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The impact of the ultra-low emission zone on high streets economy and social equality in Outer London

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ABSTRACT

Many cities are adopting transport policies that regulate vehicle emissions, informed by policy impact assessments primarily focused on traffic, air pollution, and public health. However, few studies have explored the broader economic effects of such restrictions, particularly their impact on travel behaviour and local commerce. Understanding these dynamics is crucial for balancing economic development with sustainable urban planning. This study introduces a novel Spatially Robust Interrupted Time Series (SRITS) model to assess the causal impact of the ULEZ expansion on visitation to local high streets in Outer London. Specifically, we quantify the policy's effects on social equity by incorporating local socio-economic factors. Our findings reveal that the ULEZ expansion led to increased footfall on local high streets, particularly in deprived areas, where the policy may have heightened reliance on nearby commercial hubs. Additionally, we found that the composition and scale of high streets may have significantly influenced their resilience and economic vitality. These insights contribute to a deeper understanding of how sustainable transport policies intersect with urban economic development.

1. Introduction

According to the World Health Organization (WHO), air pollution currently poses the most significant global environmental health risk. To tackle the increasing concerns about air pollution and its impacts on public health and ecological systems, many cities are adopting transport policies that consider vehicle emission levels as a common strategy (Prieto-Rodriguez et al., 2022), for example, low emission zone (LEZ) policies have been implemented mostly in Europe when there were 320 of them in 2022 (Clean Cities Campaign, 2022), including Madrid (Peters et al., 2021), Paris (Poulhès and Proulhac, 2021), and London etc. London has effectively implemented several policies. These include the Congestion Charge Zone in 2003, the Low Emission Zone in 2008, the Toxicity Charge in 2017, and the Ultra Low Emission Zone in 2019 (C40 Cities Climate Leadership Group, Greater London Authority and C40 Knowledge Hub, 2024).

In our case study city, London, during the second expansion of the Ultra Low Emission Zone (ULEZ), which extended its boundaries to include most of Outer London, the area was simultaneously grappling with its distinct socio-economic challenges. Boris Johnson's 2008 mayoral campaign team highlighted that the needs of Outer London's suburban areas, home to a significant portion of the city's population, had been largely overlooked, a point noted by Goevert and Towle (2020). ULEZ was proposed as part of the broader strategic planning framework outlined in the 2016 London Plan, released in March 2016 by the Mayor of London (Greater London

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Authority, 2016). The Plan provides guidance focusing on rejuvenating the local economy, enhancing the vibrancy of town centres, and identifying and alleviating pockets of deprivation as key economic strategies for Outer London.

While most research on impact analysis in terms of ULEZ reasonably focuses on human health and active transport (Prieto-Rodriguez et al., 2022; Ding et al., 2023), which often lack an examination of the interplay between spatial and social factors, few studies have explored the potential negative effects of restricted transport policies on economic activities. However, understanding how these changes are distributed across high streets (i.e., the primary commercial streets in the UK) with different socio-demographic groups warrants further investigation, especially in urban contexts like Outer London, where policy effects may vary considerably across different high streets due to differing demographic and economic conditions. This helps to reveal the potential risks and benefits of policy implementation, as well as the underlying mechanisms linking transport policies with socio-spatial dynamics. Such insights can inform policymakers about when and where specific interventions are most likely to support local economic development. Moreover, identifying variations in policy effects can highlight the disproportionate burdens faced by disadvantaged groups, thereby helping to address social equity issues (Gozzi et al., 2021).

However, commonly used methods for identifying the causal impact of transport interventions, such as Difference-in-Differences (DiD), Propensity Score Matching (PSM), and Spatially Interrupted Time-Series (SITS), each have notable limitations. DiD may conflate immediate level changes with long-term trend shifts, potentially oversimplifying complex policy effects. PSM often struggles to achieve adequate covariate balance especially in complex urban transport environments such as London. Meanwhile, SITS is vulnerable to time-varying confounders and simultaneous external events, which can threaten internal validity.

Against this backdrop, this paper aims to fill the knowledge gap by investigating the causal impact of the second expansion of the ULEZ on the vitality of Outer London's high streets. This study makes three key contributions. First, it sheds light on the dynamic interplay between transport interventions and local economic activity, which addresses the study gap in prior studies. Second, it leverages high-resolution footfall data (i.e., a proxy for pedestrian volume), an emerging human mobility data to capture the causal change of ULEZ, whereas most studies utilised compliance data, air quality data, and health data (Greater London Authority, 2023; Zhai and Wolff, 2021; Xiao et al., 2024). Third, it applies the Spatial Robust Interrupted Time Series (SRITS) approach, an innovative model that accounts for both temporal and spatial independencies to investigate changes in visitation numbers and examine potential socio-economic factors contributing to those changes.

2. Literature review

2.1. Impact analysis of the ultra-low emission zone

Most previous research concerning the causal impact of ULEZ or relevant transport policies primarily concentrates on the policy's primary objective: reducing air pollution, changes in travel behaviour and the resultant health benefits for residents. For instance, Zhai and Wolff (Zhai and Wolff, 2021) quantified the effectiveness of London's LEZ in reducing its target pollutant, PM10 and the reasons behind the disparity which is the changes in traffic volume. Prieto-Rodriguez et al. (Prieto-Rodriguez et al., 2022) carried out a quantitative analysis to assess the effectiveness of the ULEZ in reducing NO_2 levels. It has also been proven that the implementation of ULEZ can encourage the transition to green transportation modes, stimulating the bicycle demand within the zone (Ding et al., 2023). These findings are derived from causal inference methods, predominantly Difference-in-Differences (Diff-in-Diff) models. There has also been an overall reduction in vehicles seen driving in the zone (Greater London Authority, 2023).

While researchers focus more on the topics mentioned above, the economic impact of the policy has received little attention. Of the limited studies available, most have investigated the macroeconomic effects of ULEZ, such as the overall socio growth resulting from cleaner air and the living costs associated with ULEZ's charging regulations (Jansen, 2021). Additionally, some researchers have identified significant potential costs for small businesses and residents living within or near the boundary of the restricted zone, as their lives rely on light goods vehicles and cars, which are strictly regulated (Bailey, 2017).

Researchers have rarely focused on the economic impact of ULEZ on the performance of high streets and the perspective of consumer behaviour. Taylor (2020) documented for the Lambeth Council that interventions like the Streatham Hill Low Traffic Neighbourhood reduced traffic and enhanced business footfall by creating more attractive street environments and additional operational space, thereby boosting retail sales. Similarly, Tarriño-Ortiz et al. (2023) investigated the effects of LEZ in Madrid Central through retailers and consumer surveys. Their findings indicated that 38.17 % of respondents believed traffic restrictions could reduce their inclination to shop in the city centre, potentially decreasing sales, while 34.92 % felt shopping activity would increase due to safer and cleaner roads. However, the survey's ambiguous results may reflect social desirability bias, where respondents provide socially acceptable rather than authentic answers.

It is worth noting that, during the first month after the second expansion of ULEZ, the compliance rate for vehicles that met the ULEZ standards London-wide shows a 3.7 per cent increase from 91.6 per cent in June 2023 (Greater London Authority, 2023), which is a lighter shift compared to a 6.7 per cent increase after the second expansion. This relatively small change implies that the magnitude of observed change may be moderate in some neighbourhoods, as the expansion would not significantly alter residents' travel behaviour who already operate compliant vehicles.

2.2. High street vitality

In Britain, the term "High Street" is typically characterised as the main commercial street (or streets) within towns or cities, commonly viewed as a town or city centre location and a hub for shops and retail activities (Carmona, 2015), as well as places where varied individuals and communities interact (Hall, 2011). High streets today are increasingly facing challenges to their vitality and viability (Griffiths et al., 2008; Parker et al., 2016), due to technological advancements, social change, and the COVID-19 pandemic, with over 17,500 chain stores closing and footfall declining by over 80 % (Wang et al., 2023). Despite this, high streets remain vital community hubs, offering opportunities for regeneration that could benefit the entire community (Goevert and Towle, 2020). Revitalising these spaces has thus become a pressing priority.

