GY460 Project Report

Investigating the impact of London's Ultra Low Emission Zone on electric vehicle adoption

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1 Introduction

In recent years, Low Emission Vehicle adoption, especially battery Electric Vehicles (BEVs), has grown significantly in the UK. In London, the share of BEVs increased from 2.0% in 2018 to 35.5% in 2022, with an average annual growth rate of 8.4%, outpacing the rest of the UK, which grew at 3.8% annually. This rapid growth is partly due to the Ultra Low Emission Zone (ULEZ) policy, introduced in 2019 and expanded in 2021.

London’s poor air quality, largely due to polluting vehicles, has impacted public health. Data from the London Atmospheric Emissions Inventory (LAEI, 2019) indicates that road transport is the main source of nitrogen dioxide and particulate matter emissions in Greater London. To address this, the ULEZ policy was introduced to reduce urban air pollution. It imposes a £12.50 daily charge on non-compliant vehicles. Since its launch in 2019, the ULEZ has expanded twice. The timeline and boundaries are shown in Figure 1.

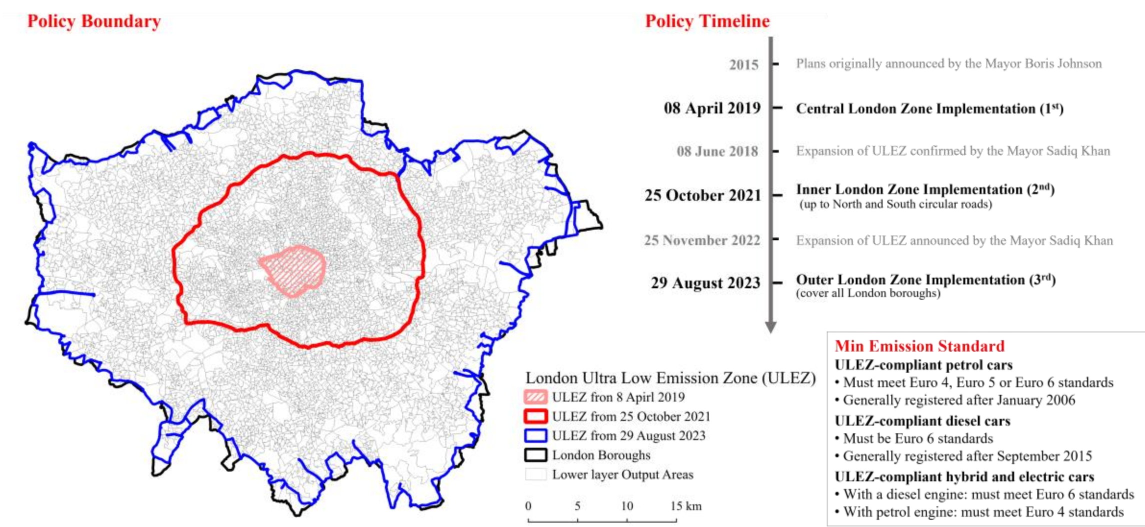

Fig. 1. Introduction of Policy Boundary, Timeline and Regulation

The ULEZ in London has been widely studied for its effects on real estate, air quality, public health, and traffic. Wolff (2014) shows ULEZ reduces vehicle emissions, improving air quality and public health. Ding et al. (2023) find it promotes green transportation, like cycling. Studies consistently show ULEZ lowers harmful emissions and shifts travel choices toward less polluting options. For electric vehicle adoption, Morton et al. (2017) and Peters et al. (2021) use econometric methods to demonstrate that ULEZ increases the uptake of low-emission vehicles. Their research also highlights spatial heterogeneity, with stronger ULEZ impacts in dense urban areas and spillover effects beyond ULEZ boundaries. Overall, these studies confirm ULEZ's effectiveness in reducing emissions and encouraging green transportation, emphasizing the need for spatial and econometric analyses to optimize such policies.

