>
<td>-0.126</td>
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<tr>
<td>(0.0202)</td>
<td>(0.0946)</td>
<td>(0.0210)</td>
<td>(0.0982)</td>
<td>(0.0210)</td>
<td>(0.0980)</td>
<td>(0.0210)</td>
<td>(0.0973)</td>
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<tr>
<td>Rain (cm)</td>
<td>-0.266</td>
<td>-14.47</td>
<td>0.480</td>
<td>-11.32</td>
<td>0.464</td>
<td>-11.39</td>
<td>-1.193</td>
<td>-21.04*</td>
</tr>
<tr>
<td>(1.723)</td>
<td>(9.112)</td>
<td>(1.794)</td>
<td>(9.314)</td>
<td>(1.789)</td>
<td>(9.309)</td>
<td>(1.863)</td>
<td>(10.30)</td>
<td></td>
</tr>
<tr>
<td>Ambient T. (°C)</td>
<td>-0.0209</td>
<td>-2.199</td>
<td>0.0699</td>
<td>-2.002</td>
<td>0.0706</td>
<td>-1.999</td>
<td>-0.776***</td>
<td>-3.986***</td>
</tr>
<tr>
<td>(0.387)</td>
<td>(1.368)</td>
<td>(0.394)</td>
<td>(1.472)</td>
<td>(0.394)</td>
<td>(1.474)</td>
<td>(0.241)</td>
<td>(0.644)</td>
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<tr>
<td>Rel. Hum (%)</td>
<td>-0.0271</td>
<td>-0.705**</td>
<td>-0.0570</td>
<td>0.591**</td>
<td>-0.0573</td>
<td>0.591**</td>
<td>-0.0113</td>
<td>1.128***</td>
</tr>
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<td>(0.0144)</td>
<td>(0.247)</td>
<td>(0.0456)</td>
<td>(0.247)</td>
<td>(0.0456)</td>
<td>(0.247)</td>
<td>(0.0394)</td>
<td>(0.274)</td>
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<tr>
<td>BP (millibars)</td>
<td>0.0243</td>
<td>0.623**</td>
<td>0.0186</td>
<td>0.577*</td>
<td>0.0175</td>
<td>0.574*</td>
<td>0.0522</td>
<td>0.935***</td>
</tr>
<tr>
<td>(0.0725)</td>
<td>(0.261)</td>
<td>(0.0766)</td>
<td>(0.275)</td>
<td>(0.0769)</td>
<td>(0.276)</td>
<td>(0.0629)</td>
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</tr>
<tr>
<td>Constant</td>
<td>70.70</td>
<td>-419.2*</td>
<td>71.78</td>
<td>-415.4*</td>
<td>77.79</td>
<td>-389.0</td>
<td>38.14</td>
<td>-1979.9***</td>
</tr>
<tr>
<td>(66.82)</td>
<td>(229.4)</td>
<td>(66.91)</td>
<td>(229.6)</td>
<td>(68.04)</td>
<td>(235.4)</td>
<td>(57.31)</td>
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<td>278,029</td>
<td>275,206</td>
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</tr>
<tr>
<td>R-squared</td>
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<td>0.300</td>
<td>0.349</td>
<td>0.300</td>
<td>0.349</td>
<td>0.300</td>
<td>0.339</td>
<td>0.289</td>
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<tr>
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<td>12</td>
</tr>
<tr>
<td>Hr. of Day FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Hr. of Day by Weekend FE</td>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Hr. of Day by Month FE</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Day of Week FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Month FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Sample Hr. FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Sample Hr. 2 FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Month by Year FE</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Cluster &amp; Panel FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Table 1 objectifies the marginal effects from an additional parameter restricting the beta coefficients to limited times and values as defined by the online electric bus fleet. Regressions 1-4 initially pool the two route side monitors under one treatment variable to ensure interest for the electric bus coefficient at the forefront of the analysis. By simply setting four parameters equal to the number of incoming electric buses across the four rollout dates and then restricting for no more than three operating during weekend hours, a relative decline in average NO$_2$ and NO$_x$ levels exists in comparison to the other monitoring sites. However, this effect is lost to unobservable variance across the pooled treatment sites once the hours of operations are accounted for, which set precedent to treat the Westminster Northbank Strand and Camden Holborn independently in regression 7 and 8 to reach a more coherent grouping of standard errors. Fear of collinearity arises from setting the precise treatment on separate panels monitoring the same route throughout the analysis. Conversely, simple intuition may already figure to not be weary of strong correlations and inflated variance between the hourly emission levels at distanced route side treatments, when bearing in mind central London’s daily traffic episodes and the underlying incentives for the bus fleet’s electrification. Statistical evidence from Table one carries forward a causal claim to continue testing the selected sites and time parameters.
Table 2: Urban Background & Roadside Bus Treatments with interactive & continuous Fixed Effects

