Department for Transport

Exploration of Mobile Data for Evaluation of Electric Vehicle Usage

Final Report

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Department for Transport
Great Minster House
33 Horseferry Road
London
SW1P 4DR

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Exploration of Mobile Data for Evaluation of Electric Vehicle Usage: Final report

Executive Summary

As of September 2023, electric vehicles (EVs) constitute approximately 2% to 3% of the overall vehicle fleet in the UK. The Zero Emission Vehicle (ZEV) mandate, which entered into force in January 2024, sets an ambitious annual trajectory on the way to all new cars and vans sold by 2035 being zero-emission. To support the switch to electric, the Department of Transport (DfT) has provided significant investment to improve the UK's charging network, including the Local Electric Vehicle Infrastructure (LEVI) Fund. Robust evaluation of these investments will be required to understand their impact on electric vehicle adoption and behaviour.

Given the relatively low number of electric vehicles currently in use within the UK, it is challenging to access detailed data on EV movements. Specifically, there are significant evidence gaps on EV ownership and usage, including geographical spread, distances travelled, origin-destination information, and charging locations. At the time of this work, DfT's EV driver behaviours and attitudes tracker had not been completed.

This project, led jointly by DfT's Advanced Analytics Division (AAD) and Social and Behavioural Research (SBR) and funded by the Evaluation Accelerator Fund (EAF), explores the use of Mobile Network Data (MND) to support the evaluation of electric-vehicle-related interventions. This dataset is derived from anonymised and aggregated data on mobile phone movements, with travel mode identified using speed of travel and approximate route taken, and EV users identified via their previous interactions with EV-related websites or apps. All data and insights were anonymised and aggregated before they were received by the department.

This two-year project considered three key questions:

- Does mobile network operator data provide valid and robust evidence on EV usage which is suitable for use in evaluation?

- If yes, how can this new data source be used to support planned evaluation of EV-related interventions?

- What additional insights on EV uptake and usage can we gain through mobile network operator datasets?

Overall, this work has established a better understanding of the benefits and challenges of using MND to support evaluation and analysis of EV-related interventions, and has

highlighted the value that early exploration of a novel data source can bring to ensure its effective use in future work. Analysis of MND throughout this project has established:

- MND is **broadly consistent with existing sources** on the gender of EV users and distances travelled, but potentially overestimates EV users (and therefore trips) in areas with only a small number of registered electric vehicles.

- The dataset is **best suited to analysis of trends** in time and comparisons where measuring absolute volume is less important and the consistent methodology behind the data is an advantage.

- Mobile data cannot directly be used to provide information around charging behaviour or travel time unless travel time is the only variable of interest or the data can be matched to different supplementary datasets.

- Overall, mobile data alone is **best suited for use in quasi-experimental impact evaluation approaches**, given its consistency, flexibility and coverage. In conjunction with other research methods or datasets that can be cross-referenced to MND, the resulting dataset could also be used in theory-based impact evaluations.

- The level of geography needs to be carefully considered during procurement, in conjunction with the time periods of interest, as data that covers a larger area can be broken into shorter periods of time, with less risk that data will be omitted due to disclosure controls. However, covering larger areas would mean variations within the area chosen cannot be analysed.

- The number of public chargers, average household size and average income (which is correlated with age) in a local authority all have a significant link to the number of EV users and EV trips observed there, but it is not possible to determine the direction or any causality of these links. Mobile phone data measures users, and not vehicles, therefore these factors may not influence the total number of EVs.

- The number of EV users and EV journeys varies greatly between Middle-layer Super Output Areas (MSOAs[1]). Therefore the findings from analysis of mobile data can vary depending on the level of geography considered; while some MSOAs may show similar trends to the local authority average, some MSOAs show different patterns. This is true for any chosen level of geography.

- EV uptake and usage are noticeably higher in London compared to the East of England and North West, and the MND has provided some analysis of trends in time across the regions that could be analysed in relation to seasonality or other influencing factors (if more data and supplementary datasets were available).

This work has also identified advice and considerations based on an increased understanding of mobile data and how it can be used in evaluation, which can help ensure future data procurements are as useful as possible for evaluating impacts of EV interventions.

[1] https://www.ons.gov.uk/methodology/geography/ukgeographies/statisticalgeographies

Contents

1. Background

Transport is the largest contributor to UK domestic greenhouse gas (GHG) emissions, responsible for 29% of emissions in 2023[2]. The Government's Carbon Budget and Growth Delivery Plan will therefore set out the need to deliver a step change in the breadth and scale of our ambition on transport emissions to reach net zero. A key part of this change will be the transition to Electric Vehicles (EVs).

The £381m Local Electric Vehicle Infrastructure (LEVI) Fund is designed to address a key challenge to delivering mass-market EV uptake: the need for a viable charging offer for those without off-street parking.

However, there are currently significant evidence gaps on EV ownership and usage that need to be addressed to enable both a more robust evaluation of these charging infrastructure investments (and similar initiatives), and a more comprehensive evaluation and understanding of the uptake and usage of EVs overall[3]. These include:

- the geographical spread of EV ownership, especially overnight home locations of EVs;
- trip frequency and trip information such as distances travelled using EVs;
- current charging locations for EVs; and
- origin-destination trip information for EVs.

In March 2023, DfT was awarded funding through the Evaluation Acceleration Fund (EAF)[4] to investigate whether Mobile Network Data (MND) could provide sufficiently robust additional insight on EV user mobility patterns, trip counts, destinations, and socio-demographics, in order to address these evidence gaps.

The DfT's Advanced Analytics Division (AAD) and Social and Behavioural Research (SBR) have used this funding to procure MND focussed on the movement of EVs and have explored its viability as a new data source to support the evaluation of initiatives and policies that target EV uptake and usage.

In order to assess the potential for MND, this work considered three key questions:

- Does mobile network operator data provide valid and robust evidence on EV usage which is suitable for use in evaluation? (Section 3)

[2] Greenhouse gas emissions from transport in 2023, DfT Statistics, https://www.gov.uk/government/statistics/transport-and-environment-statistics-2023--2/greenhouse-gas-emissions-from-transport-in-2023

[3] At the time of this work, DfT's EV behaviours and attitudes tracker that now provides some of this information, had not yet been completed: https://www.gov.uk/government/publications/electric-vehicle-ev-driver-behaviours-and-attitudes-tracker

[4] Background on the Evaluation Accelerator Fund: https://www.gov.uk/government/publications/evaluation-accelerator-fund

- If yes, how can this new data source be used to support planned evaluation of EV-related interventions? (Section 4)

- What additional insights on EV uptake and usage can we gain through mobile network operator datasets? (Sections 5 and 6)

The analysis was split into two stages of work, initially focusing on data validation and then expanding to consider baseline understanding of the data and potential evaluation methods it could support. Key considerations for evaluation and potential next steps to maximise the use of this data are outlined in Section 7.

2. Data, Assumptions and Caveats

2.1 Mobile Network Data

To explore the potential for MND to support evaluation of EV uptake and usage, DfT sourced anonymised and aggregated mobile network data on the movement of mobile phones starting, ending or passing through one of three regions of the UK during four separate months in 2023 and 2024.

This mobile dataset is created by the provider using network events[5] from handsets on the O2 network (approximately 25 million devices). This includes contracts and pay-as-you-go sim cards provided by O2 and virtual operators using O2 infrastructure (Sky Mobile, Tesco Mobile, Giff Gaff and Virgin Mobile), which together cover approximately 35% of the UK market. Filters are applied by the provider to exclude most business contracts, machine-to-machine devices and GPS units.

These events are processed by the provider to identify trips and travel mode, including EV trips (movements of mobile phones within an EV). The method used is based on the provider's analysis of weblog events data to understand users' browsing and app behaviour, to identify those most likely to own an electric vehicle.

