Journal of Transport Geography 118 (2024) 103923

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Social inequality and the changing patterns of travel in the pandemic and post-pandemic era[☆]

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ARTICLE INFO

Keywords:
COVID-19
Mobility
Inequality
Time series clustering
GPS data
UK

ABSTRACT

The COVID-19 pandemic has had an unprecedented impact on mobility patterns resulting in a significant literature investigating travel behaviours over the course of the pandemic. Missing from much existing work on pandemic mobility is an explicit handling of the time-of-day of travel, which in previous literature has been shown to be an important factor in understanding mobility and, importantly, in understanding the impact on transport networks. In this article, we present a novel analysis of anonymised individual daily mobility patterns in the UK over a 30-month period covering the COVID-19 pandemic using privacy-preserving mobile phone GPS data, collected via integration of software development kits (SDKs) into mobile apps. Our analysis is based on time series clustering of mobility profiles at an hourly level of resolution and enables us to characterize five distinct daily mobility patterns. This typology appears remarkably robust over time, albeit with varying levels of each pattern during the course of the study period. We analyse the relative frequency of these patterns in relation to two dimensions of neighbourhood deprivation in England, with a particular focus on understanding mobility post-lockdown and for over a year after the final restrictions were lifted in the UK. Our results show that although overall mobility patterns have largely returned to their pre-pandemic levels, there remain persistent inequalities in relation to 'traditional commute', 'highly mobile' and 'out in the evening' activity patterns. This finding is expected to have important ongoing policy implications.

1. Introduction

The COVID-19 pandemic has had an unprecedented impact on mobility patterns of people around the world. Much of this impact was a result of governments introducing national and regional lockdowns to limit mobility and control the spread of the disease. There is evidence, however, that mobility patterns have been impacted beyond the lifespan of the lockdowns. For instance, evidence suggests that the number of people either working from home or working a mixture from home and at the workplace (so-called *hybrid working*) has increased since pre-pandemic levels (Pew Research Centre, 2022). There are also continued impacts on other areas of society which are likely to lead to changes in the mobility of the population. For example, in 2022, unemployment levels in the UK remained higher than in the pre-pandemic period (Office for National Statistics (ONS), 2022).

An important finding emerging from many studies is that the impact of the pandemic has been felt unequally across society. A number of studies have looked at behavioural responses to lockdowns and have demonstrated an association between socioeconomic status and the level of mobility in several countries (Fraiberger et al., 2020; Bonaccorsi et al., 2020; Weill et al., 2020; Gauvin et al., 2021; Campbell et al., 2021; Dueñas et al., 2021; Glodeanu et al., 2021; Sevtsuk et al., 2022). These studies have found that mobility reduction during the height of the pandemic was strongest for the least deprived (i.e. affluent) communities, while more deprived communities were more likely to retain their (lower from the outset) levels of mobility. Contributing factors to this might be the increased opportunities afforded to less deprived workers to work from home while more deprived communities may be more

☆ Funding for this research was provided by the Economic and Social Research Council (Consumer Data Research Centre, ES/S007164/1). Charisma F. Choudhury and Arash Kalatian were supported by the 'Next Generation Travel Behaviour Models' (NEXUS) project [MR/T020423/1]. The authors are also grateful to comments from two anonymous reviewers, which have helped improve this article.

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https://doi.org/10.1016/j.jtrangeo.2024.103923
Received 28 April 2023; Received in revised form 11 March 2024; Accepted 13 June 2024
Available online 24 June 2024

associated with ‘blue collar’ jobs that cannot be done remotely. In the UK, deprived communities also tend to be more likely associated with urban areas, which may play an additional role in the resulting mobility patterns under pandemic conditions.

While it is important to understand mobility behaviours during pandemics and under non-pharmaceutical interventions such as lockdowns to improve preparedness for future pandemics, it is also important to investigate the longer-term effects of the pandemic on mobility. By studying the period following lockdowns, we may be better placed to design policy that supports those who may be most affected by the subsequent economic contraction. Such policies may be concerned with targeting those most at risk of unemployment, but may also consider steps to improve safety and perceived safety from the pandemic on public transport and in other public spaces, for example by improving hygiene, ventilation, or providing personal protective equipment.

In this article, in contrast to many existing studies, we take a longer-term view of mobility during the pandemic, using passively collected mobile phone GPS data generated by third-party apps (via the integration of a software development kit, or SDK) for a 30-month period from January 2020 to July 2022. In doing so, we are able to investigate mobility patterns at the end of lockdown periods and periods of other interventions, such as restrictions on large gatherings or the UK's attempt at stimulating the economy during the summer of 2020 via its ‘Eat Out to Help Out’ scheme. Existing research on behavioural responses to the lifting of mobility restrictions is more limited. Moreover, as we investigate in Section 2, the relationship between mobility patterns and social inequalities upon lifting of lockdown restrictions is not yet fully understood.

Our long-term perspective also allows us to investigate mobility patterns and their relationship with social inequality for over a year following the end of lockdowns in the UK. Due to the vaccination programme in the UK, there have been no restrictions on movement or gatherings since 19th July 2021. For the purposes of this article, we refer to the period following this date as the ‘post-pandemic period’, although we recognise that the pandemic continued beyond this date. By analysing our mobility data for a year following the end of any mobility restrictions, we aim to identify whether any persistent changes have occurred to everyday mobility patterns. In particular, we seek to understand whether the differential effect of social inequality on mobility identified during the height of the pandemic has persisted or changed over time. It is important to recognise such changes in the context of designing equitable transport systems and addressing other forms of social inequality.

In work to date in understanding pandemic mobility, the link between socioeconomic status and mobility has been found using temporally aggregated measures of overall mobility, usually at a daily level of analysis. However, one of the features of mobility during the pandemic was that it changed not only the magnitude of travel but also the time of day at which travel occurred (Mützel and Scheiner, 2022; Xin et al., 2022). Moreover, there is evidence to suggest that the temporal dimension of mobility took longer to recover following the lifting of lockdown restrictions than the spatial dimension (Santana et al., 2023). In this article, we construct a novel dependent variable for analysing the relationship between mobility and social inequality, which incorporates the time of day at which travel occurred and allows us, via a clustering procedure, to identify a typology of daily travel patterns. This typology captures five distinct daily mobility patterns, which vary in relation to the time and intensity at which travel occurs during the day. In this study, we first analyse the relative frequency of these patterns from a spatial and temporal perspective, before introducing a panel regression framework at a larger area level to determine how the relationship between social inequality and the frequency of these travel patterns changes over the study period.

Our work makes three significant contributions to the literature on analysing mobility patterns in the context of the pandemic. First, in contrast to much existing literature, we take a long-term view of the pandemic, allowing us to explore changes in mobility over the full 30-months from the start of the pandemic to July 2022. Second, our approach allows us to quantify responses to the lifting of lockdown conditions in the immediate aftermath and also to quantify the impact of any longer-term persistent changes to the relationship between mobility and social inequality. Third, by introducing a novel dependent variable based on clustering of GPS mobile phone data over the course of a day, we are able to characterize different types of daily mobility behaviour. This provides a more nuanced view of behaviour than a simple aggregate measure and, moreover, suggests links between the observed pattern in the data and the underlying purpose or motivation of the travel behaviour.

This article proceeds as follows. In Section 2, we explore in more detail existing literature on mobility patterns and social inequality during the course of the pandemic. Our review considers different periods of the pandemic and the findings associated with each period. For instance, a large literature exists on mobility reduction during lockdowns at the height of the pandemic and their relationship with both social inequality and the continued spread of the disease. A more limited literature considers responses to the removal of lockdown restrictions and this is one area to which our article contributes. We also consider the importance of including the time of day into the variable used in any analysis of mobility. We then describe our data sources and methods in Section 3. Due to the novelty of our analytical approach, we devote a significant section of this article to the construction, validation, and interpretation of our typology of daily mobility behaviours before proceeding with our analysis of mobility and social inequality. In Section 4, we present the results of our analysis in three stages. First, we characterize our typology of daily mobility behaviours. Second, we explore the spatiotemporal dynamics of behaviour prevalence over the course of the study period. Third, we present the results of a regression model which finds associations between cluster prevalence and social inequality over time. Finally, in Section 5, we discuss our results in relation to possible policy implications and limitations associated with our data sources and analysis.

2. Analysis of mobility patterns during COVID-19

As the COVID-19 pandemic took hold around the world, governments introduced lockdown measures in an effort to limit the spread of the disease. At the aggregate level, lockdowns largely achieved their goal of reducing visits to workplaces, public transport networks, and to retail and recreation facilities, where greater opportunities for the spread of the disease are present. This has been established in a number of studies, often using newer forms of mobility data such as mobile phone GPS data (Google, 2022; Hu et al., 2021; Jeffrey et al., 2020), but also using more traditional forms of primary data such as surveys (Barbieri et al., 2021; Borkowski et al., 2021; Balbontin et al., 2021) or transport system ridership statistics (Xin et al., 2021).

2.1. Population-level inequalities

A rapidly growing research literature has investigated behaviour changes in response to the pandemic, identifying differences in the way that different groups and communities changed their behaviour during these lockdowns. One of the more consistent findings has been that the least deprived communities (i.e. high income groups) had the greatest reduction in mobility (Almlöf et al., 2021; Fraiberger et al., 2020; Bonaccorsi et al., 2020; Dueñas et al., 2021; Campbell et al., 2021; Gauvin et al., 2021; Weill et al., 2020; Huang et al., 2021; Trasberg and Cheshire, 2021; Long and Ren, 2022; Sevtsuk et al., 2022; Lee et al., 2021; Zhang and Ning, 2023). This may be partly explained by these communities having higher levels of mobility at the outset of the pandemic (and so had greater capacity to change their behaviours), but explanations also point to such communities having more opportunity to work from home and to partake in other activities that allows them to avoid high risk activities and locations (Pew Research Centre, 2022; Ecke et al., 2022; Winkler et al., 2022; Kar et al., 2022). The impact of this has been increased inequality during the pandemic. By not reducing mobility to the same extent as less deprived communities, lower income groups have been put at greater risk of exposure to the disease (Chang et al., 2021; Kawakami et al., 2023; Kephart et al., 2021; Levy et al., 2022; Madden et al., 2021; Ossimetha et al., 2021; Tokey, 2021). More deprived communities are also more susceptible to the damaging economic impact of lockdowns via high unemployment (Office for National Statistics (ONS), 2022). For instance, Bonaccorsi et al. (2020) explores how mobility network contraction is greatest for areas with the highest level of inequality. The closure of businesses within the hospitality sector and downturns in traditional blue-collar economies such as the construction industry may have also limited the employment opportunities for lower income communities, prompting the suggestion that additional support should be considered for such groups (Dueñas et al., 2021). Inequalities have also been established in urban park use, suggesting further policies that might be considered to promote health and well-being in more socioeconomic disadvantaged areas (Yu et al., 2023).