2 Descriptive Statistics

The licensed vehicle data used in this study are from the UK Department for Transport. This dataset includes vehicle registration records by fuel type, keepership, and lower super output area (LSOA) across the UK from 2011 to 2023. Vehicles are classified by emission levels into four categories: Zero Emission Vehicles (ZEV), Low Emission Vehicles (LEV), Hybrid Electric Vehicles (HEV), and Non-Electric Vehicles (NonEV).

2.1 Temporal trend

Figure 2 shows the changes in vehicle adoption shares (including private and company vehicles) over time since 2011, reflecting trends through ULEZ policy changes. The lines represent central London (pink), inner London excluding central London (red), and outer London excluding inner London (blue).

Before 2019, vehicle adoption shares across zones were stable. Post-ULEZ implementation in central London and leading to its first expansion, electric vehicle adoption rapidly increased in all regions, while non-electric vehicles declined. Notably, after the second policy phase, ZEV and LEV adoption in outer London surpassed inner London. Meanwhile, HEV adoption in central and inner London slowed, indicating spatial spillover effects as areas outside the policy boundary also increased EV uptake.

The graph also shows that individuals preemptively switched to cleaner vehicles after the ULEZ announcement, particularly seen in the significant HEV increase post-2015 announcement. This anticipatory effect led to local EVA growth saturation by the policy's official start, potentially affecting regression estimates.

Additionally, varying emission levels among EVs may lead to internal substitution. For example, the slowdown in HEV share growth suggests ZEVs, with lower emissions, have become preferable for avoiding emission charges.

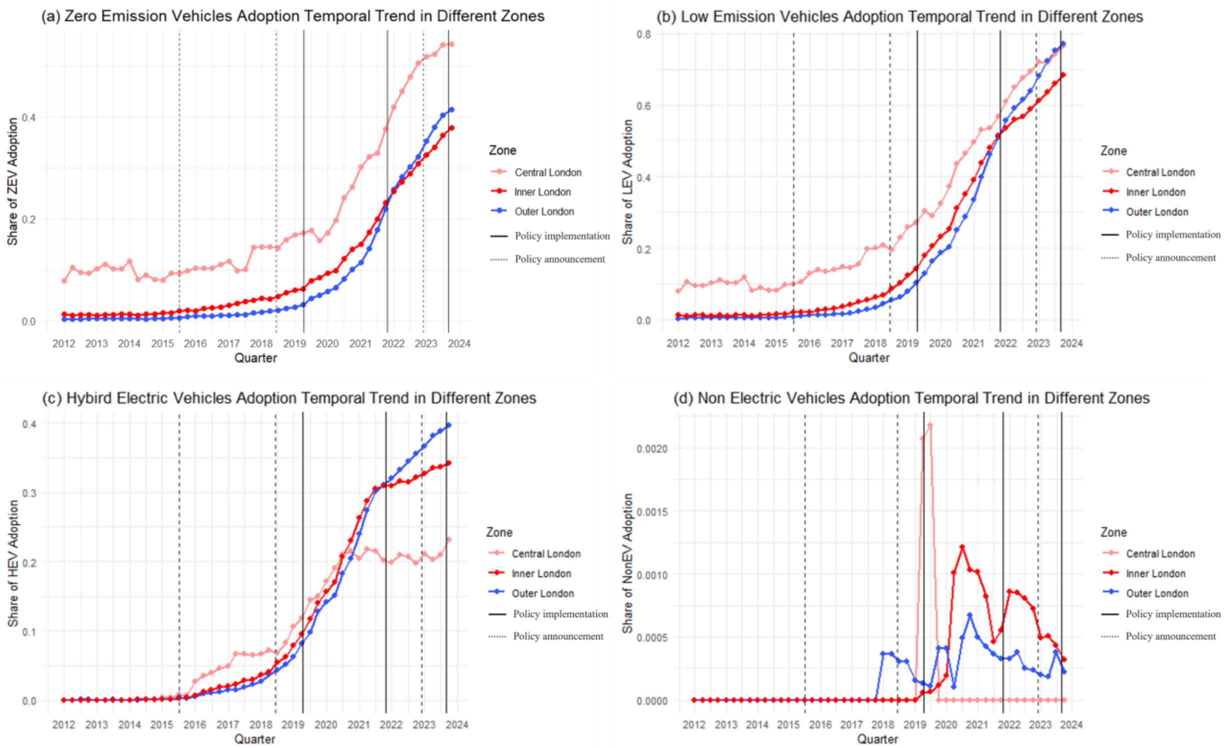

Fig. 2. Temporal Trend of Different Types of Vehicles Adoption in Different Zones