Although the performance of town centres involves complex and multifaceted concepts, there are still some measurements that can capture the dynamic activity in high streets and serve as a dependable surrogate for evaluating performance in current studies. As Parker et al. (2016) note, footfall serves as – to use the Department for Business Innovation & Skills's (Department for Business, Innovation and Skills, 2011) terminology – a metric for gauging the vitality of a commercial centre or high street and acts as an indicator of potential consumer spending. It is also acknowledged in policy and planning as a crucial indicator of a town centre's vitality and viability (DoE, 1996, as cited in Mumford et al., 2021). Along similar lines, this paper views footfall as a key measure of high street vitality and, consequently, an indicator of the impact of ULEZ policy.

It is proved that footfall patterns are shaped by a variety of factors across different levels: at the national level, by government policies; at the town centre level, by pre-existing trends, characteristics of the town centres, and seasonal effects; and at the personal level, by demographic profiles and individual experiences (Enoch et al., 2022). Enoch et al. have observed that the footfall recovery rate after the first wave of coronavirus in town centres may be influenced by differences in population profiles and scale of town centres. Wang et al. (2023) found the resilient performance of high streets after the pandemic varies between regions, highlighting the spatial heterogeneities among policy effectiveness and the importance of community engagement in the recovery. Also to support urban regeneration, Parker et al. classified the top 25 prioritized factors to improve the vitality and viability of high streets (2016), where necessities, place marketing and entertainment, etc., are indicators that have the most impact on high street's vitality and viability. Emergent critical literature has focused on understanding the dynamic activity of high streets after interventions, but no transport policy has been explored under this context.

2.3. *Social inequality in transport policy*

It is found that early in the 2000s, UK academics and policymakers started exploring the relationships that policy between poverty, transport disadvantage and social exclusion (Lucas, 2012). Numerous studies have highlighted how transport and spatial disadvantages collectively reinforce social inequality. For example, situations like road deaths and air pollution that happen to deprived groups, which are brought by living near busy roads and having non-car-based travel patterns, can be interpreted as social inequality (Titheridge et al., 2014). More studies proved that European LEZs policy does not benefit the most deprived neighbourhoods as they are commonly found near freeway rings which are the most polluted areas (Charleux, 2014). This highlights the social inequality exacerbated by mobility policies due to the existing spatial disadvantages. Transport systems can also negatively impact the quality of life by shaping spatial patterns that exacerbate inequalities between affluent and disadvantaged communities, even when regulations are effective in certain aspects (Allsop, 1980).

In addition to worsening existing social inequalities by reinforcing spatial disadvantages, traffic restriction policies can also exacerbate transport disadvantages, further deepening social inequality. Inequality exists between car owners and non-car owners. It is evident that increasing car ability in the UK has allowed citizens to travel far greater distances and supports more activities. However, this situation discouraged the viability of other transport modes and played a role in the inequality of already deprived groups in the UK population (Lucas, 2012; Lucas, 2006).

Inequality also exists within the car-owning group itself. For example, research has found that LEZ policy appears to be associated with higher proportions of non-compliant vehicles in lower-income areas (Verbeek and Hincks, 2022), where paying fines for non-compliant vehicles or replacing vehicles inadvertently increases the financial burden on deprived communities. The 2010 UK National Travel Survey (NTS) identifies that 53 % of households in the highest income quintile owned two or more cars, while only 12 % of households in the lowest income quintile had the same level of car ownership, also demonstrating an obvious private transport disadvantage in lower income groups. According to Farrington (Farrington, 2007), if a person or household is not able to use their car due to limited accessibility brought by mobility restrictions, their levels of life opportunities are constrained consequently, potentially hindering social equality.

Overall, it is unjust to deprive residents of the ability to drive to essential services located far away, without providing viable local businesses within accessible distances on nearby high streets, as in global initiatives such as the Sustainable Development Goals, C40 Cities, and WHO Healthy Cities, urban equity has become a policy priority for many cities worldwide (Suel et al., 2024). Ensuring equal opportunities and reducing the inequalities caused by discriminatory policies are also key objectives of the 2030 Agenda for Sustainable Development. In this context, it is essential to assess the inequitable conditions in deprived areas of Outer London after ULEZ.

2.4. *Causal inference in transportation research*

Most relevant transportation research adopts Difference-in-Differences (DiD), Propensity Score Matching (PSM) and Spatially Interrupted Time-Series (SITS) to identify causal effects of transport interventions in terms of travel behaviour patterns (Zhou et al., 2024; Wang and Zhong, 2025). For example, Deng and Zhao (2022) applied DiD to study the impact of the new metros on travel behaviour, where the infrastructure development is considered an external intervention. Ding et al. (2023) utilised PSM to evaluate the effect of ULEZ on the demand for public bike sharing in London. The Spatially ITS (SITS) model is among the first to be introduced by Zhang and Ning's study to detect changes in human mobility following the COVID-19 outbreak (2023), whose key concept is that it not only reveals the temporal heterogeneities but can also capture the spatial heterogeneities. It is then applied in a recent study to estimate the 2021 ULEZ expansion's impact on London's travel behaviour (Wang and Zhong, 2025).

However, these methods present notable limitations. The DiD treats the average level of change post-interrupt as the only treatment effect, without adequately distinguishing between changes in level and trend over time (Zhang and Ning, 2023) and focuses on measuring only the difference in means between groups (Warton, 2020). The PSM, on the other hand, is challenging to achieve sufficient covariate balance across spatially and contextually diverse regions, particularly in complex urban transport environments such as London (Wang and Zhong, 2025; Greater London Authority, 2021).

Although SITS presents its advantage of evaluating the value of the sudden level change as well as the slope difference before and after the interruption without a reference group, similar to its fundamental model, ITS (Warton, 2020). It is likely to be affected by time-varying confounders, which cause the issue of poor internal validity (Lopez Bernal et al., 2018; Warton, 2020). It also places high demands on data availability, as it relies on individuals' behavioural outcomes before the intervention to establish an underlying trend that serves as the counterfactual scenario (Wang and Zhong, 2025; Linden, 2015).

3. Research materials

3.1. Study area

This research analyses the second expansion of ULEZ in London. The Ultra Low Emission Zone (ULEZ) was initially launched on 8 April 2019 towards Central London, with two expansions on 25 October 2021 towards Inner London and 29 August 2023 towards most of outer London to reduce emissions from most polluting vehicles further, as illustrated in Fig. 1(a). The ULEZ zone, after the second expansion, covers the London-wide area and operates 24 h a day, every day of the year except Christmas Day (Greater London Authority, 2023). Any vehicles that do not meet the ULEZ emissions standards and aren't exempt need to pay a £12.5 daily charge to drive within the zone.

We focus on the changes of visitation to 419 high streets in Outer London within the second expansion area of ULEZ, shown in Fig. 1 (b) by yellow areas. It can be seen clearly that high streets are urban corridors, stretching for many miles along key routes through urban areas (Carmona, 2015). Each high street has its unique growth environment, collectively contributing to the complex and vibrant landscape of London's high streets.

As noted by the one-year report on the Inner London Ultra Low Emission Zone (2023), the traffic level of outer London has primarily rebounded to the pre-pandemic level. The whole period of the study will be after the COVID-19 restrictions ended on 19 July 2021 (Institute for Government analysis, 2022) to avoid being affected by it. As shown in Fig. 1(c), there were no other major concurrent transport policies overlapping with the second ULEZ expansion, which ensures the validity of applying our approach. Additionally, the power of the base causal inference model we used increases with larger sample or effect size, balanced numbers of study periods pre- and postintervention and at least 24 daily data points (12 before and 12 after) to ensure reliable estimates (Dorais, 2024).