A number of studies have used data over a longer time period, to analyse not only the impact on behaviours under lockdown but also to consider the effectiveness of lockdowns over time, showing that, for example, repeated lockdowns tend to lose their effectiveness on their ability to restrict individual mobility (Gramsch et al., 2022; Ross et al., 2021; Hu et al., 2021; Jeffrey et al., 2020; Kim and Kwan, 2021; Zhang and Ning, 2023) and, moreover, that the effectiveness and longevity of adherence to different lockdowns can vary depending on the severity and details of the intervention itself (Liu and Zhang, 2023).

2.2. Post-lockdown and longitudinal change

An important consideration in relation to the current study is the extent to which mobility patterns have recovered following a lockdown period, with a view to identifying whether there are any signs of persistent changes in mobility patterns, public transport use or urban footfall, all of which can have significant socioeconomic and urban planning implications. In the immediate aftermath of the lifting of lockdown restrictions, there is evidence that mobility patterns do not immediately revert to pre-lockdown levels (Gauvin et al., 2021; De Palma et al., 2022; Hu et al., 2021; Liu and Zhang, 2023).

Some studies have found that the differential impact of socioeconomic inequality on mobility reduces over time following the end of lockdowns (Glodeanu et al., 2021; Almlöf et al., 2021), however Kim and Kwan (2021) find that more deprived areas are in fact slower to rebound following the end of a lockdown (although the authors do point out that this may actually be an artifact of a lack of reduction in mobility in the first place). A similar finding is also found in Zhang and Ning (2023) where highly educated and high density areas are found to recover mobility patterns more quickly than other areas. Meanwhile, Lizana et al. (2023) find evidence that in fact areas that are more deprived are the fastest to return to pre-pandemic levels, emphasising that these communities often have no choice but to use public transport to meet their mobility needs. These mixed findings point to a gap in the existing literature.

Even longer term views of pandemic mobility have been considered, for instance, Long and Ren (2022), highlight the temporal dependency of regression coefficients, suggesting that determinants on mobility have changed over time, and therefore need to be accounted for in any longitudinal analysis. Furthermore, Rowe et al. (2023) find evidence for the temporary nature of any reduction in mobility as a result of the pandemic. Similar conclusions have also been found drawing on population register data in Spain (González-Leonardo et al., 2022). Concas et al. (2022) also use connected vehicle data of 308 drivers in Florida over a long time period to confirm that mobility profiles appear to be in the process of reverting to pre-pandemic trends.

2.3. Defining measures of mobility

Given the increasing richness of the mobility data when using passive collection methods (Welch and Widita, 2019), it is perhaps surprising that many existing studies converge on using a similar range of dependent variables in order to capture different levels of mobility. Carroll and Prentice (2021) explore this directly, demonstrating the importance of the design of the dependent variable, and show that variables more closely aligned to mobility behaviours do a better job of predicting outcomes. The range of dependent variables used in the existing pandemic literature includes, amongst others, distance travelled (e.g. Concas et al. (2022); Hu et al. (2021)), amount of time spent at home and away from home (e.g. Concas et al. (2022); Fraiberger et al. (2020); Hu et al. (2021)), number or proportion of trips outside a designated area (e.g. Kawakami et al. (2023); Glodeanu et al. (2021); Hu et al. (2021); Kar et al. (2022); Pullano et al. (2020)), the average daily radius of gyration, which represents the characteristic distance travelled over the course of a day (e.g. Gauvin et al. (2021); Santana et al. (2023); Lee et al. (2021)), or amount of travel performed on a particular mode over the course of a day (e.g. Liu and Zhang (2023); Xin et al. (2021)). Data-driven algorithms to defining measures of mobility, for example via the derivation of daily activity spaces (Toger et al., 2021), are less common but have potential to exploit some of the richness in the source data.

In the literature to date, the majority of variables are aggregated into daily values, either at the area or individual level. This design choice neglects an important aspect of mobility patterns, namely that the time and order at which travel occurs can contribute to the effective characterisation of the kind of travel taking place (Schneider et al., 2013; Bhat and Singh, 2000), and, moreover is also essential for the successful planning of public transport operations (Mazloumi et al., 2010; Zhong et al., 2016).

Time of day has also been explored in relation to pandemic mobility. Mützel and Scheiner (2022) incorporate time of day into their visual analysis of the change in public transport system, highlighting the heterogeneous response to the pandemic at different times of day. Pullano et al. (2020) find that the least amount of mobility reduction was during weekday nights, which may be linked to work-related travel, such as shift workers. Finally, Xin et al. (2022) use time of day as an important factor in their analysis of bike sharing data in New York City during the pandemic, demonstrating a reduction in the morning peak of bicycle use, consistent with the idea that commuting patterns took a large downturn during the pandemic. This study also highlights how considering the time of day at which travel occurred can generate insights into the type of travel and underlying behaviour.

Outside of pandemic mobility, time of day is well-established as an important research topic when investigating mobility behaviours. For example, Goulet-Langlois et al. (2016) present a clustering approach to analysing longitudinal travel patterns using data from London's public transport network. The authors identify distinct differences in the use of the transport network, with a large proportion of individuals being identified as spending a majority of their weekdays in the workplace, a secondary set of individuals that are more likely to remain at a home location, and more complex patterns that are characterised by irregular travel. They find associations between the sociodemographic characteristics of cluster membership. Using the temporal variation in user demand, clustering methodologies have been used to derived classifications of regular and ad-hoc travellers (Manley et al., 2018), identify longitudinal behaviour change (Briand et al., 2017), and address sociodemographic variation in uptake of new services (Liu and Cheng, 2020).

2.4. Contributions

Given the extensive literature on pandemic mobility to date, we now summarise our main contributions, which are in three distinct dimensions. First, our study contributes to understanding persistent inequalities that have arisen throughout the pandemic. This provides further evidence of a differential effect in returning to pre-pandemic activity patterns following disruptions to mobility brought about by lockdowns. Second, we analyse the pandemic and associated mobility patterns at a daily resolution over a 30-month period using mobile phone GPS data, something that would not be possible with more traditional data sources, and provides a relatively temporally complete understanding of mobility dynamics during the pandemic. Third, by analysing the mobility data prior to the pandemic, we construct a novel dependent variable which we use throughout our analysis. This variable directly incorporates how individuals' movements vary over the course of the day, which is used to distinguish between different types of daily mobility. Our particular form of the dependent variable, as derived from a clustering procedure applied to the mobility data, is unique (at least to our knowledge) and we therefore devote a significant portion of the next section to explaining its derivation and undertaking validation to ensure our variable captures meaningful variation of mobility patterns over the study period.

3. Data and methods

Our approach consists of two phases. The first phase is conducted at the individual level in which we construct time-of-day profiles for users within the available GPS data. We implement a clustering analysis that generates five distinct groups of daily mobility behaviour. We check the robustness of these groups via a validation approach described in Section 3.3.3. In the second phase of our analysis, we build a statistical model at the area-level to predict the prevalence of cluster membership over time and space. In this section, we first describe our study area and data sources before describing these two distinct phases of our analytical approach.

3.1. Study area

The data available for this study comprised of GPS traces within Great Britain. Subject to the filtering process and date ranges selected for our clustering procedure outlined below, we use all available data to build mobility profiles at the individual level. Due to the passive nature of the data collection process, the need for participants to have access to mobile phones, and to have opted in to the data collection, the data may not be wholly representative of the population of Great Britain. Previous studies using this same data source have considered the representativeness of the data, and shown good agreements with administrative data sources, such as census data (Ross et al., 2021; Santana et al., 2023). However, it is important to note that the GPS data used in this study does not contain demographic attributes of the users, only their GPS traces are collected, which limits our ability to accurately assess the representativeness of this data or indeed to include any demographic data within our analysis (which is why we move to an area-level analysis during phase 2). Nevertheless, the growth in number of studies that use passively collected mobile phone data demonstrate that this data source can be very valuable in understanding patterns in behaviour at a granular level and over a large sample size, which has historically not been possible. We discuss further implications around the data collection process in Section 5.

To assess the spatial distribution of cluster prevalence, we map individual daily mobility profiles to the lower-tier Local Authority District (LAD) in which each individual's estimated home location is situated (the process for estimating and validating estimated home locations is detailed in Section 3.3.1). LADs are a sub-national division of the UK for the purposes of local government. We use the December 2021 boundaries obtained from the ONS Open Geography Portal which comprise of 363 districts within Great Britain.

Finally, during the second phase of our analysis, in which we construct a statistical model for predicting cluster prevalence in space and time, due to the availability and consistency of data for our predictor variables, we further restrict our study area to the 309 LADs in England only. We further remove the districts of the Isles of Scilly, Barrow-in-Furness, Rossendale, Rutland, and the City of London due to a total sample size of fewer than 10 individuals on a single day within our analysis period, leaving 304 spatial units of analysis. Summary population statistics of these 304 spatial units are shown in Table 1.

3.2. Data sources

Access to GPS data was provided by Spectus who collect GDPR compliant, de-identified data from opted-in users of smartphone apps who have provided informed consent for their anonymised data to be used for research purposes. The data contains an anonymised user identifier, timestamp and longitude/latitude coordinates. To preserve privacy, Spectus 'up-levels' home locations to the geohash level 6. A geohash is an alphanumeric code provided by the geohash geocoding system (see http://geohash.org/). A geohash at level 6 represents a grid element of size 1.2 km × 609.4 m, inducing a systematic source of uncertainty in user home locations within our analysis.

Geohashes for user home locations are estimated by Spectus via a procedure that considers the number of days spent in a given location in the last month, the daily average number of hours spent in the location and the time of day spent in the location (nighttime/daytime). This process is updated every week to confirm or update the inferred geohash. Following a validation of this procedure described in Section 3.3.1, we use Spectus' home locations estimate in our analysis.

Our main source of independent variables are the Indices of Multiple Deprivation 2019 (McLennan et al., 2019). We also use data on COVID-19 related deaths and the Coronavirus Job Retention Scheme available via the UK Government website. Geographic data was obtained from the Office for National Statistics Open Geography Portal.