2.2 Spatial pattern

The Global Moran's I test statistic for ZEV, LEV, and HEV between 2020-2022 consistently shows significant positive values ($p < 0.001$), indicating that their growth rates are spatially clustered rather than random. In contrast, the spatial autocorrelation for NonEV is not significant.

Figure 3 shows the spatial distribution of average adoption growth for the three EV types in 2021, revealing many High-High and Low-Low clusters. These distinct patterns suggest different underlying spatial factors influencing each EV type.

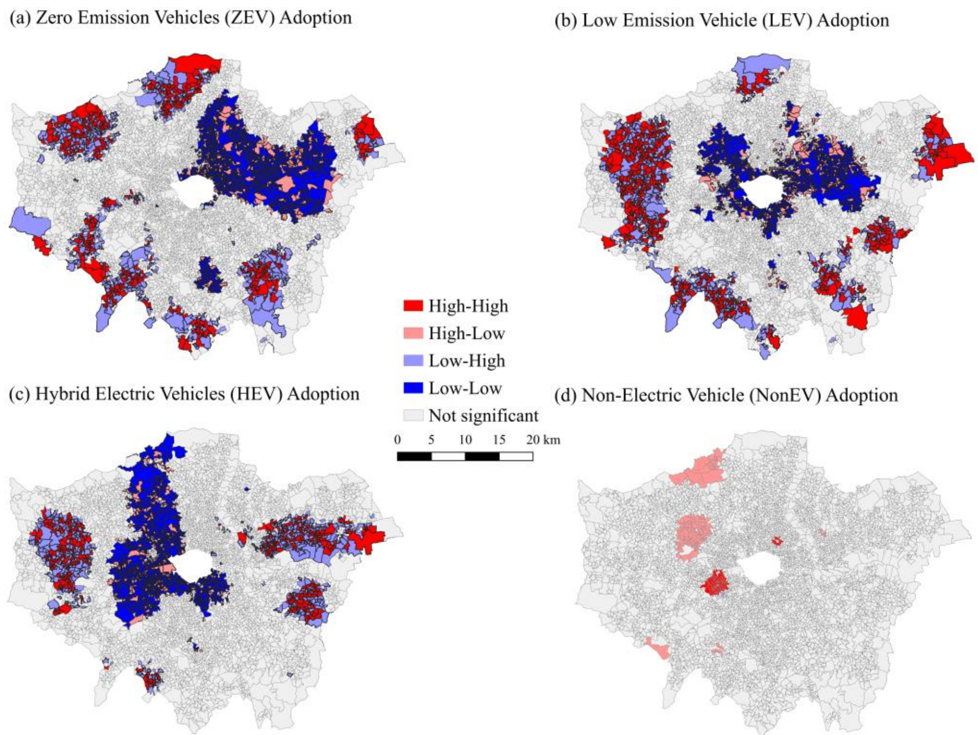

Fig. 3. LISA cluster map for the average change in different types of vehicle adoption across 2021

3 Empirical Strategy

3.1 Model specification

(1) Basic DID

This paper uses the Difference-in-Difference (DID) method to assess the impact of ULEZ on electric vehicle adoption. The DID model compares changes between a treatment group and a control group before and after the policy. Here, the dependent variable is the quarterly change in the share of electric vehicle adoption, including Zero Emission Vehicles, Ultra Low Emission Vehicles, and Hybrid Electric Vehicles.