This process includes several key steps:

- The raw events are converted into dwells and journeys, by assuming a journey ends when a handset is stationary in one place for 30 minutes or more.

- A mode of transport (Rail, Road and Active) is identified for each journey using speed of travel, proximity to other users, and approximate route taken.

- Users interacting with websites and apps that are identified as EV-related at least once per month in two or more months over the three years prior to each selected month are marked as potential EV owners.

[5] These include making calls, sending messages, moving between cell towers, turning handsets on or off, losing or regaining a connection, and time-based events triggered after 3 hours of no other activity.

- All road journeys made by users identified as likely EV owners are assumed to be EV trips.

- Trips starting, ending, or passing through one of the three regions chosen by DfT during the selected months are anonymised and aggregated to create the final datasets.

The data is extrapolated by the provider to represent the UK population aged over 12 years[6], using expansion factors based on the ratio between users and ONS population estimates, accounting for both location and demographics. These factors are not provided to DfT for data protection reasons. No further expansion has been applied to any of the data or analysis presented in this report.

All data and insights are anonymised and aggregated before they are received by DfT, ensuring that individuals cannot be identified or mapped, and that any information shared complies with relevant data protection legislation. This process includes disclosure controls, which means that where the number of trips made by a particular demographic is less than ten, data for these trips is stochastically rounded before it is provided. Stochastic rounding is a method that preserves the total volume of trips while rounding each value less than ten either to zero or ten.

2.2 Selected Data Coverage

The mobile data sourced covers all EV trips starting, ending, or passing through selected geographical zones during specified time periods. In the initial phase of the project, data was collected from three bespoke areas in England over two months across two years. For the work described in this report, the scope was expanded to cover three whole regions of England, over four months within a single year.

The regions and time periods chosen for the data were:

- **Regions**: London, North-west and East of England

- **Time periods:** July 2023, October 2023, January 2024, and April 2024

The regions of England covered by the data were selected to provide a good spread of existing public charger availability, funding for chargers, and geographic spread, including London due to the substantial funding provided and likely different behaviour there.

The four time periods selected for the data were the first month of each of the previous four quarters (at the time of procurement). These were identified for a good balance between long- and short-term trends and to enable some analysis of seasonality.

This approach was taken to maximise geographical coverage over more time periods, to enable evaluation of EV infrastructure projects in the greatest number of areas but still enable some trend analysis. Existing public analysis on driving patterns of EVs indicates

[6] Mobile providers do not collect data on children 12 and under, in accordance with the Information Commissioner's Office and GDPR guidance

that there is some seasonality in the use of EVs due to changes in electricity consumption[7,8].

Individual days that would adversely affect the data (e.g. rail strikes, bank holidays) were identified by the provider and excluded. However, regularly occurring events (e.g. school holidays) have been kept so that the data more accurately represents typical behaviour in those months. This step was not applicable in the initial data exploration as the data covered a single month that did not include any such events.

For the initial validation stage, the data procured only covered weekdays, specified as Tuesday, Wednesday and Thursday. However, for the full analysis, this was increased to include a separate dataset for weekend travel, and to include all of Monday to Friday in the weekday dataset.

2.3 Key Assumptions and Caveats

The following definitions, assumptions and caveats set by the provider have been used in the processing and subsequent analysis of the dataset:

- **The data measures mobile phone movements and not vehicles**; users with multiple vehicles or households that share vehicles may therefore affect the results.

- **EV users are identified based on web and app usage using mobile data**; EV owners who do not interact with any EV-related sites using mobile data will not be identified.

- **The data is scaled by the provider to represent the UK population aged over 12**, using weights based on the provider's market share.

- **The weekday data represents average EV trip volumes between Mondays and Fridays** in the months identified. Bank holidays and rail strike dates have all been excluded.

- **The weekend data represents average EV trip volumes on Saturdays and Sundays** in the months identified. Bank holidays and rail strike dates have all been excluded.

- **A 'trip' is defined as a movement between two dwells of at least 30 minutes.** Therefore, EV journeys that include a stop of at least 30 minutes will be broken into multiple trips, and multiple EV journeys within 30 minutes of each other may be grouped into one EV trip.

- **Disclosure control thresholds are set to 10 by the provider**; meaning that where the number of EV trips for a particular group is less than 10, the data are stochastically rounded for data protection reasons by the data provider.

[7] Mina 2023 report mina-ev-report-april-2023-winter-dec-22-feb-23.pdf
[8] Recurrent, Is Cabin Heat Killing Your Winter EV Range?

- **Age and gender are based on contract information** and are therefore unknown for pay-as-you-go users.

- **Where possible, company contracts have been removed by the provider**, so the data represents private mobile phone use only.

3. Does mobile data provide valid and robust evidence suitable for EV evaluation?

3.1 Summary of MND validation

In the initial stage of this project, the validity of mobile data on EVs was assessed in comparison to established datasets that are held within the department (DVLA vehicle licensing data, DVLA registered keeper data, DVLA MOT data) as well as other new data sources (e.g. INRIX black box data).

Analysis of users' demographic data and average distances travelled revealed the MND is broadly consistent with existing data sources. Comparisons with vehicle licensing data and National Travel Survey (NTS) results showed that it is likely that the MND correctly captures most actual EV users as EV users.

This analysis also found that the MND is likely classifying some non-EV users as EV users, and as a result tended to overestimate the number of EV users when compared to other data sources. However, this issue was mostly confined to Middle Layer Super Output Areas (MSOAs) with fewer than 50 privately registered electric vehicles. Therefore, the validation work recommended that geographical areas of interest should have a minimum of 50 privately registered electric vehicles in order to be confidently included in any analysis[9].

Overall, the initial exploration established that the MND can effectively provide a data source that can help address many of the current data gaps within DfT including the geographical spread of EV users, trip frequencies and distances, and origin-destination information. Therefore, this data could provide credible evidence for evaluations of EV-related interventions. The MND cannot directly be used to provide information around charging behaviour unless matched to different supplementary datasets

3.2 Travel time data

When assessing the validity of MND, distances were estimated using geodesic distances (the shortest straight-line distance, accounting for Earth’s geometry) between the population centroids of Middle Layer Super Output Areas (MSOAs), as a proxy for the true journey length. Whilst it was recognised that this method may have some inaccuracies, it compared well with existing data sources on the average EV trip distance and provided the ability to identify longer trips. As part of stage 2, the data procured included an additional

[9] This can be derived from the DVLA licensing data: https://www.gov.uk/government/statistical-data-sets/vehicle-licensing-statistics-data-tables#plug-in-vehicles

dataset which provides the average travel time between pairs of MSOAs based on the average time between 30-minute stops in those MSOAs. The addition of this time dataset was intended to provide more accurate trip durations than the previous centroid-based method, which would enable evaluation of interventions aimed at affecting EV journey durations.

The travel time data was provided as a separate dataset, which meant an additional processing step was required to merge this with the trip data. Figure 1 shows the distribution of trip times after this merge; overall across all regions and months of data, 81% of trips had no associated average travel time.