3.3. Phase 1: Clustering daily mobility profiles using GPS data

3.3.1. GPS data processing

To validate the estimation of home areas we found that 90% of users with an encoded home geohash had at least 95% of their GPS traces within 1 km of their estimated home areas between the hours of 3 am and 4 am. On the basis that this appears to approximate users' home areas rather well, we proceeded to use these areas as the definition of a home location for each user.

For each user with an encoded home geohash, we calculated the average distance from their home location for each hour of the day.

To impute missing hourly data following this process, an interpolation procedure is applied that uses linear interpolation between points away from home, but assumes the user remains at home for missing data between home locations. On its own, linear interpolation of missing trajectory data is known to result in error prone imputed data (Barnett and Onnela, 2020). Our approach assumes that a user pauses at home until another record is encountered away from home, which most notably prevents missing data during nighttime hours being treated as part of the journey to the first record outside of the home the following day. This anchoring of user locations towards their home locations prevents excessive imputed data outside of the home.

We tested the sensitivity of our analysis to missing data by running our analysis with only user-days that included GPS data for a minimum

Table 1
Summary statistics for our study area.

	Count	2021 Median Population	2021 Min Pop	2021 Max Pop
2021 LADs of Great Britain	363	141,036	2054	1,144,919
English LADs used in our model (due to data availability)	304	143,265	49,776	1,144,919

number of hours each day (including 12, 8 and 5 h). The results were unchanged and so we proceeded by including all of the data in our analysis.

3.3.2. Clustering procedure

Data is filtered to only include days on which users are at their home locations between 3 am and 4 am (based on the interpolated data). This ensures we only include user-days in our analysis where the user started their day at their estimated home location.

A k-means clustering algorithm is applied between 13th Jan 2020 and 10th Feb 2020. Between 81,010 and 92,528 users per day appeared in the training data (2.46 million training records in total).

Assuming that the interpolated distance from home by hour of day vector for a user i on a day t is given by the vector $\mathbf{d}(i,t) \in \mathbb{R}^{24}_{\geq 0}$ with elements $d_h(i,t)$, then our input to the k-means clustering algorithm is given by:

$$\mathbf{x}(i,t) = \left(\widehat{\mathbf{d}}(i,t), max(\mathbf{d}(i,t)), \sum_{h=1}^{n-1} \left| \widehat{d}_{h+1}(i,t) - \widehat{d}_h(i,t) \right| \right), \tag{1}$$

where the first element of Eq. (1) represents the normalised distance from home for each hour of the day (which is normalised by dividing by the maximum distance each day if it is greater than zero), the second element of Eq. (1) represents the maximum hourly-averaged distance from home on the given day, and the final element of Eq. (1) provides a measure of the total radial distance travelled from home over the course of the day.

K-means clustering requires the specification of the number of clusters. Following a random initialisation, the algorithm assigns each point in the data to its nearest cluster center. It then re-calculates the cluster centroids and re-assigns points to clusters, iterating until no further improvement in a measure known as 'inertia' is found (subject to some tolerance). K-means clustering has been successfully applied to other studies analysing the daily profile of individual mobility patterns (Pontin et al., 2021). We used the scikit-learn implementation of k-means in Python (Pedregosa et al., 2011).

To determine the number of clusters present in the data, we applied the k-means algorithm on the data with between 2 and 16 clusters and then measured the average silhouette score across the sample (Rousseeuw, 1987) for each choice of number of clusters. Fig. 1 shows the results of this process. The silhouette score provides a measure of the extent to which points within a cluster are closer to other points within that same cluster in comparison to points outside the cluster. Higher average silhouette scores correspond to better defined clusters. Based on the average scores plotted in Fig. 1, we use five clusters for the remainder of our analysis.

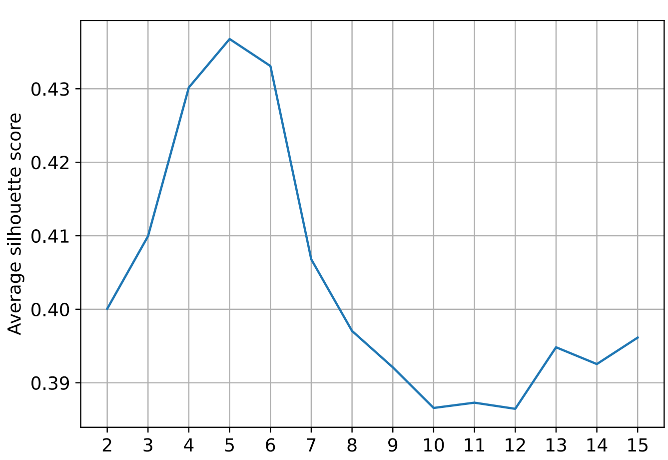


Fig. 1. Silhouette score by number of clusters.

3.3.3. Validating the characterisation of clusters

To validate the characterisation of the clusters, we employ a temporal validation approach as follows. For every two-week period over the entire period of study (January 2020–June 2022) a k-means clustering algorithm is estimated and the resulting clusters identified. The main axes of Fig. 2 shows the resulting clusters of each two-week period overlaid on each other.

To quantify the performance of the clustering algorithm against different time periods, we calculate an adjusted Youden's J statistic, weighted according to the frequency of each class. To do this, we classify each user-day according to the model estimated in Section 3.3.2, generating an out-of-sample classification $\widehat{c}_{it}$. This is compared with the in-sample classification of the same observation, c_{it}, from the validation models shown in the main axes of Fig. 2, and used to generate a multi-class Youden's J statistic as:

$$J_t = \sum_g \frac{\sum_i I(c_{it} = g)}{\sum_{i,g} I(c_{it} = g)} \left(\frac{TP_{gt}}{TP_{gt} + FN_{gt}} + \frac{TN_{gt}}{TN_{gt} + FP_{gt}} - 1 \right), \tag{2}$$

where g indexes the cluster and

$$\begin{aligned} TP_{gt} &= \sum_i I(\widehat{c}_{it} = g | c_{it} = g), \\ FN_{gt} &= \sum_i I(\widehat{c}_{it} \neq g | c_{it} = g), \\ TN_{gt} &= \sum_i I(\widehat{c}_{it} \neq g | c_{it} \neq g), \\ FP_{gt} &= \sum_i I(\widehat{c}_{it} = g | c_{it} \neq g), \end{aligned} \tag{3}$$

are the number of true positive, false negative, true negative and false positive classifications, respectively.

Intuitively, Youden's J statistic measures the ability of a classifier to make informed predictions. Values are bounded between 0 and 1 with a perfect model (one with zero false positives and zero false negatives) recieving a Youden's J statistic equal to 1. The inset axes of Fig. 2 shows the performance of the Youden's J statistic over each of the validation models constructed. With the exception of a reduction in the statistic at the beginning of April 2020 (coinciding with the start of lockdown 1 in the UK) and at the end of 2021, we observe high values close to 1. On inspection of the data, using the classifications of the clusters outlined in Section 4.1 these two reductions in the measure are caused by a large number of highly mobile users (according to the in-sample model) being predicted as taking short trips out of the home (according to the out-of-sample prediction). Despite this discrepancy, and for consistency of estimator across the time period, we use the January–February 2020 model to make predictions about the data for our analysis.

3.4. Phase 2: Modelling clustering prevalence in space and time

Each user's home location is mapped to the LAD within which it resides, using December 2021 boundaries obtained from the ONS Open Geography Portal. Then, for each LAD, we calculate the weekly proportion of cluster membership for all users residing in this district as

$$P_{cit} = \frac{N_{cit}}{\sum_c N_{cit}}, \tag{4}$$

where N_{cit} is the number of users assigned to cluster c within LAD i within week t. We aggregate to a weekly temporal measure of our cluster prevalence to remove any day of week dependence in our model and also to match the temporal granularity of our independent variables. We then normalize P_{cit} by a baseline period, taken as our training period between 13th January 2020 and 10th February 2020, to obtain:

$$y_{cit} = \frac{(P_{cit} - P_{ciB})}{P_{ciB}}, \tag{5}$$

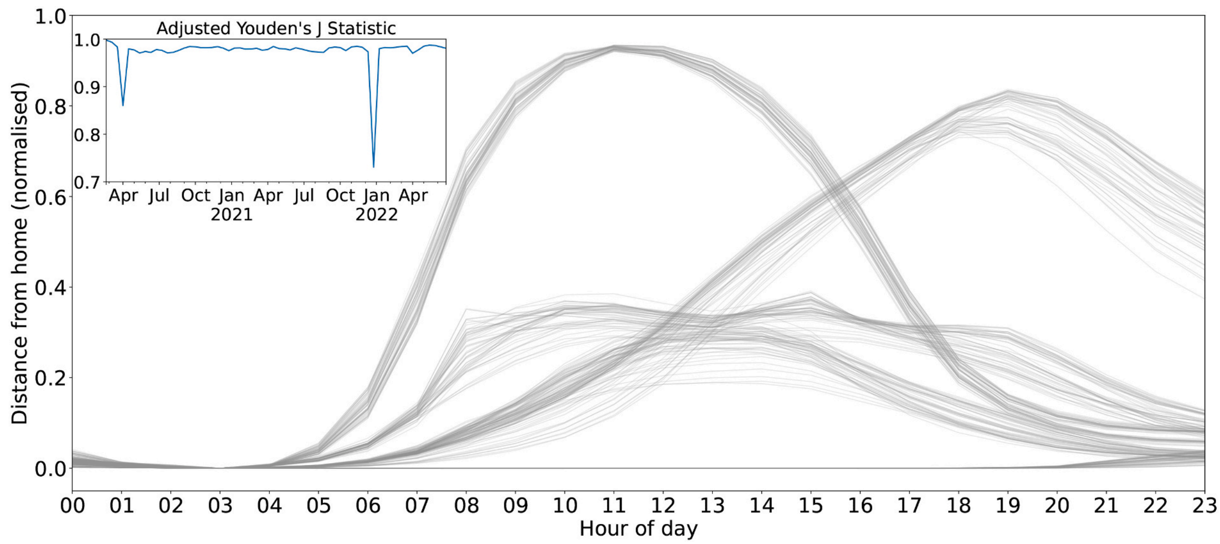


Fig. 2. Cluster Validation. Main axes show the cluster centroids following k-means clustering for two-week periods across the entire study period. The inset axis shows the adjusted Youden's J Statistic in Eq. (2) across the study period (excluding the baseline period).

where P_{ciB} is the proportion of cluster c for district i over the entire baseline period B,

$$P_{ciB} = \frac{\sum_{t\in B} N_{cit}}{\sum_{t\in B}\sum_{c} N_{cit}}. \tag{6}$$

Normalising by the baseline period means that y_{cit} captures deviance from pre-pandemic behaviours.

