Inferring trip purposes and mode substitution effect of rental e-scooters in London

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Abstract
The lack of information on trip purpose and alternative mode in micromobility service usage data remains a major analytical challenge. Conventional survey method is subject to significant sampling and stated preference biases. To overcome this challenge, this paper presents a new inference method through a case study of rental e-scooters in London. The inference method features a rule-based algorithm for matching observed rental e-scooter trips with filtered trip samples in the English National Travel Survey (NTS) series. Probability distribution of trip purposes and alternative modes are then retrieved from NTS. Inference results are validated using official data. Discrepancies, sources of biases and correction measures are investigated. Based on the inferred mode substitution pattern, we estimate greenhouse gas emissions reduction of selected rental e-scooter trips in London (36-103g CO_2e per mile). It is expected that the proposed method is applicable to a wide range of micromobility studies using service usage data.

1 Introduction
Emerging micromobility services such as the rental e-sooter/e-bike are gaining tractions across the globe. It is expected that micromobility modes would become an integral part of future urban transport systems. Understanding their demand characteristics, journey purposes, cross-mode substitution patterns and the associated environmental effects is thus crucial for informing future urban transport policy.

The prevalence of app-based service provision and the advancements in sensing technology have enabled the collection of enormous amounts of service usage data at unprecedented spatio-temporal resolution. Service usage data are usually collected back-end by service operators subject to data privacy restrictions. Compared with conventional travel surveys such as roadside interviews/questionnaires, the service usage data usually feature very high sampling rates, minimal self-reporting bias and good interoperability across operators and locations.

However, an outstanding deficiency in the service usage data is the lack of information on trip purposes and alternative modes and the lack of users' socio-demographic background. To understand trip purposes and mode substitution pattern of micromobility modes, existing studies tend to use survey data collected from potential/existing micromobility service users. Conventional survey methods have certain limitations. Firstly, sample size in existing studies tends to be limited and surveys are often conducted in a cross-sectional manner. Compared with conventional survey methods, app-based surveys often feature higher frequency and rate of responses, but large-scale and long-period studies remain rare. The government-led, national evaluation of e-scooter trials in the UK (ARUP and NatCen, 2022a) is exceptional as all service operators were mandated by the UK Department for Transport (DfT) to conduct app-base, post-ride survey for a minimum period of 12 months. Such a national-level, long-period, systematic and mandated data collection is, to the best of our knowledge, unseen in other countries and studies, in part due to its resource-intensive nature. A model-based inference method, once empirically validated, is thus desirable as it offers a viable alternative to continuously monitoring how trip purposes and mode substitution effect of micromobility services may progressively change using real-time service usage data. Secondly, micromobility service demand and mode substitution effect are highly sensitive to the time of the day (e.g. peak vs non-peak time), day of the week (e.g. workdays vs weekends), trip distance, purpose and seasonality. However, most survey questions asking the propensity, purpose and alternative mode of service usage do not specify these contextual factors. A context-sensitive approach is thus needed to understand the nuanced demand and impacts of micromobility services.

The contribution of this paper is twofold. First, it proposes a novel method for inferring trip purposes and cross-mode substitution pattern of micromobility modes. The new method features a rule-based algorithm for matching micromobility trips with stratified trip samples in large-scale travel survey which is widely available as public data in major cities and metropolitan areas. The trip matching algorithm considers a wide range of trip-level (time of the day, day of the week, trip duration and length) and individual-level (age and driving license status) factors. The inference method is demonstrated through a case study of rental e-scooter trial in London. Inference results are validated using the benchmark data on trip purpose and alternative mode for London, sourced from the 'National evaluation of e-scooter trials' database (ARUP and NatCen, 2022a). Discrepancies, potential sources of biases and correction measures are discussed. Secondly, based on the inferred mode substitution pattern, the potential greenhouse gas (GHG) emissions reduction effect of rental e-scooters in London is estimated. Our analysis provides one of the first evidence confirming the emissions saving effect of rental e-scooters in London.

The structure of the paper is as follows. Section 2 reviews relevant literature, with a particular focus on trip purposes and mode substitution effect of the rental e-scooter mode. Section 3 presents research questions, data and methods. Inference results and emissions reduction estimates including sensitivity test results are discussed in Section 4. Conclusion, limitations and directions for future research are discussed in Section 5.

2 Literature Review

The literature review is focused on the following three topics: i) rental e-scooter demand pattern; ii) trip purposes and mode substitution effect of rental e-scooter trips; and iii) emissions reduction effect of rental e-scooters.

2.1 Overview of rental e-scooter case studies

Table 1 presents a non-exhaustive summary of rental e-scooter schemes by 2022 from the literature. For more recent and international comparative studies, see Li et al. (2022), Badia and Jenelius (2023) and Foissaud *et al.* (2022). In England, a total of 32 trials across 55 local areas including London have been implemented since July 2020. In terms of average trip length/duration, the tendency of rental e-scooters serving short-distance journeys is evident (Badia and Jenelius, 2023). London, Paris, Hamburg, Malaga and Melbourne witness longer average length and duration than other cases, which suggests that rental e-scooters have the potential to serve wider trip purposes, as opposed to merely first-/last-mile journeys as a feeder mode for public transport. The large number of trips recorded and the fact that several trials have been extended beyond the initial trialling period reflect the general popularity of the novel mode.

Table 1. A non-exhaustive summary of rental e-scooter case studies

City/Source	Observation period[1]	Number of trips	Number of e-scooters deployed	Average trip length/duration
Singapore (Cao *et al.*, 2021b)	Oct. 2018 - Nov. 2018.	23,319	Around 400	2.1 km / 22 mins[2]
Louisville, Kentucky (Hosseinzadeh *et al.*, 2021)	Nov. 2018 – Feb. 2020	501,952	Monthly increment of 100[4], up to 650 per operator	2.1 km / 16 mins[3]
Portland (Portland Bureau of Transportation, 2018)	Jul. 2018 – Nov. 2018	700,369	2,043	1.9 km
Austin, Texas (Bai *et al.*, 2021)[5]	Jan. 2019 – Feb. 2019	351,921	13,530	1.1 km / 6 mins
Minneapolis (Bai and Jiao, 2020)	Not specified	225,543	Up to 400	2.1 km / 19 mins
Washington DC (McKenzie, 2019)	Jun. 2018 – Oct. 2018	937,590	287 (daily average)	0.6 km / 5 mins

City/Source	Observation period[1]	Number of trips	Number of e-scooters deployed	Average trip length/duration
Chicago (City of Chicago, 2020)	Jun. 2019 – Sep. 2019	406,984	1,722	2.4 km / 18.5 mins
Melbourne (RACV, 2022)	Feb. 2022 – Jun. 2022	Appr. one million	1,500	2.5 km / unknown
Los Angeles (LADOT, 2020)	Apr. 2019 – Mar. 2020	10.3 million	10,500 inc. e-bikes & pedal bikes	1.6 km (e-scooters) / unknown
Auckland (Auckland Council, 2019)	Apr. 2019 – Oct. 2019 (2nd trial)	Over 2 million	1,875	1.3 km / 7 mins
Paris (Foissaud *et al.*, 2022)	Aug. 2019 – Oct. 2019	7330	338	3.0 km / 14 mins
Bordeaux (Foissaud *et al.*, 2022)	Aug. 2019 – Oct. 2019	29,609	275	2.8 km / 11 mins
Malaga (Foissaud *et al.*, 2022)	Aug. 2019 – Oct. 2019	37,313	661	2.0 km / 11 mins
Hamburg (Foissaud *et al.*, 2022)	Aug. 2019 – Oct. 2019	143,880	3195	2.8 km / 10 mins
London and other 31 trials in England (ARUP and NatCen, 2022a)	Jul. 2020 – Dec. 2021	London: 548,261 Total: 14.5 million	Dec. 2021 (daily average): London: 3,521[6] Total: 22,935	London: 2.5 km / 19 mins Total: 2.2 km / 14 mins

Notes
1. Observation period is based on the empirical data used in the academic paper and does not necessarily cover the full e-scooter operation period in the city.
2. Based on one-way trips with O/D both inside the parking locations from four operators.
3. Average trip length and duration obtained from another study of Louisville by Noland (2019), whose trip samples were slightly different from Hosseinzadeh *et al. (2021)*, hence possible discrepancies.
4. Monthly increment is granted only if daily ridership is above four rides per vehicle.
5. An earlier study of Austin is presented by Caspi, Smart and Noland (2020).
6. Sum of all three operators in London.

Among academic studies examining the demand and impacts of rental e-scooters, most studies use survey (stated preference) data, typically collected online or roadside (City of Chicago, 2020; Moreau *et al.*, 2020; Christoforou *et al.*, 2021; Lee *et al.*, 2021). Studies based on actual service usage data are emerging (Caspi, Smart and Noland, 2020; Bai *et al.*, 2021; Cao *et al.*, 2021a). One notable contribution is the English National evaluation of e-scooter trials (ARUP and NatCen, 2022a, 2022b), commissioned by the UK Department for Transport, which uses service usage data pooled from multiple operators and trials, complemented by survey and interview data.

2.2 Rental e-scooter demand pattern

We assemble rental e-scooter usage characteristics from recent literature and summarise them in Table 2.

Table 2. Summary of general patterns of rental e-scooter usage [expanded from Hosseinzadeh et al. (2021, p. 10)]

	General patterns
Spatial dimension	• E-scooter trips tend to concentrate in places with high population density, of commercial, university and recreational land use (e.g. parks, museums); industrial land use would reduce e-scooter ridership. • Walkability, bikeability and access to public transit are positively correlated to trip density, but there is conflicting evidence on whether transit stations/stops would attract e-scooter uses, subject to vehicle deployment constraints.
Temporal dimension	• Significant differences among weekdays and also between weekdays and weekends; Fridays and Saturdays tend to have higher ridership than other days of the week. • E-scooter usage peak tends to appear at lunchtime or in the afternoon on weekdays; morning peak is rarely significant on weekdays except for London; usage usually picks up from 11am; late night use on Fridays and Saturdays seems common.
User profile	• Male and young population (<35 years) is overrepresented among e-scooter riders. • Amongst those who used rental e-scooters, men and younger people are also more likely to rent e-scooters frequently.
Trip purpose	• Recreational and casual use of e-scooters seems dominant except for English cities where commuting is a major purpose. • As the trial progresses, the proportion of trips taken for no particular purpose would fall while the proportion taken for commuting would increase, implying more purposeful e-scooter usage as first-timers became regular users.
Others	• Weather affects ridership; higher temperature (implying warm, sunny days) would increase e-scooter usage whereas heavy rain and wind would reduce ridership; lower (higher) ridership in winter (summer). • Major events (e.g. musical/art festivals) would increase e-scooter ridership.
Sources: Portland Bureau of Transportation (2018); Auckland Council (2019); LADOT (2020); Cao et al. (2021); Hosseinzadeh et al. (2021b); ARUP and NatCen (2022a); RACV (2022); Christoforou et al. (2021); Li et al. (2022); and Sorkou *et al.*(2022).	

2.3 Trip purposes and mode substitution effect of rental e-scooters

For investigating trip purposes and mode substitution effect of rental e-scooters, existing studies tend to 1) use survey data collected by either researchers or service operators (see Christoforou et al., 2021; Lee et al., 2021); or 2) infer what trip purposes may be fulfilled by e-scooters using secondary, structured travel survey data (see Gebhardt, Wolf and Seiffert, 2021). Both approaches have certain limitations. For the former, most survey-based studies have rather limited sample size hence potentially significant sampling bias. For the latter, the design of inference rules is based on perceived *average* characteristics of e-scooter trips/users (e.g. short distance trips and young age groups), ignoring the significant heterogeneity of e-scooter usage (e.g. variations across different times of the day and days of the week). Another potential source of inference error is that structured travel survey often adopts stratified sampling to ensure the representativeness of the data. But the demographic profile of micromobility service users may not follow the population-wide profile. Such inference error has not yet been investigated in the literature. To the best of our knowledge, no existing academic studies have explored an integrated use of micromobility service usage data and structured large-scale travel survey.

2.3.1 TRIP PURPOSES

For studies using self-reporting survey data, Christoforou et al. (2021) conducted a survey of potential e-scooter usage in Paris (N = 459), and found that e-scooters would mainly serve leisure and visiting friends/family purposes, rather than commuting. This finding has been corroborated by studies of other cities (Caspi, Smart and Noland, 2020; Younes *et al.*, 2020; Bai *et al.*, 2021). However, a survey of e-scooter users in Seoul (Lee *et al.*, 2021) showed that a significant proportion of e-scooter users (33.6%) may utilise the e-scooter as a viable commuting mode, though the overall sample size was modest (N = 363). A similar argument was made using survey data collected and analysed by Lime (2018), a leading e-scooter operator, that work and school commute is the primary trip purpose for 55 % of Lime rental e-scooter riders in San Francisco. According to the recent national evaluation of rental e-scooter trials in England (ARUP and NatCen, 2022a), the top reasons for e-scooter trips are commuting (33%), other reason (27% including e.g. education-related), leisure (13%) and personal errands (13%) across all trials. For the London trial specifically, the top reasons for e-scooter trips are leisure (31%), commuting (26%), personal errands (15%) and enjoyment /

no particular purpose (11%). The relatively high share of commuting in London contrasts to previous studies (e.g. McKenzie, 2019; Reck *et al.*, 2021).

For studies that infer e-scooter trip purposes using structured travel survey data, Aarhaug, Fearnley and Johnsson (2023) conducted a user survey in Oslo (N = 1617) and found that commuting/education (40%), leisure including meeting friends/family (36%) and errands (18%) and were dominant trip purposes for rental e-scooters. Gebhardt, Wolf and Seiffert (2021) estimated the suitability of e-scooter usage by considering the following factors: trip length (<= 4 km), trip purposes (excluding social service/care, freight trips and passenger trips), traveller age (14-70), weather conditions, physical impairments and travel accompaniment (<= 1 travel companion). They found that professional/business, shopping and private errands have a relatively high potential to be substituted by e-scooters. Leisure trips have relatively low potential (6.3%) mainly because of the relatively long average trip distance for leisure in Germany (21 km, including day trips and holiday trips). The potential for education trips is also low (2.2%) and the authors argued that such trips are often escorting trips (e.g. escorting dependent children to school), thus not substitutable for e-scooters.