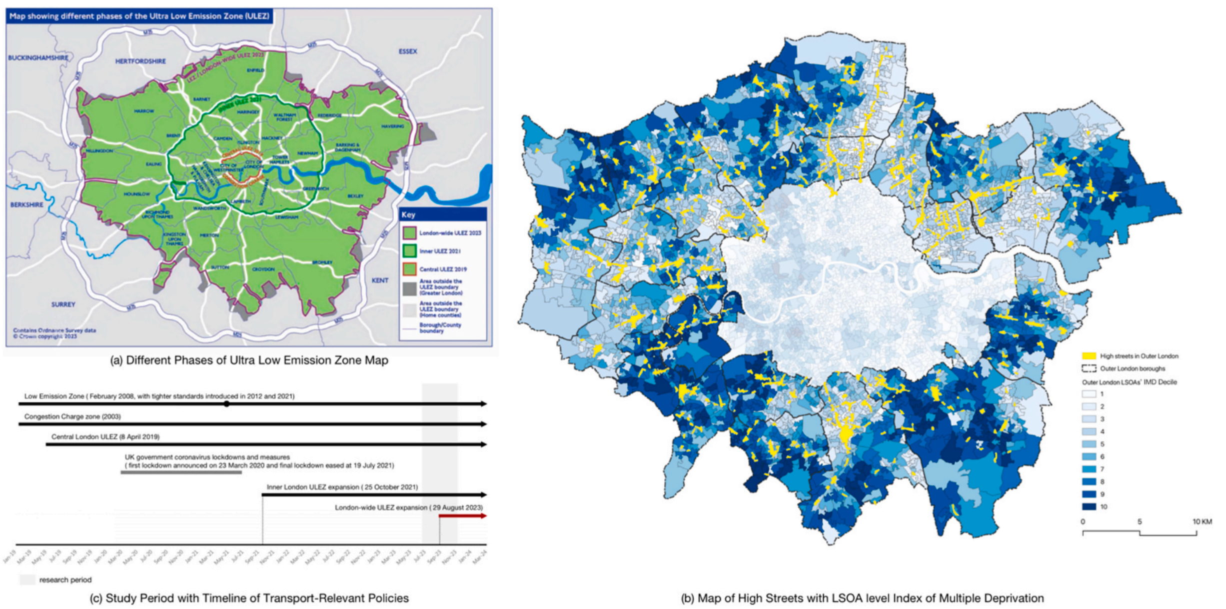

Fig. 1. (a) Different phases of Ultra Low Emission Zone map (Map sourced from: Greater London Authority, 2023), (b) map of high streets with LSOA level index of Multiple Deprivation, (c) Study period with timeline of transport-relevant policies (Data sourced from: Greater London Authority, 2023; C40 Cities Climate Leadership Group, Greater London Authority and C40 Knowledge Hub, 2024; Institute for Government analysis, 2022).

Thus, this paper will utilise 8 weeks of daily data points from both before and after the intervention, which took place on 29th August 2023 and was benchmarked to the same period in 2022. This approach also helps the study avoid unnecessary impacts from other transportation policies or COVID restrictions (Nguyen, 2020).

Theoretically, if the second ULEZ expansion achieves its goal of restricting vehicle usage and encouraging a shift toward more active travel modes (Greater London Authority, 2023), a rise in short-distance or neighbourhood-level travel activity could be expected. This is because people who previously drove for shopping or leisure purposes may shift their travel behaviour, such as adjusting their destinations to more accessible, walkable local high streets, as a response to the restrictions. As a result, local high streets in Outer London may experience an increase in pedestrian volume.

3.2. Data

This study utilises fine-grained spatial and temporal data, enhancing the ability to discern spatiotemporal heterogeneity in the causal effects of ULEZ intervention. As illustrated in Table 1, this research is supported by five datasets under two main aspects: high street footfall data and socio-spatial data.

This study mainly uses visitors' footfall data from the Greater London Authority (GLA), provided by British Telecom (BT), which aggregates and anonymises counts of individuals spending over 10 min in each hex grid across London at 3-hour intervals daily to analyse pedestrian volume. To represent daily pedestrian volume, we average the eight 3-hour counts for each day into a single metric, referred to as "visitation". Additionally, to figure out the socio-spatial features underlying the impact of ULEZ, the English Indices of Deprivation (IMD) 2019 and Premises Data were chosen for the second-level model. The former dataset contains the Index of Multiple Deprivation (IMD), a comprehensive measure of relative deprivation at the LSOA level, constructed by combining seven domains of deprivation, each weighted accordingly. The premises dataset includes shop locations and their retail information, which is sourced from Experian's Business Data.

To identify the factors contributing to seasonality in visitor footfall, Fig. 2 aggregates daily 3-hour footfall counts, revealing a clear seasonal trend with noticeable drops in footfall during the summer months, likely due to holiday absence (Lai et al., 2022).

4. Methodology – Spatially Robust Interrupted Time-Series (SRITS)

This study aims to quantify the effects of the second expansion of ULEZ on the rejuvenation of the local economy and explore how these effects vary between the geographic hierarchy of different socio-economic components and built environment features.

4.1. Generic SRITS model structure

To address the methodological limitations highlighted in the literature review, this research develops a Spatially Robust Interrupted Time-Series (SRITS) model that builds on the Robust ITS method (RITS) (Warton, 2020), and further adapts the Spatially Interrupted Time-Series (SITS) approach (Zhang and Ning, 2023). This innovative model is based on the scenario that the effectiveness of a mobility policy is likely to vary between locations due to differences in local attributes, such as the built environment and social factors, rather than spatial relationships like distance or connectivity. It not only keeps the advantage of SITS, which is revealing the spatiotemporal heterogeneity at one framework (Zhang and Ning, 2023), but also addresses the poor internal validity limitation by incorporating RITS, which is also referred to as multiple-group ITS (Linden, 2015), or controlled (or comparative) interrupted time series (CITS) analysis (Lopez Bernal et al., 2018). It is an efficient way to minimise potential confounding from coinstantaneous events by including a control group (Lopez Bernal et al., 2018). Comparing the outcomes of the treatment group with control groups enables

Table 1
Data source and description.

Theme	Datasets	Spatial/temporal resolution	Notes	Data source
High street data	Footfall Data (BT)	350 m hex level/in each 3-hour period daily	counts by visitors, workers, residents	High Street Data Service by GLA[a]
	Spend Data (Mastercard)	150 m grid level/in each 3-hour period daily	total transaction count	High Street Data Service by GLA
Socio-spatial data	English Indices of Deprivation 2019	LSOA level	Statistics on relative deprivation	Ministry of Housing, Communities & Local Government[b]
	Premises Data (Experian)	Shop point with Goad location	Retail category	High Street Data Service by GLA
Geographic data	High Street Boundaries	/	/	London Datastore[c]
	Lower Super Output Area (LSOA) 2021	/	/	Office for National Statistics[d]

[a] https://data.london.gov.uk/high-street-data-service.
[b] https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019.
[c] https://data.london.gov.uk/dataset/gla-high-street-boundaries-map.
[d] https://geoportal.statistics.gov.uk/search?q=BDY_LSOA%20DEC_2021.

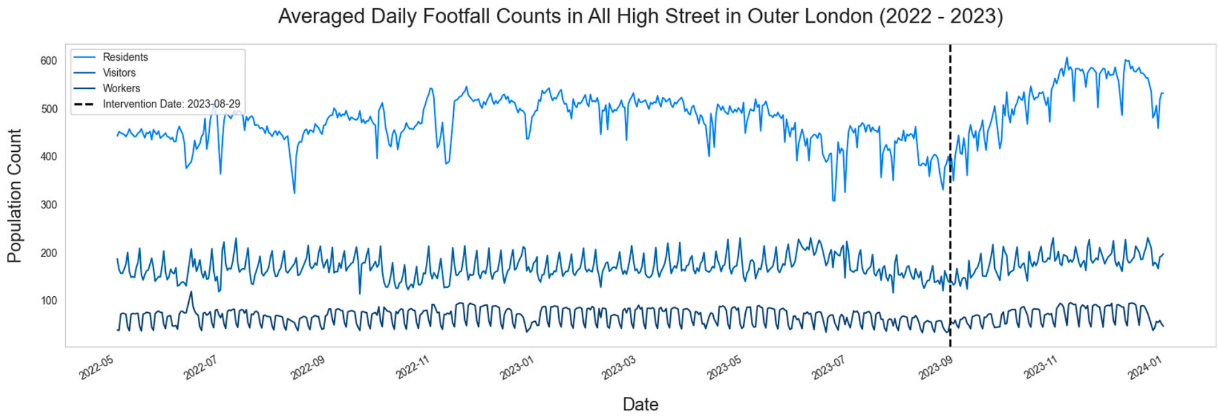

Fig. 2. Averaged daily footfall counts of all high streets in Outer London.

effective management of potential confounding variables that might otherwise be missed, thereby naturally enhancing internal validity (Linden, 2015).