We are interested in understanding the how the impact of deprivation influences the prevalence of each cluster during different periods of the pandemic. As such, we model y_{cit}, as derived in Eq. (5) using an unobserved effects modelling framework to control for time-invariant heterogeneity within each LAD as

$$y_{cit} = \theta_{2c} I_2 + \ldots + \theta_{Tc} I_T + I_2 \mathbf{z}_i \gamma_{2c} + \ldots + I_T \mathbf{z}_i \gamma_{Tc} + \mathbf{w}_{it}\delta_c + d_{ic} + u_{cit}, \tag{7}$$

where I_v are indicator variables for time period v (which are provided in Table 2), θ_{vc} are parameters which capture the district-invariant temporal effects relative to a baseline period (notionally given by $v = 1$), such as those caused by national lockdowns, $\mathbf{z}_i$ are a collection of time-invariant variables that are interacted against I_v and γ_{vc} measures the effect of this interaction (the effect is again relative to a baseline period $v = 1$). $\mathbf{w}_{it}$ are a collection of time-varying independent variables, d_{ic} represents the time-invariant district-level heterogeneity of district i and u_{cit} is a collection of error terms that are assumed to be uncorrelated. Our model specification in Eq. (7) is similar to studies that implement an interrupted time series approach to investigate changes in levels of a variable of interest following interventions (Zhang and Ning, 2023).

Table 2
Time Indicator Definition. Start dates and end dates are aggregated to the nearest week. The exact dates of lockdown are subject to local and regional variation. The lockdown dates chosen above are chosen to reflect points at which the majority of the population were under restrictions in England.

Label	Description	Start date	End date
t_0	Baseline period	17th Feb 2020	23rd Mar 2020
t_1	Lockdown 1	23rd March 2020	11th May 2020
t_2	Lockdown 1 easing	11th May 2020	3rd August 2020
t_3	Eat out to help out	3rd August 2020	31st August 2020
t_4	Pre-lockdown 2	31st August 2020	5th November 2020
t_5	Lockdown 2	5th November 2020	2nd December 2020
t_6	Pre-lockdown 3	2nd December 2020	4th January 2021
t_7	Lockdown 3	4th January 2021	8th March 2021
t_8	Lockdown 3 easing	8th March 2021	19th July 2021
t_9	No restrictions 2021	19th July 2021	1st January 2022
t_{10}	No restrictions 2022	1st January 2022	1st July 2022

A limitation of the data used in this study was the varying cohort size over the study period. Although one of the advantages in using digital footprint consumer data such as these are the large sample sizes, one has to be wary of any systematic variation in sample representation. Previous work has demonstrated a close correspondence between the representation of the data used in this study and the population using census data (Ross et al., 2021). To help control for the varying cohort size, we used the Pelt method (Killick et al., 2012) within the Ruptures python package (Truong et al., 2020) to detect two changepoints in the cohort count time-series. Within our regression model, we included indicator variables for each regime between the detected breakpoints. We estimated the regression model using the PanelOLS class within the Linearmodels python package.

Our dependent variable derived in Eq. (5) incorporates information about individual daily travel routines and our research question is to explore whether this information enables novel insights into the relationship between socioeconomic status of neighbourhoods and their corresponding mobility patterns. We include two measures of deprivation at the small area level in England, representing two different dimensions or *domains* of deprivation, according to the 2019 English Indices of Deprivation (McLennan et al., 2019): a measure of income deprivation, taken as the proportion of usual residents who are defined as experiencing deprivation relating to low income; and a measure of geographic barriers to services, derived as a composite measure of road distance to a post-office; a primary school; a general store or supermarket; and a GP surgery. The inclusion of the geographic barriers to services domain captures the extent to which individuals residing in different neighbourhoods may travel to perform daily activities. These measures are captured at the more granular level of Lower Super Output Area, an administrative geographic area for the purpose of census reporting designed to contained around 1500 individuals, and are provided as ranks for each of the 32,844 Lower Super Output Areas in England. We restrict our regression model to England only, which has the largest sample size in our raw data. In order to generate a variable at the spatial level of our analysis, we take the ranks of each Lower Super Output Area and aggregate to LADs by taking the mean rank in each dimension.

We capture the varying effect of these deprivation variables by interacting with indicators for each time period (if we did not do this, the static variables would be averaged out by the fixed effects). We therefore estimate how the association with our independent variables varies over time. The time indicators we interact with are summarised in Table 2 and are chosen to correspond with distinct phases of the pandemic and the government response in England, aggregated to the nearest week.

We also include temporally dependent measures for the number of COVID deaths at the LAD level throughout the course of the pandemic and a measure of the number of applicants to the UK Government's Coronavirus Job Retention Scheme (CJRS), which was established to allow employers to furlough their staff between 20 March 2020 and 30 September 2021. The CJRS data was available at the UK region level, a sub-national division of the UK into 12 distinct areas. The CJRS value for each LAD was taken as the regional value in which the LAD sits. These variables were included to control for impact due to concerns of COVID within the local area and to capture the changes to the local labour force respectively (Gauvin et al., 2021). A complete summary of the independent variables used in our regression model, and a summary of their corresponding analytical units is provided in Table 3.

Our model contains no explicit spatial dependence. We tested the spatial auto-correlation of our model residuals for each of the 124 time units and for each of the five clusters, resulting in 620 total tests. Of these, 484 (78%) were found to have no significant levels of spatial auto-correlation present in the model residuals. This means that although the introduction of a spatial model may improve model specification in some cases, it is not the principle factor in the dynamics observed. This may be due to the relatively large spatial units of analysis, but also due to the spatial auto-correlation being indirectly captured and therefore accounted for by the explanatory variables in our model.

4. Results

In the presentation of our results, we start by explaining the clusters that were identified, providing some context into the behaviours reflected by each cluster. Second, we present how the proportion of each cluster evolved in space and time during the period of study. Third, we present results of our regression model which investigates the relationship between cluster prevalence and income and accessibility to services.

4.1. Characterisation of clusters

We identified five distinct and robust clusters in daily mobility patterns. Analysing the centroids shown in Fig. 3 enabled us to characterize these five clusters as follows:

1. *Traditional commute*: Associated with a strong pattern of travelling away from the home in the morning (between 6 and 9 in the morning) and then a corresponding return journey to the home between 15 and 18 in the afternoon. Participants were typically located at their furthest point from the home location during the middle of the day. 23% of records in the training data were allocated to this cluster.
2. *Short trips out of the home*: Characterised by a smaller peak than the traditional commute during the middle part of the day (slightly skewed into the afternoon). Closer examination of this cluster showed that this peak represented the average of many shorter trips - both in terms of distance from home and time out of the house - than those in the traditional commute cluster. For many participants, these shorter trips occurred at different times of the day, which average out to form the peak observed in Fig. 3a. 33% of records in the training data were allocated to this cluster.
3. *Stay at home*: Represented by individuals whose distance from home remains close to zero for the entire day. 27% of records in the training data were allocated to this cluster.
4. *Highly mobile*: Represented by a higher than average total radial distance travelled metric and by significant variation in the average distance from home over the course of the day. Participants belonging to this cluster typically made several stops at different locations, and therefore are likely to include mobile workers such as delivery drivers but also other participants that travelled to a variety of locations throughout the day. 7% of records in the training data were allocated to this cluster.
5. *Out in the evening*: Represented by a peak in the maximum distance from home occurring between 19:00 and 20:00. This may include participants who leave the home for social/leisure purposes but also may include shift-workers and workers in the hospitality sector. The higher than average maximum distance travelled for the out in the evening cluster may be explained by participants who do not return to their home location on that same day. 10% of records in the training data were allocated to this cluster.

Table 3
A description of independent variables and their spatial and temporal resolution.

Variable	Source	Spatial units and aggregation if applicable	Temporal units
Income deprivation	English Indices of Deprivation 2019 (McLennan et al., 2019).	2011 Lower Super Output Area (administrative area designed to contain around 1500 residents), aggregated to 2021 LADs using lookup from the ONS Open Geography Portal.	2019, single value per area.
Geographic barriers to services	As above.	As above.	As above.
COVID cause of death occurrence	Office for National Statistics (ONS) Death registrations and occurrences by local authority.	LAD	Weekly counts for the duration of the study period.
Coronavirus job retention scheme uptake (count)	HM Government CJRS statistics	Regional level, matched to 2021 LADs using lookup from the ONS Open Geography Portal.	Weekly counts from 1st July 2020 - 30th September 2021.

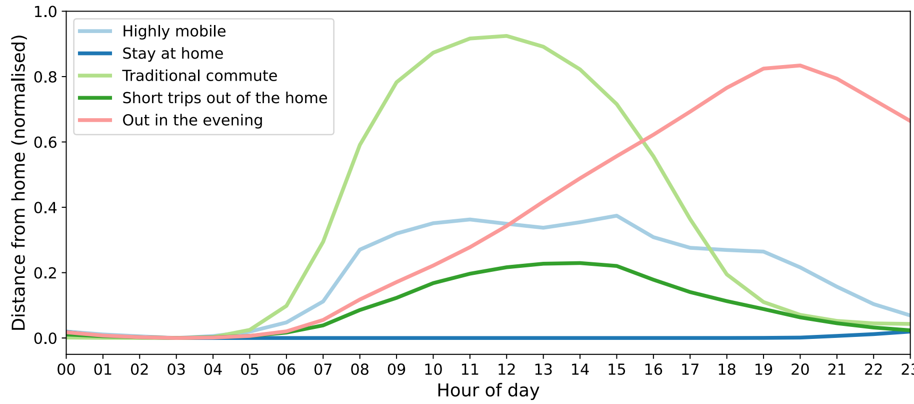
4.2. Cluster evolution in time and space

Based on our validation of the clusters (see Section 3.4), we are able to predict cluster membership using the base model for the entire study period of January 2020 to June 2022. The proportions of cluster membership over time are shown in Fig. 4. During the first lockdown period in the UK from 23rd March to 11th May 2020 we initially observe a large reduction in the more mobile cluster types (‘traditional commute’, ‘highly mobile’ and ‘out in the evening’) together with a large increase in the proportion of individuals staying at home. These deviances gradually recover towards their pre-pandemic levels over the course of the first lockdown and the gradual easing of lockdown measures until 4th July 2020.

