Trajectories of mobility during England's first national COVID-19 lockdown0F[[1]](#footnote-2)

# Authors

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# Highlights

* People's mobility changed substantially in response to COVID-19 pandemic
* V-shaped trend in mobility shows sharp decline but gradual return over time
* The trajectories of mobility were different across local authorities in England at different stages of the lockdown.
* Further evidence of flexible responses to COVID-19 is provided by differences in mobility resilience

# Abstracts

The UK government imposed a lockdown across England in the spring of 2020 to reduce community transmission of COVID-19 and avoid health services becoming overwhelmed. The measures led to large reductions in everyday mobility, but not everywhere to the same extent. Using call detail records from more than 1.1m mobile phones, we explored spatial differences between local authorities in how people’s mobility changed during the first national lockdown in the initial phases. Four groups of local authorities are identified, which differ in trajectories of mobility, and their membership was mainly associated with their income level, self-employed workers, and car availability, although ethnic/racial make-up of the population and health-related neighbourhood features, estimated by the classification model. The analysis shows that the greatest reduction in mobility after the imposition of the lockdown, and the continuation of low levels of mobility afterwards occurred in high-income areas with comparatively high levels of self-employed workers and cumulative COVID-19 infection rates before stay-at-home orders. It thus indicates that the greatest reductions have been achieved in areas where it is relatively easy for people to stay at home or in areas the risk of infection and severe illness was relatively high. More generally, the results highlighted the need to consider differences in mobility resilience towards sustainable and resilient urban management is explicitly linked to the ability to restrict everyday mobility among people.

**Keywords**: COVID-19; Pandemic; Resilience; Time-series clustering; Classification model.

# Introduction

The COVID-19 pandemic has rapidly changed our everyday lives, particularly mobility. Implementing various social distancing policies, such as travel restrictions and compliance with stay-at-home orders, were correlated with the reduction in mobility (Hale et al., 2021; Kishore et al., 2021). Working from home has become the *new normal* to avoid social contact, and mitigate the risk while using public transport for work-related travel and on-site working (Beck & Hensher, 2020). Inevitably, transport mode use has been strongly affected by the risk of travellers being exposed to the virus during their journey (Barbieri et al., 2021; de Séjournet et al., 2022; De Vos, 2020). Transit attractiveness is down, and massive service cuts on public transport systems while uptake in private vehicle use and active travel, i.e., walking and cycling (Department for Transport, 2020; Vickerman, 2021). In short, the risk of COVID-19 and travel-related measures have rapidly reshaped our *mobility habits* (Cartenì et al., 2020). Although the magnitude of this change varies across and within cities and social groups.

In England, the UK government recognised the importance of rapid control and implemented countermeasures to tackle the outbreak since COVID-19 reached in late January 2020 (Scally et al., 2020). However, the nationwide lockdown was imposed as an emergency measure on 23 March 2020 to mitigate the transmission, and the new, more transmissible variant of COVID-19 continues to spread. As a result, people’s everyday mobility has to face new challenges and massive adaptions to COVID-19 (Borkowski et al., 2021; Lee et al., 2021; Marsden & Docherty, 2021), it ranged from travel restrictions to social distancing orders, curfews, quarantines, and finally, lockdown measures come into force to diminish the physical interactions and order people to “Stay-at-home”.

Greater attention should be paid to analysing changes in people’s mobility throughout the first COVID-19 lockdown, and a more detailed understanding of how mobility changes spatio-temporally is needed during the prolonged period of strict lockdown. Recent work has highlighted this by using examining changes in mobility over seven months or more (J. Kim & Kwan, 2021; Long & Ren, 2022; Molloy et al., 2021) and decomposing it into successive stages, i.e., *intra-pandemic dynamics* (Kellermann et al., 2022) through longitudinal perspective. Taking short-term effects by implemented travel restrictions or interventions and long-term effects under mobility circumstances, such as working from home or homeschooling, the way of *new normal* in mobility into account.