However, the perceived unsuitability of using e-scooters for accompanied travel is contestable. Our real-world observation suggests that rental e-scooters can accommodate certain accompanied/escorting trips, particularly before/after leisure and entertainment activities. Despite accompanied travel with e-scooters often being perceived as a risky behaviour (Gioldasis, Christoforou and Seidowsky, 2021), whether/how micromobility modes may serve accompanied travel remains an understudied topic in both academic and marketing research.

2.3.2 MODE SUBSTITUTION EFFECT

Understanding the cross-mode substitution effect of the rental e-scooter mode is crucial for evaluating the sustainability impact and its role in the wider urban transport systems. In terms of empirical findings from European cities, evidence from Paris by Christoforou et al. (2021) showed that rental e-scooters would, on average, incur a modal shift from walking (35%), public transit (27%), other shared mobility services (9%), taxi and ride-hailing (6%), and private car (4%). They also found that for occasional users (defined as 'few times per year'), about 45% (23%) of their e-scooter trips would have had done by walking (public transit) if there were no rental e-scooters. However, for frequent e-scooter users (defined as 'over three times per week'), nearly 50% of their e-scooter trips would replace public transit. In addition, Gebhardt, Wolf and Seiffert (2021) found that overall the e-scooter mode has the potential to replace 10-15% of observed individual motor vehicle trips in Germany.

Mode substitution effect is sensitive to trip distance. Specifically, for e-scooter trips under 10min, rental e-scooters would predominantly replace walking (58%) as per Christoforou et al. (2021). As trip distance increases, the probability of substituting public transport and bike increases. The substitution of public transit would peak for trips of 20-29min. On induced demand, only 6% of the e-scooter trips surveyed are regarded as new trips (Christoforou *et al.*, 2021).

Moreau et al. (2020) provided a useful meta-analysis of the mode substitution effect across five rental e-scooter schemes, which include three US cities (Rosslyn, Portland and Releight) and two European cases (France and Brussels). All studies involved used survey data. Overall the metaanalysis showed that the mode substitution effect of rental e-scooters is context-sensitive. Specifically, the probability of rental e-scooters substituting private car is much higher for US cities (appr. 40%) than that for European cities. Among European cities, the effect of e-scooters substituting private cars is notably more significant in Brussels (appr. 28%) than that in France (9%). Such difference may be attributed to the distinct contexts of the two cases where private car use is prevalent in Brussels despite heavily subsidised public transport, in contrast to the dominance of public transport in Paris. The probability of substituting public transport is similar between Brussels and France (appr. 30%), but much higher than the average of three US cities (appr. 10%).

However, the quality and representativeness of the survey data remain a major concern for some of the studies. The studies of Portland (N = 3,444), Brussels (N = 1,181) and France (N = 4,000+) appear to have a reasonable sample size, but the survey data for Rosslyn and Raleight only have 56 and 61 e-scooter user samples, respectively. For the Rosslyn case, James et al. (2019) actually provided some conflicting findings from another stated preference survey (N = 181), where e-scooters replaced trips by taxi or ride-hailing (39%), walking (33%), bicycle (12%), bus (7%) and personal car (7%). The big discrepancies between the two studies for the same city reflect certain limitations of the stated preference approach.

National post-ride survey data from England suggests that the mode shift to rental e-scooters from private vehicle (car/van/motorbike), public transport (bus, train, taxi) and active modes (walking and cycling) is 15%, 22% and 63% (rescaled after removing non-mode answers such as ‘Don’t know’), respectively (ARUP and NatCen, 2022a). Figures for the London trial are 9%, 27% and 62%. ARUP and NatCen (2022a, p. 35) also include a comparison of international evidence (Los Angeles, Portland and Auckland) on mode shift from e-scooters. Data from the three selected cities shows that mode shift from the car ranges from 12% to 21%, and 42% to 59% from active modes. About 9% of national trips in Dec. 2021 (end of the evaluation period) would not have been made in the absence of the rental e-scooter mode (i.e. induced demand), which is similar to the proportion in Paris reported by Christoforou et al. (2021).

2.4 Emissions reduction effect of rental e-scooters

The potential of rental e-scooters as a green travel mode has been widely discussed in the literature, though empirical evidence for such greenhouse gas (GHG) emissions reduction effect seems limited. Factors affecting the emissions reduction effect of rental e-scooters are summarised below.

- Positive factors (Philips et al., 2022; Aarhaug et al., 2023):
  - Replacing high-emitting travel modes (e.g. petrol/diesel vehicles)
  - Complementing public transit services through improving first/last mile accessibility
- Negative factors (Cao *et al.*, 2021b; Badia and Jenelius, 2023):
  - Replacing active modes (cycling and walking) and public transport
  - Induced demand
- Life-cycle factors (Hollingsworth et al., 2019; de Bortoli and Christoforou, 2020):
  - Primary energy source for manufacturing and charging e-scooters
  - Material use and recycling strategy
  - Secondary emissions incurred by transporting e-scooters from the place of production to place of usage and by re-distributing vehicles for maintenance and operation purposes
  - Lifespan of shared e-scooters

Hollingsworth, Copeland and Johnson (2019) found that materials and manufacturing account for 50% of the life cycle emissions impact of e-scooters through a Monte Carlo analysis. Based on a two-year lifespan, average life cycle emissions of rental e-scooters were estimated to be 141g CO_2e per passenger-mile (88g CO_2e per passenger-km), which is significantly lower than the average emissions intensity of personal automobile (414g CO_2e per passenger-mile). The study confirmed the environmental benefits of rental e-scooters through substituting personal automobile travel.

Moreau et al. (2020) also reported that a short lifespan and the carbon emissions from the manufacturing and distribution are main causes of high carbon intensity of the rental e-scooter mode. By increasing the lifespan of shared e-scooters (9.5 months as a minimum) and optimising the distribution process, the life-cycle carbon intensity of shared e-scooters would decrease hence improving the sustainability performance. A recent report from the Centre for London suggested that life-cycle carbon intensity of shared e-scooter could be as low as 35g CO_2e per passenger-km, compared to average 162g CO_2e per passenger-km for a privately owned motor car over the vehicle's lifetime (Cottell, Connelly and Harding, 2021).

Existing studies tend to focus on estimating emissions reduction of rental e-scooters without using observed service usage data as input. The England national evaluation of e-scooter trials (ARUP and NatCen, 2022a) is one of the few studies using service usage data to quantify the potential emissions reduction effect in a location-specific manner. The calculation of trip distance by alternative modes is conducted at origin-destination level using Google Directions. About 2,500 queries were run per case study trial. However the calculation of car distance saved (a key input into the estimation of emissions impact) uses city-average mode substitution rate for cars and city-average distance travelled by car, rather than trip-level figures. Mode substitution estimation based on trip-level data (e.g.

considering the variation of mode substitution with respect to trip distance), as conducted in this study, is likely to improve the accuracy of the analysis.

3 Research Questions, Data and Methods

3.1 Research questions

This study aims to demonstrate a novel method for inferring trip purposes and mode substitution effect of micromobility modes through a case study of the rental e-scooter trial in London. For the London case study, it addresses the following four research questions.

RQ1: What are the demand characteristics of a) short-distance travel and b) rental e-scooters in London?

RQ2: What trip purposes do rental e-scooters serve in London?

RQ3: What is the mode substitution effect of rental e-scooters in London?

RQ4: Whether/to what extent observed rental e-scooter trips would reduce greenhouse gas (GHG) emissions in London?

RQ1 is descriptive in nature and will be investigated through examining London trip samples from the National Travel Survey (NTS) series (RQ1.a) and rental e-scooter usage data (RQ1.b). The investigation of short-distance travel demand in London provides a useful context for understanding rental e-scooter demand. RQ2 and RQ3 examine the trip purposes and mode substitution pattern of rental e-scooters, respectively. The lack of Information on trip purpose and alternative travel mode remains a major analytical challenge for making sense of micromobility service usage data. To address this gap, a novel rule-based algorithm is proposed which matches rental e-scooter trips with intra-London trip samples in the NTS data. Results for RQ2 and RQ3 will be validated using external data.

Based on the mode substitution pattern from RQ3, potential GHG emissions reduction of rental e-scooter trips is estimated (RQ4) including a sensitivity test.

3.2 Data

Key data inputs for this study include 1) rental e-scooter usage data collected and provided by TIER Mobility, a leading e-scooter operator in Europe and one of the three selected rental e-scooter operators in the London trial; 2) English National Travel Survey (NTS) series from 2010 to 2019; 3) self-reported rental e-scooter trip purpose and alternative mode, collected from app-based, post-ride survey; and 4) greenhouse gas emission benchmark data. A list of key data inputs is provided in Table 3.

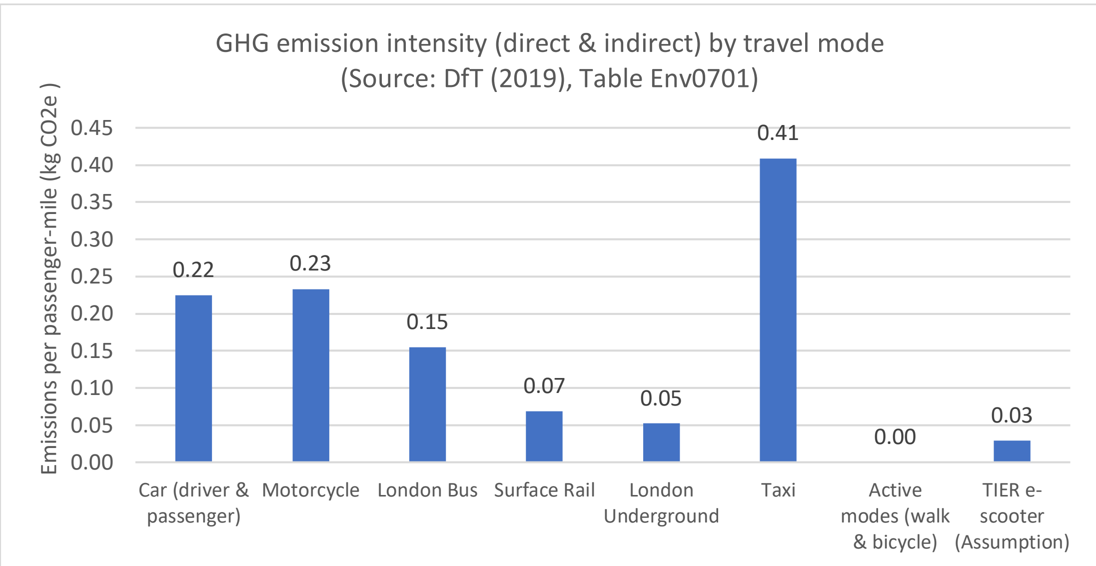
Table 3. List of input data

Data	Description	Source
Rental e-scooter usage data	Anonymized records of rental e-scooter rides: date, start/end time, coordinates of origin and destination; June 2021 to March 2022 (N > 200k trips)	TIER Mobility
National Travel Survey (NTS) data	Anonymized samples who conducted intra-London trips (i.e. trips starting and ending in London regardless of residence location of the respondent); $N \approx$ 2500 respondents per survey year (2002 to 2019)	UK Data Service[1]
Database of the National evaluation of e-scooter trials	Trip purpose and alternative mode collected from post-ride survey; Mar 2021 to Dec 2021 (N = 80,147 for Transport for London area; national response rate: 13%)	ARUP and NatCen (2022a, 2022b)
Emissions from journeys by mode	Table ENV0701: kg CO2e per passenger-mile by travel mode, including both direct and indirect emissions[2]	UK Department for Transport (DfT)[3]

Notes:
[1] https://beta.ukdataservice.ac.uk/datacatalogue/series/series?id=2000037
[2] Direct emissions are emissions produced by the vehicle itself with distinctions over primary energy sources (petrol, diesel and electricity); and indirect emissions are emissions produced by the extraction, refining, and transportation of the fuel used to power the vehicle. Other life-cycle carbon emissions such as embedded carbon in materials and emissions incurred by the manufacturing processes are excluded.
[3] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1129875/env0701.ods

The estimation of GHG emissions reduction from rental e-scooters is based on the following assumptions. 1) Zero direct emissions are assumed for all maintenance vehicles (e.g. for distributing rental e-scooters across the trial areas) as all participating operators in London commit to using zero-emission maintenance vehicles; indirect emissions of maintenance vehicles are not considered; 2) emissions intensity for car mode is based on 'average petrol car' as per the official emission intensity data from DfT (Table ENV0701); and 3) the unit emission for rental e-scooter is assumed to be 0.029 kg CO_2e per passenger-mile, which is 50% of unit emission of 'Small Battery Electric Car' as per DfT data (env0701). Our assumed emissions intensity is conservative compared with existing literature. For example, Moreau et al. (2020, p. 7) conducted a life-cycle GHG emissions analysis for e-scooters, among which the unit emission for charging e-scooters (i.e. direct emissions) is 0.005 kg CO_2e per passenger-km (equivalent to 0.008 kg CO_2e per passenger-mile). GHG emission intensities by travel mode are summarised in Figure 1**Error! Reference source not found.**.