Focusing on the first ULEZ expansion to inner London on October 25, 2021, this study covers the period from Q1 2020 to Q4 2022, avoiding the initial implementation and the second expansion to outer London. The study area is Greater London, analyzed at the LSOA level. Central London is excluded due to its unique Congestion Charging Policy. The Basic Model is shown below:

$$\Delta \mathrm{EVA}_{it} = \alpha_n + \alpha_0 X_{it} + \beta \mathrm{ULEZ}_{it} + \epsilon_{it} \tag{1}$$

Where ΔEVA_{it} is the change in the share of electric vehicle adoption in LSOA *i* across Quarter *t*. ULEZ_{it} is an indicator that LSOA *i* is in the 2021 ULEZ. α_n is the year fixed effect, which controls for time-variant factors affecting all LSOAs equally at year n. X_{it} represents a set of control variables regarding the varying abilities and willingness for electric vehicle adoption across different regions, which will be detailed in the next section.

(2) Spatial spillover

Based on the descriptive statistics mentioned earlier, it is evident that in Greater London, EVA growth was affected regardless of being inside or outside the ULEZ. Therefore, this section's regression analysis further incorporates the policy's spatial spillover effects from three alternative perspectives.

(i) Distance decay

$$\Delta\text{EVA}_{it} = \alpha_m + \alpha_0 X_{it} + \beta\text{ULEZ}_{it} + \gamma\text{Distance}_i + \epsilon_{it} \tag{2}$$

The regression estimation here is based on the assumption that the policy spillover decays with distance outside the boundary (Morton and Craig, 2017). It uses the shortest distance from the centroid of each LSOA outside the policy boundary to the boundary line, which is set to zero for areas within the policy boundary.

(ii) Spatial interaction

$$\Delta\text{EVA}_{it} = \alpha_m + \alpha_0 X_{it} + \beta\text{ULEZ}_{it} + \gamma_t\text{ShareDriveULEZ}_{it} + \epsilon_{it} \tag{3}$$

Merely considering the spatial proximity of the policy might be insufficient, as the real impact of the ULEZ policy on EVA outside the boundary should be based on the proportion of residents driving to inner London, who must consider switching to new electric vehicles to avoid daily commuting charges. Here, I use $\text{ShareDriveULEZ}_{it}$, which is the share of residents in an LSOA *i* area driving to workplaces located in the ULEZ (weighted by the number of vehicles in the household), to represent this spatial interaction. This is achieved by calculating the origin-destination workplace flow data from the 2021 UK Census data.

(iii) Spatial autocorrelation

$$\Delta\text{EVA}_{it} = \alpha_m + \alpha_0 X_{it} + \beta\text{ULEZ}_{it} + \gamma W\Delta\text{EVA}_{jt} + \epsilon_{it} \tag{4}$$

The occurrence of spatial autocorrelation in the dependent variables can indicate the presence of spatial dependence regarding the phenomenon being evaluated. In the context of policy spatial spillover, SAR (Spatial Autocorrelation Regression) models specifically capture the spatial correlated effects between adjacent areas inside and outside the policy boundary. Here, I primarily use the inverse distance weighting method with a threshold of 5 km and the Rook-contiguity method to define neighborhood relationships for constructing the spatial weight matrix W.

(3) Region-pair fixed effect

Region-pair fixed effects address unobserved heterogeneity over time between specific region pairs that might otherwise bias the estimates. I created 2 km buffer zones extending from the 2021 ULEZ boundary until covering all of Greater London. Then, I divided the region into 10 equal wedge-shaped sectors centered on the ULEZ. The intersection of these wedges with the buffer zones formed 100 annular sectors (Figure 4). LSOAs within the same sector share the same region ID. These sector pairs account for radial and directional heterogeneity in urban development related to socio-economic and infrastructural characteristics, as validated by Tang (2016).

$$\varDelta \text{EVA}_{it} = (\pi_k \cdot \alpha_m) + \alpha_0 X_{it} + \beta \text{ULEZ}_{it} + \gamma_t \text{ShareDriveULEZ}_{it} + \gamma W \varDelta \text{EVA}_{jt} + \epsilon_{it} \quad (5)$$

Where $\pi_k \cdot \alpha_m$ is the interaction item of the region-pair fixed effect π_k and Year fixed effect, allowing for the capture of spatiotemporal heterogeneity. This model retains the terms related to spatial interaction and spatial autocorrelation mentioned earlier.