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) NO2</th>
<th>(2) NOx</th>
<th>(3) NO2</th>
<th>(4) NOx</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta_1 ) NBrEB_{it}</td>
<td>-0.410***</td>
<td>-2.038***</td>
<td>-0.427***</td>
<td>-2.138***</td>
</tr>
<tr>
<td></td>
<td>(0.0394)</td>
<td>(0.311)</td>
<td>(0.0314)</td>
<td>(0.282)</td>
</tr>
<tr>
<td>( \beta_2 ) ChrEB_{it}</td>
<td>-0.197***</td>
<td>-0.669**</td>
<td>-0.188***</td>
<td>-0.579*</td>
</tr>
<tr>
<td></td>
<td>(0.0289)</td>
<td>(0.231)</td>
<td>(0.0268)</td>
<td>(0.276)</td>
</tr>
<tr>
<td>( \beta_3 ) ubEB_{it}</td>
<td>-0.498***</td>
<td>-2.740**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.124)</td>
<td>(0.925)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \beta_4 ) WCGubEbus_{it}</td>
<td></td>
<td></td>
<td>-0.637***</td>
<td>-3.823***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.136)</td>
<td>(1.023)</td>
</tr>
<tr>
<td>Wind (m/s)</td>
<td>-7.556***</td>
<td>-25.59***</td>
<td>-7.469***</td>
<td>-29.46***</td>
</tr>
<tr>
<td></td>
<td>(0.559)</td>
<td>(5.102)</td>
<td>(0.499)</td>
<td>(5.195)</td>
</tr>
<tr>
<td>Wind Direction</td>
<td>1.381</td>
<td>-7.186</td>
<td>1.115</td>
<td>-4.228</td>
</tr>
<tr>
<td></td>
<td>(1.667)</td>
<td>(8.775)</td>
<td>(1.466)</td>
<td>(8.137)</td>
</tr>
<tr>
<td>Rain (cm)</td>
<td>0.0318</td>
<td>0.898***</td>
<td>0.0251</td>
<td>0.804***</td>
</tr>
<tr>
<td></td>
<td>(0.0425)</td>
<td>(0.194)</td>
<td>(0.0382)</td>
<td>(0.191)</td>
</tr>
<tr>
<td>Ambient T. (°C)</td>
<td>0.0252</td>
<td>0.649**</td>
<td>0.0201</td>
<td>0.555*</td>
</tr>
<tr>
<td></td>
<td>(0.0755)</td>
<td>(0.263)</td>
<td>(0.0754)</td>
<td>(0.283)</td>
</tr>
<tr>
<td>Rel. Hum (%)</td>
<td>-0.0399*</td>
<td>-0.141</td>
<td>-0.0301**</td>
<td>-0.100*</td>
</tr>
<tr>
<td></td>
<td>(0.0200)</td>
<td>(0.0924)</td>
<td>(0.0124)</td>
<td>(0.0527)</td>
</tr>
<tr>
<td>BP (millibars)</td>
<td>-2.101***</td>
<td>-13.05***</td>
<td>-1.805***</td>
<td>-10.38***</td>
</tr>
<tr>
<td></td>
<td>(0.245)</td>
<td>(1.257)</td>
<td>(0.313)</td>
<td>(1.407)</td>
</tr>
<tr>
<td>Constant</td>
<td>81.32</td>
<td>-366.1</td>
<td>96.44</td>
<td>-180.4</td>
</tr>
<tr>
<td></td>
<td>(72.09)</td>
<td>(247.5)</td>
<td>(75.57)</td>
<td>(285.6)</td>
</tr>
</tbody>
</table>