Our SRITS model is implemented within a two-level framework. The first-level formulation estimates temporal causal changes among spatial units. These estimated coefficients—capturing both immediate and long-term effects in visitation—are then passed to the second-level model, which investigates how these temporal effects vary across different spatial units to capture spatial heterogeneity by modelling a linear regression with socio-spatial variables. This design is based on the concept of spatiotemporal heterogeneity in causal inference proposed by Zhang and Ning (2023), wherein the immediate and long-term effects of the policy intervention, as well as pre-intervention mobility levels, are moderated by spatial covariates (e.g., socio-economic characteristics) of each unit. Fig. 3 provides an overview of the relationships between the basic ITS, SITS, Robust ITS, and our proposed SRITS.

4.2. Demonstrating SRITS in ULEZ study

This section provides a detailed explanation of the multiple-level SRITS model used in this study, highlighting the model's key features and providing a detailed explanation of each variable used in the SRITS model, ensuring that future researchers can follow and replicate SRITS model.

4.2.1. Level 1 model specification

The level 1 model is a mixed-effects model which uses the observed daily visitor counts occurring in 237 high streets of 112 days as the dependent variable over time. Following the structure of Robust ITS outlined in Linden (2015), the equation can be written as:

$$\begin{aligned} Visitation_{it} = {} & \beta_{0i} + \beta_{1i}{*}Time_t + \beta_{2i}{*}Intervention_t + \beta_{3i}{*}Time_t{*}Intervention_t + \beta_{4i}{*}Exposed_t + \beta_{5i}{*}Exposed_t{*}Time_t \\ & + \beta_{6i}{*}Exposed_t{*}Intervention_t + \beta_{7i}{*}Exposed_t{*}Intervention_t{*}Time_t + \sum\nolimits_{k=1}^{6}\beta_{k+7}DayofWeek_{kt} + \varepsilon_{it} \end{aligned} \quad (1)$$

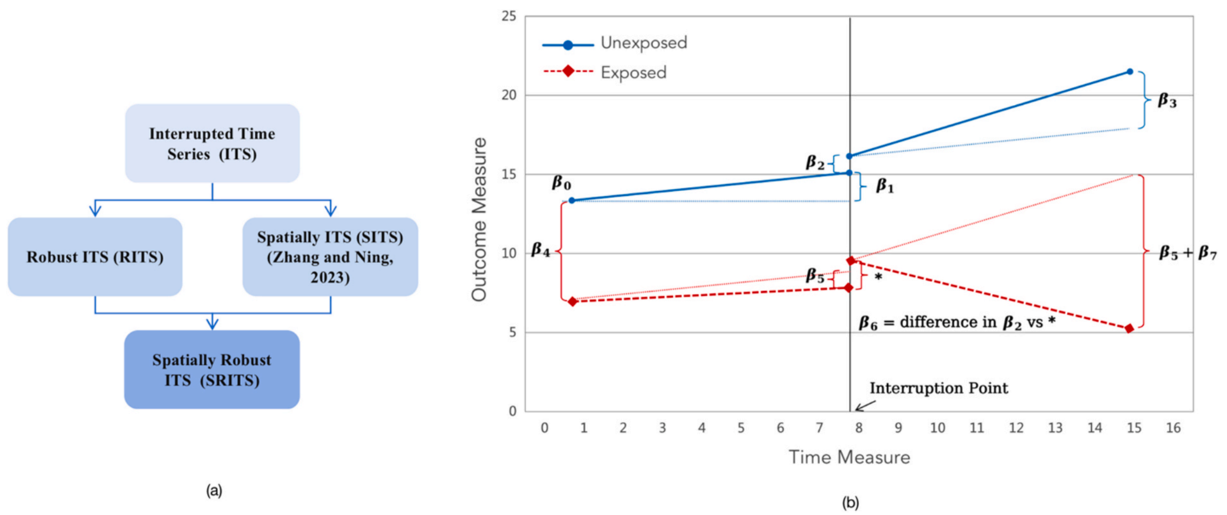

Fig. 3. (a) Relationship between ITS, SITS, RITS, SRITS (b) the fundamental ITS model – interrupted time series design with model coefficients.

Here $Visitation_{it}$ is the daily counts of visitors staying at least 10 min on the high street i ($i = 1, 2, \cdots, 237$) per 3 h on day t ($t = 1, 2, \cdots, 112$). $Time_t$ is the serial number for each day over the study period, which is equal to t on day t. $Intervention_t$ is an indicator variable of the ULEZ, which takes on a value of 1 from 29th August 2023 to 24th October 2023 ($t = 56 \sim 112$), and 0 otherwise, indicating that the data point falls outside the intervention period. *Exposed* is a binary variable indicating the treatment status, where $Exposed = 1$ for the ULEZ group (data from 2023) and $Exposed = 0$ for the control group (data from 2022). $Exposed_t{*}Time_t$, $Exposed_t{*}Intervention_t$, and $Exposed_t{*}Intervention_t{*}Time_t$ are additional interaction terms used in Robust ITS. $Exposed_t{*}Time_t$ functions similarly to $Time_t$, but specifically indicates the trend in treatment group post-ULEZ. $Time_t{*}Intervention_t$ is an interaction term that tracks the number of days since 29th August 2023. $Exposed_t{*}Intervention_t{*}Time_t$ exists for capturing the slope of visitation changes in high streets post-ULEZ expansion. It starts in the observation period immediately following the establishment of the ULEZ ($t = 56$) and runs sequentially until the last observation when $t = 112$.

β_{0i} and β_{1i} represents the level and slope of the counts before the intervention; which is the pre-ULEZ secular trend. β_{2i} represents the immediate jump in observed visitation counts at the point of intervention. β_{4i} captures the level difference in visitation counts between unexposed year and intervention year, while β_{5i} presents the variation in trajectory of visitation counts between 2022 and 2023 pre-intervention. β_6 represents the difference of change on the ULEZ expansion day between groups. β_{3i} reflects the change in slope after ULEZ in the control group, while β_{7i} captures the slope change in the treatment group relative to β_{3i}.

A series of confounders were also controlled in the Level 1 model. The *DayofWeek* dummy variables (with Friday as the omitted baseline) control for weekly seasonal patterns. Thus, β_8 through β_{14} are the coefficients for weekly seasonality and ε_{it} is the residual.

4.2.2. Level 2 model specification

Both the immediate effect (i.e., change in level) and the gradual effect (i.e., change in slope) of the ULEZ intervention, along with the footfall levels on the high streets prior to the policy, are influenced by the spatial context of the surrounding neighbourhoods. In this study, these contexts are considered to vary based on the deprivation levels within the communities and the condition of the high street premises.

Table 2
Summary of definition and notation for β_0 to ζ_{144}.

Level of model	coefficient parameters	Variable names	Definition
Level 1	β_0	Intercept	Initial level of pre-ULEZ counts in unexposed group
	β_1	Time	Slope of pre-ULEZ counts in unexposed group
	β_2	Intervention	Sudden change of counts in unexposed group when ULEZ interrupt
	β_3	Intervention*Time	Slope of post-ULEZ counts in unexposed group
	β_4	Exposed	Difference in level in exposed group compared to unexposed group pre-ULEZ
	β_5	Exposed*Time	Difference in slope in exposed group compared to unexposed group pre-ULEZ
	β_8	Mon	Effect of time-varying confounders on counts (treat Friday as baseline)
	β_9	Tue	
	β_{10}	Wed	
	β_{11}	Thu	
	β_{12}	Sat	
	β_{13}	Sun	
			Temporal heterogeneity in policy effects
	β_6	Exposed*Intervention	Difference of sudden change on counts due to ULEZ
	β_7	Exposed*Intervention *Time	Difference in slope between pre- and post-ULEZ in exposed group on counts
	$\beta_{14}(\beta_5 + \beta_7)$	Net Change	Net difference in slope between comparison groups on counts post-ULEZ
Level2			**Socio-spatial heterogeneity in high streets**
	ζ_{01}	IMD decile	Effects of socioeconomic and built facilities features on pre-ULEZ counts level (p = 0, α = 1)
	ζ_{02}	Leisure service	
	ζ_{03}	Convenience	
	ζ_{04}	Area (ha)	
			Spatiotemporal heterogeneity in gradual policy effects
	ζ_{141}	IMD decile	Effects of socio-economic and built facilities features on gradual counts change (p = 14, α = 1.5)
	ζ_{142}	Leisure service	
	ζ_{143}	Convenience	
	ζ_{144}	Area (ha)	
			Spatiotemporal heterogeneity in abrupt policy effects
	ζ_{61}	IMD decile	Effects of socio-economic and built facilities features on abrupt counts change (p = 6, α = 1)
	ζ_{62}	Leisure service	
	ζ_{63}	Convenience	
	ζ_{64}	Area (ha)	