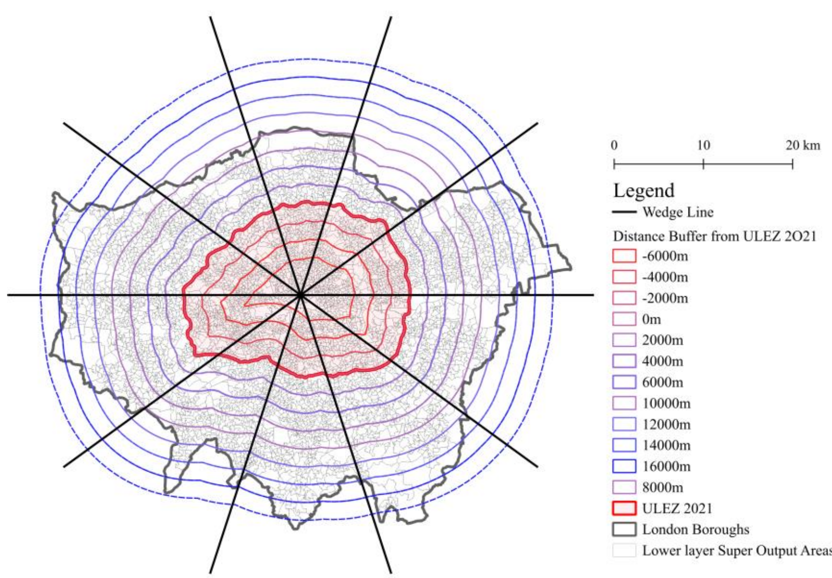

Fig. 4. Region-pair sectors divided by buffers and wedge lines

3.2 Control variables

To improve the accuracy of the estimation, I selected a range of time-variant and time-invariant control variables from the aspects of transportation, land use and socio-economics, which have been confirmed to be correlated with EVA (Morton et al., 2017).

(1) Transportation

Charging station density (*CS*): The availability of electric vehicle charging stations in an area can be a key factor in deciding whether to purchase an EV by residents (Peters et al., 2021). I used amenity=charging_station as the search criterion to retrieve OSM historical data from each quarter between 2020-2022 and calculated the density of charging stations at the LSOA level.

Private charging availability (*PriCS*): Residents who own private garages in their homes are more likely to install home charging facilities, thus purchase electric vehicles (Pamidimukkala et al., 2023). I calculated the number of detached houses with private garages divided by all types of dwellings in UK Dwelling type data as an estimate.

Public transport substitution: Commuters may also substitute towards public transport in response to the tax on highly polluting vehicles (Schneebacher et al., 2024). I use highway=bus_stop, amenity=bicycle_rental, and public_transport=station as the search criterion to retrieve the OSM historical data respectively, and calculated Bus stops density (*BS*), Bicycle stations density (*ByS*) and Proximity to transit stations (*ProxStn*).

(2) Land Use

Residential Density (*ResiD*): High-density residential areas may have higher private electric vehicle demand. I calculated number of households per kilometer at the LSOA level using UK Census data.

Commercial Density (*CommerD*): High-density commercial areas may have higher business electric vehicle demand. I use building=commercial as the search criterion to retrieve the OSM historical data.

(3) Socio-economics

The studies by Liu et al. (2017) indicate that variables such as Age group (*Age*), Education level (*HighEdu*), Occupation class (*Occup*), Population density (*PopD*) and Unemployment rate (*Unemp*) are effective in explaining variations in EVA.