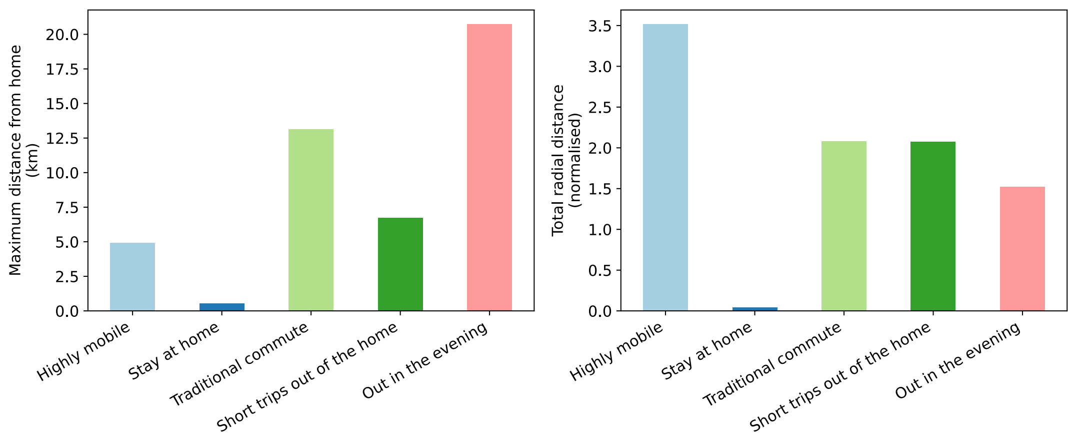
The ‘short trips out the home’ cluster gradually increases during the period of the first lockdown and then maintains the highest proportion of all clusters. This cluster might include activities consistent with working at home, in which short trips out of the house may represent daily exercise or other errands which were permitted under lockdown rules in the UK.

During the summer of 2020, as lockdown restrictions eased, we see an increase in the proportion of both ‘traditional commute’ and ‘out in the evening’ clusters. During August 2020, the UK government introduced the ‘Eat Out to Help Out’ scheme, which offered price discounts to those eating out in restaurants during weekdays. This period coincides with the increase in the ‘out in the evening’ cluster.

The second lockdown in the UK occurred between 5th November 2020 and 1st December 2020. Prior to this, we observe a small increase



(a) Distance from home by hour of day.



(b) Maximum distance from home and total radial distance (normalised) by cluster.

Fig. 3. Cluster centroids.

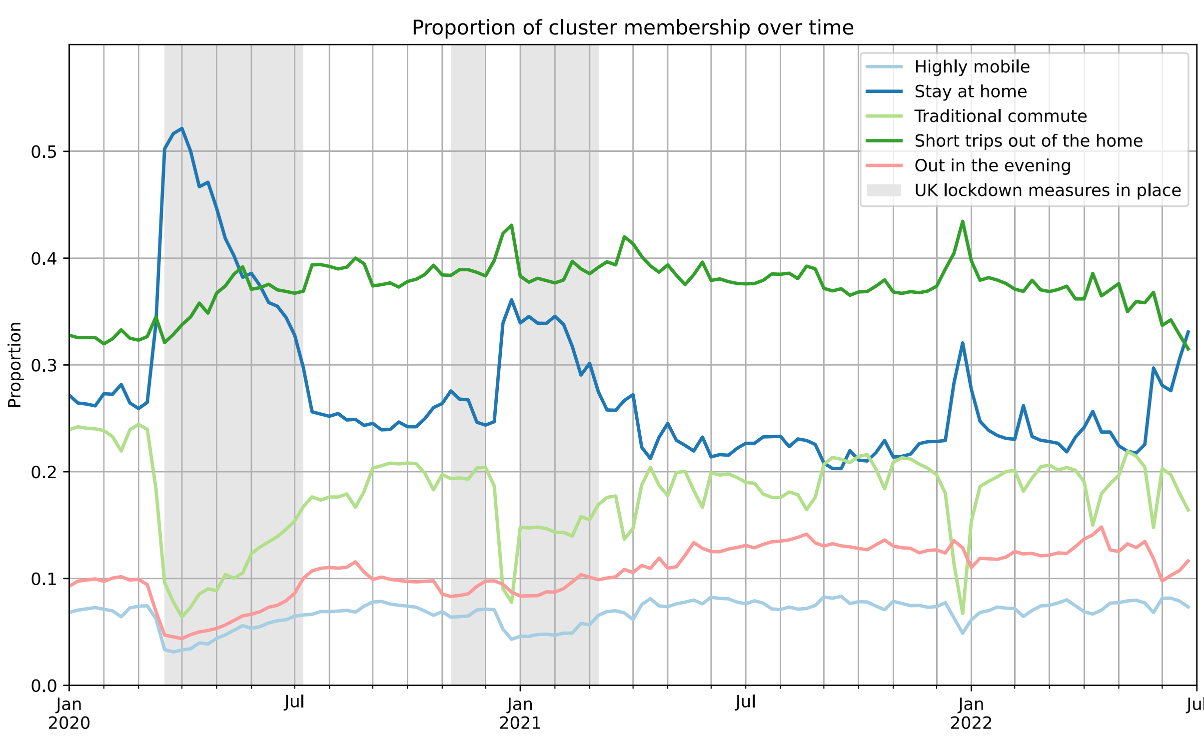


Fig. 4. Cluster membership proportion over time.

in the proportion of participants 'staying at home' and a reduction of those belonging to the 'out in the evening' cluster. However, these reductions quickly recover, partly during the lockdown period itself. For the third lockdown, between 6th January 2021 and 7th March 2021, we see an initially large increase in those staying at home but without a sustained reduction in the traditional commute cluster. This is consistent with previous work which found the effectiveness of lockdowns at restricting individual mobility reduced over time (Ross et al., 2021; Santana et al., 2023).

Fig. 5 shows the geographic distribution of the most elevated cluster incidence for a series of different time periods. We plot the cluster that attains the maximum value of our dependent variable in Eq. (5) over the time period for each Local Authority in Great Britain. The variable y_{cit} compares the prominence of each cluster in comparison to a baseline period prior to the pandemic. This means that the cluster plotted is not necessarily the most prominent but the cluster that most exceeds its baseline level. During lockdown 1, we see a universal increased prevalence of the 'stay at home' cluster. This contrasts with the period during the 'Eat Out to Help Out' scheme, which sees an increase in the 'out in the evening' cluster, particularly in the Midlands, the North of England and Wales. We also see some 'highly mobile' behaviours emerging in London and the South of England with large areas of London and surrounding areas showing a relatively high prevalence of 'short trips out to the home', a pattern that in many cases persists during lockdown 2. Lockdown 3 shows a more strict adherence to the 'stay at home' order, although the incidence of the stay at home cluster is not as widespread as during lockdown 1, with areas such as Greater Manchester largely showing 'short trips out of the home' as the most exceeded cluster. Under the no restrictions regime, the 'out in the evening' and 'highly mobile' clusters become the most exceeded in comparison to baseline levels, which is indicative of the population becoming more mobile in general in comparison to the baseline period.

4.3. Cluster membership and neighbourhood deprivation

We present the results of the regression model defined in Section 3.4 in graphical form to ease interpretation of effect direction, magnitude and statistical significance. Within each of the Figures below, point estimates of each variable are plotted for different time periods with error bars representing a 95% confidence interval of the estimate. Estimates

Fig. 5. Cartograms displaying the cluster taking the maximum value of Eq. (5) by LAD for different time periods. This represents the most elevated cluster incidence within each time period for each LAD in comparison to the baseline period.

with p-values less than 0.05 are coloured blue. Full point estimates and standard errors are presented in the Appendix.

For time effects, income, and accessible services, the static variables are interacted with the time period of interest and we therefore plot an estimate for each period, with the exception of the pre-lockdown period which is used as a baseline to provide relative estimates of variable effects across the other time periods. We exclude the initial baseline period used to normalize the dependent variable (i.e. the training data) and use 10th February 2020 to 23rd March 2020 as a reference period for the remaining parameter estimates. That is, the parameters associated with each period represent the change in effect of the corresponding parameter in reference to this period and, as such, can be interpreted as a departure from pre-pandemic patterns.

The independent variables for COVID deaths, CJRS counts, and the two change points are dynamic variables applied over the period of study and thus only a single estimate is plotted for these variables.

Beginning with the 'traditional commute' cluster, shown in Fig. 6, our results show a significant negative association with income and the 'traditional commute' across all time periods in comparison to the pre-lockdown period. That is, all else being equal, more income deprived areas were more likely to engage in 'traditional commute' behaviours during the course of the study period than in comparison to the pre-lockdown period. This provides further support to the finding in the wider literature that the biggest impact on mobility patterns was experienced by the least deprived and that it was the most deprived areas that continued to be more mobile during the pandemic. The same relationship holds in the periods following lockdowns. This effect is still apparent even during the period where there are no remaining restrictions from the pandemic in 2021 and in 2022, which perhaps reflects the greater level of more flexible, hybrid working in less deprived communities since the pandemic. This finding suggests that there may well be persistent inequalities in mobility patterns, despite overall patterns largely returning to their pre-pandemic levels (Rowe et al., 2023; González-Leonardo et al., 2022).

The results for the traditional commute also show significant associations between the prevalence of this mobility pattern and the lack of accessible services in an area for the majority of the study period, in comparison to the pre-lockdown period. This further highlights potential inequality persisting in more deprived areas, perhaps also pointing to an underlying cause as to why those areas are associated with higher levels of commuting during the pandemic. In this case, the final result for 2022 shows a non-significant relationship, suggesting a return to the pre-pandemic relationship. We also observe a number of significant associations for time effects, with lockdown reducing the overall prevalence of 'traditional commute' behaviours followed by a rise towards the latter part of the study period (although with larger standard errors for this period).

Fig. 7 shows the regression estimates for the 'short trips out of the home' cluster. The relationship between income and the prevalence of this cluster in this case is positive for the majority of the study period, which suggests that, all else being equal, this mobility pattern was more prevalent in less deprived areas during this time than in comparison to the pre-lockdown period. The short trips out of the home cluster is consistent with individuals basing themselves at home during the working day and potentially running short errands or exercising. We also observe a positive relationship between this cluster and the level of accessible services for the first half of the study period, suggesting that areas with greater provision of local services were more likely to make shorter trips out of the home in comparison to the pre-lockdown period.