To this end, this research quantify and measure changes in mobility under the lockdown phases of COVID-19 pandemic, by using anonymised call-detail records (CDRs) data collected from mobile phones. By doing this, this research investigates the long-term effects of government-mandated lockdown on people’s mobility spanning seven months, by measuring changes in mobility over time and quantified how it evolved. This task is achieved by deploying data mining techniques to reveal different socioeconomic status likely to be correlated with different trajectories of mobility under England’s first nationwide lockdown. Specifically, the research addresses the following questions:

* How has mobility changed over the initial phases of the lockdown?
* What makes disparities in mobility recovery trends in lockdown phases?
* Does socioeconomic status associated with trajectories of mobility reduction throughout the lockdown?

# Related works

COVID-19 is transmitted between people in three main ways; contacts, droplets, and airborne transmission. A major transmission route is large infected droplets in line with the most respiratory virus (The Lancet Respiratory Medicine, 2020). The risk of droplet transmission by physical contact among people outlines scientific evidence suggesting social distancing guidelines to prevent the spread of COVID-19 (Rosti et al., 2020). Therefore, monitoring changes in mobility has become valuable in assessing the effectiveness of government-imposed social distancing policies (Oliver et al., 2020).

Academic literature on transport and COVID-19 has burgeoned since the Spring of 2020. Many papers have examined V-shaped mobility trends in the early stage of COVID-19 pandemic to reveal substantial changes in people’s mobility and travel behaviours with the support of large-scale mobile phone data and online panel surveys. There is abundant evidence that overall levels of people’s mobility dropped instantly but recovered rapidly based on longitudinal data analysis following longer than a year following the onset of the COVID-19 pandemic (Kellermann et al., 2022; J. Kim & Kwan, 2021; Long & Ren, 2022; Wang et al., 2022) by using traditional mobility metrics, such as daily distanced travelled per person (Hong et al., 2021; Lou et al., 2020; Pan et al., 2020; Weill et al., 2020; Xiong, Hu, Yang, Younes, et al., 2020), time spent travelling per person per day (Borkowski et al., 2021), and a total number of trips per day (Lou et al., 2020; Pan et al., 2020; Xiong, Hu, Yang, Younes, et al., 2020; Zhang et al., 2021).

There is now a substantial number of studies demonstrating the effects of government-mandated lockdowns on mobility. For instance, the share of stay-at-home depicts the percentage of people staying entirely at home and avoid leaving their house all day (Fu & Zhai, 2021; Hu et al., 2021; Jay et al., 2020; Pan et al., 2020; Weill et al., 2020) is robust evidence to assess the effectiveness of government interventions in people’s everyday lives. Traffic flows reconstructed from mobile phone data measured changes in population movements between city pairs (Beria & Lunkar, 2021; Schlosser et al., 2020; Xiong, Hu, Yang, Luo, et al., 2020). Also, the radius of gyration is popularly used to measure the radial distance moved within a certain time period, such as a day (Gauvin et al., 2020; Hernando et al., 2020; Lee et al., 2021; Park et al., 2021; Pepe et al., 2020; Santana et al., 2020; Yabe et al., 2020).As the study shows, using mobile data to generate mobility metrics was very helpful in evaluating the impact of containment and closure policies, in the form of various travel disruptions and restrictions. Interestingly, people’s mobility levels dropped sharply and then gradually bounced back to normal throughout the COVID-19 pandemic (J. Kim & Kwan, 2021; Lee et al., 2021). Recent studies also revealed how mobility changed in the different pandemic stages, and exhibited some notable differences in lockdown phases. *Voluntary social distancing* (Linka et al., 2020; Xiong, Hu, Yang, Younes, et al., 2020) was observed between pre-pandemic and implemented stay-at-home orders. It suggests that people would practice voluntary social distancing depending on their ability to self-regulate capacity (Cronin & Evans, 2020). Also, increased mobility observed that people went outside more during the coming months after the lockdown, entitled to *Quarantine fatigue* (J. Kim & Kwan, 2021; Kwan, 2021; Pan et al., 2020; Zhao et al., 2020).