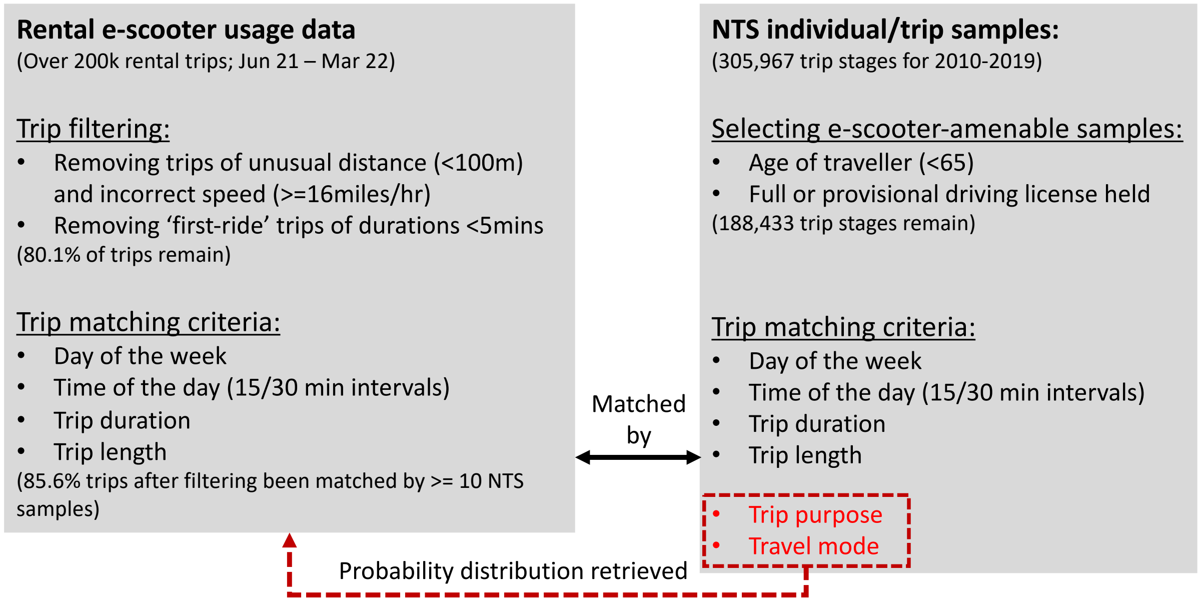
Figure 1. GHG emission intensity (direct and indirect) by travel mode (Source: DfT (2019), Table Env0701; emission for car based on 'average petrol car'; unit emissions for the rental e-scooter based on 50% of emissions of 'small battery electric car')



3.3 Methods

RQ1 is investigated through descriptive analysis of the NTS and rental e-scooter data. For RQ2 and RQ3, a rule-based, trip matching algorithm is proposed to infer the trip purposes and mode substitution pattern of rental e-scooter trips in London. A schematic diagram of the inference method is provided in Figure 2.

Figure 2. Method for inferring trip purposes and mode substitution pattern of rental e-scooter trips in London



The proposed method matches pre-selected NTS trip samples to the observed e-scooter data based on four trip attributes, 1) day of the week, 2) time of the day, 3) trip duration and 4) trip length[1]. These attributes are selected because they are readily available in both rental e-scooter usage data and the NTS data. Trip purpose distribution and potential mode substitution pattern are then extracted from the matched NTS trip samples.

Two individual-level conditions are applied to pre-select the NTS samples, 1) traveller age under 65 years old and 2) full or provisional driving license held. These conditions are adopted to ensure that the selected NTS trip samples are amendable to the rental e-scooter mode, the use of which currently requires a driving licence in the UK trials. The age threshold (<65) reflects the prevalence of young people among rental e-scooter users. According to the national evaluation report (ARUP and NatCen, 2022a), the share of rental e-scooter users over 65 years in the London trial is less than 0.5%.

[1] See Appendix A for detailed discussion on trip length estimation.

For efficiency concerns, the matching is conducted at trip-group level. Observed rental e-scooter trips are grouped by the four trip attributes, among which the time of the day, trip duration and trip length are continuous variables and thus need to be discretised. The categorisation scheme from the NTS (see Appendix B) is adopted for discretising the three continuous variables. For each e-scooter trip group, our trip matching algorithm will search for similar trip samples at the *stage* level in the NTS data based on the four attributes. All four attributes must be met simultaneously such that a successful match can be made. Using less granular categorisation (e.g. on time of the day, using 2-hour time intervals instead of 0.5 hour) can ease the burden of matching if the survey data is limited.

The proposed trip-matching algorithm incorporates a new and important trip filtering procedure that addresses a specific analytical challenge for inferring trip purposes and mode substitution effect of novel micromobility modes, where the trip purpose and alternative mode of the first ride of a new user are hardly predictable. This is in line with our real-world experience where the first ride is often induced by the novelty of the mode rather than serving a particular purpose. To address this challenge, all first-ride trips with a duration under 5 minutes (appr. 19% of raw data) are removed before trip matching. The possible impact on the inference results will be discussed in an empirical setting in the following sections.

The sample pool of NTS trips includes data from 2010 to 2019. All trips with both origin and destination falling in London are included, regardless of the residence location of the traveller. The sample pool effectively includes all intra-London trips made by either

Londoners or domestic visitors to London in the survey week. Data for 2020 are excluded due to drastic changes of sample base and travel behaviour incurred by the COVID-19 pandemic. To ensure the temporal consistency of NTS trip samples, we empirically test the temporal stability of short-distance travel demand in London (see results in Section 4.1). For cities with less frequent travel survey schedules, combining historical data into a larger trip sample pool is suggested, and the temporal consistency should be checked.

To ensure matching quality, a minimum matching ratio is imposed. Each rental e-scooter trip category must be matched with at least ten NTS trips (short walking weighting applied in NTS trip counts). To further increase the likelihood of successful trip matching, considering the relatively fine categorisation of time of the day in our study (15/30 min), we allow trip searching to expand to the immediate neighbouring periods if the minimum matching ratio does not meet. For example, for a given rental e-scooter trip happened during 03:00-03:59, if the number of matched NTS trip samples is less than ten within the 03:00-03:59 window, the algorithm will then expand the search to the immediate neighbouring periods, namely 02:00-02:59 and 04:00-04:59. The relaxed rule for trip searching reflects the inherent scheduling flexibility for short-distance trips and would effectively improve the likelihood of successful trip matching.

To validate inferred trip purposes and mode substitution pattern of rental e-scooters, inference results are compared against the benchmark data for London sourced from the

National evaluation of e-scooter trials (ARUP and NatCen, 2022a). Specifically, trip purpose[2] and alternative mode[3] data collected from the post-ride survey are used as the benchmark data (N = 80,147 for Transport for London area). The post-ride survey appeared in users' app after every trip was completed. Discrepancies between the inference and the benchmark data, potential sources of biases and correction measures are investigated.

To answer RQ4, this study focuses on GHG emissions reduction primarily from mode substitution and excludes the effect of induced demand. The potential emission reduction is estimated by quantifying how much GHG would have been emitted if the trip had been made by alternative modes. The exclusion of induced demand is likely to cause downward bias to the emissions estimation. However, post-ride survey data suggests that the proportion of rental e-scooter trips for ‘enjoyment or no particular purpose’ (hence most likely induced trips) has gradually decreased from 12% in March 2021 to 7% in Dec 2021 (ARUP and NatCen, 2022a, p. iv). It indicates that as people get more familiar with the rental e-scooter mode, the effect of induced demand is likely to diminish. Therefore our emissions estimate reflects a longer-term effect, as opposed to the short-term effect at the early stage of the trial.

4 Results and Discussion

Section 4.1 discusses short-distance travel demand in London using the NTS data, which provides a useful background for understanding rental e-scooter demand in London (Section

[2] Survey question: What was your main reason for using an e-scooter for this journey? (ARUP and NatCen, 2022a)
[3] Survey question: Had you not used an e-scooter for this journey, which mode of transport would you have been most likely to use, if any? (ARUP and NatCen, 2022a)

4.2). Inference results on mode substitution pattern and trip purposes are presented in Section 4.3 and Section 4.4, respectively. Lastly, Section 4.5 examines the GHG emissions reduction effect.

4.1 4.Short-distance travel demand in London

To investigate short-distance travel demand in London, we select short (<= 4 miles), intra-London trip samples from the NTS data series (2010-2019). The selection of the 4-mile distance threshold is informed by our empirical analysis of the rental e-scooter data, where 99% of observed trips are under 4 miles. In terms of sample size, the NTS data have, on average, about 2,500 annual respondents who conducted intra-London trips of all distances prior to the COVID-19 pandemic, and the sample size dropped significantly to about 770 in 2020. Detailed time-series data on sample size and weekly trip rate, and validation results using aggregate trip rates from the London Travel Demand Survey are provided in Appendix C.

Figure 3 presents weekly trip rates of short-distance (<= 4 miles), intra-London trips by trip purpose between 2002 and 2019. Overall, weekly trip rates by trip purpose have remained broadly stable over time, indicating the feasibility of using pooled historical data for trip purpose inference. Shopping (including food and non-food), commuting and education feature relatively high trip rates among the selected trip purposes based on 2019 ranking. Shopping has a higher weekly trip rate than commuting because the distance filter (<= 4 miles) has effectively removed commuting trips over 4 miles and the average distance of commuting tends to be relatively long.

Figure 3. Weekly trip rates by trip purpose based on short-distance (<= 4 miles), intra-London trips (Data source: NTS, 2002-2019; top 5 trip purposes selected by 2019 ranking)

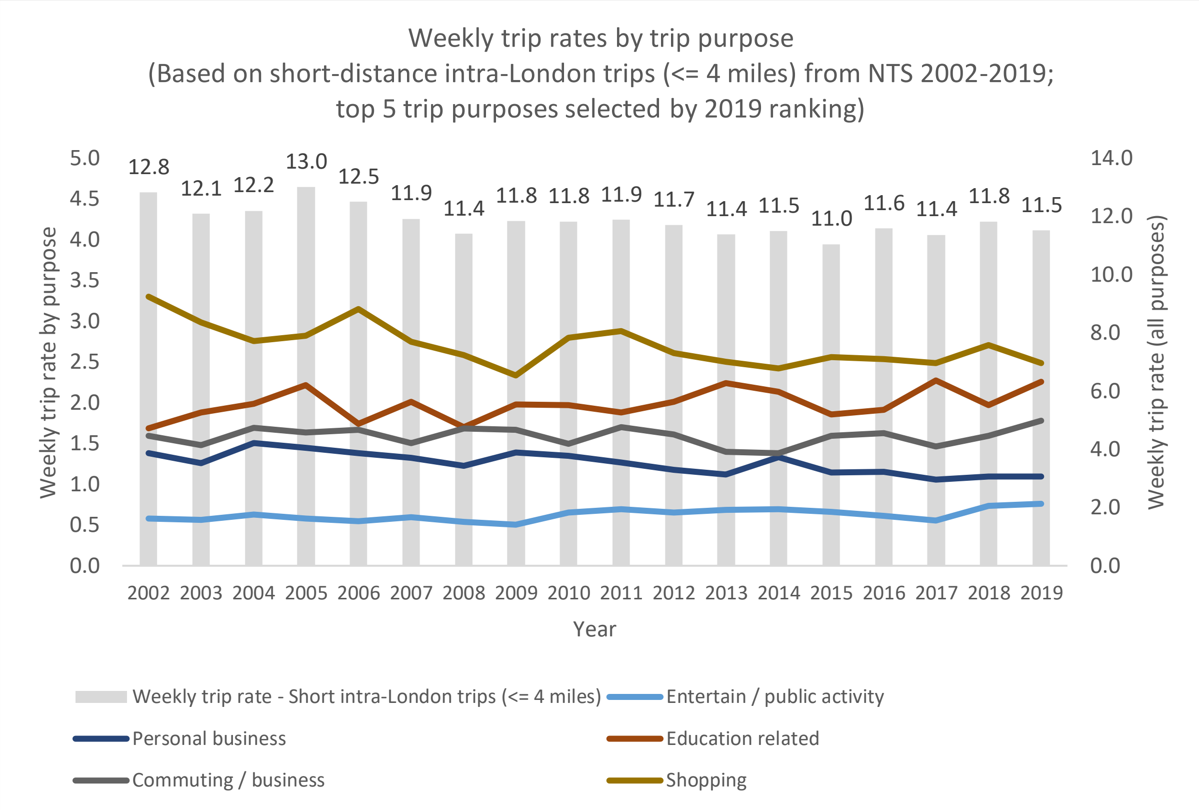


Figure 4 and Figure 5 present stage-level mode share by trip purpose and by distance band in 2019, respectively. It is evident that model share varies significantly across trip purposes and distance bands. The average share of private modes (car/van/motorcycle including both driver and passenger) is 38% for all trip purposes, but is significantly lower for commuting (17%) and higher for shopping and escorting trips. The average share of public transport modes is 33% for all trip purposes, ranging from 12% (other escort) to 51% (commuting). In terms of the mode share variations by distance band, the share of active modes drops significantly as trip distance reaches beyond 2 miles, while the share of public transport continues to increase as trip distance increases. The significant variation of mode share across trip purposes and distances indicates that surveying alternative modes of travel without specifying trip purpose and other contextual factors (e.g. time of the day, day of the week and trip distance) may lead to significant biases in mode substitution estimation.