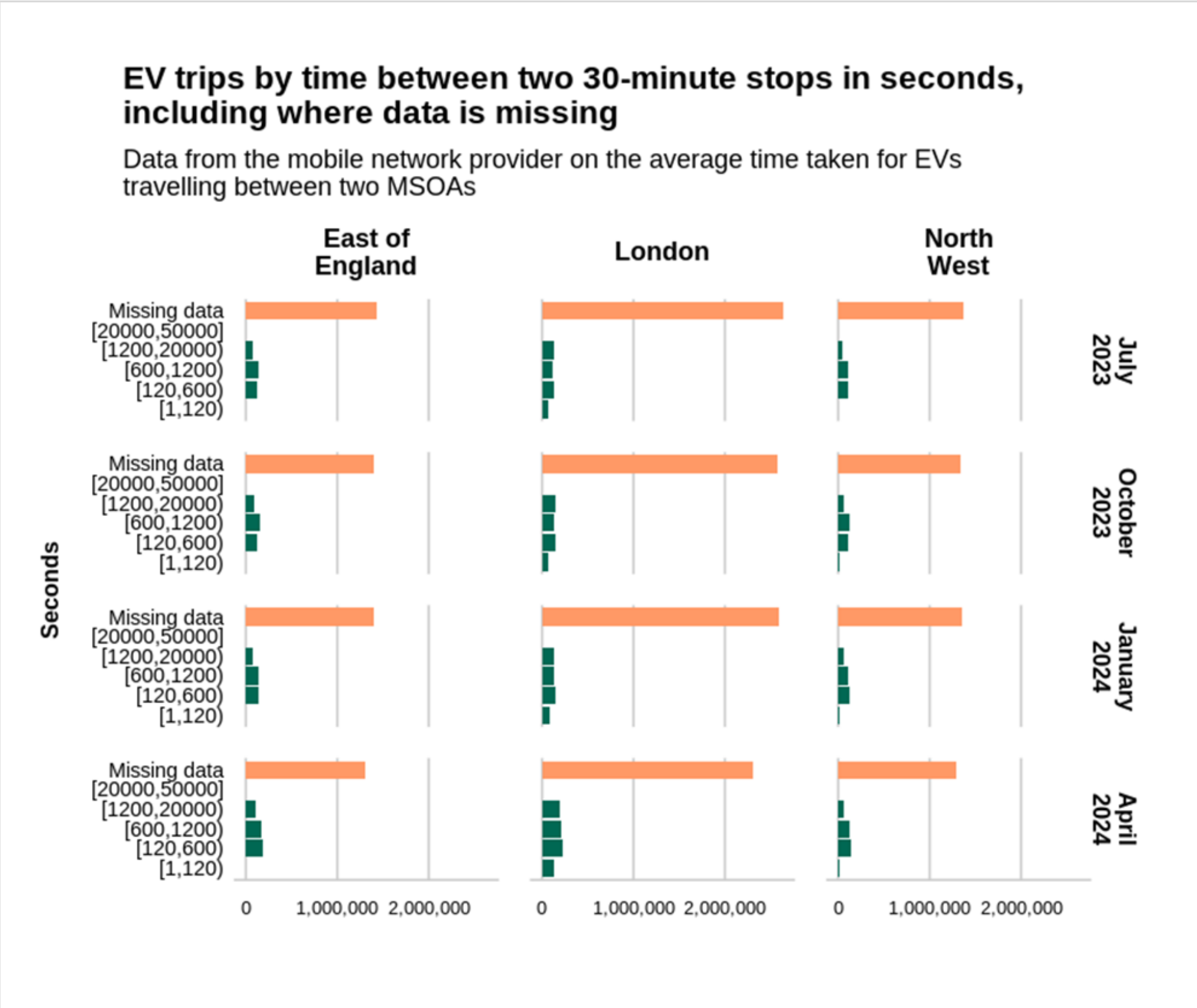

Figure 1 Graph showing the number of EV trips by time between two 30-minute stops, in seconds, including trips that could not be matched to corresponding travel time data.

Following discussions with the mobile network provider, the large proportion of missing travel time data is possibly due to the disclosure threshold for travel time being higher than that for total trip numbers. Therefore, for less common trips (which may include longer distance trips, for example), the total trips themselves may be sufficient to reach the disclosure threshold, but the travel time may be unavailable or represent only a small subset of days with higher trip frequencies (e.g. school holidays).

As this is an independent dataset and could not be matched to the trip data, it is recommended that trip distances are approximated using geodesic distances between MSOA centroids. With appropriate caveats, this method can provide sufficient information and would allow different assumptions to be tested. However, if travel time is the only variable of interest or can be matched to a different supplementary dataset, the independent travel time dataset could potentially be useful.

4. How can mobile data be used to support evaluation of EV-related interventions?

In stage 1, it was established that MND could be used for evaluation purposes, as it provides good coverage of EV users, with both a comprehensive geographical spread and historical values available. For stage 2, to consider how MND could be used to support evaluation, possible evaluation methods were taken from the Magenta Book[10] and the suitability of mobile data considered for each method, using the dataset procured for this stage and discussions with the DfT's Evaluation Centre of Excellence.

MND is better suited to some evaluation methods than others. Overall, mobile data alone is best suited for use in quasi-experimental impact evaluation methods, given its comprehensive coverage and consistency of calculation approach. In conjunction with other datasets, MND can be used to support theory-based impact evaluation methods. For all methods of evaluation, the limitations, assumptions and caveats of this data, identified in Section 2, need to be considered.

4.1 Quasi-experimental impact evaluation methods

Mobile data is suitable for use in most quasi-experimental impact evaluation methods because of its consistency and coverage of historical time periods, and inclusion of some supplementary variables (such as age, gender and socioeconomic status). It also offers flexibility to cover different geographical areas. For example, it would be suitable for use in a difference-in-difference analysis, as the dataset provides historical time series data with extensive geographical coverage, which would enable comparison of key outcomes (EV uptake or usage) for intervention and comparator areas before and after an intervention.

Major providers of MND offer both historical and real-time data, which can be procured at any stage of a project. This flexibility allows for ongoing evaluations as well as ad-hoc and retrospective assessments and monitoring, and the data can be used to create time series or regressions for use in evaluation, although it is important to consider seasonality when procuring the data. Section 5 looks at some of the seasonality in EV usage and uptake apparent in the stage 2 data.

Mobile data is also available at different sizes of geographical areas that can be tailored for the needs of the evaluation. For this work, the data was procured at MSOA level, although other projects have used much smaller geographical hexagonal grids. It is important to consider disclosure controls during procurement, as trips made by fewer than 10 users are stochastically rounded by the provider and therefore more data will be

[10] https://www.gov.uk/government/publications/the-magenta-book

excluded when smaller areas and shorter time periods are chosen. However, for interventions which occur at local authority, regional, or national levels, or for which monthly or annual time periods are appropriate, MND is likely to be suitable.

This project has also facilitated the development of a list of relevant factors that influence EV usage and uptake at the local authority level. These factors are further discussed in later sections, with an emphasis on the feasibility of propensity score matching, which may enable identification of comparator areas for quasi-experimental evaluations.

4.2 Theory-based impact evaluation methods

Mobile data could be used to support most theory-based impact evaluation methods, but its application depends on the hypothesis being tested and the variables of interest.

The MND investigated in this project covers EV uptake and usage. However, during procurement the data providers stated they can provide additional information on audience insights (website usage) and visitor data (including international visitors) if needed (these were not relevant to this project). They also collect and provide some demographic data, through their contracts, which was validated during stage 1 and can be used to target specific audiences.

In addition, mobile network data could be used for triangulation alongside other datasets or primary research methods. It can support the analysis of travel behaviour for groups and events but does not provide any specific data on individual behaviour or attitudes that could be gained through surveys, observational studies or focus groups.

For example, analysis of MND could provide the general destinations of people departing a specific MSOA, such as the area surrounding the O2 arena, on a specific day when an event is occurring, provided that the number of people making that trip exceeds the disclosure threshold. This analysis may even include mode and some demographic information but cannot include the actions or journeys of each individual, or onward travel for those groups smaller than 10.

MND also does not collect data on the reason for travel or journey decisions, which would need to be inferred from other data sources or from primary research. If data from individuals was collected and could be cross-referenced to MND, this could enhance the insights available on travel behaviour.