However, limited attention has been given to a consideration of how mobility changed over time and its variation in different phases alongside the shift in government response. People’s mobility has been influenced by the prevalence of government measures, and individually perceived risk and ability to restrict everyday mobility together, all of which are time-varying. To further elucidate this issue, we examined changes in mobility throughout government-mandated lockdowns added on pre-pandemic and post-lockdown periods (i.e., ±2 months) in this study.

# Data and methods

## Data

Measuring mobility fluctuation is a key indicator to assessing compliance with government-mandated lockdowns. This research deploys anonymised and aggregated GDPR-compliant CDRs[[4]](#footnote-5) for more than one million users spanning seven months to compute the daily median radius of gyration for users in each LTLA area (*n*=317) in England[[5]](#footnote-6). The radius of gyration is widely used to capture mobility patterns through density metrics using the combined timestamp of CDRs (described above). We have estimated the daily median mobility levels of 315 LTLA areas in England to use it as a comparison throughout our analysis. It can provide useful insights into people’s mobility were influenced by implemented travel and physical distancing interventions (Grantz et al., 2020; J. Kim & Kwan, 2021; Kishore et al., 2020). In these terms, it measures the spatial extent of activity space (Lu et al., 2021) through summation of the distance from all points of user travels among the time-stamped () locations on day from the trajectory’s mean location can be formulated as on that day. Locations are approximated by the nearest mobile phone tower, and mobility will be underreported if individuals do not take their phone along. User-level values are aggregated to the LTLA areas in which individuals reside.[[6]](#footnote-7) Formally, the radius of gyration can be expressed as:

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| --- | --- |
|  | (1). |

This mobility metric was aggregated to present the generalised mobility level of each LTLA level in England. We explored trajectories of mobility reduction over time by calculating the (percentage) change in mobility levels compared to a reference day. To do this, we replicate the approach taken by Lee et al. (2021). It suggests a single-day reference, Tuesday 3 March. This approach has been validated by conducting the sensitivity analysis with an alternative reference period.

Previous literature highlighted it was highly correlated with socioeconomic status (Huang et al., 2021; Lee et al., 2021), particularly ethnicity compositions and age groups (Harris, 2020; Hong et al., 2021), which have been explicitly linked to the reduction in mobility. This study uses various socioeconomic characteristics, including the ethnic composition of the LTLA areas. Data were retrieved from the 2011 Census and other sources provided by the Office for National Statistics (ONS). We have aggregated data from the Lower Layer Super Output Area (LSOA) level to the LTLA area. The full list of variables used in the models is given in Table 2. Also, COVID-19 infection and mortality rates in a given spatial unit were included to consider the variation in everyday mobility affected by the perceived risk of COVID-19 before government-mandated lockdowns. COVID-19 activity metrics were retrieved from the UK official COVID-19 dashboard open data API service (UK government, 2020) and processed.

## Methods

### Time-series clustering analysis

A clustering analysis technique was used to find the commonalities, i.e., identifying prominent clusters based on similar trajectories of mobility reduction during the lockdown (i.e., from 23 March to 11 May 2020). Dynamic time warping (DTW) algorithm was chosen to compute an optimal (warping) distance between time-series (Berndt & Clifford, 1994) that minimise the alignment elements by iteratively stepping through the local cost matrix (Sardá-Espinosa, 2019). It is widely used for shape-based clustering to collect similar shapes of time series (Aghabozorgi et al., 2015). Because of the robustness (Chen et al., 2017; Petitjean et al., 2011) compared to other conventional measures. Given two time-series, and , DTW distance can be mathematically formulated as follows.

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|  | (2). |

The sequence of and can be arranged to form a -by- grid, where is a distance function, to represent the magnitude of the difference between the sequence elements () to (). denotes a sequence of grid points (1 to ), is a warping function to find the path through the grid. A warping path aligns the elements of two sequences when the distance between them is minimised.

