

Quantify the Impact of the Ultra Low Emission Zone on Modal Shift and Mobility Equity across London: An Interrupted Time Series Analysis on Spatial Units

Student name: Xinyu Wu

Student number: 23079501

Research question

Does the intervention of the second expansion of the Ultra Low Emission Zone stimulate London's modal shift to greener and equitable transport? Primarily, this paper aims to quantify the effects of the second expansion of ULEZ on the modal shift in London and meanwhile how these effects vary between the geographic hierarchy of different socio-economic components and built environment features. Subsequently, by analysing how the policy impacts various spatial units differently, this study wants to reveal whether inequity is exacerbated or attenuated because of the expansion of ULEZ, such as unintentionally favours more affluent regions or effectively supports economically disadvantaged areas.

Background

The Ultra Low Emission Zone (ULEZ) was initially launched on 8 April 2019, with two expansions on 25 October 2021 and 29 August 2023, to reduce air pollution. This policy is proposed within the larger socio-environmental goal of the Net Zero 2030 Target for Greater London, which was released on 18 January 2022 and seeks a substantial reduction in petrol and diesel vehicle usage in favour of walking, cycling, and public transport. Meanwhile, it aligns with research suggesting modal shift (Allen *et al.*, 2023) and active commuting (Chng *et al.*, 2016; Shannon *et al.*, 2006) are essential for health benefits and daily physical activity.

While previous research on ULEZ or related transport policies primarily focuses on their causality impact on air quality and population health (Zhai and Wolff, 2021; Prieto-Rodriguez *et al.*, 2022) by using causal inference methods – most are Diff-in-Diff models –, its influence on travel behaviour merits further examination. It has been proven the implementation of ULEZ can encourage the transition to green transportation modes, stimulating the bicycle demand within the zone (Ding *et al.*, 2023). However, it is unjust to deprive residents of the right to drive without offering viable transportation alternatives (Gao *et al.*, 2022), while providing access to affordable and accessible transport systems for all is one of the key targets in the 2030 Agenda for Sustainable Development.

Methodology

In this paper, the spatially interrupted time-series (SITS) method will be applied to evaluate the influences of ULEZ on transport shift, with which the effects of confounding factors – socio-economic components – will be accounted for. SITS is a quasi-experimental design developed by Zhang and Ning (2023) based on Interrupted time series (ITS), which is widely adopted in public health and road safety (Lopez Bernal, Cummins and Gasparrini, 2016; Abegaz *et al.*, 2014), to causally infer the spatiotemporal heterogeneities in the mobility control policies' effects.

By comparing the behaviour of individuals before and after the intervention (treatment group) with the underlying trend established based on preintervention (control group), ITS can capture the change of level and slope of the causal effect. It has several advantages towards this research. First of all, because it compares outcomes over time within one single group of individuals, it avoids the problematic effect of unobservable confounding factors between the control group and the treatment group (Lopez Bernal, Cummins and Gasparrini, 2018; Zhang and Ning, 2023), compared to using controlled designs such as the difference-in-difference method (Prieto-Rodriguez et al., 2022; Zhai and Wolff, 2021) and propensity score matching approach method (Ding et al., 2023) in spatial analysis. Second, it can identify both sudden and gradual shifts in long-term trends, excluding the erroneous result from treating the average level of change as the only treatment effect (Zhang and Ning, 2023).

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 pre-pandemic level. The whole period of the study will be after the COVID restrictions ended on 19 July 2021 (Institute for Government, 2022) to avoid being affected by it. At the same time, since ITS method is difficult to distinguish multiple events (Zhang and Ning, 2023; A Guide on Data Analysis, 2024), this research will only focus on the second expansion of ULEZ, which has no concurrent policies as shown in Figure 1. Additionally, the power of ITS increases when the size of sample or effect size increases, as well as using balanced numbers of study periods pre- and postintervention (Zhang, Wagner and Ross-Degnan, 2011), this study will use daily data involving at least 24 data points before and after the intervention, which is suggested to make the power estimates reliable (Zhang, Wagner and Ross-Degnan, 2011; Dorais, 2024).