5. What additional insights on EV uptake and usage can be gained through mobile network operator datasets?

5.1 Trends in time

The coverage of data procured for this stage allowed some analysis of EV usage over the course of a year, as well as changes in uptake of EVs over the period. Initial validation of the data indicated that MND is best suited to monitoring changes over time, so, while the datasets can be used to support other metrics, analysis in this section focuses on trends.

Note that while the number of licenced vehicles in England has remained fairly stable since July 2023 (approximately 28,000,000 total cars were licenced at the end of each quarter over the period[11]), there is some evidence that general car sales are lower in December and January, and higher in March and April[12]. This might suggest any shift towards zero-emission vehicles will be slower in December and January and more rapid in March and April, in line with these trends.

Figure 2 shows the average number of EV users per MSOA (to account for differing size and population of the three regions) for each month of mobile network data, split by the three regions covered by the mobile data. In general, MSOAs have a population of between 5,000 to 15,000.

As outlined in section 2, EV users are users who have been using EV related apps in at least two months over the past 3 years. Previous work found that this method corresponds well with the number of EVs, but note that this still represents individual users rather than vehicles and therefore there may be multiple users (e.g. driver and passenger) associated with each vehicle.

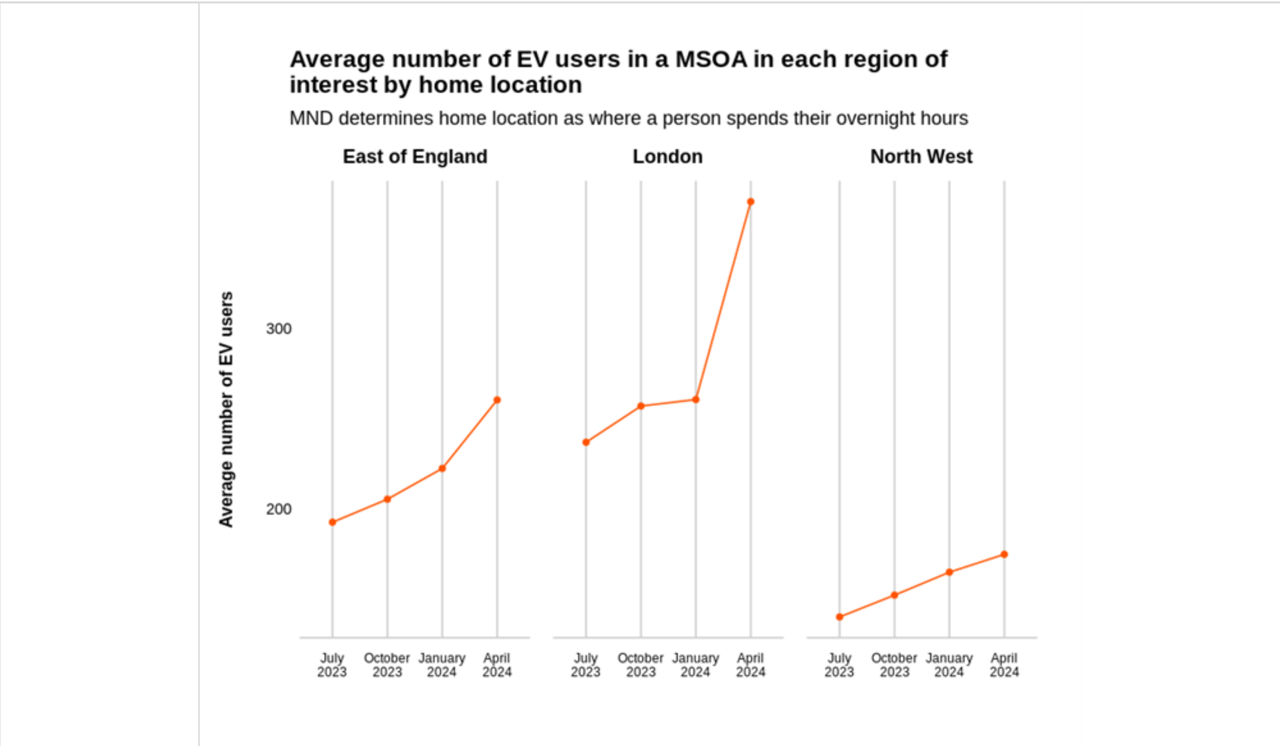

Figure 2 Average EV users per MSOA, based on home location, within each of the three regions covered by the mobile data

Figure 2 shows a general increase in the number of EV users between July 2023 and April 2024 across all three regions, but highlights differences between them, with more users

[11] https://www.gov.uk/government/statistical-data-sets/vehicle-licensing-statistics-data-tables, table VEH0101
[12] Seasonality in Automotive Sales - Factors, Trends and Tips | eCarsTrade

per MSOA in London and a noticeably lower average EV users per MSOA in the North West.

In the East of England and particularly in London, Figure 2 also appears to provide some evidence to support a faster increase in March/April as suggested above, whereas in the North West there has been a consistent increase each quarter. However, with only four data points, it is not possible to say whether these trends in Figure 2 are seasonal patterns or outliers caused by other factors.

Figure 3 shows the average daily number of road trips started per MSOA (to account for differing size and population of the three regions) among EV users as well as for all road users, for each month and region covered by the mobile data. A proportion of road trips made by EV users has also been calculated as the ratio between the two. Solid lines indicate weekday averages, while dashed lines indicate weekend averages.