Hierarchical clustering methods were deployed to test different agglomerative hierarchical clustering algorithms with a DTW distance (Dau et al., 2016; Sardá-Espinosa, 2019). In order to group LTLA areas into clusters based on their similarity. We used the standardise cluster evaluation metric to determine the appropriate number of clusters, i.e., cluster validity indices (CVIs), using *dtwclust* package for R. We tested the different clusters, where *K=* [2, 20) and evaluated it by using a Silhouette index (*Sil*). Arbelaitz (2013) notes that Sil is the best-performing CVIs for the validation of clustering. It depicts how close each object is in one cluster (i.e. intra-cluster) by contrast to the nearest cluster (i.e. inter-cluster) while ranges from -1 to +1. The high value denotes the overall clustering quality as the separation distance between the resulting clusters (Rousseeuw, 1987). By definition, *Sil* calculates the average intra-cluster distance , and the average nearest-cluster distance . When each object , in terms of any given LTLA area, belongs to cluster , can be expressed as follows.

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|  | (3). |

Where is the average distance between to other LTLA areas in the same cluster , is the smallest average distance from to other LTLA area(s) in the nearest cluster. For to be close to 1, it requires that is a measure of how dissimilar is belonging to cluster Thus, a small value of which means clustering analysis performed well.

### Classification model

A penalised regression model is similar to linear regression but has an additional penalty term to constrain (or regularise) the estimated coefficients. It can reduce the variance and decrease sample error to help generalise models (Boehmke & Greenwell, 2019). The LASSO (Least Absolute Shrinkage and Selection Operator) regression is a penalised regression model proposed by Tibshirani (1996). It minimises the residual sum of squared errors (RSS) while constraining the sum of the absolute values of the regression coefficients (Usai et al., 2009). In the mathematical form, the penalised likelihood function is given by

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| --- | --- |
|  | (4). |

Here is a constraint as a tuning parameter (, is the number of predictors, and is the penalty parameter that controls the amount of regularisation (i.e., the size of the coefficients). Setting to 1 allows the purely penalising the sum of the absolute values of the regression of coefficients , i.e., the 1 norm of coefficients. LASSO regression uses 1 regularisation technique can result in sparse models with the coefficient of the unimportant features towards zero, and get eliminated in the model (Friedman et al., 2010).

The multinomial logistic regression model (MLR) utilises the logit link function to model the logarithm of the odds ratio for multi-category response variables (Krishnapuram et al., 2005). Let has multi categories to denote number of clusters with a predictor vector, the linear logistic regression model can be generalised to a multi-logit model (Friedman et al., 2010). The probability for each cluster to generalise the linear logistic regression into logits as Equation (5), and modifying term as Equation (6).

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| . | (5). |
|  | (6). |

Here is a vector of coefficients, is a constant, and is the predictors corresponding to cluster , and denotes vector/matrix transpose. Friedman et al. (2010) suggest fitting the model by regularised maximum (multinomial) likelihood. Denote be the indicator response matrix, with elements . The log-likelihood part of is given by

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|  | (7). |

Krishnapuram et al. (2005) applied the 1 norm into the log-likelihood function by replacing the residual sum of squares with the corresponding negative log-likelihood function . For the multinomial LASSO logistic regression model (hereafter MLR LASSO), Hossain et al. (2014) summarised the penalised likelihood function can be expressed as Equation (8):

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| --- | --- |
|  | (8). |

Finally, the MLR LASSO can shrink and delete the coefficients (Hossain et al., 2014). Another advantage of this approach is ranking model predictors based on the absolute value of the coefficients, using an embedded feature selection process (K. Kim, 2018). It confirms the difference in predictor importance between distinct clusters of time-series data. The MLR LASSO is constructed to exhibit the significant factors between clusters using *glmnet* package for R (Friedman et al., 2010).

# Results

## Mobility in pandemic times across England

People’s mobility has been inherently affected by the government’s emergency response in the absence of a vaccine or efficient antiviral medication in the early stage of the pandemic (Haug et al., 2020). Mobility in pandemic times across England, i.e., the average daily median radius of gyration, has declined substantially (see Figure 1). In early March 2020, the average level of mobility dropped significantly by about 50% before the pandemic (see Figure 3). This finding corresponds with Lee et al. (2021) and is also broadly comparable with other studies (XXX)

Further mobility reductions were indicated when England entered the first nationwide lockdown. The UK government encouraged people to start working from home, and banned the mass gatherings and all unnecessary social contact (Public Health England, 2020) since the mid of March. Whilst the lockdown has imposed in England on 23 March 2020, mobility levels in England have been suppressed more, represented by less than 1km radial distance per day. However, mobility levels gradually return to normal, changing as restrictions ease. In other words, lockdown lifting has changed people’s mobility.