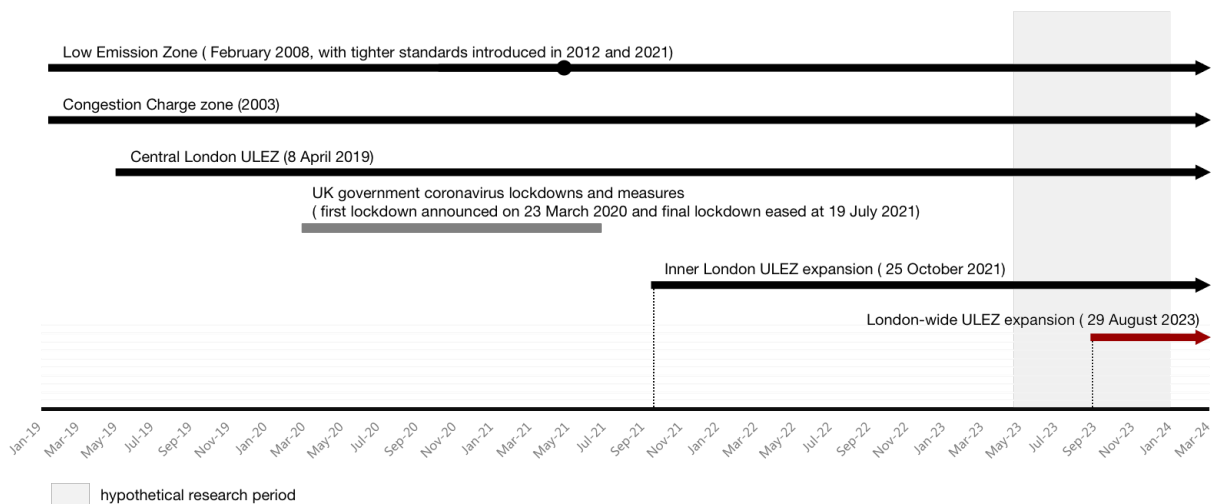


Figure 1. Timeline of Transport-Relevant Policies (Data sourced from: Mayor of London, 2023; the C40 Knowledge Hub, 2019; Institute for Government Analysis, 2022)

This research will encompass two distinct data categories: transport data and socio-spatial data (including socio-economic environment and built environment data) as shown in Table 1, which will be integrated based on common geographic characteristics and filtered by the expanded ULEZ zone. The study object will mainly focus on working-age people and commuting traffic.

In terms of transport OD data, tap-in records would be used based on the assumption that daily commuting passengers are likely to return to their initial departure station during that day (Cabrera-Arnau *et al.*, 2023). The Built environments mainly regard transportation's accessibility which will be measured by a methodology proposed by Welch and Mishra (2013), using several attributes such as frequency, capacity, speed and built environment in a multi-modal transit network. The spatial units of this research would be determined based on Middle Layer Super Output Areas (MSOAs), which most of datasets are based on and meanwhile support detailed spatial analysis. Time-varying confounders such as non-labour days would be added to avoid cyclical or seasonal effects and random fluctuations (Ramsay *et al.*, 2003; Prieto-Rodriguez *et al.*, 2022).

Initially, the research will examine the influence of ULEZ's second expansion on active commuting patterns across fine-grained daily public transport data, exploring whether London's travel pattern has a positive response to it. Subsequently, it will explore the association between these effects and the socio-economic or spatial characteristics of the regions under study. The result of SITS could show how the causal effect of the intervention of ULEZ varies between different spatial units (Zhang and Ning, 2023). Lastly, examine whether areas with deprivation or those with less accessibility to public transportation experienced less benefit from ULEZ implementation, indicating potential inequality exacerbation.

Table 1. Hypothetical variables and descriptive statistics

Variables	Description	Data source
Transport Data		
Daily vehicle count	Daily number of vehicles driving within the zone	daily number of vehicles driving in the ULEZ (TFL data need request)
Daily proportions of compliant vehicles	Daily proportions of compliant vehicles	
Daily tube distance	Daily per-capita tube average length of travel of each spatial unit	15 mins tube OD data (TFL data need request)
Daily cycle distance	Daily per-capita cycle travel distance of each spatial unit	Cycle Hire trip data (TFL open data)
Daily bus count	Daily per-capita bus travel count of each spatial unit	Daily travel journey count data of bus / 15 mins bus tap-in data (TFL data need request)
Daily tube count	Daily per-capita tube travel count of each spatial unit	Daily travel journey count data of tube / 15 mins tube OD data (TFL data need request)

Daily cycle count	Daily per-capita cycle travel count of each spatial unit	15 mins cycling count data at 1,000 sampling sites (TFL data need request)
Socio-economic environment		
Working age residential density	By each spatial unit	Index of multiple deprivation 2019 / Census 2021 data
Income deprivation	Income rank of each spatial unit	Index of multiple deprivation 2019 / Census 2021 data
Education deprivation	Education rank range from GCSEs to higher degree	Index of multiple deprivation 2019 / Census 2021 data
Employment deprivation	continues data of each spatial unit	Index of multiple deprivation 2019 / Census 2021 data
Built environment		
Car accessibility	car availability for households	Census 2021 data
Tube accessibility	Considering distance to transit stops, frequency, capacity of transport	Station locations, etc. (TFL open data)
Bus accessibility	Considering distance to transit stops, frequency, capacity of transport	Bus stop locations and routes, etc. (TFL open data)
Cycle accessibility	Considering distance to transit stops, frequency, capacity of transport	BikePoint data, etc. (TFL open data)

Bibliography

Abegaz, T., Berhane, Y., Worku, A. and Assrat, A. (2014). 'Effectiveness of an improved road safety policy in Ethiopia: an interrupted time series study'. *BMC Public Health*, 14 (1), p. 539. doi: 10.1186/1471-2458-14-539.

Allen, R., Bennett, and, H., Cooper, C. and Haggard, P. (2023). 'Moving on: greener travel for the UK'.