Observations: 278,029
R-squared: 0.368
Number of Monitors: 12
Hour of Day FE: Y
Hour of Day: Weekend FE: Y
Weekend: Y
Hour of Day*Month FE: Y
Hr.*Wind Dir. FE: N
Wind Speed*Hr.: Y
Hour*Month*Windspeed: N
Day of Week FE: Y
Hour of Day * Speed: Y
Temp*Month: Y
Month*Windspeed: N
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<thead>
<tr>
<th>Month FE</th>
<th>Y</th>
<th>Y</th>
<th>Y</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample Hr. FE</td>
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<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Sample Hr.² FE</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>N</td>
</tr>
<tr>
<td>Month by Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Day*Year</td>
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<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Year FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Cluster &amp; Panel FE</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2 regression results convey sequentially consistent negative coefficients with high certainty, as the signs, magnitudes, and standard errors on all the predictors withstand interactivity between the enhanced weather and time demeaners. Although the route side electric bus estimators sustain negative values within their range of standard error, even after imposing over five hundred average treatment effects across the panel, the four resulting coefficients treating for the nearby online electric buses hypothetically effective NO₂ or NOₓ reduction, stage higher magnitudes of predictive power at both urban background monitors as well as with wind speed and barometric pressure, especially compared to Camden Holborn. However, the slightly higher electrification coefficient at Westminster Covent Garden, \( \beta_{4,CBubEBus_{it}} \), compared to Westminster Strand Northbank on route, \( \beta_{1,NBrEB_{it}} \), may be explained by the background’s ability to capture a more representative, larger, and steadier sample air space, with a greater rate of exposure to a wider range of emitting sources. Table 2’s final pair of regression columns highlight the highest explained variations in predicted levels of NO₂ and NOₓ from the model thus far, where impacts from the weather covariates predict the reductions from the electric bus coefficient, as it is most obvious that climatic factors such as wind speeds and air particle density provide the most deterministic explanation for the average changes in downward emissions reductions. Interacting the weather covariates with the beta electric bus coefficients may help to explain for variations between wind and the buses at the respective monitors. The study’s
inability to control the environment’s overwhelming chemical and climatic influences on the boundary layer lifetime of nitrogen oxides and dioxide raises scientific uncertainty in controlling for the unobserved environmental factors affecting each monitor’s range of sources. To check the magnitude of Regression 4’s statistically significant treatment coefficient on NO\textsubscript{x},

\[ \beta_1 \text{BrEB}_{it} = -2.138 \text{ cubic micrograms per hour per bus}, \]

compare this coefficient against the Transport for London’s (2016) press release on the route’s electrification, where it was first publicized that the fifty-one electric buses entering routes 507 and 521 would reduce NO\textsubscript{x} by 10 metric tonnes per year. If there were 51 route side monitors equally distanced, assuming parallel trends, measuring all 51 electrified bus operations per hour—simply multiply the model’s most predictive treatment coefficient on NO\textsubscript{x}, -2.138 micrograms per bus per hour, by the total 51 buses, by the 8760 hours per year to get a predicted reduction of ~955,173 cubic micrograms, which explains less than 0% of the tons saved. The analysis is showing major difference between reduced tailpipe emissions versus reduced sidewalk emissions, which conveys the magnitude of electrification may not be significant compared to total traffic pollution.
Table 3: Natural Logs & Standard Error Diagnostic