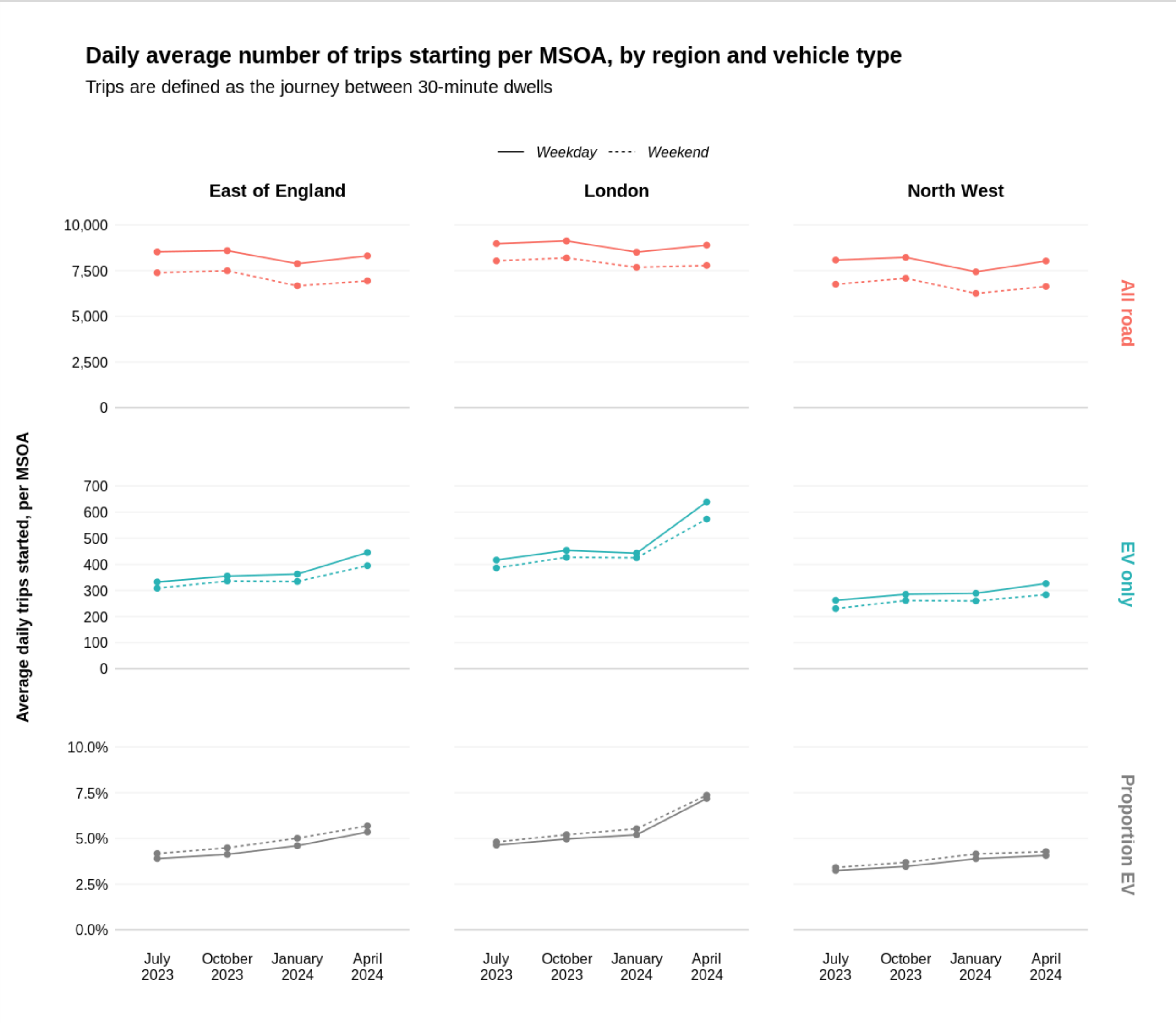

Figure 3 Daily average road trips, EV trips and proportion of trips denoted as EV for each of the three regions and across the four months of mobile data

While road traffic can be entirely dependent on localised issues (such as roadworks and access) general patterns in travel suggest there is a seasonal element to road traffic.

Sources suggest that, especially on major roads, including motorways, there is a dip in road travel in the winter months of December and January compared with other months of the year[13].

For trips that are denoted as road, Figure 3 appears to support this, showing a small drop in average daily trips in January 2024 across all regions. However, as before, with only four data points, it is not possible to say whether these trends are true seasonal patterns or outliers caused by other factors.

Weekend travel is consistently lower than weekday travel and there are noticeable differences between the three regions: London has the highest average trips per day, while the North West has the lowest.

For trips denoted as EV trips, however, Figure 3 shows a steady increase over the year of mobile data, with similar regional trends and differences to the uptake of EVs shown in Figure 2. For example, in April 2024 there is a sharp increase of EV trips in London, corresponding to the increase in EV users.

Because road trips have remained fairly stable over this period, but EV trips have increased, this means that the proportion of road trips that are denoted as EV has also increased across the three regions. Note that while average weekend travel is lower for both EVs and general road users, the drop in EV trips is smaller and therefore the proportion of trips denoted as EV is higher for weekends than weekdays, across all regions and months of data.

5.2 Regression Analysis

To understand and identify what factors could be associated with EV uptake and usage, regression analysis was performed at local authority level. Regression using the full MSOA data was considered but insufficient data is currently available at this level of granularity.

Potentially important factors were identified with key stakeholders and evaluation leads, and local authority level data from ONS for each was combined with the average EV uptake and number of trips from the mobile data in April 2024. This month was chosen as ONS data for all four months was not available.

Factors included were:

- Age
- Gender
- Income
- Unemployment
- Household size

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[13] Seasonality in traffic flow – Graham James

- Availability of public chargers
- Rurality, based on 2011 ONS rural-urban classification

For regression analysis to be valid, the factors under consideration should be as independent as possible. The analysis of trends in time in section 5.1 suggests that geographic region (London, East of England or North West) is probably important, but it is also heavily related to many other factors considered (e.g. age, income and rurality, as London is 99.8% urban). Since these factors, and not geography alone, are more likely to explain variations in EV uptake and usage, geographic region has been excluded from the regression.

Figure 4 shows the correlation between each pair of variables in the data; lightly coloured values close to zero indicate the factors are not strongly correlated and can be considered independent, darker coloured values indicate some level of correlation.

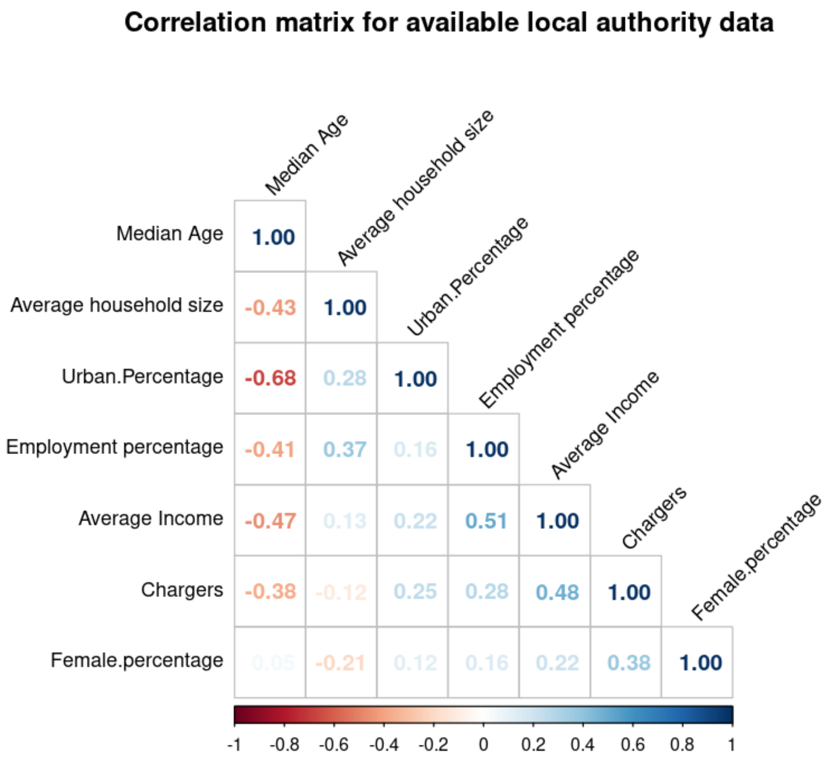

Figure 4: Correlation matrix for variables considered in the regression analysis. The dependent variable, EV uptake or EV usage, is omitted.

Figure 4 suggests that there is a reasonable correlation between employment and income (51% of variations in income can be attributed to changes in employment levels). Therefore, employment has been excluded from further analysis. The median age shows reasonable correlation with most other variables (except gender), and can be excluded from the analysis but will be considered later.

Annex A shows the p-values for each of the regression models considered. These showed:

- **The availability of chargers** was significantly linked to both uptake ($p < 0.001$) and usage ($p < 0.001$) of EVs, but note that this analysis cannot determine directionality, i.e. it is possible that increased availability of chargers increases local EV uptake, but it is also possible that increased local EV users increases the demand for chargers.

- **Average household size** was also significantly linked to both EV uptake ($p < 0.001$) and usage ($p = 0.002$), however this could be due to the methodology used to identify EV users in the data. If a household has access to an EV, then it is likely that all household members will interact with EV-related applications to some extent and will all be flagged as EV users in the mobile data. Increased household sizes therefore increases this effect and may cause greater EV users and trips even when the actual number of vehicles does not change.

- **Average income** was significantly linked to EV uptake ($p = 0.033$) and usage ($p = 0.030$). Note that average income is reasonably correlated with age, and therefore age has a significant influence on EV uptake and usage. This analysis cannot conclude which of these two factors is the true influence, but as age is also correlated with other, non-significant variables, it is more likely to be income.

- **Gender** was significantly linked to EV uptake at the 0.1 significance level ($p = 0.051$), but not significantly linked to EV usage.

- **Rurality** was not significantly linked to either EV uptake or usage at any level.