Figure 4. Mode share by trip purpose (Based on short-distance intra-London trip stages (< 5 miles) in NTS 2019)

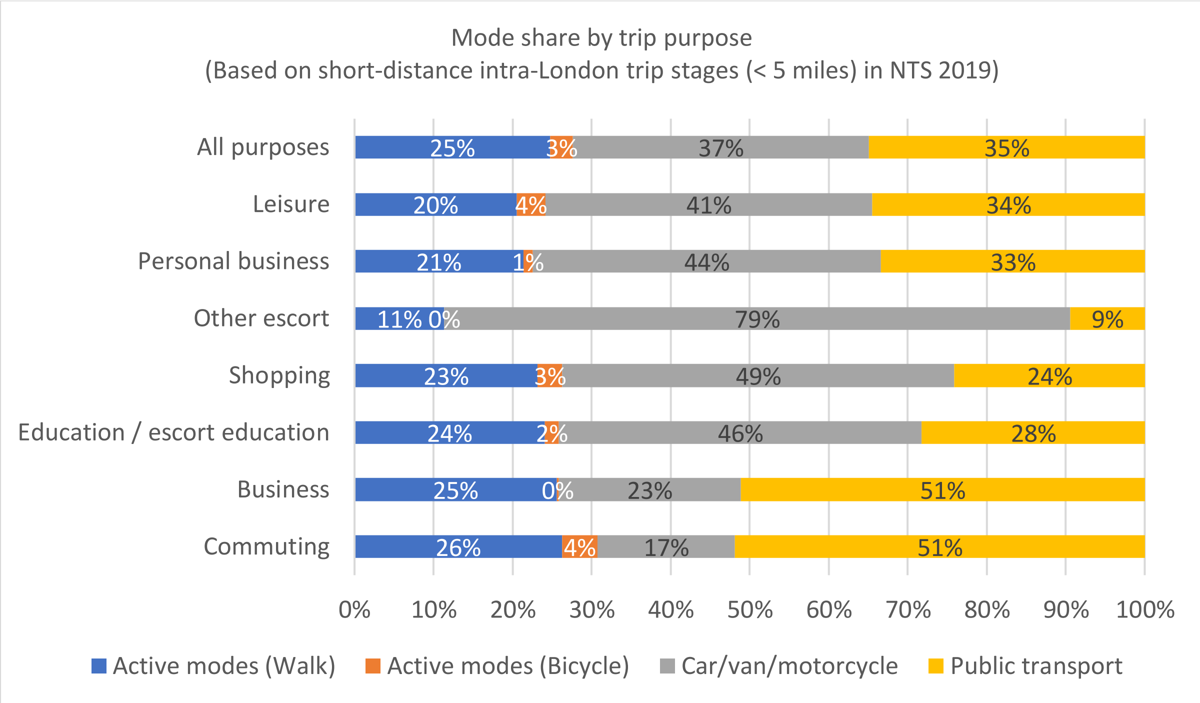
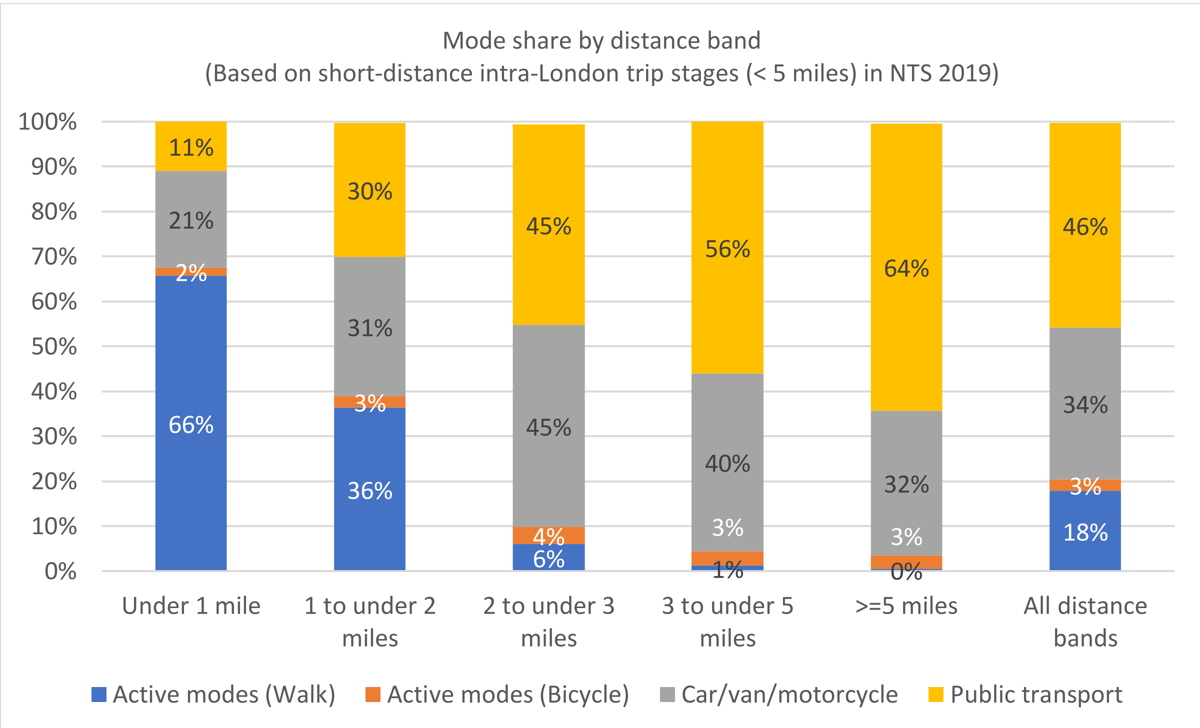


Figure 5. Mode share by distance band (Based on short-distance intra-London trip stages (< 5 miles) in NTS 2019)



4.2 Demand characteristics of rental e-scooters in London

In this section, we discuss demand characteristics of rental e-scooters in London. The e-scooter usage data cover a trialling period from June 2021 to March 2022. The raw data include a total of over 200,000 trips made by over 50,000 unique, anonymised users. Attributes include trip ID, user ID, vehicle ID, timestamps and coordinates of trip origin and destination. On average, each unique rental e-scooter user has made 4.2 trips during the observation period. 46% of users have made at least 2 trips during the observation period.

Rental e-scooter demand varies significantly across different months of the year, days of the week and times of the day (see Figure 6 and 7). User demand appeared to stabilise three months into the trial[4], which features notable usage peaks in the morning (7:30-9:30) and afternoon (16:00-19:00), with the afternoon peak load significantly higher and more extended than the morning peak. In addition, service usage tends to be higher in afternoons, which is in line with literature review findings from other city cases. The evident two daily peaks of rental e-scooter usage in London suggests that rental e-scooters may well serve commuting purpose, which contrasts to the literature where leisure tends to be the dominant purpose.

[4] According to the information provided by the operator, the number of rental e-scooters deployed in London has been gradually increasing from the start of the trial and stabilised from Sep 2021. Other possible confounding factors include seasonality and the emergence of Omicron variant of COVID-19, which may explain the notable fall of rental e-scooter usage between Dec 2021 and Feb 2022.

Figure 6. E-scooter trip count by time of the day and month of the year (Jun 2021 – Mar 2022)

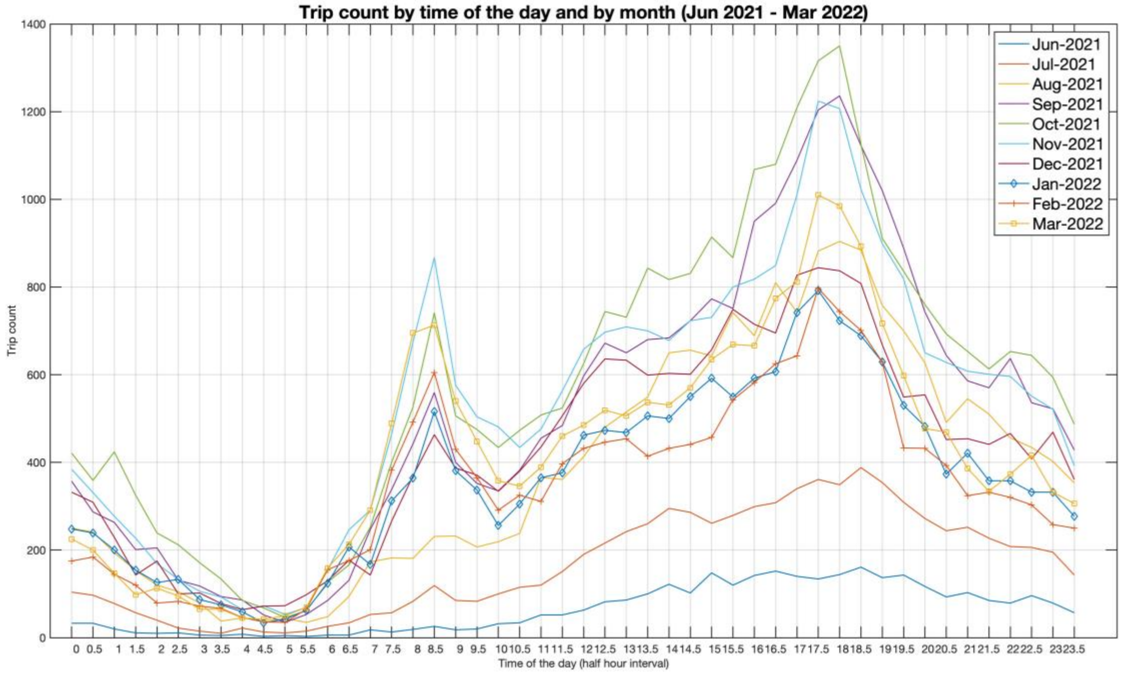
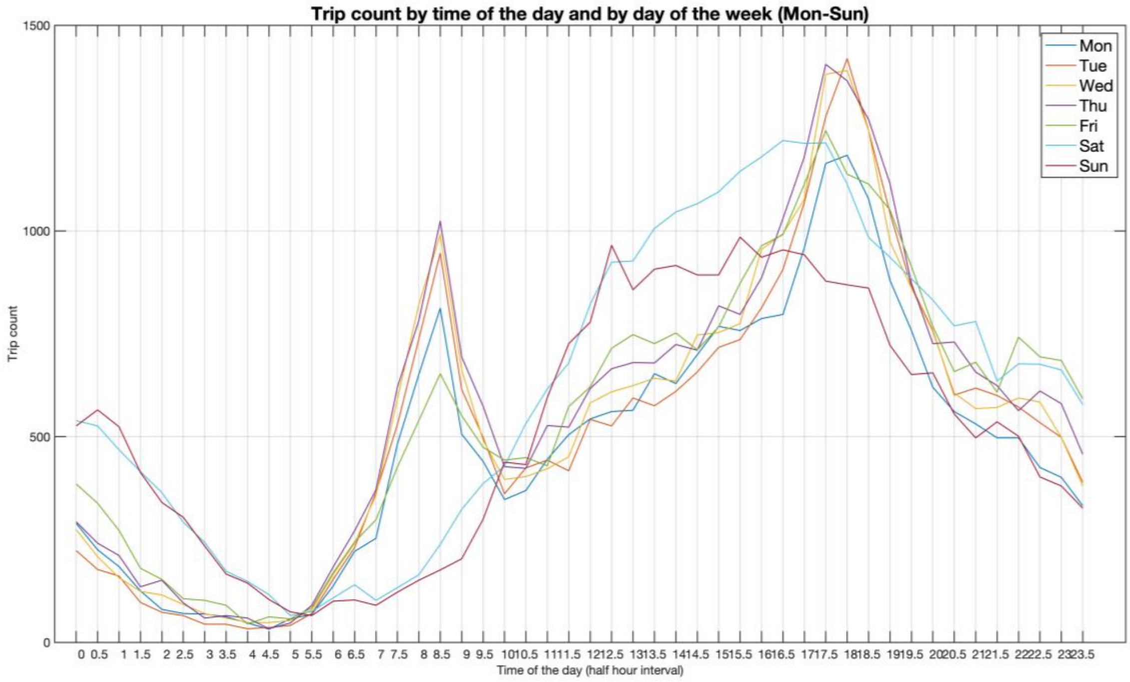


Figure 7 further shows the demand variation across times of the day by day of the week. The two daily usage peaks remain visually discernible for weekdays. Rental e-scooter usage pattern on weekends is distinctly different from that on weekdays. Key differences on weekends include 1) the absence of morning peak; 2) higher usage starting from 10:30 to the afternoon; and 3) higher usage on Saturday than Sunday. Among weekdays, rental e-scooter usage on Fridays differs from other weekdays for a notable rise of ridership after 21:30 on Friday nights, which lasts till 1:30am the next day. It shows a strong tendency to use rental e-scooters for leisure activities and the associated escort/visiting trips on Fridays.

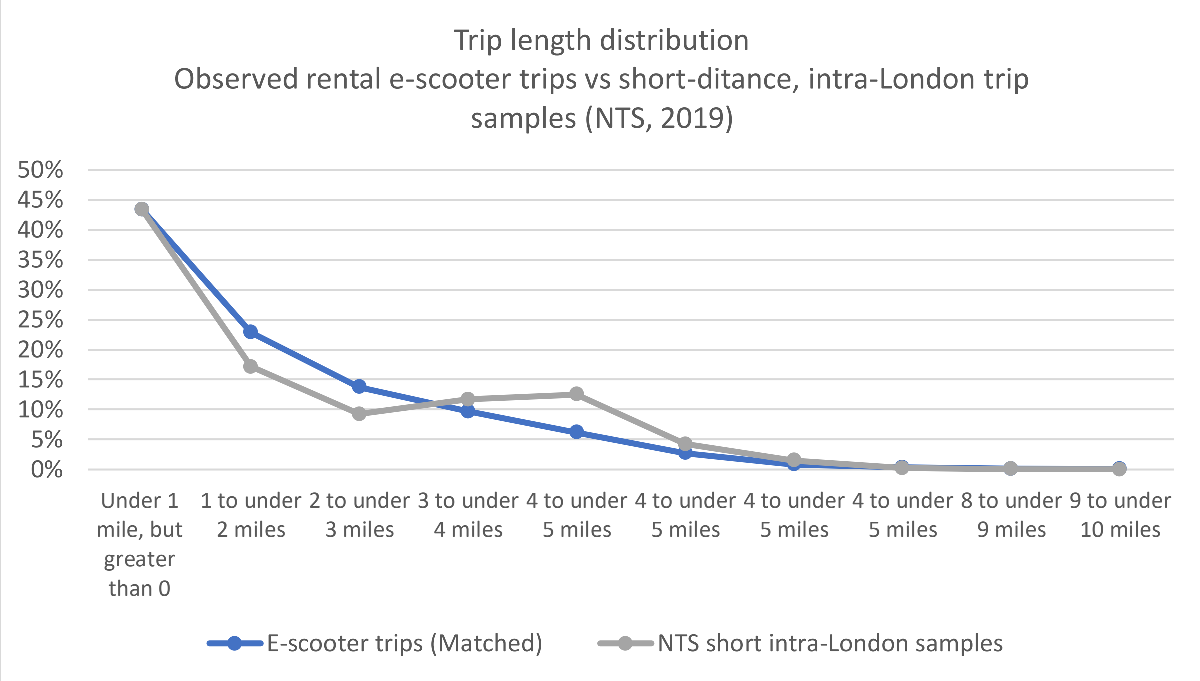
Figure 7. E-scooter trip count by day of the week (Jun 2021 – Mar 2022)



4.3 Inferring rental e-scooter mode substitution pattern

In terms of trip matching outcome, we report that 81.6% of all selected rental e-scooter trips are successfully matched with at least 10 NTS trip samples. Those non-matching rental e-scooter trips are discarded. The total trip length of matched rental e-scooter trips is appr. 133k miles for the observation period. A comparison of trip length distribution between the matched rental e-scooter trips and NTS intra-London trip stage samples in 2019 is presented in Figure 8**Error! Reference source not found.**. It shows that the matched e-scooter trips feature a higher share of short-distance (0-3 miles) trips than the NTS benchmark. We have also conducted sensitivity tests by using different matching criteria. By lowering the minimum matching ratio from 10 to 5, matching rate would increase from 81.6% to 88.2%. Our sensitivity test results show that the differences in inference results are minimal if a threshold of 5 is used. All findings presented in the following sections are based on the threshold of 10.