<table>
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<th>(2) lnox</th>
<th>(3) lno2</th>
<th>(4) lnox</th>
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<tbody>
<tr>
<td>$\beta_1 NBE_lB_{it}$</td>
<td>-0.00296***</td>
<td>-0.00551***</td>
<td>-0.00296**</td>
<td>-0.00551***</td>
</tr>
<tr>
<td></td>
<td>(0.000742)</td>
<td>(0.00150)</td>
<td>(0.00139)</td>
<td>(0.00192)</td>
</tr>
<tr>
<td>$\beta_2 CHeEB_{it}$</td>
<td>-0.00352***</td>
<td>-0.00563***</td>
<td>-0.00352***</td>
<td>-0.00563***</td>
</tr>
<tr>
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<td>(0.000812)</td>
<td>(0.00154)</td>
<td>(0.00114)</td>
<td>(0.00200)</td>
</tr>
<tr>
<td>$\beta_3 WCgubEB_{it}$</td>
<td>-0.00458***</td>
<td>-0.0104***</td>
<td>-0.00458***</td>
<td>-0.0104***</td>
</tr>
<tr>
<td></td>
<td>(0.00121)</td>
<td>(0.00280)</td>
<td>(0.000569)</td>
<td>(0.000634)</td>
</tr>
<tr>
<td>$\beta_4 CBubEB_{it}$</td>
<td>-0.00382***</td>
<td>-0.00796***</td>
<td>-0.00382***</td>
<td>-0.00796***</td>
</tr>
<tr>
<td></td>
<td>(0.000818)</td>
<td>(0.00159)</td>
<td>(0.00114)</td>
<td>(0.00165)</td>
</tr>
<tr>
<td>Wind (m/s)</td>
<td>-0.186***</td>
<td>-0.250***</td>
<td>-0.186***</td>
<td>-0.250***</td>
</tr>
<tr>
<td></td>
<td>(0.0129)</td>
<td>(0.0126)</td>
<td>(0.0118)</td>
<td>(0.0231)</td>
</tr>
<tr>
<td>Wind Direction</td>
<td>-0.000522**</td>
<td>-0.00853*</td>
<td>-0.000522***</td>
<td>-0.000853***</td>
</tr>
<tr>
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<td>(0.000229)</td>
<td>(0.000393)</td>
<td>(0.000113)</td>
<td>(0.000123)</td>
</tr>
<tr>
<td>Rain (cm)</td>
<td>-0.0122</td>
<td>-0.0363</td>
<td>-0.0122</td>
<td>-0.0363</td>
</tr>
<tr>
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<td>(0.0211)</td>
<td>(0.0370)</td>
<td>(0.0221)</td>
<td>(0.0350)</td>
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<tr>
<td>Ambient T. (°C)</td>
<td>-0.0284***</td>
<td>-0.0510***</td>
<td>-0.0284***</td>
<td>-0.0510***</td>
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<td>(0.00654)</td>
<td>(0.0118)</td>
<td>(0.00274)</td>
<td>(0.00402)</td>
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<tr>
<td>Rel. Hum (%)</td>
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<td>0.00377***</td>
<td>0.000331</td>
<td>0.00377***</td>
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<td>(0.000658)</td>
<td>(0.000900)</td>
<td>(0.000467)</td>
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<tr>
<td>BP (millibars)</td>
<td>0.00125</td>
<td>0.00405*</td>
<td>0.00125*</td>
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</tr>
<tr>
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<td>(0.00135)</td>
<td>(0.00207)</td>
<td>(0.000684)</td>
<td>(0.000923)</td>
</tr>
<tr>
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<td>3.615**</td>
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<td>3.219***</td>
<td>1.051</td>
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<td>(1.286)</td>
<td>(1.987)</td>
<td>(0.726)</td>
<td>(0.958)</td>
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</table>

Observations 278,027 275,206 278,027 275,206
R-squared 0.447 0.477 0.600 0.657
Number of sites 12 12 12 12
Hour of Day FE Y Y Y Y
Hour of Day: Weekend FE Y Y Y Y
Weekend Y Y Y Y
Hour of Day*Month FE Y Y Y Y
Hr.*Wind Dir. FE Y Y Y Y
Wind Speed*Hr. Y Y Y Y
Hour*Month*Windspeed Y Y Y Y
Day of Week FE Y Y Y Y
Hour of Day * Month FE Y Y Y Y
Temp*Month Y Y Y Y
Month*Windspeed Y Y Y Y
Month FE Y Y Y Y
Sample Hr. FE N N N N
Sample Hr.^2 FE N N N N
Month by Year FE N N N N
Table 3 and Plot 3 exhibit a smoother, more accurate interpretation of the resulting downward trends in pollution happening during the time of bus 521’s electrification; however, the pattern in which the data points deviate from where the residual line equals zero suggest that the variances of the error term remain unequal and the model still slightly suffers from heterogeneity. Regression 3 and 4 show less precise confidence intervals when allowing for cross-site correlation across within a month of the year, but the robust standard errors still convey highly similar magnitudes.

By utilizing the tight range in statistical variation across the Table’s electric bus coefficients, a conservative estimate of 0.3% NO₂ & 0.5% NOₓ reduction per electric bus per hour at the route side monitors accepts viability. Hypothetically, if each operating electric bus were running simultaneously and being monitored under the same conditions as the treatment, multiplying -0.3% by the number of electric buses in operation at 521 or 507, predicts a reasonable, simultaneous sidewalk reduction in NO₂ cubic micrograms per hour for the fully
operating 521 and 507 route. To check the total predicted magnitude of the simultaneous electrification episode at Waterloo station, the regression results forecast a cumulative ~15% reduction in total hourly NO₂ attributed from the 507 and 521 operation. Considering the Transport for London’s conveyed bus fleet contribution of 27% NO₂ to aggregate central London levels, the model’s -15% aggregate hourly NO₂ reduction estimate, which combines each Waterloo bus reducing its operating location’s nearby NO₂ concentrations by -0.3%, we equate the Transport for London’s noxious fleet contribution to be cut by ~50% in Central London.