In this scenario, the coefficients β_{0i} and β_{6i} from Eq. (1) are influenced by the socio-economic profiles of the high streets. $\beta_5 + \beta_7$ indicates the slope difference between comparison groups after interruption and is denoted by a new coefficient β_{14}. Due to the significant differences in scale between the variables, the level 2 model uses a log–log regression to avoid the model being dominated by extreme values and make the contribution of small and large values to the model more balanced. The corresponding functional

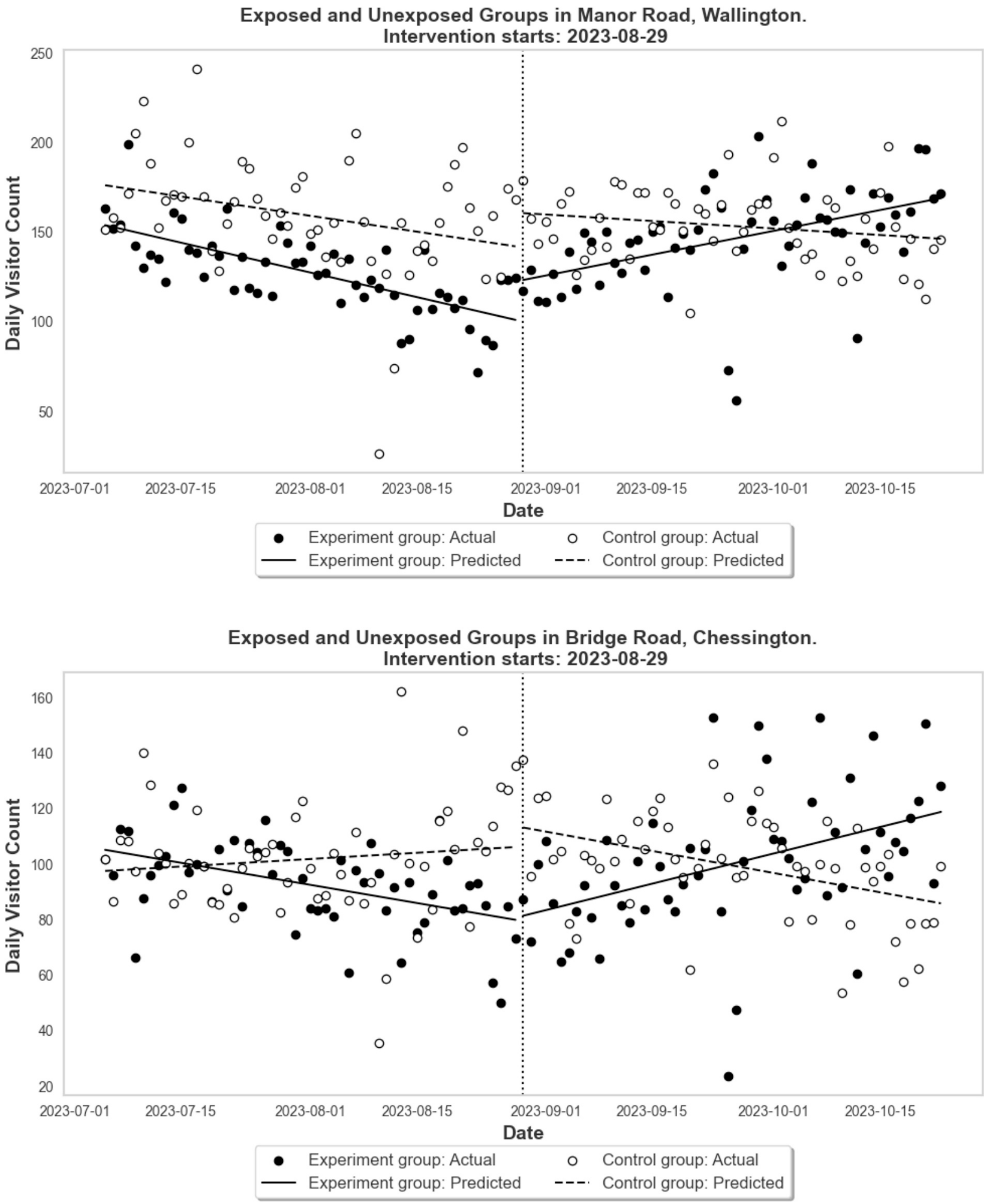

Fig. 4. Segmented regression plot of manor road high street (top) and bridge road high street (bottom).

relationships are provided by the level 2 model as outlined below:

$$\log(\beta_{pi}) = \zeta_{p0} + \zeta_{p1} * \log(IMD_i) + \sum_{k=1}^{3} \zeta_{p,k+1} * \log(Spatial_{ik}) + \gamma_{pi}, p = 0 \tag{2}$$

$$\log(\beta_{pi}) = \zeta_{p0} + \zeta_{p1} * \log(IMD_i) + \sum_{k=1}^{3} \zeta_{p,k+1} * \log(Spatial_{ik}) + \gamma_{pi}, p = 6, 14 \tag{3}$$

Where IMD_i represents the equity features of high streets by a mixed measure based on 7 aspects of deprivation, and $Spatial_{ik}$ ($k = 1 \sim 6$) represents the built environment features of high streets, including shop categories which are number of leisure services and convenience service, and area of high streets in hectare unit. ζ_{p0} is the mean value of logged β_{pi} at the high street level, which represents the average daily visitation counts at the high street level pre-ULEZ ($p = 0$), and post-ULEZ averaged policy effect ($p = 14$). γ_{pi} is the high street level error. In a log–log regression model, the coefficient can be interpreted as the effect of the relative change in independent variables on the relative change in dependent ones, which is the elasticity coefficient (Benoit, 2011). By transferring value of β_{pi} from Eq. (1) to Eqs. (2) and (3), the spatiotemporal variations in the causal effects of the ULEZ can be estimated. Table 2 below provides a comprehensive summary of the definitions and notations used for the model parameters.

4.2.3. Matching control groups

The most important step before modelling with a Robust Interrupted Time Series is to match suitable control groups for treatment groups. Data points from the year 2022 are chosen as a control group, under the consideration of controlling locational variations and cyclical trends to avoid bias or unmeasured confounding factors. Firstly, to assess covariate balance, the holiday schedule and week are properly aligned between comparison groups.

Additionally, to control for seasonality confounders, a basic ITS analysis is run to evaluate the statistical significance of comparability between groups, where groups with a p-value greater than the specified threshold for the β_5 coefficients were retained as controls for the final model. Ultimately, out of 419 high streets, 237 were identified as having statistically significant control groups (e.g., Manor Road, Wallington, Fig. 4, top) and kept for the SRITS. Non-comparable high streets, like Bridge Road, Chessington (Fig. 4, bottom), showing clearly diverted trends before intervention were excluded.