Figure 8. Trip length distribution – Observed rental e-scooter trips vs intra-London trip samples (source: NTS 2019)



VALIDATION: MODE SUBSTITUTION

Table 4 presents the inferred probability of rental e-scooter substituting other modes in London, which is compared against the benchmark data for London sourced from the national evaluation report (ARUP and NatCen, 2022a) and additional data from Brussels (Moreau *et al.*, 2020). The probabilities reported are weighted averages of all matched e-scooter trips. The sum of substitution probabilities for all alternative modes is 100%.

Significant discrepancies are observed across the three data sources. Particularly, our mode substitution estimates for the car (active modes) are considerably higher (lower) than the London benchmark data (ARUP and NatCen, 2022a), while the data from Brussels is somewhat in between. Among active modes, the substitutability between rental e-scooter and walking is notably higher (and closer to the literature) than that between rental e-scooter and bicycle in our inference results. This finding appears congruous with our lived experience as rental e-scooter would have a bigger comparative advantage over walking in terms of travel speed, compared with cycling.

Table 4. Comparison of mode substitution probability: Inference vs literature

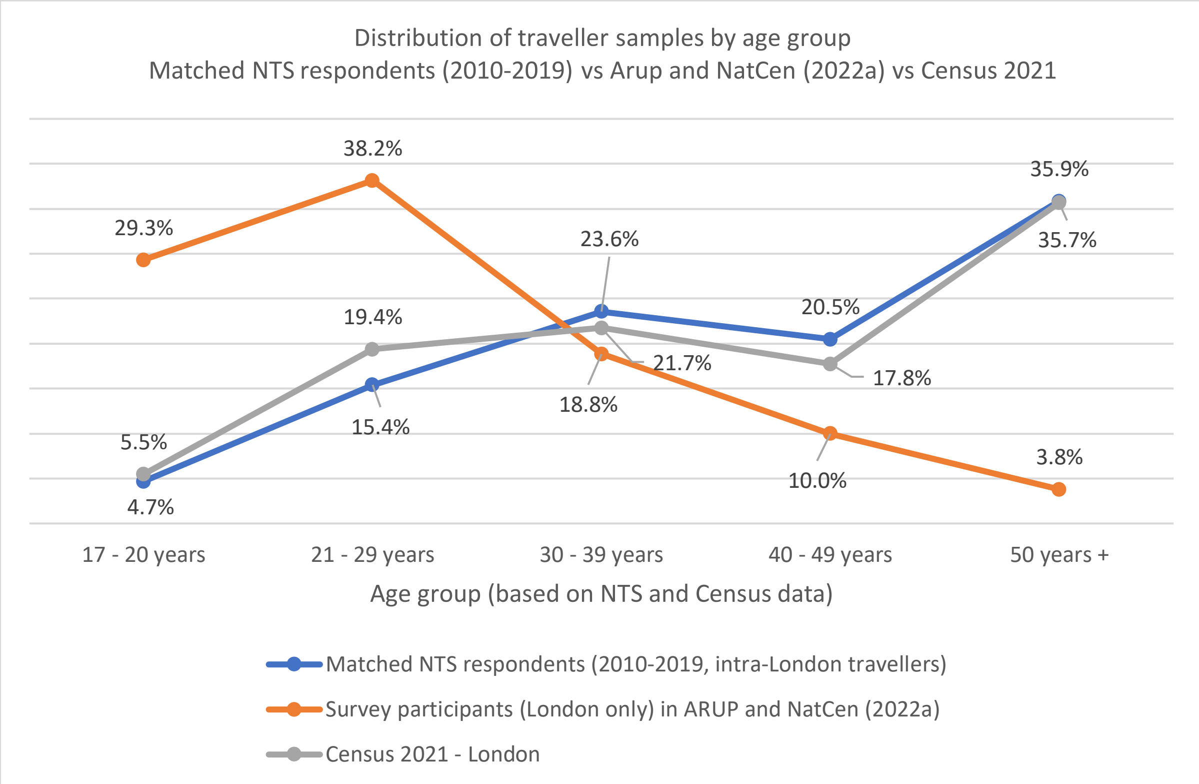
Mode substituted by rental e-scooters	**Inferred probability of mode substitution (unadjusted)**	**Probabilities from literature**	
		Moreau *et al.* (2020)[1]	ARUP and NatCen (2022)[2]
Car[3]	40.5%	26.7%	8.7%
Motorcycle	0.2%	0.4%	2.9%
Public transport	30.9%	29.2%	26.7%
London Bus	21.9%	-[4]	12.2%
Rail	1.9%		8.2%
London Underground	5.8%		
Taxi	1.3%		6.4%[5]
Active Modes	28.3%	40.3%	61.7%
Walk	24.6%	26.1%	44.3%
Bicycle	3.2%	14.2%	17.4%

[1] Based on e-scooter user survey in Brussels (N = 1,181; 757 were non-personal e-scooter users).
[2] Based on post-ride survey collected by Transport for London (Mar-Dec 2021; N = 80,147; rescaled after removing non-mode answers).
[3] Including car /van as driver and as passenger.
[4] No breakdown is provided in the literature.
[5] Including app-based minicab services e.g. Uber

The significant discrepancies prompt us to investigate potential sources of biases and explore correction measures. Our investigation reveals that the stratified sampling in NTS data may be the main cause for such discrepancies, as the demographic profile of rental e-scooter users (more precisely, those users who responded in the post-ride survey) is significantly skewed towards younger age groups. Specifically, as shown in Figure 9, the age distribution in the matched NTS data (2010-2019 pooled samples) is in line with the demographic profile from Census 2021 for London, which corroborates the representativeness of the NTS intra-London subset. By contrast, the age profile of London rental e-scooter users reported in ARUP and NatCen (2022a) shows that young travellers (16-34 years old as per ARUP and NatCen's age bands) are notably overrepresented compared with the NTS/Census distribution. Relatedly, travellers over 45 years old (as per

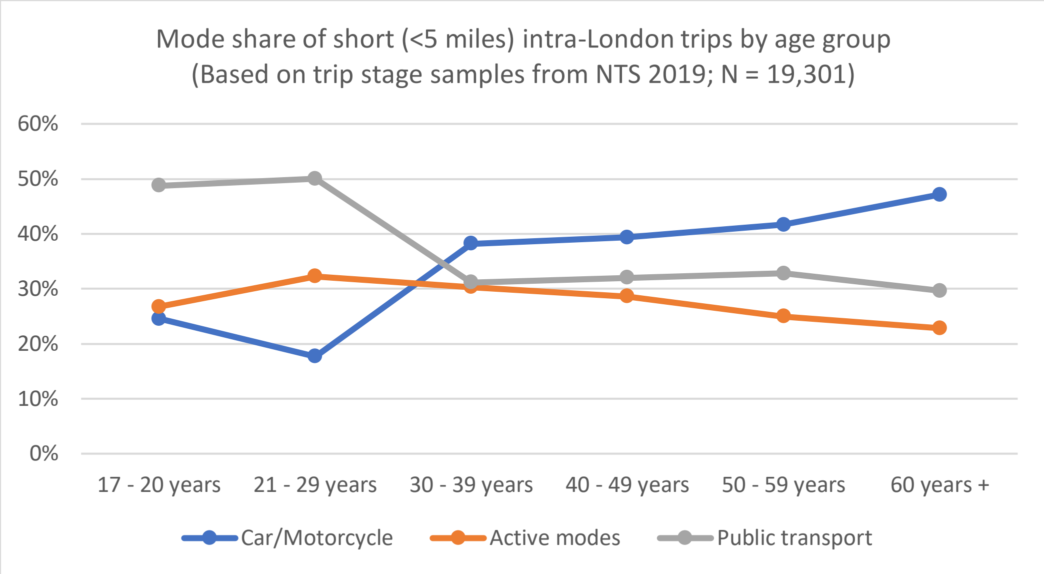
ARUP and NatCen's age bands) are underrepresented. Although the post-ride survey data reflect the fact that rental e-scooters are particularly popular among young people, the possibility of certain sampling bias (i.e. overrepresentation of young respondents and/or short-distance trips) cannot be ruled out in ARUP and NatCen (2022a).

Figure 9. Comparison of age profile: Matched NTS respondents (2010-2019) vs ARUP and NatCen (2022a) vs Census 2021 for London (Note: the age grouping in ARUP and NatCen is different from the NTS and Census data; the comparison is based on a best match between the two sets of age bands)



The implication of the prevalence of young rental e-scooter users on mode share inference is unfolded in Figure 10. According to the NTS short intra-London data for 2019, as travel's age increases from early 20s, the share of public transport (car) decreases (increases). Share of active travel is notably less sensitive to the change of age, albeit a moderate decreasing trend as age increases. Our inference based on NTS data (which adopts stratified sampling) is thus likely to cause overestimation of car use.

Figure 10. Mode share of short (<5 miles), intra-London trips by age group (Based on trip stage samples from NTS 2019; N = 19,301)



ADJUSTMENTS THROUGH RE-WEIGHTING

In light of the sampling bias discovered above, a set of age-based weights is proposed to correct our inference results. The weights are applied to adjust the number of NTS trip samples to be matched with the rental e-scooter trips. For example, if a matched NTS trip was made by a 60 years old, a weight would then be applied to discount this trip count. The method for applying the weights is very similar to the standard weighting exercise adopted in the NTS (see NTS Technical Report by Department of Transport, 2022, p. 68). The age-band specific weights presented in Table 5 are calculated as the ratios between the benchmark age share and the NTS share as per Figure 9. In future studies, a provisional age distribution of service users could be obtained from user survey of a modest sample size, which could then be refined when larger survey or new data (potentially provided by service operators after anonymisation) become available.

Table 5. Age-band specific weights for adjusting inference biases

Age band	Weight
17 - 20 years	6.24
21 - 29 years	2.47

30 - 39 years	0.80
40 - 49 years	0.49
50 - 59 years	0.11
60 - 64 years	0.11

Adjusted mode substitution pattern is presented in Table 6. It shows that the proposed adjustments lead to a lowered substitution probability for car (from 40.5% to 34.4%) and an increased probability for public transport (from 30.9% to 37.7%). Figures for other modes remain broadly stable. The pattern of change is in line with the mode share differences between age groups as presented in Figure 10.

Table 6. Adjusted mode substitution effect of the rental e-scooter mode

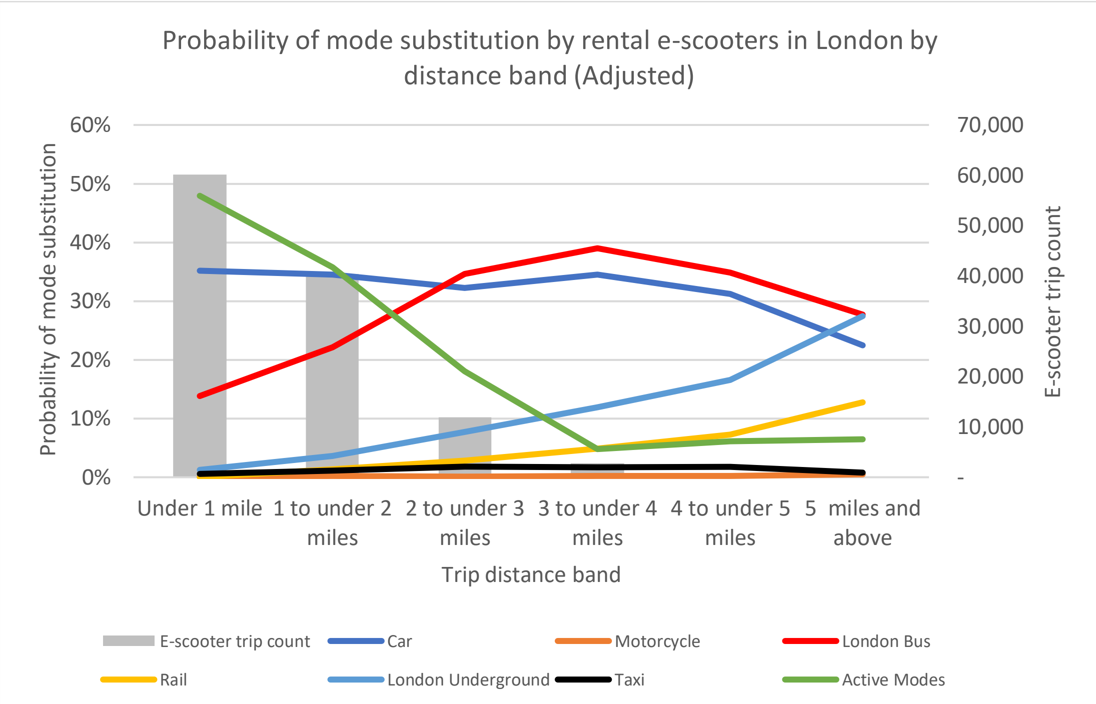
Mode substituted by rental e-scooters	Inferred probability of mode substitution (Unadjusted)	Inferred probability of mode substitution (Adjusted)
Car	40.5%	34.4%
Motorcycle	0.2%	0.1%
Public transport	30.9%	37.7%
London Bus	21.9%	27.1%
Rail	1.9%	2.6%
London Underground	5.8%	6.7%
Taxi	1.3%	1.3%
Active Modes	28.3%	27.8%
Walk	24.7%	24.6%
Bicycle	3.6%	3.2%

Despite the adjustments, our mode substitution rate for car (34.4%) remains qualitatively higher than the benchmark figure (6.4%). While further estimation bias may well remain, we argue that the benchmark figure appears too low compared with background mode share statistics in London. First, it has been shown that the share of car use for intra-London trips under 5 miles would increase as traveller's age increases (see Figure 10). However, even if all rental e-scooter users were in the 21-29 years group (which has the lowest mode share for car across all age bands) about 18% of their short trips (<5 miles) would be made by car. To further corroborate our argument, even if all rental e-scooter trips were under 1 mile (which has the lowest mode share for car across all distance bands – see Figure 5), about 21% of those trips would be made by car. Both figures (18% and 21%) are significantly higher than the 6.4% substitution rate reported by ARUP and NatCen (2022a). It is thus contested that the potential of rental e-scooters in replacing car journeys (as both driver and passenger) in London should be higher than the reported figure in ARUP and NatCen (2022a), possibly close to 18% as per the background mode share data in London.