For the 'stay at home' cluster (Fig. 8), the relationship with income is positive and significant for the majority of the study period, suggesting that those in less deprived areas were more likely to stay at home than in comparison to the pre-lockdown period. This is consistent with those in less deprived areas being more likely to be able to work from home, while those in more deprived areas were less impacted by changes to overall mobility patterns. We also see a positive relationship for the first half of the study period with accessible services, suggesting that areas with better access to local services were more likely to be associated

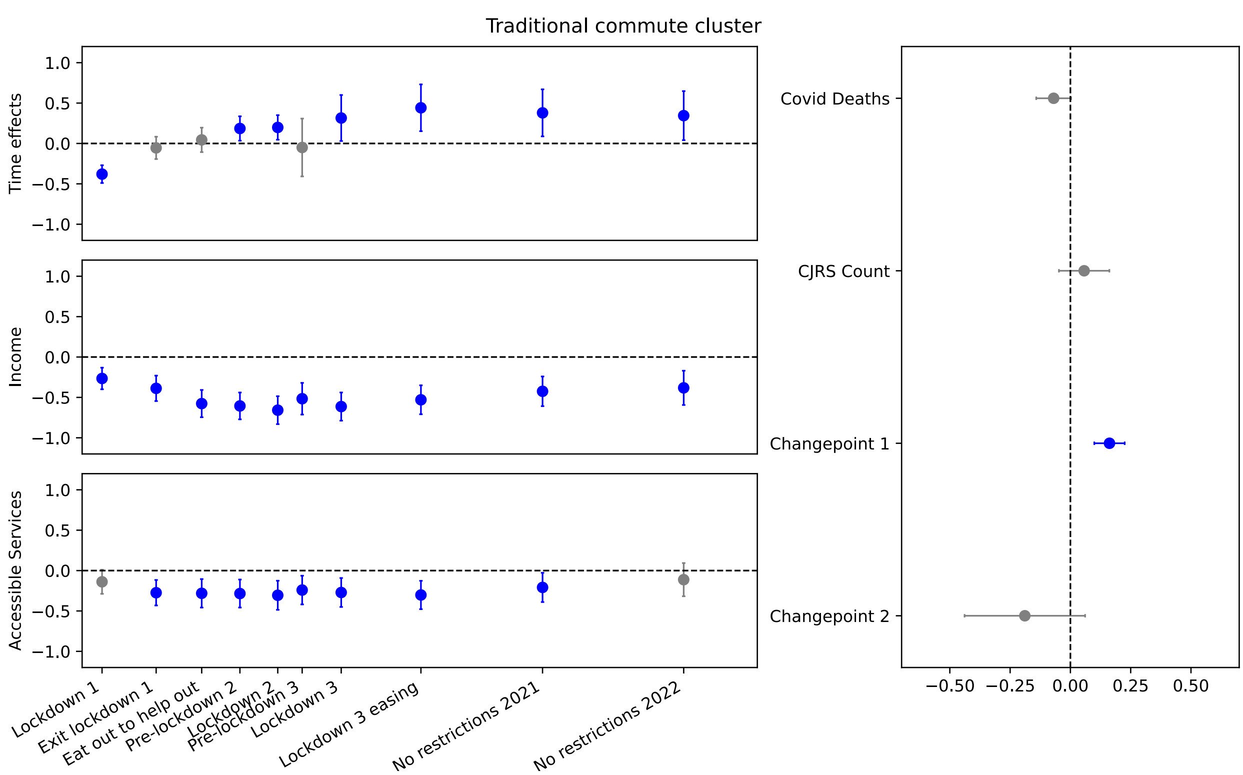


Fig. 6. Regression results for traditional commute cluster. Error bars represent a 95% confidence interval of the estimates. Points shown in blue are significant at $p < 0.05$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

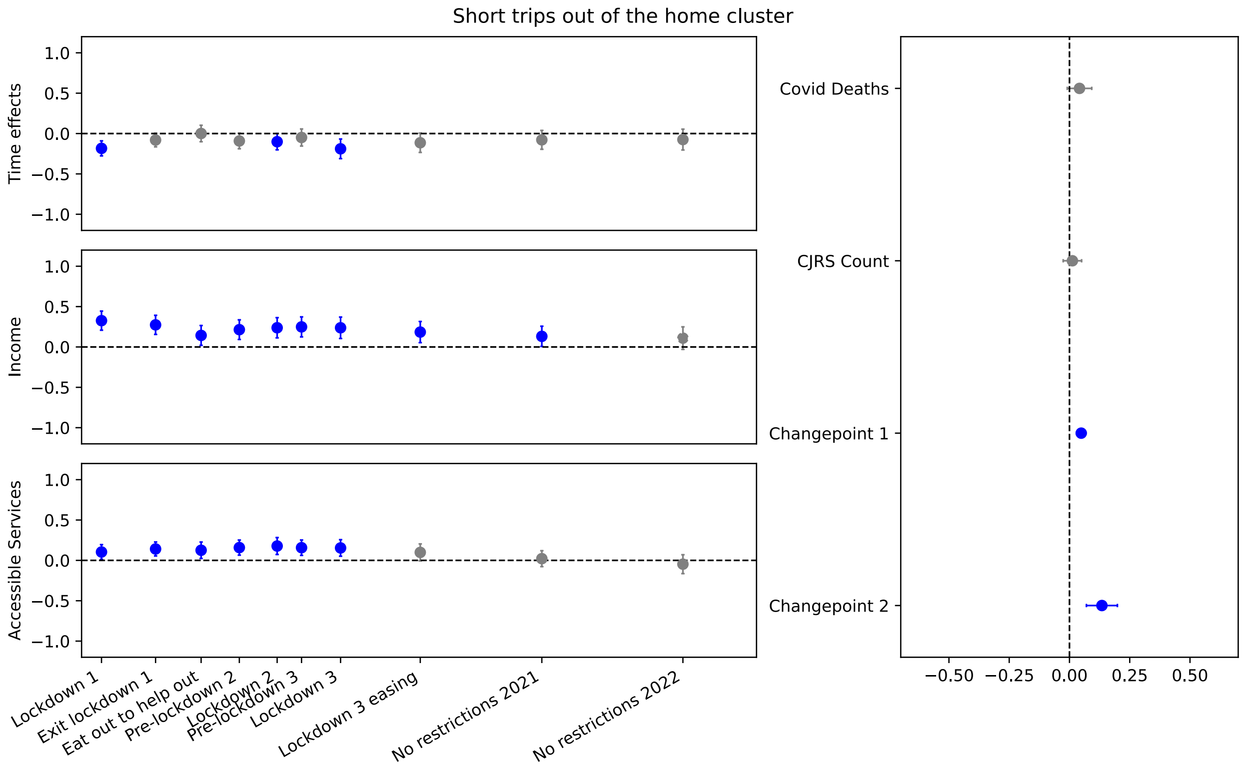


Fig. 7. Regression results for short trips out of the home cluster. Error bars represent a 95% confidence interval of the estimates. Points shown in blue are significant at $p < 0.05$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

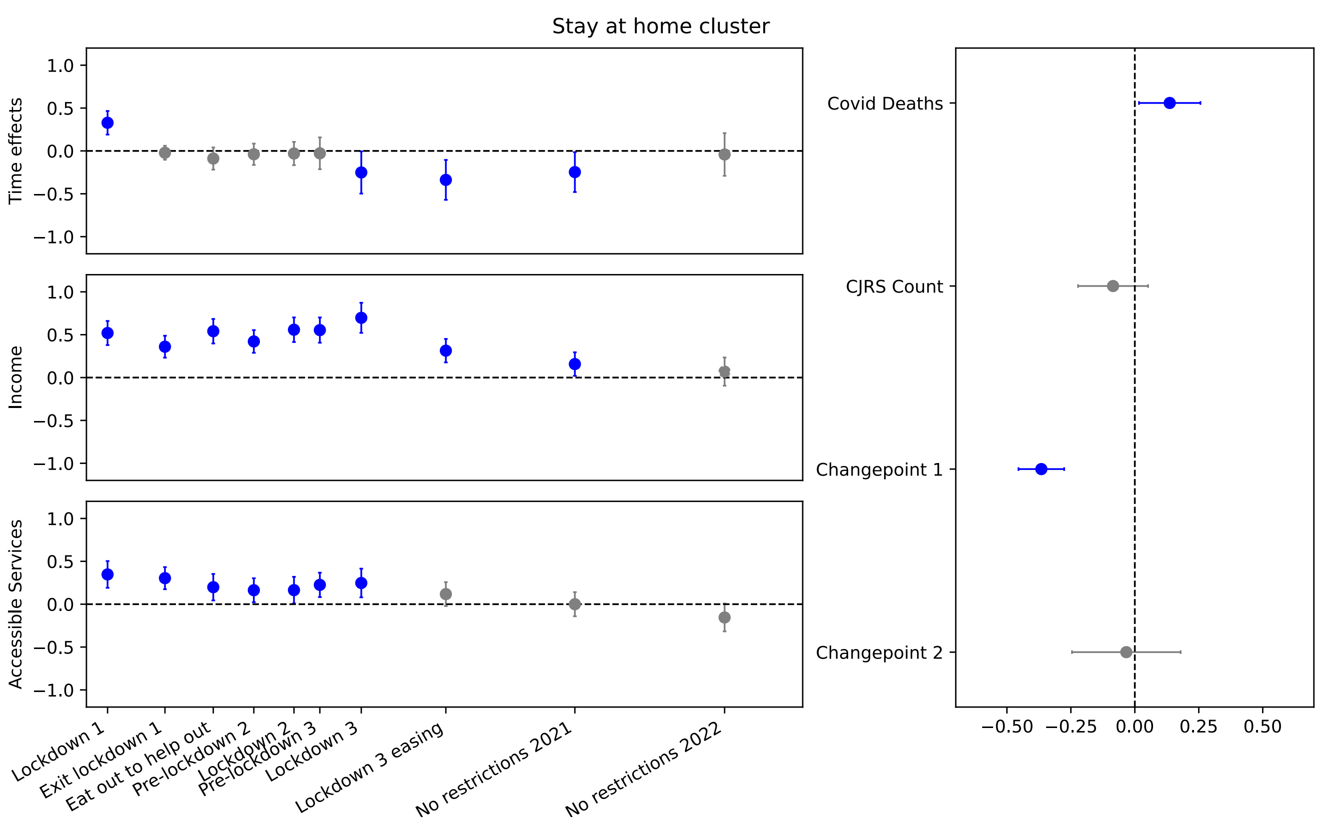


Fig. 8. Regression results for stay at home cluster. Error bars represent a 95% confidence interval of the estimates. Points shown in blue are significant at $p < 0.05$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

with staying at home. Although perhaps a counter-intuitive finding, this may be linked to a greater availability of home delivery services which saw significant uptake during the pandemic. It is interesting to note how the relationship with income and accessible services becomes weaker during the second half of the study period, suggesting that inequalities that might have been present during the pandemic are not as present following the lockdown and that mobility patterns may have reverted back to their pre-pandemic patterns. Finally, we find a significant association between the number of COVID deaths in an area and the prevalence of the stay at home cluster, which suggests that people were more likely to reduce their level of mobility during the worst periods of the pandemic.