4.2.4. Building socio-spatial profiles for high streets

As Carmona (2015) notes, one-third of users on high streets come from more than 1 km away, and Londoners travel a lot to do their shopping, on average 1.9 miles for food shopping and 3.5 miles for non-food (GLA Economics, 2006). Therefore, the Inverse Distance Weighting (IDW) is incorporated into the data generation process of the second-level model to address the limitation of SITS when data lacks individual socio-economic attributes. IDW is a widely used spatial interpolation and weighting method, where weights are assigned based on the distance between spatial objects nearby (Gu et al., 2021). The weight formula is:

$$Weight = \frac{1}{Distance^{\alpha}}$$

The parameter α indicates the weight decays with distance by the inverse of the α power of distance, usually used in a range from 1 to 2 in the social science area (Yang et al., 2022), where a higher value indicates more concentrated values. It can be adjusted depending on the research question, and it is found that IDW with smaller power values performs better (Lu and Wong, 2008). Thus, α value of both 1 and 1.5 are used here as a sensitivity analysis to explore whether high streets are more influenced by the characteristics of residents living in nearby LSOAs or those further away. We set IDW to run within a 5-km distance to catch the socio-economic makeup of potential consumers to dictate the high street profile. Profiles are considered from two dimensions, which are equity heterogeneity and spatial heterogeneity, and two IDW distance weights.

5. Results

5.1. Temporal heterogeneity in policy effects

Table 3 below presents the results of the two-level model, categorised according to the relevant themes of the model. The "Temporal heterogeneity in policy effects" and above refer to the first-level result, while the "Socio-spatial heterogeneity in high streets" shows the result from Eq. (2), "Spatiotemporal heterogeneity in gradual policy effects" and "Spatiotemporal heterogeneity in abrupt policy effects" include results from Eq. (3).

This section focuses on the estimation of temporal heterogeneity in the treatment effects of the ULEZ intervention policy. According to Table 3, before the ULEZ expansion in 2023, the average counts at $Time_t(t = 0)$ on high streets in Outer London captured by footfall data is significantly 166 people ($\beta_0 + \beta_4$) per day. Notably, the post-ULEZ trend shows that the treatment group experienced an increase of 1.8 visitations per high street per day, while the counterfactual counts decreased by 0.58 per high street per day over the same period. Hence, the second expansion of the ULEZ across London led to a net daily increase of 1.6 visitations (β_{14}) on average across all high streets, with both difference estimations pre- (β_5) and post- (β_7) ULEZ are highly significant. Given that the visitation metric reflects footfall within a 3-hour interval, the small value is both expected and reasonable. Additionally, the results indicate that the abrupt response of visitations on high streets to the ULEZ on the policy implementation date was a sharp decline of nearly 32.8 visitations (β_6) per high street. It is also found that high streets in Outer London are not only active on weekends but also on Mondays.

Table 3
Full estimates of the spatially robust interrupted time-series model for the model results with two IDW parameters, only the one demonstrating higher relevance is presented below.

Category	Variable name	Coefficient	P-value
Temporal heterogeneity in policy effects within whole study period	Intercept	175.397	***
	Time	−0.286	***
	Intervention	9.464	***
	Intervention*Time	−0.580	***
	Exposed	−9.034	***
	Exposed*Time	−0.193	***
	Mon	10.624	***
	Tue	−7.797	***
	Wed	−10.833	***
	Thu	−13.284	***
	Sat	10.798	***
	Sun	6.998	***
	Exposed*Intervention	−32.679	***
	Exposed*Intervention *Time	1.758	***
	Net Change	1.565	
Socio-spatial heterogeneity in high streets (p = 0, α = 1)	IMD decile	−0.526	***
	Leisure service	0.036	***
	Convenience	−0.001	***
	Area (ha)	0.191	***
Spatiotemporal heterogeneity in gradual policy effects (p = 14, α = 1.5)	IMD decile	−0.622	***
	Leisure service	0.066	***
	Convenience	0.003	*
	Area (ha)	0.121	**
Spatiotemporal heterogeneity in abrupt policy effects (p = 6, α = 1)	IMD decile	0.413	***
	Leisure service	−0.014	ns
	Convenience	−0.002	ns
	Area (ha)	−0.099	*
Group Variation for Level1	9063.17		
R-squared for level2 (p = 0)	0.33		
R-squared for level2 (p = 14)	0.29		
R-squared for level2 (p = 6)	0.13		
No. Groups	237		

* p value ≤ 0.1, ** p value ≤ 0.05, *** p value ≤ 0.01, not significant (ns) p value > 0.1.

According to Table S3 in the appendix, it is evident that following the expansion of ULEZ, the level of spending count in high streets in Outer London has increased by 3.5 units (β_6) compared to the benchmark, indicating that a portion of visitations have been converted into consumers. This shift can also be seen in Fig. S2 in the appendix. Despite this increase, the slope of spending count shows a slight increase of 0.071 units per day (β_{14}) in the long run. Additionally, the average spending amount shows no significant change, suggesting that the nature of the shopping content may remain the same as before. This aligns with empirical evidence from Guy (2009) that similar policies have a limited impact due to the persistence of routine shopping habits, especially car use for shopping and convenience.

To ensure robustness, we conducted multiple placebo tests and sensitivity tests. We randomly reassigned the intervention date multiple times. The resulting treatment effects were statistically insignificant, supporting the internal validity of our causal findings. We also adjusted the observation window by excluding the first and last weeks of the study period, and reaggregated footfall metrics at daily intervals instead of 3-hour periods. Results remained consistent across all specifications, with no statistically significant changes observed in either immediate or gradual effects. This reinforces the validity and reliability of our findings.

5.2. Socio-spatial heterogeneity in high-street visitation and ULEZ effects

As explained earlier, linking to socio-economic variables involves the IDW weighting parameter. Our sensitivity analysis shows that α = 1 demonstrates a higher R-value and lower P values compared to α = 1.5, indicating that high street visitation is contributed by not only nearby LSOAs but also distant ones (i.e., within a 5 km radius). With α fixed to 1.5, we found that before ULEZ expansion, if the IMD decile of the LSOAs served by high streets increases by 1 %, the average visitation volume on those high streets tends to decrease by 0.53 % (ζ_{01}), further proving that deprived families in Outer London are more likely to frequent nearby high streets. This may be due to the high rates of non-car ownership among deprived households (Lucas et al., 2019), limiting their ability to travel longer distances. Additionally, a 1 % increase in the number of shops in leisure service is associated with more than a 0.04 % (ζ_{02}) rise in visitations. However, there appears to be no correlation between the number of convenience stores and high street footfall. Finally,