This analysis provides evidence for key variables that affect uptake and usage, which could be used to aid selection of comparator areas for areas of interest and policy interventions as part of quasi-experimental evaluations of EV-related interventions. In some cases, with more data, it may also be possible to use this regression to infer possible EV uptake and usage in areas where mobile data has not been procured.

6. Case Study

As the delivery of infrastructure and outcomes of LEVI grant funding is still ongoing, it has not been possible to use the MND procured to evaluate the effectiveness of the LEVI programme during this project, but the data procured provides a baseline which could be used in future work.

The dataset covers three regions of England, each with a number of local authorities that can be baselined using this data. This can be used to create a baseline for the evaluation of funding schemes and to understand the current uptake and usage of EVs.

For this report, Lancaster has been chosen as an example to demonstrate possible analysis as it has a mix of rural and urban areas, but many of the themes and conclusions are relevant for all local authorities.

Since the MND is provided at MSOA level, but funding is granted to local authorities that comprise many MSOAs, aggregated trends can be helpful but often mask underlying variations and patterns. This case study therefore demonstrates the challenge in representing combined statistics, and why it is important to consider what questions and outcomes are relevant to an evaluation when deciding the geographical coverage and format of any MND procured.

6.1 Lancaster Background

Lancaster has a population of 143,000 people[14], divided into 18 MSOAs, each with between 2,000 and 6,000 households and a resident population of 5,000 to 15,000. Just under 30% of the population live in rural areas, with the rest in cities and local towns.

6.2 EV Uptake

Figure 5 shows the number of EV users whose home location is one of the 18 MSOAs in Lancaster, in each of the four months of mobile data procured. The average number of EV users per MSOA across Lancaster is superimposed in green.

A user's home and work locations are determined by the provider and are based on where they spend a significant amount of time overnight ('home') or a significant portion of traditional working hours ('work').

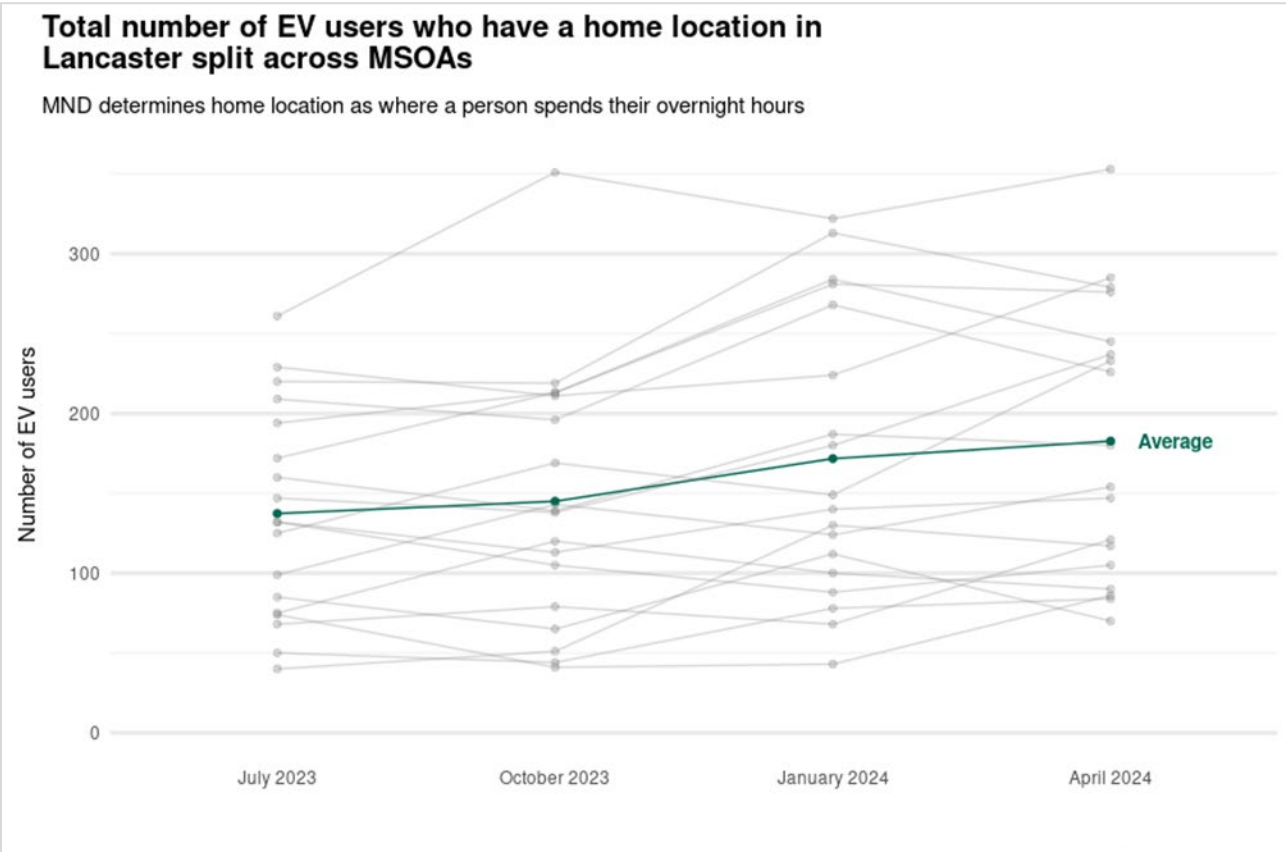

Figure 5 Total EV users per month with a home location in each of Lancaster's MSOAs

[14] https://www.nomisweb.co.uk/sources/census_2021/report?compare=E07000121

Figure 5 shows considerable variability between MSOAs (which is the case for most local authorities) and demonstrates why it is important to consider what questions and outcomes are relevant to the evaluation when deciding the geographical coverage and granularity of the data. For example, in July 2023, the MSOA with the highest number of EV users (~260) has over five times as many users as the MSOA with the lowest number of EV users (~40).

Overall, the average number of EV users per MSOA in Lancaster (and therefore total EV users) increased by 41% between July 2023 and April 2024, but this was not uniform and varied between a 20% decrease up to a 200% increase.

6.3 EV Usage

Similar to EV uptake, Figure 6 shows the average daily number of trips denoted as EV originating within each of the 18 MSOAs in Lancaster, in each of the four months of mobile data, separately for weekdays and weekends. The average daily number of EV trips starting across Lancaster as a whole is superimposed in green.