Table 3’s statistically significant treatment coefficients ranging from predicted -0.296% to -0.458% decreases in local NO₂ per electric bus rollout at the respective site proves rather small in comparison to central London’s average hourly noxious concentrations; but in respect, improvements are shown.

**Discussion on Limitations and Further Research**

The central limitations reside with the model’s inability to predict a higher magnitude on noxious emissions reductions, but this may just be the case given London’s total traffic congestion. The presence of an uncontrolled and unobservable, downward variance in noxious emissions across the sample may have likely led to correlations across the entire group, which violates the central assumption that the control errors are uncorrelated while the treatment errors belonging to the same cluster are correlated. Possible mismeasurements may still rely on confoundedness in clustering the panel’s standardized errors across too few clusters—where the model’s variation in the covariate matrix across clusters yields significant variability. However, Table 3, Regression 3 and 4 do not define the magnitude of cross site correlation as significant. Given the data available, the beta bus coefficient’s three parameters signifying the number of
electric buses online were not perfectly precise in calculating the mitigation as there may still exist endogenous variances in combustion across the control sites and different minor uncontrolled, hourly correlations between the treatments. Extensions may be made with higher degree polynomials and weather to beta-electric-bus interactions.

Another potentially overlooked limitation within the analysis draws from unexpected, and unexplained, NOx and NO2 variation flooded by the idiosyncratic vehicle fleet composition. Nitrogen dioxide emitted from diesel engines remains inadequately controlled for in the UK and is still today a particular problem within London, where nearly half of cars run on diesel, as well as virtually all trucks, lorries, water transport, trains, construction, and farm machinery (Holgate, 2016). This potential endogeneity may have been enhanced as a result of insufficient clustering, which would lead to bias in the prediction. For this study, common trends in London fleet vehicle composition are assumed, but the possibility of an isolated, electrified commercial or residential fleet created a bias.

Heterogeneous treatment effects are the primary concern in the study’s potentially underestimated effect of electric buses on noxious pollution. For example, unobserved noxious heterogeneity could have been controlled if the panel contained statistical levels for ozone, solar radiation, or boundary layers, each of which instigate major variations in nitrogen oxide concentrations through temperature inversions or secondary formations of NO2 through photovoltaic reactions. This uncontrolled effect is particularly relevant as the electric buses were rolled out during winter, when morning inversions are most frequent, which may have contributed to an underestimation on the bus electrification coefficient if these effects vary across monitors.
The analysis also missed controlling for potential causality in reduced nitrogen oxides emissions within the time of the electric buses by unexplained fading glow bias. Suppose London citizens were attracted to the publicity surrounding the press release on bus route electrification as a means of reducing toxic pollution and chose to ride the buses during the rollouts but returned to private drives as the public glow from the electric bus reform faded over time.

Although the method assumes homogeneous effects from governmental regulation, an increase in the congestion toll on high emitting vehicles entering London past October 23, 2017, as well as the enactment of Euro VI emission standards in June, 2016 may also explain the unobserved downward trending variance (Dipnarine, 2018).

Moving forward, an extension of this research may consider the case of Antelope Valley, CA, where a shock at a local air monitor from the electrification of 85 buses may be more definitive, as the entire fleet is being converted in 2018 and there exists less of an effect from diesel vehicles in the United States. Bootstrapping inferences may also be extended from this area of research and can further be used to help explain if the use of clustering is optimal.

**Final Conclusions**

Excluding the highest polluting traffic is efficient in its direct method of reducing public externalities, as well as a popular way for European cities to clean up their diesel pollution. Bans, emission taxes, tolls, emission standards, and retrofitted or electrified public transport have all proven effective. Public governance over air quality embraces future security through authority and awareness, rather than relying on the lags of vehicle replacement within the private market. In the case of London, it is valuable to see downward trends in noxious pollution as well as a measurable control over air pollution from an activer public transport agency. Effective public
action over emission concentrations is a central cause in determining the future landscape of urban environments, as public financed agencies have the power to be effectively faster in controlling pollution than reactions within the free-market. As a public agency, the Transport for London has set a model precedent for unambiguous air quality benefits through its transition to clean-energy transport.

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