4 Regression Results

The regression results from a series of DID models in table 1 show varying ULEZ policy effects on ZEVs adoption across different model specifications. In the Basic DID Model, ULEZ_{it} has a significant negative effect (-0.007, $p < 0.001$), which contradicts our initial hypothesis. However, when control variables (model 2) and region-pair fixed effects (model 6) are included, the impact of ULEZ_{it} diminishes in both magnitude and significance until non-significant. This suggests that the effects previously captured are likely attributed to dynamic regional heterogeneity rather than the ULEZ policy itself.

Introducing distance decay (models 3) and spatial interaction terms (models 4) does not substantially change the influence of ULEZ_{it}. Thus, the assumption that the ULEZ policy's impact spills over in these two specific patterns beyond the boundary is at least not supported within Greater London.

The consistently significant control variables shown in table across different models emphasize their importance in explaining the dependent variable's variance. The coefficient for $Occup_i$ (the percentage of higher-level occupations) is 0.037 ($p < 0.001$). This means that for each 1 percentage point increase in the proportion of higher-level occupations, the change in ZEV adoption increases by 0.037 percentage points. This suggests that areas with a higher proportion of residents in higher-level occupations are more inclined to adopt zero-emission vehicles, likely due to higher income levels and greater environmental awareness.

The spatial lag term of the dependent variable, derived from the inverse distance weighted spatial weighting method in model 3, has a higher effect and significance level compared to the Rook adjacency method. This may be because the spatial autocorrelation of EVA extends beyond just adjacent areas. It consistently shows strong significance in models 5 and 6, indicating that the growth in electric vehicle adoption in one area is influenced by the growth in neighboring areas. This partially explains why areas outside the ULEZ boundary also experienced significant increases in electric vehicle adoption following the policy implementation.

Overall, the low but improving R-squared values in more complex models and the consistently significant F-statistics suggest that while the models are robust, the policy's impact is nuanced and highly dependent on model specifications.

Table 1 Effects of ULEZ Policy Across Different DID Models

	(1) Basic DID Model	(2) With Control	(3) Distance Decay	(4) Spatial Interaction	(5) Spatial Autocorrelation	(6) Region-pair Fixed Effect

ULEZ	-0.007***	-0.005*	-0.005*	-0.004	-0.005*	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
BS		0.00004	0.00004	0.00005	0.00001	0.00001
		(0.00003)	(0.00003)	(0.00003)	(0.00003)	(0.00003)
Distance			-0.00003			
			(0.0003)			
ShareDriveULEZ				-0.002		
				(0.002)		
DeltaZEV_lag_d					0.314***	0.329***
					(0.042)	(0.041)
Occup		0.038***	0.038***	0.038***	0.037***	0.037***
		(0.010)	(0.010)	(0.011)	(0.010)	(0.010)
PopD		-0.00000**	-0.00000**	-0.00000**	-0.00000***	-0.00000***
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
factor(Year)2021	0.012***	0.012***	0.012***	0.012***	0.008***	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
factor(Year)2022	0.011***	0.010***	0.010***	0.010***	0.008***	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Controls	NO	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YSE	NO
Region-pair FE × Year	NO	NO	NO	NO	NO	YES
Observations	53,405	51,557	51,557	48,708	51,557	51,502
R^2	0.002	0.005	0.005	0.005	0.006	0.006
F Statistic	30.916***	14.985***	14.197***	13.533***	17.200***	16.102***

*p**p***p<0.001

Table 2 further compares the estimated results for different vehicles, considering all variables included in the regression. Unlike the regression estimates for ZEVs, even with the addition of region-pair fixed effects, ULEZ_{it} still exerts a significant negative effect on the growth in the share of LEV and HEV, with coefficients of -0.013 and -0.009 respectively, but the lower uptake of hybrids in inner London should be understood in the context of the higher uptake of ZEVs. The ULEZ policy and a series of variables had no significant impact on NonEVs, likely because the share of petrol and diesel vehicles in London has gradually become negligible and stabilized.