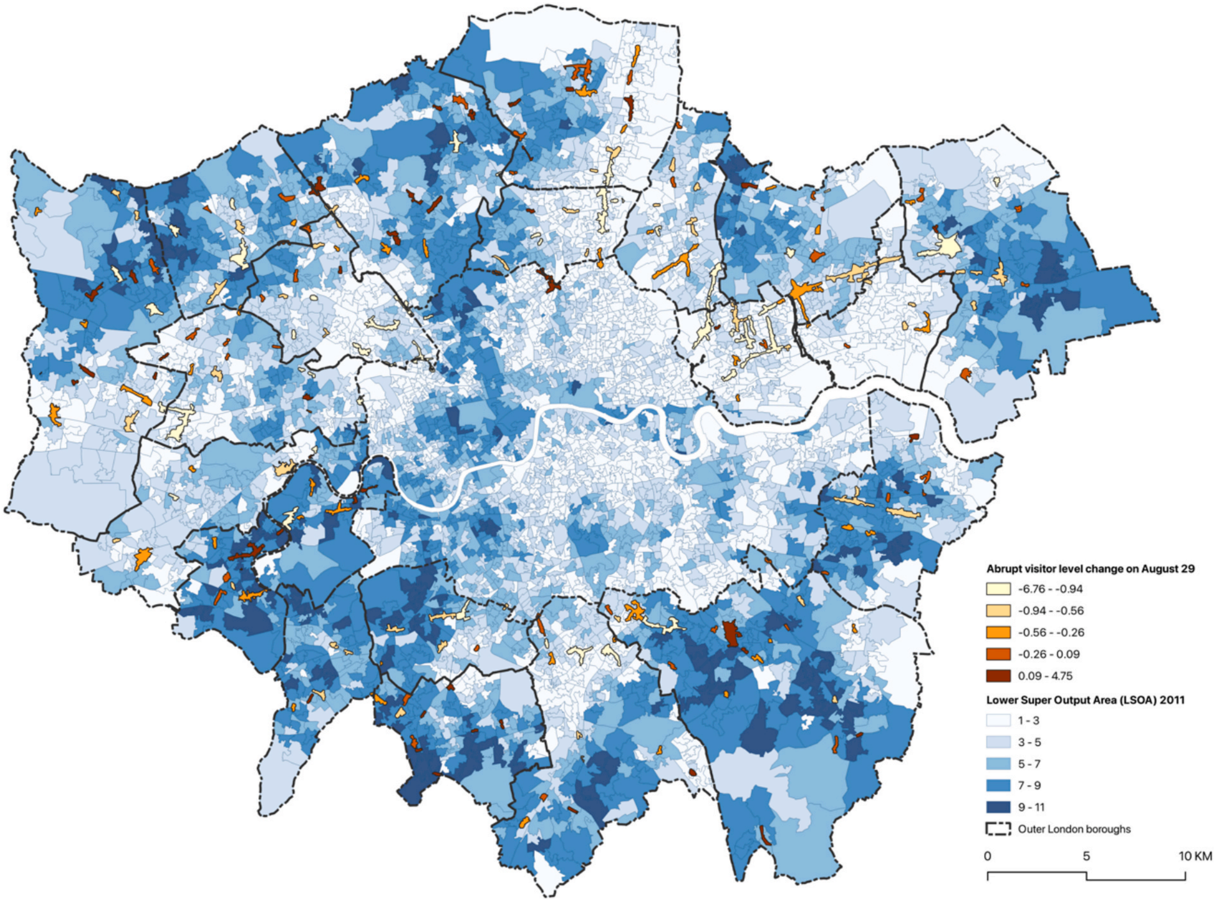

Fig. 5. Map of abrupt visitation change in each high street on ULEZ expansion date.

when the scale of high streets goes up by 1 %, the number of visitations attracted by high streets rises by 0.19 % (ζ_{04}). This can be seen in the appendix Fig. S1, which is plotted by the actual β_0 in each high street as above, demonstrating the spatial variations of the baseline counts.

5.2.1. *Abrupt policy effects*

On the day of ULEZ implementation, areas with a 1 % increase in the IMD decile saw a statistically significant 0.52 % rise in the number of visitations. This aligns with Fig. 5, where wealthier high streets – those surrounded by darker blue MSOAs – see a decline in visitations, while poorer ones show a slight increase. Interestingly, this change is unrelated to the retail category of the high streets but rather to their size. Specifically, for every 1 % decrease in the high street area, footfall increased by 0.19 %. It suggests that smaller commercial centres experienced more pronounced effects on the day of implementation, indicating that ULEZ has influenced the behaviour of small-centred town residents, prompting them to visit nearby high streets rather than travel further afield. This model result shows better relevance between counts and distinct LSOAs' profiles, just as the baseline condition. However, this result only represents a snapshot of the changes, as it is based on the impact of a single day and falls on a weekday.

5.2.2. *Gradual ULEZ policy effects*

According to Table 3, the gradual net difference in treatment groups shows a significantly strong positive correlation with the IMD decile, where a 1 % increase in the IMD decile corresponds to a 0.62 % (ζ_{141}) decrease in visitation growth. This suggests that after the ULEZ implementation, residents in deprived communities began frequenting high streets more than those in affluent areas. Fig. 6 below illustrates the spatial distribution of the IMD decile for each LSOA alongside the change in visitation slope. There is a noticeable correlation on the map between more deprived areas and a higher increase in visitation counts, suggesting that the ULEZ restrictions have a greater impact on limiting travel for people in deprived areas, preventing them from visiting their usual shopping destinations. This trend could be attributed to a lower compliance rate with ULEZ standards among car owners in more deprived areas since, generally, higher-emission vehicles are cheaper to purchase compared to lower ones (Icct, 2024). Also, this model using socio-economic indicators with $\alpha = 1.5$ shows a higher relevance with visitation counts compared to $\alpha = 1$, suggesting that high streets attract more nearby LSOAs' residents after the policy. Additionally, it is evident that the mix level of businesses on the high street also

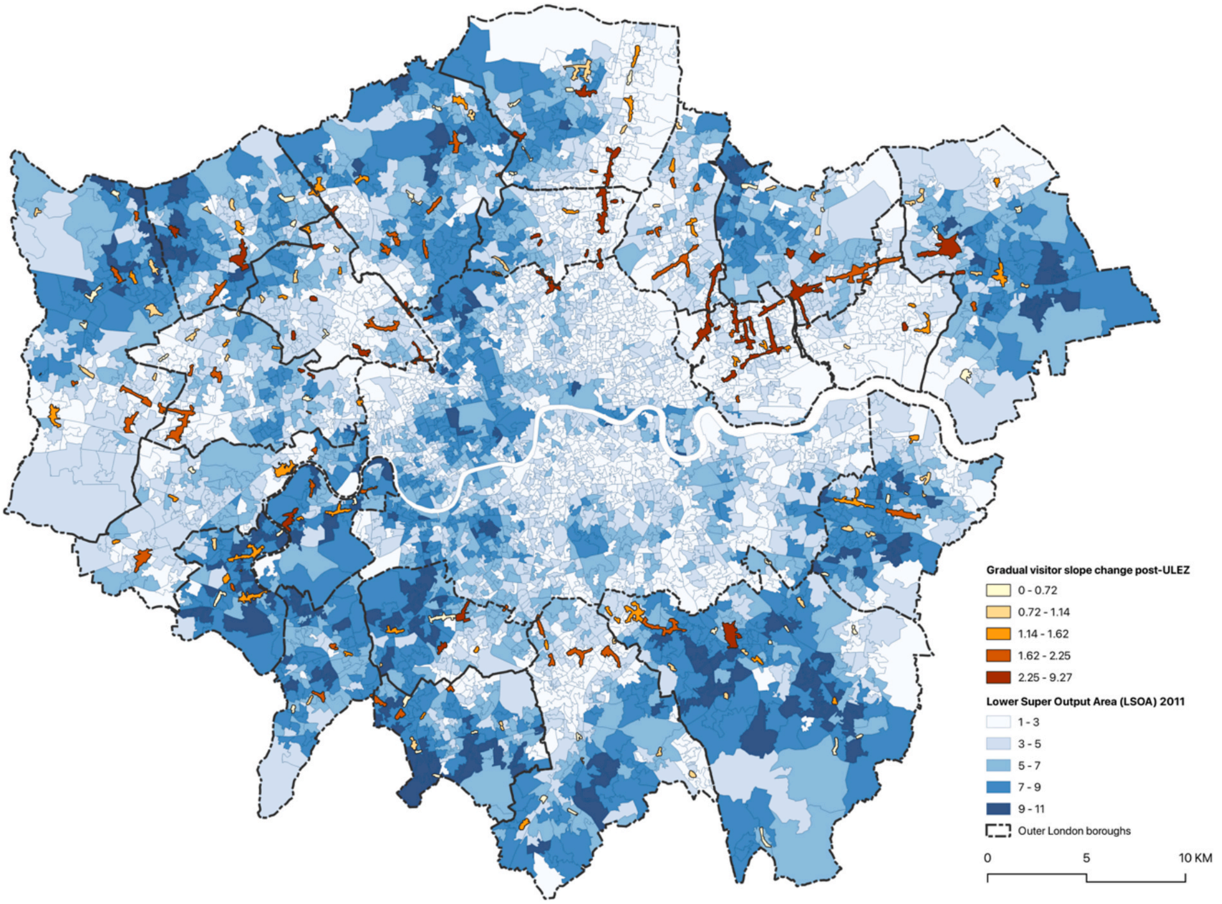

Fig. 6. Map of gradual visitation change in each high street post-ULEZ.

enhances its vitality after ULEZ. It is noted that the decline in the diversity of key local businesses on high streets had led to increased car dependency and potentially weaken the fabric of local communities (New Economics Foundation, 2003; All-Party Parliamentary Small Shops Group, 2006), lending support to our findings. Diversity is also treated as a key indicator to 'measure the range of potential destinations or attractions, and can also indicate resilience and adaptability' of high streets (Department for Business, Innovation and Skills, 2011). Those with a greater number of leisure services are notably more attractive than convenience services to residents. When the number of stores offering leisure services increases by 1 %, it results in a 0.66 % (ζ_{142}) rise in the overall visitation count, while the result is nearly zero for convenience. This suggests a possible shift in travel behaviour, with residents increasingly engaging in local leisure activities within walkable distances.