Next we consider the highly mobile cluster, whose results are shown in Fig. 9. For this pattern, we find a varying relationship with time effects, although one which is largely in line with what might be expected from a highly mobile cluster type (i.e. negative associations during the height of the pandemic and a positive association towards the end of the study period). We also see a positive relationship with income towards the end of the study period, linking less deprived areas with greater prevalence of the highly mobile cluster as restrictions are lifted than in comparison to the pre-lockdown period. This again suggests some persistent inequality in mobility patterns. The prevalence of the highly mobile cluster was also negatively associated with the number of COVID deaths in an area, again supporting the idea that people reduced their mobility in line with the increasing local COVID death rate.

Our final cluster whose regression estimates are shown in Fig. 10 represents those individuals more likely to be at their furthest point from home during the evening. Time effects are negatively associated during lockdown 1 and positively associated with this cluster during the second half of the study period. We also observe a strong association between higher levels of income deprivation and the prevalence of the out in the evening cluster in comparison to the pre-lockdown period. During the most severe stages of the pandemic, this finding may be explained by an increased number of shift workers in these areas, but it is important to note that this pattern has persisted into 2022. A similar, but less strong pattern is also observed for accessible services. We also see a negative association between out in the evening patterns and the local COVID death rate.

5. Discussion

We have presented a novel analysis into the daily mobility patterns of individuals in England during the COVID-19 pandemic using mobile phone GPS data. By deriving our independent variable by hourly-level clustering of individual mobility profiles, we have identified a robust typology comprising of five distinct mobility behaviours and have demonstrated that the relative frequency of these behaviours evolves during the lockdown in line with expectations (e.g. a reduction in more mobile behaviours during times of lockdown). We have demonstrated some interesting geographic variations of these mobility behaviours. We have then explored the relationship with behaviour prevalence at the area level in England, identifying important relationships between mobility behaviours and social inequality over the duration of the pandemic. Our findings can be summarised as follows. First, at the height of the pandemic, the study confirms findings elsewhere that show more income deprived areas were more likely to continue having more mobile daily travel patterns, such as ‘traditional commuting’ and ‘out in the evening’. Our results also confirm the complementary association, that less deprived areas were more likely to ‘stay at home’ or to exhibit ‘short trips out the home’ behaviour, which is consistent with leaving the home for a short amount of time during the day, perhaps to exercise or visit local retail centres. At the height of the pandemic, we have also found significant results that highlight the importance of geographically accessible services and their associated effect on mobility patterns. Areas with worse access to services were more likely to be associated with ‘out in the evening’ and ‘traditional commute’ behaviours.

By separating our analysis into distinct time periods, our study contributes to an understanding of how mobility in England changes

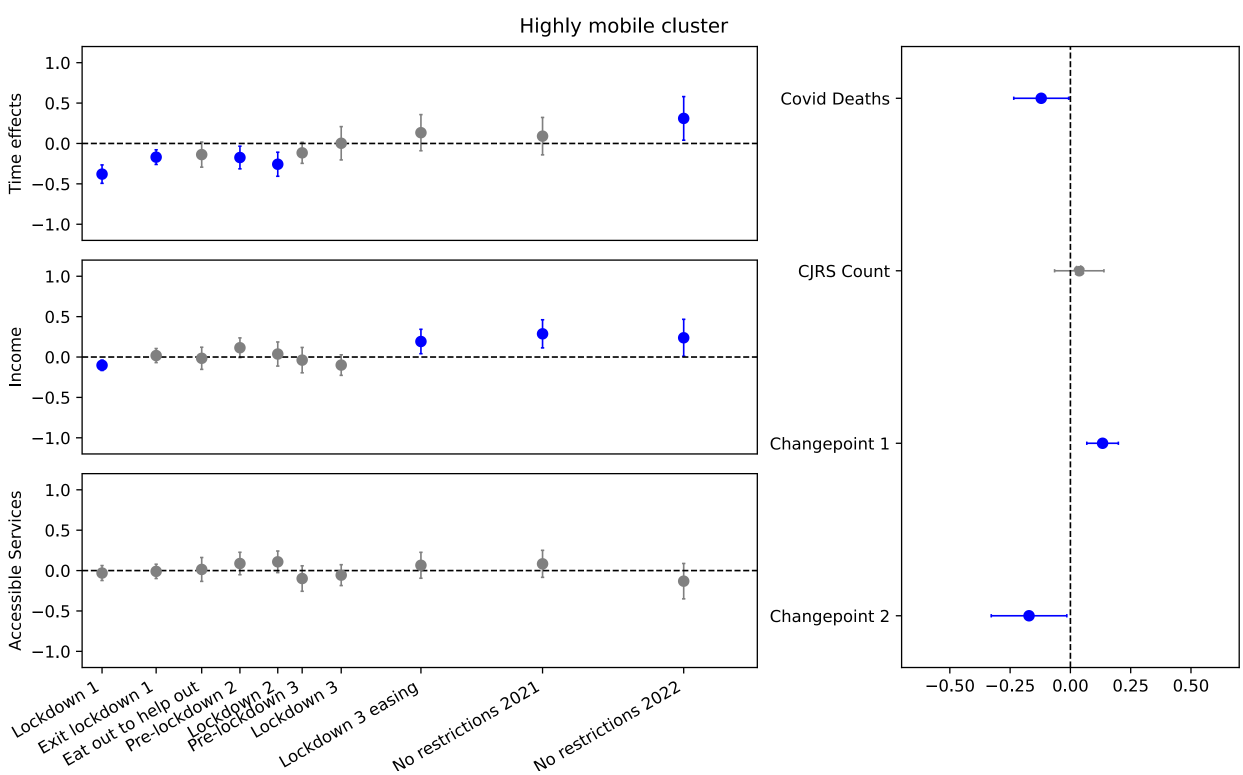


Fig. 9. Regression results for highly mobile cluster. Error bars represent a 95% confidence interval of the estimates. Points shown in blue are significant at $p < 0.05$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

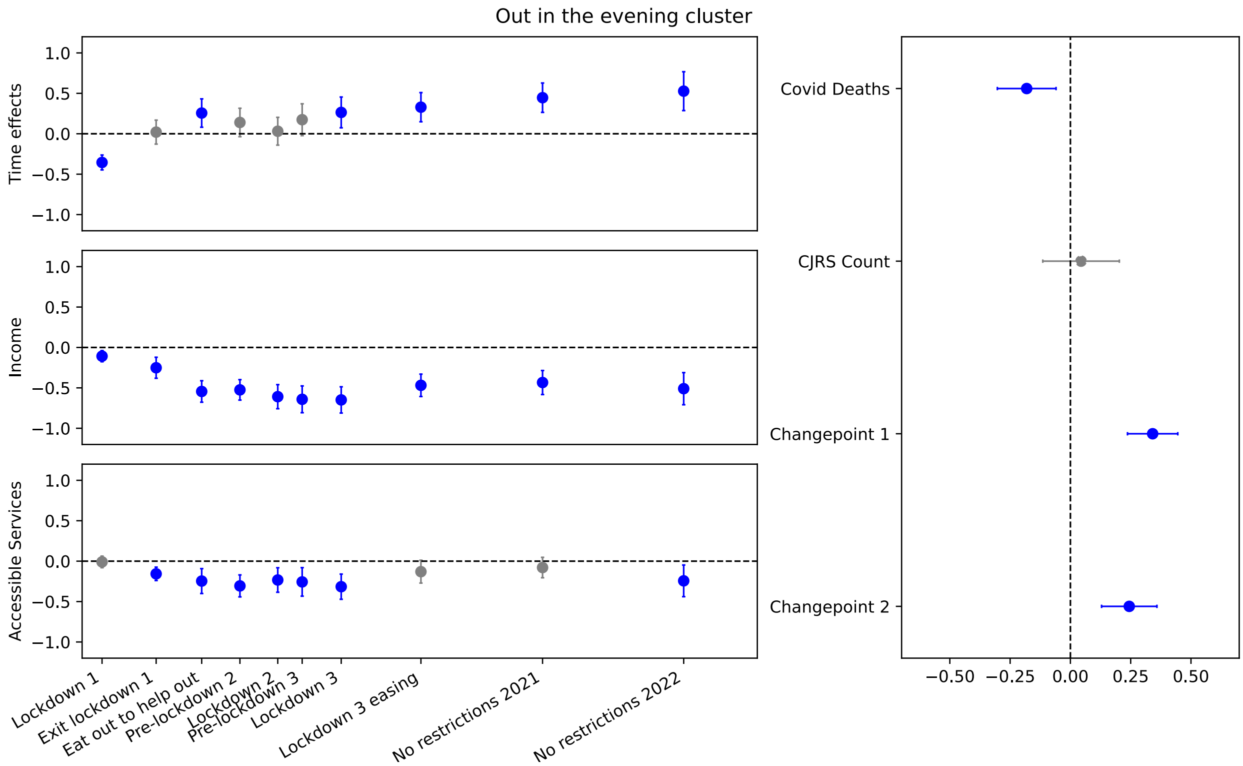


Fig. 10. Regression results for out in the evening cluster. Error bars represent a 95% confidence interval of the estimates. Points shown in blue are significant at $p < 0.05$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

when lockdowns are lifted. For example, despite overall levels of traditional commuting rising following the end of the first lockdown period, as shown in Fig. 4, the negative association between traditional commute patterns, and both income and geographic access to services in the periods following lockdown remained strong during these post-lockdown periods. This means that more deprived communities were more likely to participate in 'traditional commute' behaviours than in comparison to pre-pandemic behaviours. This pattern is also seen for 'out in the evening' clusters. This is consistent with wealthier communities having more opportunities to work from home. In relation to the 'stay at home' cluster, we even see some evidence that the association between this behaviour is more strongly associated with income in the periods following lockdowns, although confidence intervals for these periods do intersect. These findings support the conclusions of Lizana et al. (2023), which is that more deprived communities were the first to revert to commuting behaviours in comparison to less deprived areas.