Cabrera-Arnau, C., Zhong, C., Batty, M., Silva, R. and Kang, S. M. (2023). 'Inferring urban polycentricity from the variability in human mobility patterns'. *Scientific Reports*, 13 (1), p. 5751. doi: 10.1038/s41598-023-33003-7.

Carleton, P. R. and Porter, J. D. (2018). 'A comparative analysis of the challenges in measuring transit equity: definitions, interpretations, and limitations'. *Journal of Transport Geography*, 72, pp. 64–75. doi: 10.1016/j.jtrangeo.2018.08.012.

Chng, S., White, M., Abraham, C. and Skippon, S. (2016). 'Commuting and wellbeing in London: The roles of commute mode and local public transport connectivity'. *Preventive Medicine*, 88, pp. 182–188. doi: 10.1016/j.ypmed.2016.04.014.

C40 Cities Climate Leadership Group, Greater London Authority, C40 Knowledge Hub. (2019) 'How road pricing is transforming London and what your city can learn'. Available at: https://www.c40knowledgehub.org/s/article/How-road-pricing-is-transforming-London-and-what-your-city-can-learn?language=en_US. (Accessed: 18 March 2024).

Ding, H., Sze, N. N., Guo, Y. and Lu, Y. (2023). 'Effect of the ultra-low emission zone on the usage of public bike sharing in London'. *Transportation Letters*. Taylor & Francis, 15 (7), pp. 698–706. doi: 10.1080/19427867.2022.2082005.

Dorais, S. (2024). 'Time series analysis in preventive intervention research: A step-by-step guide'. *Journal of Counseling & Development*, 102 (2), pp. 239–250. doi: 10.1002/jcad.12508.

Gao, Q.-L., Yue, Y., Zhong, C., Cao, J., Tu, W. and Li, Q.-Q. (2022). 'Revealing transport inequality from an activity space perspective: A study based on human mobility data'. *Cities*, 131, p. 104036. doi: 10.1016/j.cities.2022.104036.

Institute for Government (2022) 'Timeline of UK government coronavirus lockdowns and restrictions'. Available at: <https://www.instituteforgovernment.org.uk/data-visualisation/timeline-coronavirus-lockdowns> (Accessed: 18 March 2024)

Lopez Bernal, J., Cummins, S. and Gasparrini, A. (2016). 'Interrupted time series regression for the evaluation of public health interventions: a tutorial'. *International Journal of Epidemiology*, p. dyw098. doi: 10.1093/ije/dyw098.

Lopez Bernal, J., Cummins, S. and Gasparrini, A. (2018). 'The use of controls in interrupted time series studies of public health interventions'. *International Journal of Epidemiology*, 47 (6), pp. 2082–2093. doi: 10.1093/ije/dyy135.

Mayor of London, (2023). 'Inner London Ultra Low Emission Zone One Year Report'.

Prieto-Rodriguez, J., Perez-Villadoniga, M. J., Salas, R. and Russo, A. (2022). 'Impact of London Toxicity Charge and Ultra Low Emission Zone on NO₂'. *Transport Policy*, 129, pp. 237–247. doi: 10.1016/j.tranpol.2022.10.010.

Ramsay, C. R., Matowe, L., Grilli, R., Grimshaw, J. M. and Thomas, R. E. (2003). 'INTERRUPTED TIME SERIES DESIGNS IN HEALTH TECHNOLOGY ASSESSMENT: LESSONS FROM TWO SYSTEMATIC

REVIEWS OF BEHAVIOR CHANGE STRATEGIES'. *International Journal of Technology Assessment in Health Care*, 19 (4), pp. 613–623. doi: 10.1017/S0266462303000576.

Shannon, T., Giles-Corti, B., Pikora, T., Bulsara, M., Shilton, T. and Bull, F. (2006). 'Active commuting in a university setting: Assessing commuting habits and potential for modal change'. *Transport Policy*, 13 (3), pp. 240–253. doi: 10.1016/j.tranpol.2005.11.002.

Welch, T. F. and Mishra, S. (2013). 'A measure of equity for public transit connectivity'. *Journal of Transport Geography*, 33, pp. 29–41. doi: 10.1016/j.jtrangeo.2013.09.007.

Zhai, M. and Wolff, H. (2021). 'Air pollution and urban road transport: evidence from the world's largest low-emission zone in London'. *Environmental Economics and Policy Studies*, 23 (4), pp. 721–748. doi: 10.1007/s10018-021-00307-9.

Zhang, F., Wagner, A. K. and Ross-Degnan, D. (2011). 'Simulation-based power calculation for designing interrupted time series analyses of health policy interventions'. *Journal of Clinical Epidemiology*, 64 (11), pp. 1252–1261. doi: 10.1016/j.jclinepi.2011.02.007.

Zhang, W. and Ning, K. (2023). 'Spatiotemporal Heterogeneities in the Causal Effects of Mobility Intervention Policies during the COVID-19 Outbreak: A Spatially Interrupted Time-Series (SITS) Analysis'. *Annals of the American Association of Geographers*, 113 (5), pp. 1112–1134. doi: 10.1080/24694452.2022.2161986.