In the models where different types of electric vehicles are used as dependent variables, specific control variables, spatial lag terms, and region-pair fixed effects consistently remain statistically significant. These findings underscore the importance of accounting for regional heterogeneity and spatial dependencies when evaluating the effectiveness of such environmental policies.

Table 2 Effects of ULEZ Policy on the adoption of different electric vehicles

	DeltaZEV	DeltaULEV	DeltaHEV	DeltaNonEV
	(1)	(2)	(3)	(4)

ULEZ	-0.002 (0.002)	-0.012*** (0.003)	-0.009*** (0.003)	-0.00003 (0.0002)
Occup	0.038*** (0.011)	0.057*** (0.017)	0.011 (0.015)	-0.0002 (0.001)
ShareDriveULEZ	-0.003 (0.002)	0.0005 (0.004)	0.001 (0.003)	0.0001 (0.0002)
Distance	-0.0001 (0.0003)	0.0004 (0.0005)	0.0003 (0.0004)	-0.00001 (0.00003)
DeltaZEV_lag_d	0.305*** (0.042)			
DeltaULEV_lag_d		0.232*** (0.045)		
DeltaHEV_lag_d			0.180*** (0.047)	
DeltaNonEV_lag_d				0.041 (0.048)
RegionID:factor(Year)2020	-0.0001** (0.00002)	-0.00002 (0.00004)	0.00002 (0.00003)	-0.00000 (0.00000)
RegionID:factor(Year)2021	0.00005* (0.00002)	0.0001*** (0.00004)	0.00004 (0.00003)	-0.00000 (0.00000)
RegionID:factor(Year)2022	0.00001 (0.00002)	-0.00003 (0.00004)	-0.0001* (0.00003)	-0.00000 (0.00000)
Controls	YES	YES	YES	YES
Region-pair FE × Year FE	YES	YES	YES	YES
Observations	48,708	48,708	48,708	48,708
R^2	0.006	0.004	0.004	0.0002
F Statistic	13.525***	9.891***	8.981***	0.338

*p**p***p<0.001

5 Conclusion and Discussion

This study examines the impact of ULEZ on the growth of electric vehicle adoption, using the 2021 inner London Boundary to distinguish between the treatment and control groups. I additionally employed variables based on distance decay, spatial interaction and spatial autocorrelation to capture the policy’s spatial spillover patterns. I constructed wedge-shaped urban sectors, which effectively account for radial and directional heterogeneity in urban spatial development, offering an improvement over conventional area fixed effect.

Regression results indicate that the effect of the ULEZ policy is insignificant after conducting region-pair fixed effects, suggesting that the policy's impact on EVA growth shows no significant difference within and outside the regulation boundary, at least not within Greater London. Additionally, Although the synchronized growth of electric vehicle adoption rates inside and outside the boundary after the policy might suggest spatial spillover effects, the model's insignificant related variables indicate that these spillover effects are more likely due to complex socio-economic factors and transportation infrastructure rather than just spatial distance decay or commuting patterns. The identification issues related to the insignificant positive effects of the ULEZ policy in this study may stem from the following points:

(1) Anticipatory Effects: Anticipation of the ULEZ policy might have prompted individuals to switch to compliant vehicles before its official start, slowing EV adoption growth afterward and complicating policy effect identification.

(2) Spillover Effects: The design assumes areas within the boundary as the treatment group and those outside as the control group. However, socio-economic interactions in Greater London cause inevitable spillover, biasing results by diluting the estimated effect due to positive spillover.
(3) Spatial and Temporal Context: Outer London's higher car dependency and limited public transport could lead to a stronger response to the ULEZ policy. The study period also overlaps with early 2021's severe COVID-19 impact, which increased telecommuting and reduced travel, potentially limiting the policy's observed effects.

Due to the influence of these complex factors, the insights provided by this study are limited. Future research on such topics could employ Staggered DID to handle multi-period data and use more advanced methods like Propensity Score Matching to match similar individuals and reduce the impact of confounding variables.

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