Another factor contributing to our high substitution rate for car pertains to the removal of short (< 5 mins), first-ride trips as part of the data cleaning process. As a result, about 19% of rental e-scooter trips are excluded as first-ride trips in our inference. Our primary consideration for the removal is that the trip purpose and alternative mode of first-ride trips are difficult to infer. These short, first-ride trips are nevertheless included in ARUP and NatCen (2022a). We acknowledge that removing these short trips (43% under 1 mile and 66% under 2 miles) in our inference is likely to lead to an underestimation for substituting active modes and consequently an overestimation for substituting car mode. Nonetheless, evidence from England shows that the share of trips without a particular purpose (most likely first-ride trips) has been reducing as rental e-scooter trials progress (ARUP and NatCen, 2022a, p. iv), indicating that the above estimation bias would diminish and our estimates may reflect a long-term substitution pattern.

A unique analytical advantage of the proposed inference method is to produce a detailed mode substitution breakdown, which is not feasible otherwise. Figure 11 presents the inferred mode substitution pattern of rental e-scooters by distance band. For short-distance trips (< 2 miles), the probability of rental e-scooters replacing active travel is significantly higher than that for longer distances, which is in line with the literature (see Figure 5) and close to the benchmark data (ARUP and NatCen, 2022a). It implies possible sampling bias (i.e. overrepresentation of short trips) in the benchmark data. The probability of substituting the car mode would decrease as trip distance increases. For London bus, the substitution effect becomes notably stronger when the trip distance reaches 2 miles and beyond. The increasing probability of substituting London bus may be attributed to the fact that as trip distance increases, the access/egress time to/from the bus stop and the number of bus stops along the journey are likely to increase, thus the speed advantage of bus over the rental e-scooter diminishes. Similar substitution effect also applies to London Underground and rail, but the elasticities of substitution with respect to distance are much lower than that of London Bus. In contrast, the substitution effect for motorcycle and taxi seems not correlated strongly with trip distance.

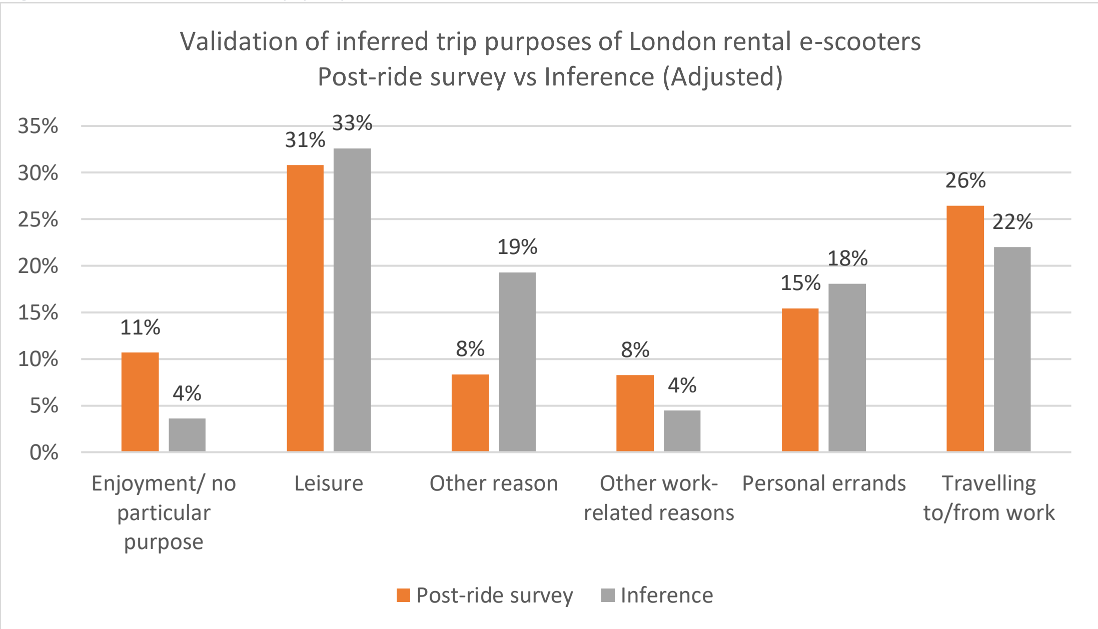
Figure 11. Probability of mode substitution by rental e-scooters in London by distance band (Adjusted)



4.4 Inferring rental e-scooter trip purposes

Figure 12 shows inferred trip purposes of rental e-scooter trips in London after applying the re-weighting adjustments, compared against the benchmark data (ARUP and NatCen, 2022a). Our inferred trip purposes have more detailed categories inherited from the NTS. For facilitating the comparison, inferred trip purposes are aggregated to match the trip purpose classification in the benchmark: enjoyment/no particular purpose = Holiday + Day trip + Just walk; Leisure = Visit/eat/drink with friends + Entertain/public activity + Other social + Sport + Non-food shopping; Personal errands = Food shopping + Personal business (medical/eat/other) + Other non-escort; Other work-related = Business + Other work + Escort business & other work; Other reason = Education + Escort education/shopping/personal business/home. A breakdown of inferred trip purpose by the time of the day is provided in Appendix D.

Figure 12. Validation of trip purposes: Inference vs benchmark data



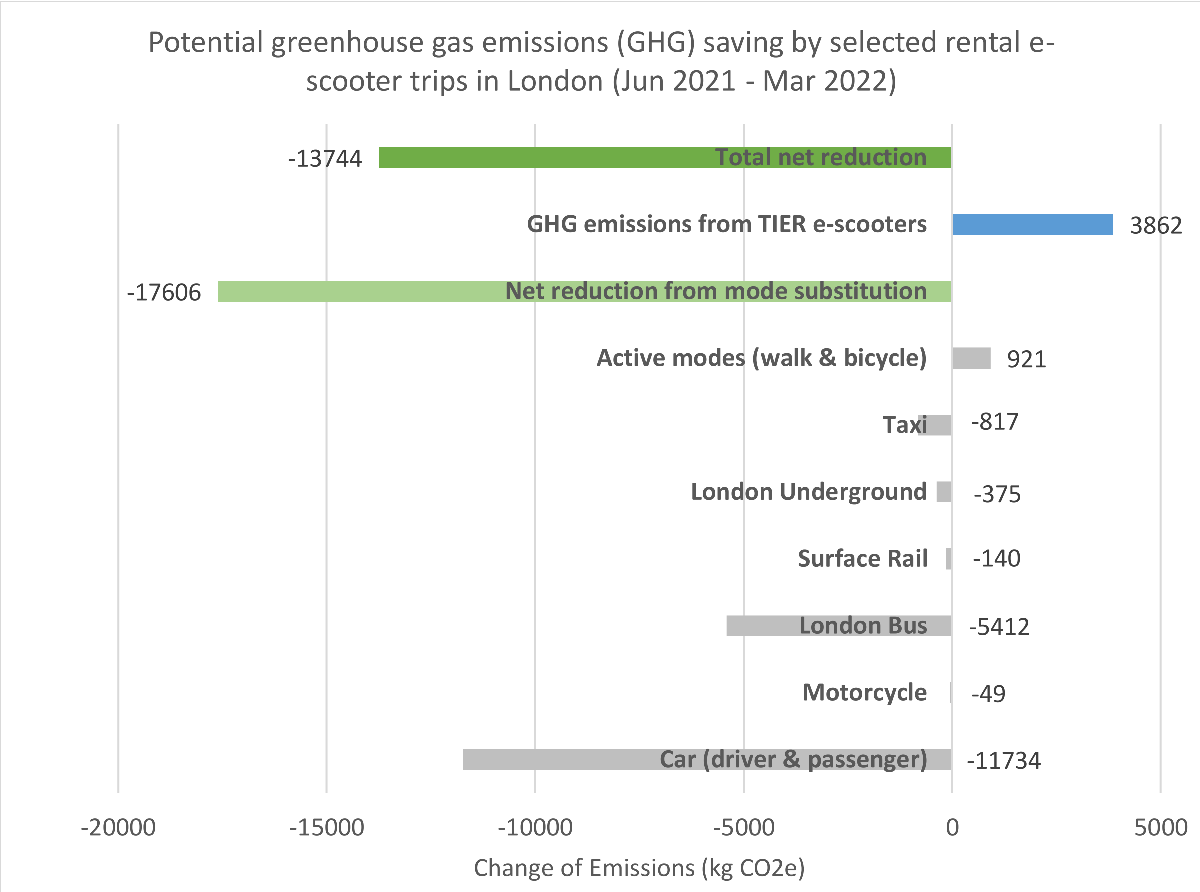
The comparison shows a reasonably good match between our inference and the benchmark data, particularly on major purposes such as leisure and commuting. A notable discrepancy appears for ‘Enjoyment / no particular purpose’ and ‘Other reason’. For the former, the removal of short first-ride rental e-scooter trips would explain the underestimation. For the latter, 'other reason' includes several escorting trip purposes (e.g. escort education/shopping/personal business/home) in our trip purpose consolidation. On the one hand, the construction of the NTS trip sample pool considers the age and driving license status of travellers only, but not other mobility constraints such as certain physical impairments or illnesses, which may explain the overestimation of escorting trip purposes. On the other hand, our real-world observation suggests that rental e-scooters can be used for group travel and thus can serve certain escorting purposes, for example, escorting friend(s) home after evening leisure activities. However, the benchmark data does not include escorting as an explicit trip purpose, which may result in certain measurement errors in the post-ride survey.

4.5 Estimating emissions reduction effect of rental e-scooters in London

4.5.1 EMISSIONS SAVING EFFECT OF RENTAL E-SCOOTERS

Based on the inferred mode substitution pattern after adjustments (see Figure 11) and the emission intensity data (see **Error! Reference source not found.**), we estimate potential greenhouse gas (GHG) emissions reduction should the selected rental e-scooter trips had been made by alternative models. Mode-specific change of emissions E_j is calculated by: $E_j = \widehat{E_j} \sum_l D_l P_{lj}$, where $\widehat{E_j}$ is the unit emission intensity of mode j, D_l is the distance of e-scooter trip l and P_{lj} is the estimated probability of e-scooter substituting mode j for trip l. Total net reduction is then calculated by summing up all mode-specific emissions including the emissions from the rental e-scooter mode. No induced travel demand is considered. Results are presented in Figure 13.

Figure 13. Potential greenhouse gas emissions saving by selected rental e-scooters in London (per passenger-mile GHG emissions obtained from UK official data (Table: env0701); unit emissions for rental e-scooters is 0.029 kg CO_2e per passenger-mile by assumption; only direct and indirect emissions included)



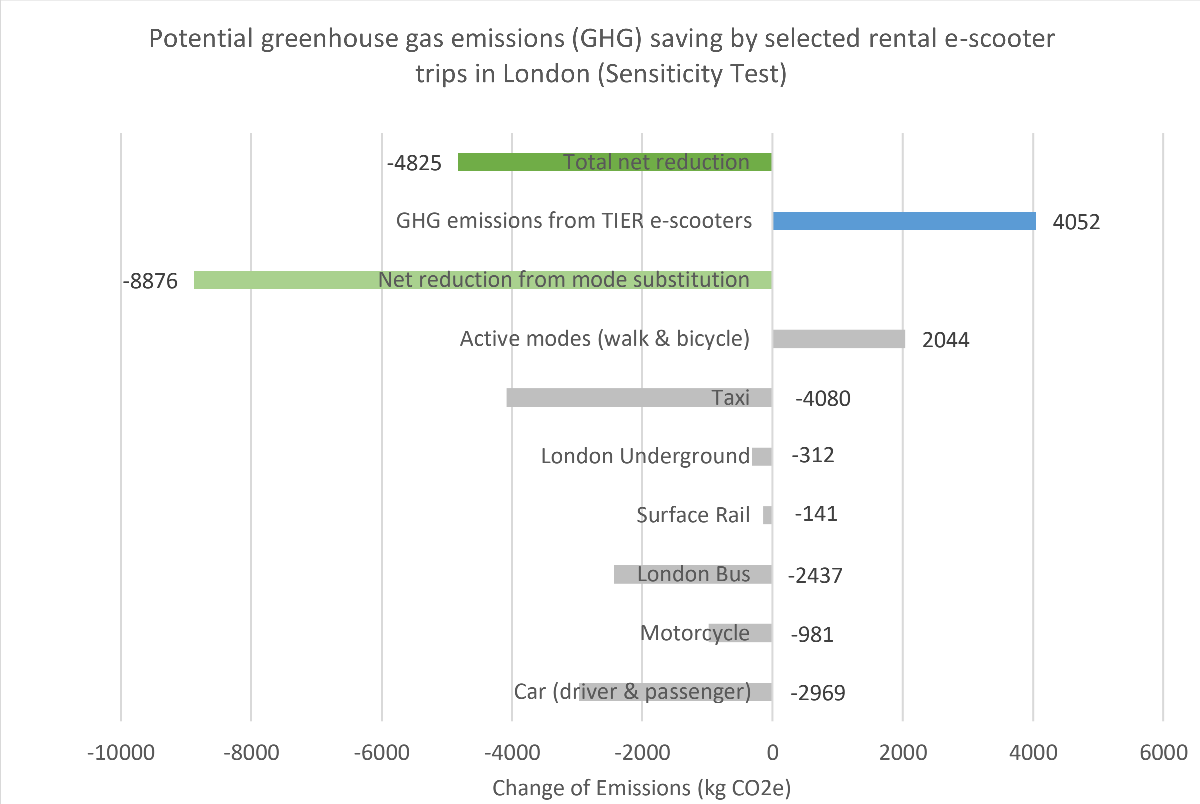
By considering both positive (replacing high-emitting modes) and negative (replacing active travel) effects of rental e-scooters, our analysis shows that if all selected rental e-scooter trips had been made by alternative modes, it would have led to a net increase of GHG emissions of approximately 17.6 tonnes CO_2e, among which about 67% come from car journeys. The 17.6 tonnes CO_2e reduction effect is net of the 0.9 tonnes emissions increase from substituting active modes. The increase of emissions caused by replacing active travel seems marginal compared with the magnitude of total emissions saving from other emitting modes. Our data only cover one of the three rental e-scooter operators in the London trial. It can thus be postulated that overall GHG emissions saving from the London e-scooter trial would be more significant than the current estimates based on a single operator.