A significant contribution of our study has been the ability to observe how the relationships between different types of mobility behaviour and social inequality have changed over time. Despite in some cases differences appearing to reduce over time, it is clear that persistent inequality in the types of mobility pattern observed still exist when compared to the pre-lockdown period. For instance, during 2022, areas with more income deprivation were still more likely to adopt 'traditional commute' patterns and 'out in the evening' patterns, while being less likely to adopt 'highly mobile' patterns than more affluent communities.

Our analysis offers a finer-grained approach to analysing mobility patterns at the area-level than previous work, enabling the identification of varying dynamics, effects and interactions across five distinct mobility clusters. Not only do these results provide insights into heterogeneity in behaviour during the pandemic policy restrictions, they point to where lasting effects might be found. Perhaps most significantly, the approach outlined here establishes significant differences in travel behaviour change across socioeconomic groupings and regions. This component of variation points to differing levels of resilience to this form of disruption - whereby some groups, dependent on income and services, are able to adapt more readily to major threats to personal health, with greater opportunity for self-protection. In the event of future public health crises, more readily available understanding of this heterogeneity can support policy guidance and interventions.

These conclusions, however, should be moderated by the known limitations associated with the data used in this study. In particular, the mobile phone GPS data used in our analysis is a biased sample of participants, for which no demographic data were available, limiting our ability to assess the representativeness of the sample. Previous work using the same data has shown that our sample is somewhat representative, at least in terms of population counts at the small level (Ross et al., 2021; Santana et al., 2023). However, we also identified two important change-points in our analysis concerning the overall number of individuals. There may have been causes for the significant reduction in sample size which correlated with the outputs in our model. We have mitigated the impact of this by explicitly modelling the change-points in our model. The robustness of our identified clusters over time also suggests that the impact of this is minimal. Finally, we also chose not to include an explicit representation of the workplace in our study, which may have further validated the traditional commute cluster pattern. Our logic here was guided by recent work suggesting that during the pandemic anchor points relating to the workplace become less prominent and individuals instead reoriented towards more local experiences and practices (Gatti and Procentese, 2021). Despite these limitations, our work demonstrates how time of day can be usefully integrated to characterize daily activity patterns via such 'consumer' data sources (Birkin, 2019) and that they can usefully complement existing traditional data sources for understanding mobility patterns.

Our approach presented here confirms significant associations between mobility patterns and behaviour over time, demonstrating the applicability of our derived dependent variable and validating our analytical approach. Our model specification in Eq. (7) is very similar to an interrupted time series model framework (e.g. such as employed in

Zhang and Ning (2023)) that seeks to estimate level changes in the time series of interest following a series of policy interventions and/or changes to the system of interest. Such studies have been used previously to estimate causal effects on a variable from an intervention. Since our primary research question is on how inequality mediated changes in mobility brought about by changes due to both policy and the pandemic itself, and for which the causal link is indirect, we have maintained an observational style to this study. However, we note that there is scope for future work that investigates more closely the causal links between pandemic interventions and mobility response. Despite this, our study is valuable in identifying important relationships and structural inequalities that have persisted over time in relation to people's travel behaviour.

From a policy perspective, our study highlights persistent structural inequalities that should be incorporated into the design of equitable transport systems. Moreover, our results show that more deprived areas have greater requirements for traditional commuting and being out in the evening than they did prior to the pandemic. Policies aimed at improving the outcomes of more deprived areas, such as the UK's ‘Levelling Up’ agenda, should also be cognisant of this persistent change deriving from the pandemic, whether that be in the allocation of additional services, economic support or greater protection of deprived communities in relation to future pandemic preparedness.

CRediT authorship contribution statement

Peter Baudains: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Arash Kalatian:** Writing – original draft, Validation, Methodology, Conceptualization. **Charisma F. Choudhury:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Ed Manley:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing.

Data availability

The authors do not have permission to share data.

Appendix A. Full regression results

Table A.4
Parameter estimates (and standard errors) for fixed effects model for relative proportion of each cluster type. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

	Highly mobile	Stay home	Trad. Com.	Short trips	Evening
COVID deaths	−0.1211*	0.1364*	−0.0695	0.0416	−0.1813**
	(0.0581)	(0.0612)	(0.0369)	(0.0259)	(0.0621)
CJRS Count	0.0367	−0.0851	0.0570	0.0121	0.0442
	(0.0522)	(0.0698)	(0.0534)	(0.0195)	(0.0810)
Changepoint 1	0.1334***	−0.3655***	0.1621***	0.0487***	0.3411***
	(0.0334)	(0.0456)	(0.0321)	(0.0099)	(0.0532)
Changepoint 2	−0.1716*	−0.0332	−0.1890	0.1346***	0.2440***
	(0.0800)	(0.1084)	(0.1275)	(0.0328)	(0.0586)
t_1: Lockdown 1	−0.3795***	0.3283***	−0.3796***	−0.1836***	−0.3552***
	(0.0581)	(0.0701)	(0.0561)	(0.0474)	(0.0469)
t_2: Exit lockdown 1	−0.1691***	−0.0213	−0.0547	−0.0803	0.0203
	(0.0462)	(0.0415)	(0.0706)	(0.0431)	(0.0756)
t_3: Eat out to help out	−0.1378	−0.0889	0.0443	0.0006	0.2562*
	(0.0823)	(0.0660)	(0.0772)	(0.0519)	(0.0894)
t_4: Pre-lockdown 2	−0.1739*	−0.0391	0.1852*	−0.0920	0.1399
	(0.0716)	(0.0635)	(0.0769)	(0.0493)	(0.0896)
t_5: Lockdown 2	−0.2572***	−0.0303	0.1985*	−0.1012*	0.0312
	(0.0759)	(0.0692)	(0.0776)	(0.0514)	(0.0876)
t_6: Pre-lockdown 3	−0.1160	−0.0279	−0.0500	−0.0491	0.1739
	(0.0663)	(0.0947)	(0.1827)	(0.0539)	(0.1003)
t_7: Lockdown 3	0.0024	−0.2512*	0.3150*	−0.1891**	0.2641**
	(0.1052)	(0.1257)	(0.1453)	(0.0619)	(0.0970)
t_8: Lockdown 3 easing	0.1334	−0.3380**	0.4416**	−0.1140	0.3288***
	(0.1142)	(0.1187)	(0.1478)	(0.0611)	(0.0920)
t_9: No restrictions 2021	0.0906	−0.2467*	0.3788*	−0.0781	0.4462***
	(0.1182)	(0.1188)	(0.1485)	(0.0596)	(0.0926)
t_{10}: No restrictions 2022	0.3103*	−0.0414	0.3446*	−0.0747	0.5271***
	(0.1376)	(0.1271)	(0.1549)	(0.0658)	(0.1226)
Income t_1	−0.1021**	0.5195***	−0.2656***	0.3260***	−0.1078**
	(0.0330)	(0.0717)	(0.0683)	(0.0603)	(0.0351)
Income t_2	0.0182	0.3600***	−0.3878***	0.2738***	−0.2513***
	(0.0444)	(0.0652)	(0.0804)	(0.0603)	(0.0662)
Income t_3	−0.0157	0.5407***	−0.5765***	0.1429*	−0.5445***
	(0.0699)	(0.0729)	(0.0861)	(0.0627)	(0.0678)
Income t_4	0.1150	0.4211***	−0.6055***	0.2144***	−0.5248***
	(0.0622)	(0.0675)	(0.0847)	(0.0619)	(0.0646)
Income t_5	0.0372	0.5579***	−0.6480***	0.2380***	−0.6089***
	(0.0761)	(0.0732)	(0.0881)	(0.0638)	(0.0760)
Income t_6	−0.0384	0.5537***	−0.5163***	0.2487***	−0.6416***
	(0.0801)	(0.0751)	(0.1000)	(0.0632)	(0.0845)
Income t_7	−0.0997	0.6970***	−0.6134***	0.2375***	−0.6491***
	(0.0648)	(0.0895)	(0.0889)	(0.0677)	(0.0828)
Income t_8	0.1921*	0.3139***	−0.5294***	0.1845**	−0.4686***

(continued on next page)

Table A.4 (*continued*)

	Highly mobile	Stay home	Trad. Com.	Short trips	Evening
	(0.0772)	(0.0698)	(0.0914)	(0.0668)	(0.0706)
Income t_9	0.2871**	0.1573*	−0.4246***	0.1314*	−0.4339***
	(0.0888)	(0.0701)	(0.0937)	(0.0640)	(0.0758)
Income t_{10}	0.2382*	0.0697	−0.3817***	0.1095	−0.5100***
	(0.1167)	(0.0840)	(0.1082)	(0.0712)	(0.1014)
Accessible services t_1	−0.0303	0.3472***	−0.1388	0.1039*	−0.0094
	(0.0472)	(0.0796)	(0.0761)	(0.0464)	(0.0364)
Accessible services t_2	−0.0098	0.3037***	−0.2741***	0.1413**	−0.1569***
	(0.0451)	(0.0657)	(0.0805)	(0.0441)	(0.0421)
Accessible services t_3	0.0142	0.1985*	−0.2814**	0.1253*	−0.2464**
	(0.0754)	(0.0787)	(0.0899)	(0.0519)	(0.0785)
Accessible services t_4	0.0876	0.1631*	−0.2843**	0.1584***	−0.3062***
	(0.0709)	(0.0713)	(0.0884)	(0.0476)	(0.0693)
Accessible services t_5	0.1085	0.1640*	−0.3057***	0.1778***	−0.2332**
	(0.0681)	(0.0792)	(0.0920)	(0.0535)	(0.0773)
Accessible services t_6	−0.0984	0.2254**	−0.2412**	0.1572**	−0.2568**
	(0.0804)	(0.0725)	(0.0907)	(0.0485)	(0.0899)
Accessible services t_7	−0.0563	0.2473**	−0.2712**	0.1541**	−0.3159***
	(0.0659)	(0.0853)	(0.0914)	(0.0522)	(0.0795)
Accessible services t_8	0.0658	0.1178	−0.3021***	0.0990	−0.1301
	(0.0819)	(0.0712)	(0.0896)	(0.0536)	(0.0719)
Accessible services t_9	0.0836	−0.0001	−0.2084*	0.0213	−0.0792
	(0.0853)	(0.0719)	(0.0924)	(0.0502)	(0.0644)
Accessible services t_{10}	−0.1310	−0.1551	−0.1124	−0.0470	−0.2436*
	(0.1118)	(0.0826)	(0.1049)	(0.0596)	(0.1000)

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