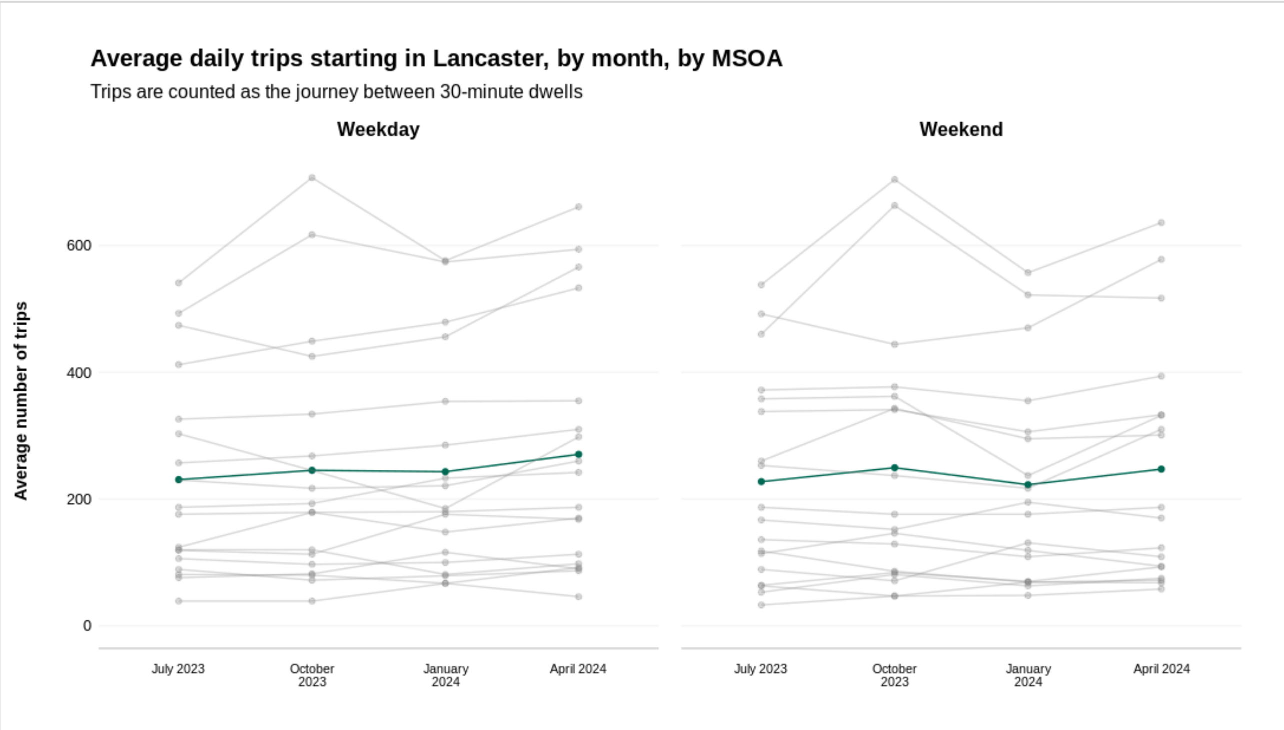

Figure 6 Average daily EV trips starting in each of the 18 MSOAs within Lancaster

As with EV users, Figure 6 shows considerable variability between MSOAs (which is the case for most local authorities), with a maximum spread in October 2023, ranging from 30 to over 600 average daily trips on both weekdays and weekends.

Figure 6 also shows some variations between weekday and weekend travel. However, while a direct weekday and weekend comparison for individual MSOAs is possible using

MND, this has not been considered in this analysis, so it is not possible to say here whether the apparent variations are a consistent trend.

6.4 Proportion of road trips made in EVs

The MND also contains data on general road trips, which can be compared with EV trips. Figure 7 shows the percentage of trips denoted as EV, among road trips originating within each of the 18 Lancaster MSOAs. The average proportion of trips denoted as EV across Lancaster as a whole is superimposed in green.

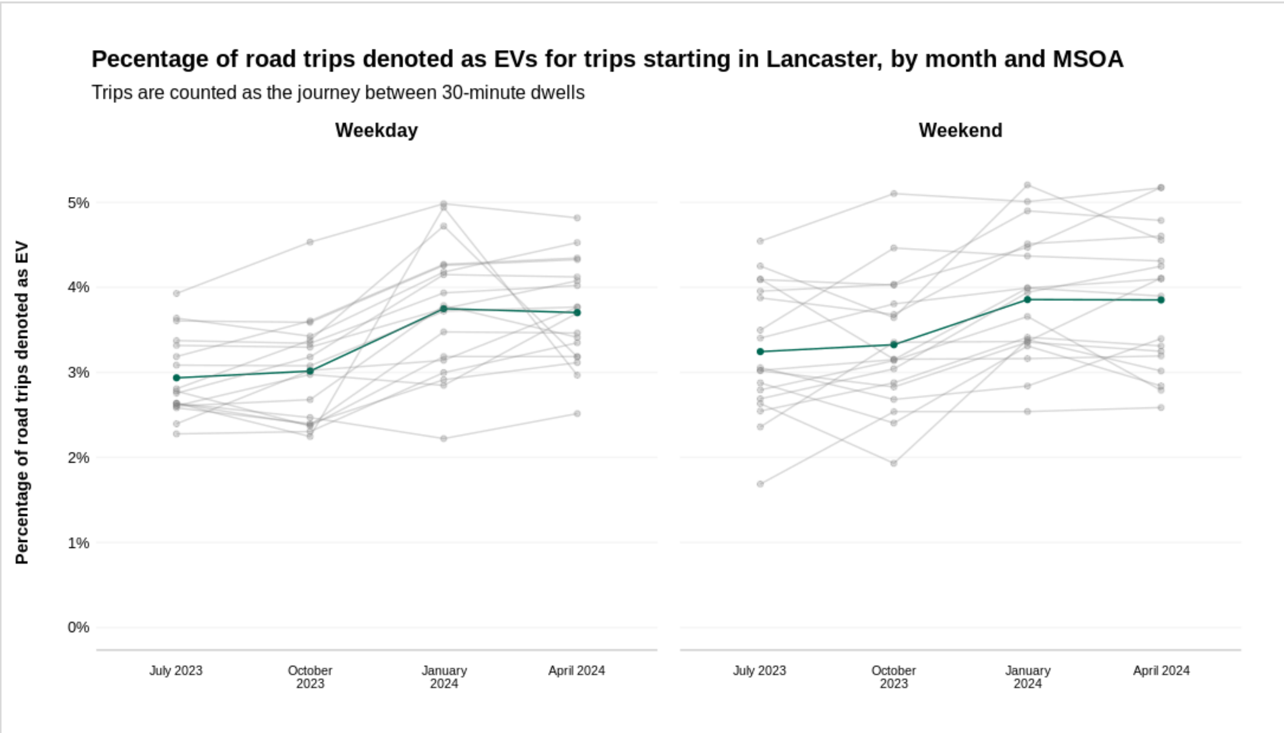

Figure 7 Percentage of trips starting in each of Lancaster's MSOAs that were denoted as EV

Figure 4 shows a small overall increase in the proportion of trips that are assumed to be made in an EV over the period (0.8pp at weekdays and 0.6pp for weekends). This varies greatly between MSOAs, ranging from a nearly 1pp drop to a 1.75pp increase.

6.5 EV use by journey type

The MND provider determines a user's home and work locations based on where they spend significant time overnight and during typical work hours. Using this, they are able to indicate whether trips are likely commutes between home and work. Figure 8 shows the average daily number of trips denoted as EV originating within each of the 18 MSOAs in Lancaster, in each of the four months of mobile data, split by day type (weekday or weekend) and purpose. The average daily number of EV trips starting across Lancaster is again superimposed in green.