Despite zero direct emissions from rental e-scooters, indirect emissions (for sourcing primary energy for charging rental e-scooters) are estimated to be 3.9 tonnes. Overall, the total net reduction of GHG emissions is approximately 13.7 tonnes CO_2e (equivalent to appr. 276 round trips between London and Bristol by an average diesel car). Given the total distance travelled of selected rental e-scooter trips (about 133k miles), the net GHG emissions reduction effect is about 103g CO_2e per e-scooter mile in London. The unit emissions reduction effect is in line with the estimates (141g CO_2e per passenger-mile) from Hollingsworth, Copeland and Johnson (2019).

4.5.2 SENSITIVITY TEST

To address the uncertainty in our mode substitution assumption, sensitivity tests are conducted. Specifically, the sensitivity test assumes that the mode substitution probability for the car and active modes would adopt the same values from ARUP and NatCen (2022a), that is, 8.7% for the car, 26.7% for public transport and 61.7% for active modes (see Table 4), while the probability for all other modes remains constant. Based on this new assumption, GHG emission saving results are presented in Figure 14.

Figure 14. Sensitivity Test - Potential greenhouse gas emissions (GHG) saving



It shows that the GHG emissions reduction from the car reduces from 11.7 tonnes CO_2e in the baseline analysis to 3.0 tonnes, whilst emissions incurred from replacing active travel increase from 0.9 tonnes to 2.0 tonnes. As a result, total net emissions saving drops from 13.7 tonnes to 4.8 tonnes. The per-mile emissions reduction effect of rental e-scooters is thus lowered to 36g CO_2e. Our emissions reduction estimate (4.8 - 13.7 tonnes CO_2e) is broadly in line with the benchmark estimate for London (16.4-32.9 tonnes CO_2e for all three operators) in ARUP and NatCen (2022a), assuming equal market share among three London operators.

5 Conclusion

The paper presents a novel method for inferring trip purposes and mode substitution pattern of micromobility services through a case study of rental e-scooters in London. The proposed inference method features a rule-based algorithm for matching observed rental e-scooter trips (>220k anonymised rental e-scooter trips between June 2021 and March 2022) with pooled intra-London trip samples from the National Travel Survey (NTS) data (2010-2019). The design of rules considers not only trip-level attributes (travel time, day of the week, duration and length) but also individual-level attributes (age and driving license status) for constructing the trip sample pool. The new method enables trip purpose and mode substitution to be inferred at a context-sensitive manner, that is, inferences are conditional on trip-level attributes. This contrasts to conventional survey approach where questions asking the purpose and alternative mode of micromobility services usually do not specify contextual factors such as time and duration of travel.

The study also proposes a new data cleaning procedure which removes all short 'first-ride' trips (i.e. first rental e-scooter trip of each unique user; appr. 19% in the raw data) because of inherent difficulties in inferring trip purposes and alternative mode of these trips. It is expected that this data cleaning procedure and the proposed inference method would apply to a wide range of micromobility studies using large-scale service data.

Leisure (33%) and commuting (22%) are dominant trip purposes in the London rental e-scooter trial. In terms of mode substitution, after correcting the age-related sampling bias, the estimated probability of rental e-scooter replacing car, public transport and active travel (walking and cycling) is 34%, 38% and 28%, respectively. Based on the estimated mode substitution, we provide one of the first evidence on the emissions reduction effect of rental e-scooters in London. Net reduction of GHG emissions from rental e-scooter trips is estimated to be in the range of 36-103g CO_2e per mileage travelled.

Despite the rivalry between rental e-scooters and public transport and active modes, we argue that the addition of rental e-scooter as a new travel mode is likely to further reduce car dependence and overall GHG emissions in London. Rental e-scooters, if properly deployed and priced, can complement public transport (not only as a feeder mode but also enhancing the resilience of the transit system in the event of technical failures or emergencies such as the pandemic). Rental e-scooter mode could also bring mobility benefits to those who predominantly travel via active modes, through offering a novel travel option hence reducing the propensity of car use if they need to travel faster. Rental e-scooters, public transport and active modes can and should be seen as a bundle of complementary mobility options, which altogether provide viable alternatives to private motor modes.

To maximise the benefits of rental e-scooters and more generally micromobility services, our analysis suggests that certain activity demands (e.g. commuting, leisure, shopping and education) seem more amenable to rental e-scooter penetration. Therefore tailoring rental e-scooter services and pricing models in relation to specific trip purposes, particularly those of high car dependence, could boost the sustainability benefits rental e-scooters.

The proposed method could be refined in future research on the following aspects. First, the removal of short ‘first-ride’ trips intends to improve the accuracy of the inference; but the nature of ‘first-ride’ trips could be further investigated, potentially through targeted roadside survey at different stages of the scheme. Secondly, certain technical constraints of rental e-scooters (e.g. in-vehicle luggage storage) may hinder their usage for some trip purposes such as weekly grocery shopping. The inference can be thus improved by incorporating these constraints. Thirdly, the construction of trip sample pool could be refined by considering more factors such as mobility constraints, car ownership, lifestyle preference, seasonality and the specific e-scooter trial areas. This study uses intra-London trip samples in the NTS series, while the London e-scooter trial area is limited to certain areas in London. Lastly, the efficacy of the method could be further verified in other locations of distinct contexts, e.g. the geography and the quality of public transport and active travel infrastructure.

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Appendix A

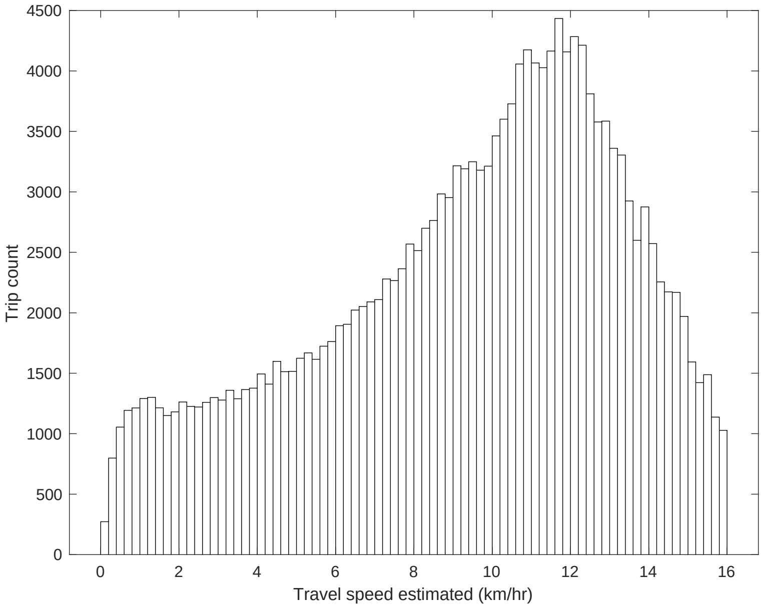
Estimating trip length of rental e-scooter rides

The rental e-scooter usage data do not include full trip trajectory nor vehicle stationary time. To estimate travel distance, there are three alternative approaches, 1) estimating distance travelled based on constant speed assumption (11km/hr, suggested by the operator); 2) estimation based on shortest path between trip origin and destination obtained from online map queries (see example in ARUP and NatCen, 2022b), and 3) estimating the Euclidian distance between trip origin and destination and then approximating the network distance using a distance multiplier (see example in Wan et al., 2021a).

We test the performance of each distance estimation method using, and find that the first method (based on constant speed assumption) tends to work well for short trips (e.g. less than 15 min). This is because for short e-scooter trips, stationary time along the ride, typically waiting time at traffic lights, tends to be negligibly short. However, for longer e-scooter trips (over 15min in our case), stationary time could be significant, including but not limited to waiting time at traffic lights, short breaks for route searching along the journey and possible *en-route* activities. Using constant speed is thus likely to lead to upward bias in distance estimation. The second approach adopts the cost minimisation assumption in route choice. However, our test and informal interviews with rental e-scooter users suggest that users rarely follow the shortest path as suggested by mainstream online map services. The tendency to deviate from the shortest path in rental e-scooter routing is also confirmed by ARUP and NatCen (2022b, p. 25). In addition, the second approach is computing intensive given the large number of trips observed.

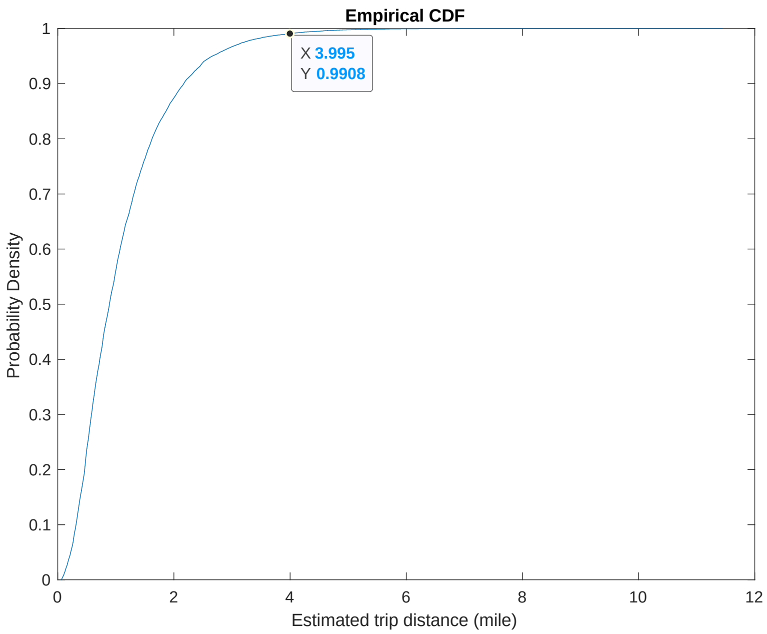
We therefore adopt the last approach, which represents a balanced option. Firstly estimate the distance between trip origin and destination using the Haversine formula (see Sofwan et al., 2019), which considers the distance correction on a sphere, then apply a distance multiplier of 1.414 to approximate the network distance. As a validation exercise, we calculate e-scooter trip speed based on the estimated trip distance (see the distribution in Figure A1). For a majority of observed e-scooter trips, the average speed falls within a speed range of 10-14 km/hr, with an average close to 11km/hr, which is in line with the operator specification. We deem this distance estimation method better than the constant-speed method, for it captures probable variations of average speed across a wide range of trip distances for e-scooters.

Figure A1. Speed distribution of TIER e-scooter trips (based on estimated trip length)



Based on the estimated network distance, we analyse the distribution of trip length (see **Error! Reference source not found.**A2) and find that 99% of observed e-scooter trips are under 4 miles, which informs our definition of 'short-distance trips' applied in the early analysis. Average trip distance is 1.77 miles (appr. 2.8 km), which is in line with benchmark data for London (2.5 km) reported in the national evaluation report (ARUP and NatCen, 2022a).