Again, similar to the results of abrupt changes, high streets with greater area size encourage more visitation activity in the long run, as a 1 % increase in high street size notably results in a 0.12 % (ζ_{144}) boost in foot traffic. This might likely be due to their greater scale allowing for a more diverse composition of establishments. This diversity enables them to better meet the varied needs of the local population (Carmona, 2015), allowing them to have greater potential to accommodate a wider range of activities.

Looking at Fig. 6, a densely packed cluster of high streets in Northeast Outer London with significantly higher visitation growth can be observed, where Westfield Stratford is located. Similarly, in North London, several interconnected high streets stretch from Haringey to Enfield, also showing substantial visitation increases. This demonstrates a potential siphoning effect: high streets with large shopping centres and strong connectivity to surrounding shopping areas tend to attract more visitations.

Comparing spatiotemporal heterogeneities in terms of abrupt and gradual policy effects suggests that high streets around deprived LSOAs, particularly those with a larger scale and higher percentage of leisure premises, may have been less immediately responsive to the ULEZ at the beginning but appear to have attracted more visitations after the policy in the long run. What's more, for baseline levels and abrupt changes, distant LSOAs seem to be more strongly associated with visitation counts. However, this pattern appears to reverse for gradual changes, indicating that after ULEZ expansion, high streets may have become more attractive to residents from nearby LSOAs more than those farther away.

5.3. Summary: ULEZ effects on the vitality of high streets and inequality

While ULEZ initially appears to have suppressed footfall on high streets on the day of its implementation, over time, as daily routines and leisure activities resumed, the policy began to help local high streets attract more footfall, which also led to a statistical increase in spending counts, which can be seen in Table A1 of the Appendix. The overall findings suggest that the expansion of the ULEZ across London has encouraged Outer London residents to frequent their local high streets. Car traffic restrictions may have effectively promoted active travel or improved the safety and air quality of high streets due to reduced traffic. In turn, these factors could revitalise local businesses and enhance the vibrancy of town centres.

It is evident that deprived neighbourhoods tended to visit nearby high streets more frequently before the ULEZ expansion, indicating that social inequality was present due to both spatial and transport disadvantages. Transport disadvantages may stem from the fact that, for low-income households, driving is often a luxury, as these families are more likely to be without car ownership (Lucas et al., 2019). Additionally, affordable and sustainable transport options are not as widely promoted in Outer London as in Inner London (Mahmud et al., 2023). As a result, deprived communities have limited capacity for long-distance travel. Spatial disadvantages, on the other hand, likely arise from the poor quality of local high streets, evidenced by the reluctance of wealthier residents to drive to these areas. All these have resulted in an inverse relationship between the IMD index and high street activity even before the ULEZ implementation.

The second expansion of ULEZ might has further intensified this existing social inequality. While most high streets have seen an overall increase in footfall, the growth in visitation numbers has been significantly larger on high streets located in more deprived areas compared to those in affluent LSOAs. This disparity may stem from the fact that, although certain vehicles are banned in these neighbourhoods, the impact is more pronounced for deprived households, as higher-emission vehicles tend to be more affordable in the market (Icct, 2024), aligning with the lower purchasing power of these families. The ULEZ mobility policy disproportionately restricts the ability of less affluent households to drive for shopping and leisure, increasing their financial burden and exacerbating existing inequalities. Additionally, Outer London is a car-dependent area where sustainable transport options are not as widely encouraged as in Inner London (Mahmud et al., 2023). This lack of alternative transportation further deepens the strain on deprived families. According to a report by the Social Exclusion Unit (Social Exclusion Unit, 2003), issues with transportation availability and the location of services can exacerbate social exclusion by hindering access to essential local resources and activities. Overall, while ULEZ appears to have boosted footfall on high streets, it may have also exposed and heightened the differences in its impact, deepening the existing inequalities in these disadvantaged areas, which may ultimately lead to social exclusion.

The positive correlation between IMD and the increase in visitations suggests that the lives of the vulnerable groups in Outer London are facing problems. In addition to economically disadvantaged populations, more deprived neighbourhoods also tend to have a higher concentration of unhealthy, vulnerable, and less mobile groups, such as the elderly and people with disabilities, who have high care needs (Department for Business, Innovation and Skills, 2011). Therefore, in terms of developing policies aimed at enhancing high street vitality, planners might need to consider building more facilities and services that cater to the needs of these populations and improving the socio-economic make-up of high streets for them. As Carmona (2015) suggested, improving public transport accessibility further and capitalising on the current significant concentration of mixed-use developments are sustainable and humanised solutions to stimulate existing development potential. Policymakers should recognise the variations of demographic profiles that high streets serve and design targeted interventions and incentive measures that respond to the unique circumstances of each community.

In addition to deprived residents, poorly built environments are also worth noting. IMD indicates a neighbourhood has a higher percentage of victimisation, worse road traffic and outdoor air quality, causing safety issues that people are concerned about (Carmona, 2015). The estimation results presented in the results chapter indicate that more deprived LSOAs' residents are limited to shopping on nearby high streets, which is equal to forcing residents to frequent less well-maintained or lower-quality areas. However, it is unjust to restrict people's right to travel to safer, more vibrant high streets for shopping and leisure without providing them with equally high-quality alternatives in their vicinity. Moreover, social exclusion happens when developments like retail centres are situated in areas that are difficult to reach without a car, limiting access for those without private transportation (Social Exclusion Unit, 2003). Therefore, the government is suggested to focus on improving Outer London's high streets by enhancing safety, promoting sustainability, and fostering liveability, which aligns with 'integrated enhancement' according to the Department for Transport (DfT, 2008, as cited in Carmona, 2015). These improvements would better accommodate the evolving lifestyle of residents while also playing a significant role in addressing and reducing social inequalities in the area. It is crucial to acknowledge the needs and potential of the large residential populations already living on and around Outer London's high streets. Developing and updating high street retail and quality of service for these users and significantly benefits their quality of life is the direct way for success on the rejuvenation of the local economy and enhancement of town centres vibrancy.

6. Conclusion

This study contributes an empirical study of transport policy's impact on economic activities, using an innovative causal inference model and emerging human mobility data. In particular, we proposed a generic SRITS that strengthened the latest SITS model's ability to control for seasonal trends by incorporating comparative groups. Additionally, the unique multi-level structure of the model enabled an analysis of socio-spatial disparity. Based on this, we quantified the causal impact of the second expansion of the ULEZ policy on visitations and spending patterns in Outer London. It also explores the policy's effects on social equity and examines the socio-spatial heterogeneity in these causal impacts.

The findings indicate that the ULEZ expansion in Outer London did encourage more residents to visit nearby high streets. However, this effect was not evenly distributed; it disproportionately impacted deprived neighbourhoods, exacerbating the tendency for residents of these areas to frequent their closest high streets. The study also revealed the types of visitors that high streets attracted both before and after the ULEZ expansion and how the composition and size of high streets influence their vitality. These insights offer valuable guidance for developing strategies and priorities for Outer London's high streets.

Several limitations should be highlighted in this study. First, although the methodology in this research introduced some innovations, further research is still needed to refine the approach to spatiotemporal causal inference. Second, future research could integrate finer-grained spatial data and account for population density when calculating socio-spatial weights, allowing for a more accurate representation of real-world conditions. Besides, this study considered limited variables in terms of the built environment and customer group in the model. A typical high street is a complex and dynamic socio-spatial entity (Griffiths et al., 2008) that may attract people's visits for various purposes, such as shopping, work and leisure (Carmona, 2015), all of which are tied to the composition of high street facilities. And more specific demographic profiles of visitors in the high street should be included. Future research could benefit from combining more relevant and detailed variables into the model to provide more robust control and comprehensive exploration.

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CRediT authorship contribution statement

Xinyu Wu: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Chen Zhong:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Yikang Wang:** Writing – review & editing, Validation, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Ethical approval and informed consent statements

This research has been approved by the University College London Research Ethics Committee (project id: 21949/001).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2025.104612.

Data availability statement

Some of the data supporting this work's findings were derived from the following public domain resources: https://geoportal.statistics.gov.uk. The footfall data has restricted access and is provided by High Street Network—Greater London Authority for research use.

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