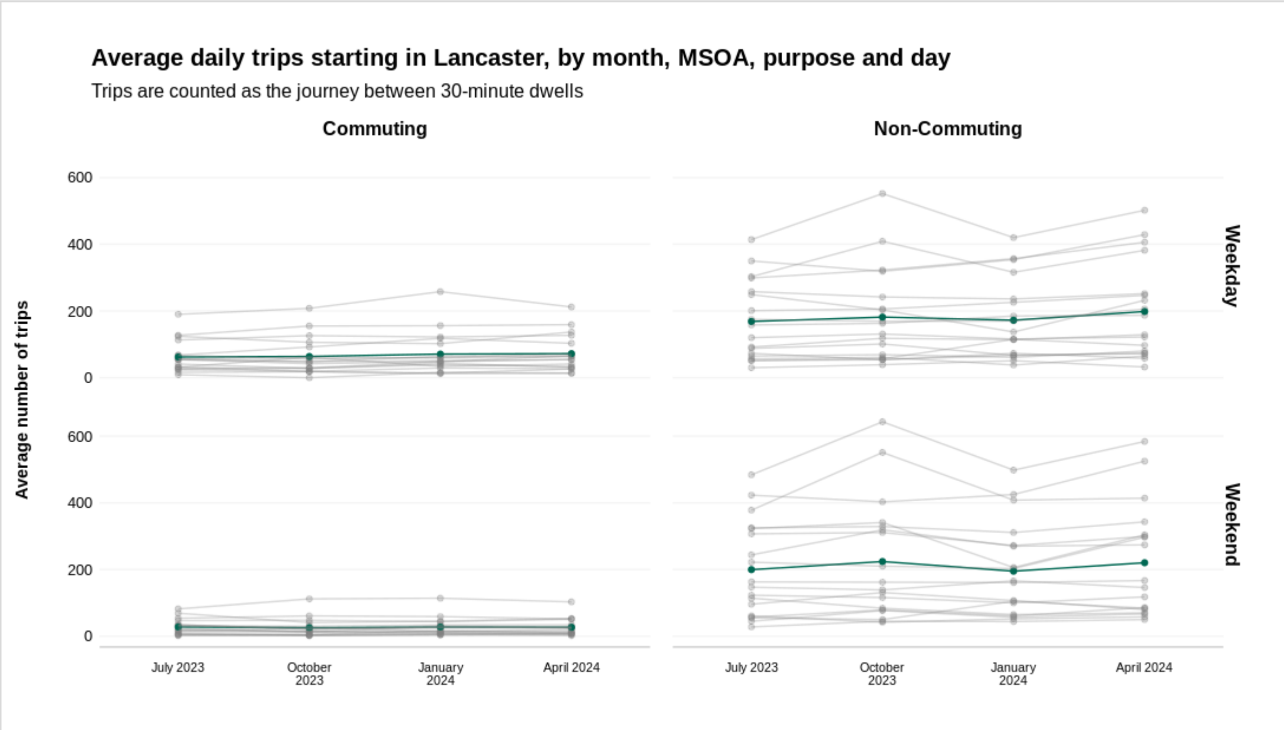

Figure 8 Average daily EV trips starting in each of Lancaster's MSOAs, split by day and purpose

Figure 8 shows more non-commuting trips than commutes on both weekdays and weekends, although there are more commuting trips during weekdays than weekends. National Travel Survey data on general road travel behaviour shows that most trips in cars are made for non-commuting trips[15], which is also the case in Lancaster among EV trips.

6.6 Case study conclusions

The mobile data shows Lancaster was home to approximately ~3,300 local EV users in April 2024, which represents an increase since July 2023. However, this case study also demonstrates that the number of EV users and EV journeys varied greatly between MSOAs. Therefore, the findings from analysis of mobile data can vary depending on the level of geography considered; while Lancaster as a whole shows similar trends to the regional average (Section 5), some MSOAs within Lancaster show different patterns. Likewise, there may be other local authorities within the North West that show different trends to the regional average.

This highlights how the level of geography needs to be carefully considered during procurement of MND, and should be considered both in the context of the evaluation questions and in conjunction with the time periods of interest.

Data that covers a larger area (e.g. local authority averages) can be broken into shorter periods of time with less risk that trips will be missing due to disclosure controls. This allows for analysis of changes over shorter periods of time, but may hide considerable variation within the area.

[15] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/821479/nts0409.ods

Conversely, data that covers smaller areas can provide some analysis of this variability, but requires averages over longer time periods (e.g. monthly) in order to ensure trips are not missing due to disclosure controls.

7. Conclusions

7.1 Findings and recommendations

This work has established a better understanding of the benefits and challenges of using MND to support evaluation and analysis of EV-related interventions, and highlights the value that early exploration of a novel data source can bring to ensure its effective use in future work.

This two-year project considered three key questions:

- Does mobile network operator data provide valid and robust evidence on EV usage which is suitable for use in evaluation?
- If yes, how can this new data source be used to support planned evaluation of EV-related interventions?
- What additional insights on EV uptake and usage can we gain through mobile network operator datasets?

The first year of the project addressed the first of these questions, establishing that MND is **broadly consistent with existing sources** on the gender of EV users and distances travelled, but potentially overestimates EV users (and therefore trips) in areas with only a small number of registered electric vehicles. As such, until EV uptake is higher across the UK, the dataset is **best suited to analysis of trends** in time and comparisons where measuring absolute volume is less important and the consistent methodology behind the data is an advantage. MND can therefore provide credible evidence for evaluations of EV-related interventions.

However, the MND cannot directly be used to provide information around charging behaviour, and this work found that travel time data could not be matched to the trip data at the time periods and geographic granularity procured. Therefore, it is recommended that trip distances are approximated using calculated distances instead, unless travel time is the only variable of interest or can be matched to a different supplementary dataset.

For the second question, to consider how MND could be used to support evaluation, possible evaluation methods were taken from the Magenta Book and this project has found that MND is better suited to some evaluation methods than others. Overall, mobile data alone is **best suited for use in quasi-experimental impact evaluation methods**, given its coverage, consistency and flexibility. In conjunction with other datasets that can be cross-referenced to MND, the resulting dataset could be used for to support theory-based impact evaluation methods.

Across all methods, it is important that the theory of change and evaluation questions are considered when procuring the MND, to ensure it is as useful as possible. The level of geography needs to be carefully considered during procurement, in conjunction with the time periods of interest, as data that covers a larger area can be broken into shorter periods of time with less risk that data will be omitted due to disclosure controls, but this may hide considerable variation within the area chosen.

This project has established the following additional insights to support the third key question:

- The number of public chargers, average household size and average income (which is correlated with age) in a local authority all have a significant link to the number of EV users and EV trips observed there, but it is not possible to determine the direction or any causality of these links. Mobile phone data measures users, and not vehicles, therefore these factors may not influence the total number of EVs.

- The number of EV users and EV journeys varies greatly between MSOAs. Therefore the findings from analysis of mobile data can vary depending on the level of geography considered; while some MSOAs may shows similar trends to the local authority average, some MSOAs show different patterns. This is true for any chosen level of geography.

- EV uptake and usage are noticeably higher in London compared to the East of England and North West, and the MND has provided some analysis of trends in time across the regions that could be analysed in relation to seasonality or other influencing factors (if more data and supplementary datasets were available).

7.2 Procurement lessons

This work has also identified advice and considerations based on an increased understanding of mobile data and how it can be used in evaluation, which can help ensure future data procurements are as useful as possible for evaluating impacts of EV interventions:

- Careful consideration of the **format and granularity** of the data in the context of the evaluation question is needed. Data procured at both a very granular level and short time periods may not reach disclosure control thresholds and can be difficult to combine for larger areas, whereas less granular data or averages covering longer periods are more likely to reach disclosure thresholds but may mask underlying variations.

- Procurement of novel data can be time intensive and **sufficient time is needed** for the providers to schedule and process the data into its final format. This can be an **iterative process** to get the right product and coverage.

- In both years of this project, initial data had some small issues such as incomplete coverage or duplicate values, which were corrected during the data cleaning process, but **input and validation by domain and data specialists** is therefore needed in the procurement stages.

- The datasets are large and can be complex so consideration should be given to **storage and analysis tools**. Even when processed by the provider, the data is too complex to present directly in policy documents, so analyst involvement is needed.

Annex A: p-values from regression analysis

Uptake

Variable	p-value	Coefficient
Chargers	**0.000138**	**3.144**
Average income	**0.033258**	**0.1245**
Average household size	**0.00000022**	**10,390**
Percentage of women	**0.051478**	**922.2**
Percentage of urban authorities	**0.116292**	**20.79**

Usage (number of trips)

Variable	p-value	Coefficient
Chargers	**0.0000000391**	**17.56**
Average income	**0.02978**	**47.33**
Average household size	**0.00196**	**22,110**
Percentage of women	**0.82644**	**-382.9**
Percentage of urban authorities	**0.17342**	**66.96**

Uptake (age only)

Variable	p-value	Coefficient
Chargers	**0.00807**	**2.260**
Age	**0.00000484**	**-319.4**
Percentage of women	**0.03307**	**1,073**