Figure A2. Distribution of e-scooter trip distance using probability density function



Appendix B

Categorisation of time of the day (Table B1), trip duration (Table B2) and trip length (Table B3) for rental e-scooter trips

Table B1. Categorisation of 'time of the day'

AM	PM
0000 - 0059	1200 - 1229
0100 - 0159	1230 - 1259
0200 - 0259	1300 - 1329
0300 - 0359	1330 - 1359
0400 - 0459	1400 - 1429
0500 - 0559	1430 - 1459
0600 - 0629	1500 - 1529
0630 - 0659	1530 - 1559
0700 - 0714	1600 - 1629
0715 - 0729	1630 - 1644
0730 - 0744	1645 - 1659
0745 - 0759	1700 - 1714
0800 - 0814	1715 - 1729
0815 - 0829	1730 - 1744
0830 - 0844	1745 - 1759
0845 - 0859	1800 - 1814
0900 - 0914	1815 - 1829
0915 - 0929	1830 - 1859
0930 - 0959	1900 - 1929
1000 - 1029	1930 - 1959
1030 - 1059	2000 - 2029
1100 - 1129	2030 - 2059
1130 - 1159	2100 - 2129
	2130 - 2159
	2200 - 2229
	2230 - 2259
	2300 - 2329
	2330 - 2359

Table B2. Categorisation of 'trip duration'

Less than 3 mins
3 under 8 mins
8 under 15 mins
15 under 30 mins
30 under 45 mins
45 mins under 1 hour
1 under 1.5 hours
1.5 under 2 hours
2 under 2.5 hours
2.5 under 3 hours
3 under 4 hours
4 under 5 hours
5 under 6 hours
6 hours +

Table B3. Categorisation of 'trip length'

Under 1 mile, but greater than 0
1 to under 2 miles
2 to under 3 miles
3 to under 4 miles
4 to under 5 miles
4 to under 5 miles
4 to under 5 miles
4 to under 5 miles
8 to under 9 miles
9 to under 10 miles
10 to under 15 miles
10 to under 25 miles

Appendix C

Figure C1. Weekly trip rate and sample size of intra-London travellers (unweighted) in NTS data series (2002-2020)

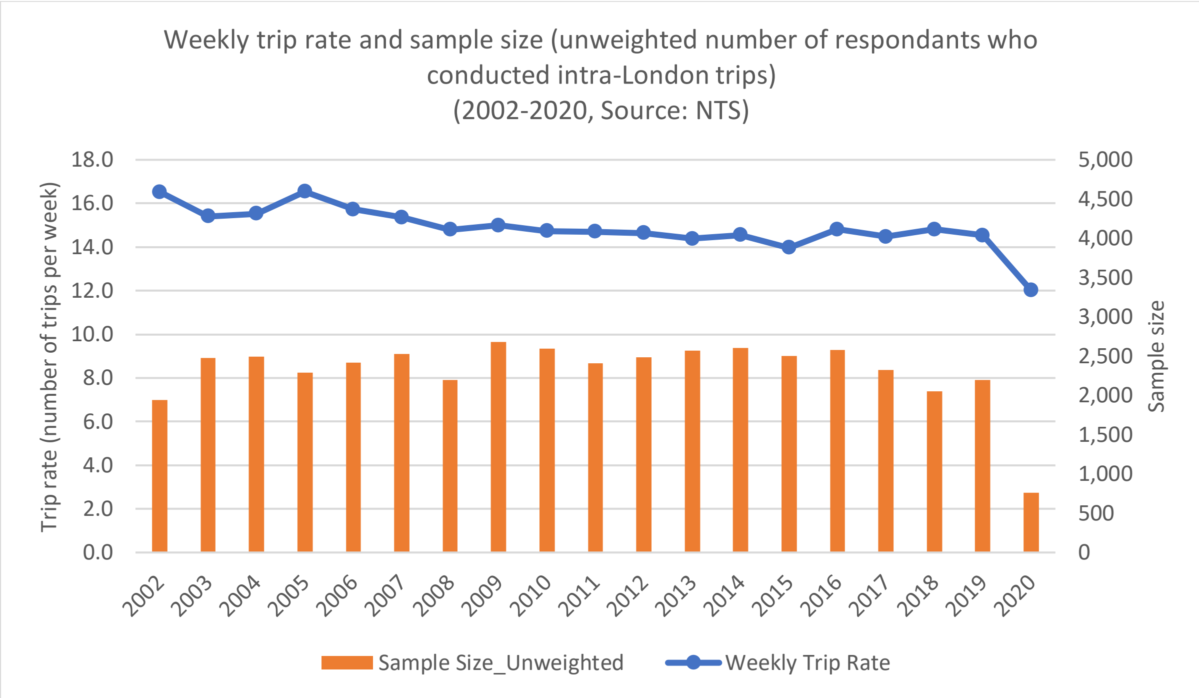
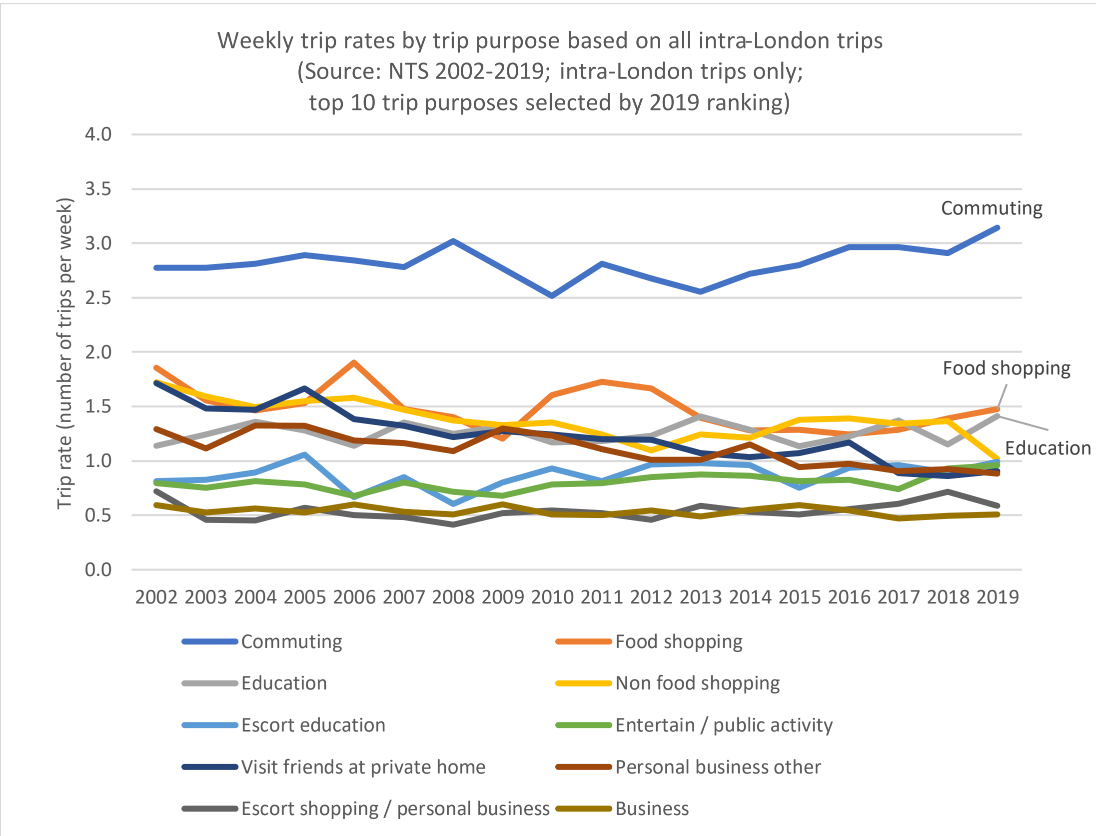


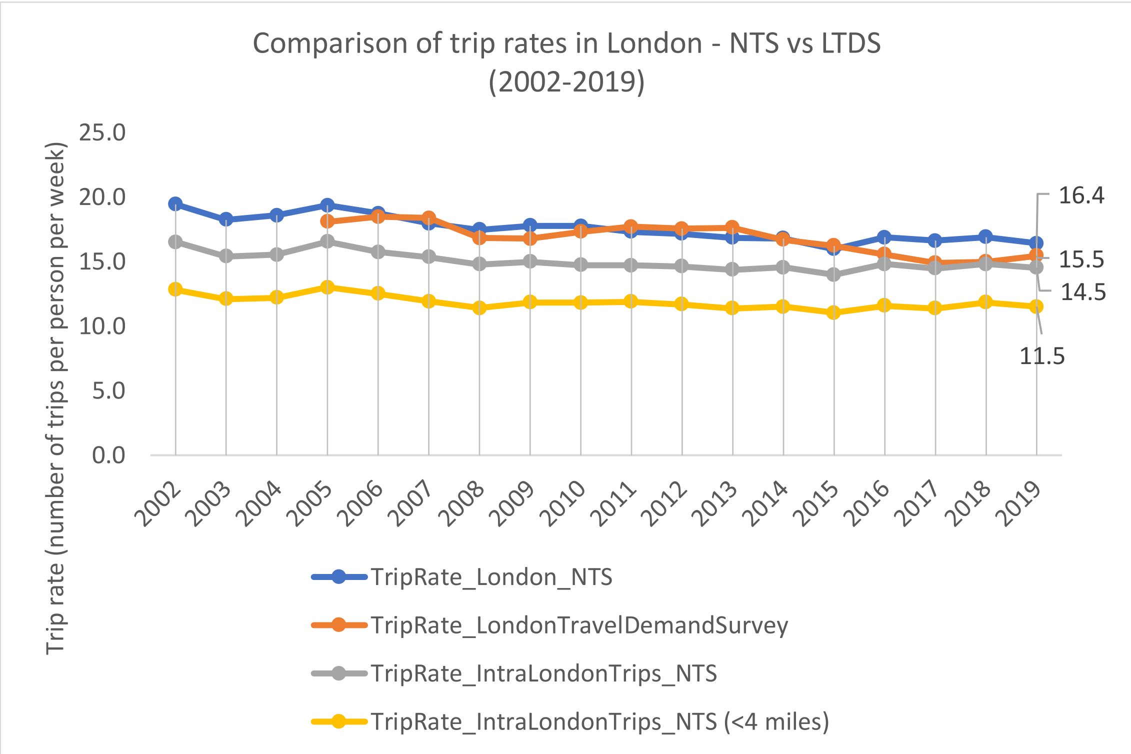
Figure C2. Weekly trip rate by trip purpose in London (Source: NTS 2002-2019; all intra-London trips (all distance bands); top 10 trip purposes selected by 2019 ranking)



An alternative source of travel survey data for London is the London Travel Demand Survey (LTDS), which has a much bigger sample size of around 8,000 households and 19,000 persons. To verify the representativeness of the NTS data for London and its consistency with the LTDS data, Figure B3 compares the average weekly trip rate for London between the NTS data and the LTDS data. Three different trip rates are provided from the NTS data. ‘IntraLondonTrips_NTS’ is based on trips with both origin and destination in London regardless of the residence location of the traveller; ‘London_NTS’ is based on trips made solely by usual residents in London; ‘IntraLondonTrips_NTS (<4 miles)’) is based on the first type but considering short-distance trips (<4 miles) only.

It shows that the four selected trip rates are numerically comparable, with ‘London_NTS’ trip rate being the highest (16.4 trips/wk), LTDS trip rate being the second highest (15.5 trips/wk) and ‘IntraLondonTrips_NTS (<4 miles)’ being the lowest (11.5 trips/wk). The high consistency between the ‘London_NTS’ and the LTDS trip rate confirms the representative of NTS London samples. The study adopts NTS London samples rather than the LTDS data due to contractual difficulties for accessing LTDS microdata.

Figure C3. Comparison of trip rates in London - NTS vs LTDS (2002-2019)



Appendix D

Table D1. Inferred trip purposes of rental e-scooter trips by time of the day (Weekdays only)

Time of the day	Most probable trip purpose	Prob.	2nd Most probable trip purpose	Prob.
0000 - 0059	Visit friends at private home	76%	Commuting	24%
0100 - 0159	Other social	58%	Visit friends at private home	42%
0200 - 0259	Entertain / public activity	100%	Business	0%
0300 - 0359	Commuting	99%	Entertain / public activity	1%
0400 - 0459	Commuting	97%	Entertain / public activity	3%
0500 - 0559	Commuting	99%	Business	1%
0600 - 0629	Commuting	100%	Education	0%
0630 - 0659	Commuting	92%	Entertain / public activity	7%
0700 - 0714	Commuting	99%	Business	1%
0715 - 0729	Commuting	99%	Escort home (not own) & other escort	1%
0730 - 0744	Commuting	92%	Education	3%
0745 - 0759	Commuting	100%	Education	0%
0800 - 0814	Commuting	93%	Education	7%
0815 - 0829	Commuting	77%	Education	23%
0830 - 0844	Commuting	74%	Education	26%
0845 - 0859	Commuting	78%	Education	20%
0900 - 0914	Commuting	78%	Education	15%
0915 - 0929	Commuting	55%	Eat / drink with friends	6%
0930 - 0959	Commuting	42%	Education	14%
1000 - 1029	Non food shopping	26%	Personal business medical	17%
1030 - 1059	Food shopping	22%	Non food shopping	19%
1100 - 1129	Food shopping	28%	Non food shopping	24%
1130 - 1159	Food shopping	34%	Escort shopping / personal business	17%
1200 - 1229	Food shopping	32%	Non food shopping	22%
1230 - 1259	Food shopping	45%	Commuting	12%
1300 - 1329	Non food shopping	39%	Food shopping	28%
1330 - 1359	Visit friends at private home	16%	Non food shopping	15%
1400 - 1429	Non food shopping	37%	Commuting	13%
1430 - 1459	Visit friends at private home	19%	Food shopping	17%
1500 - 1529	Education	64%	Commuting	12%
1530 - 1559	Education	43%	Visit friends at private home	17%
1600 - 1629	Education	27%	Commuting	23%
1630 - 1644	Commuting	34%	Education	27%
1645 - 1659	Commuting	26%	Education	18%
1700 - 1714	Commuting	68%	Education	12%
1715 - 1729	Commuting	58%	Escort home (not own) & other escort	13%
1730 - 1744	Commuting	77%	Education	8%
1745 - 1759	Commuting	49%	Escort shopping / personal business	24%
1800 - 1814	Commuting	86%	Visit friends at private home	7%
1815 - 1829	Commuting	53%	Food shopping	12%
1830 - 1859	Commuting	72%	Escort home (not own) & other escort	7%
1900 - 1929	Commuting	37%	Visit friends at private home	14%
1930 - 1959	Commuting	30%	Visit friends at private home	17%
2000 - 2029	Entertain / public activity	22%	Food shopping	17%
2030 - 2059	Entertain / public activity	17%	Food shopping	14%
2100 - 2129	Entertain / public activity	27%	Eat / drink with friends	27%
2130 - 2159	Visit friends at private home	23%	Commuting	15%
2200 - 2229	Other social	31%	Visit friends at private home	27%
2230 - 2259	Other social	29%	Visit friends at private home	21%
2300 - 2329	Visit friends at private home	28%	Commuting	24%
2330 - 2359	Other social	29%	Visit friends at private home	17%