It confirms that mobile phone data will help assess the effectiveness of implemented policies in monitoring mobility (Oliver et al., 2020). At the same time, it also shows the effects of the pandemic on mobility, not without limitations. No study has yet to uncover trajectories of mobility that would strongly depend on socioeconomic characteristics, which varied markedly across space.



Figure . Changes in (the average levels of) mobility across England in 2020

Note: Using the daily median radius of gyration (km), the trend in mobility over time was estimated by using the local polynomial regression function (with span *s*=0.2), and dotted lines highlighted the important days; black – baseline (3 March 2020), and red – 2020 Spring lockdown period in England.

## Trajectories of mobility in lockdown phases

Quantifying similar trajectories of mobility under the lockdown has been identified by employing time-series clustering analysis. 315 LTLA levels in England were grouped into *K* clusters benchmarked using eight agglomerative hierarchical clustering algorithms[[7]](#footnote-8). The optimal number of clusters has been selected through the levels of performance, i.e., *Sil*. Figure 2 shows variations in the *Sil* against the number of clusters. *Sil* dropped when *K* increases (except *K*=6 and 9), in other words, the decrease of average inter-cluster similarity. Finally, the above-described cluster analysis generated four prominent clusters based on their similarities.



Figure . Variations in the *Silhouette index* against the number of Clusters (*K*= 2 to 20).

In overview, Figure 3 depicts identified clusters (*K*=4) based on trajectories of mobility in lockdown phase. It was reflected in the timestamps of generated clusters in Figure 4. More importantly, Table 1 presents the characteristics of change in mobility during lockdown between clusters. We computed the median value of mobility levels for each cluster to avoid the bias in each tail of the distribution and disguise intra-cluster variations more accurately on a given day. By examining the relative magnitude of mobility levels throughout the lockdown to describe the heterogeneous nature between clusters.

Two observations can be made in these figures and table. First, G1 have shown the largest reduction on 29 March, in terms of day 7 of lockdown, 88.5% mobility reduction compared to normal levels before the pandemic. In contrast, G4 observed the lowest 67.3% mobility reduction on the same day. There was an accelerated mobility decline in G4 (31.1%) relative to G1 (21.4%) during the lockdown by calculating the maximum mobility reduction during the lockdown compared to the mobility level on the first day of the lockdown . To date, lockdown measures were effectively diminished people’s mobility levels for G4 relative to G1. Second, G4 has shown the highest people’s mobility bounce back during the lockdown at 40.6%, compared to the lowest mobility recovery at 15.3% in G1.

The first observation confirms our hypothesis on group heterogeneity in trajectories of mobility change between clusters. Figure 5 illustrates the spatial cluster distributions when *K* is 4. G1 (45 LTLAs) consists of relatively wealthy and diverse local authorities mainly distributed over Inner London. In contrast, G4 (69 LTLAs) is relatively deprived local authorities located in North West and Yorkshire and The Humber. In general, G2 (96 LTLAs) and G3 (105 LTLAs) represent the majority of the clusters. G3 resembles G4, with abundant clinical capacity (hospitals) and allowed premises (parks) in North West and East Midlands. While G2 is more homogenous to G1, fairly affluent local authorities in Outer London and Southern England. Descriptive statistics showed that local socioeconomic characteristics differed between clusters (see Table 2).

The second observation also revealed differences in the recovery of mobility levels during the lockdown between clusters. Lockdown measures had worked effectively for at least a week according to the minimum level of mobility indicated on seven-day of the lockdown (i.e., 29 March). However, its effectiveness had declined over time, and was observed to lessen the reduction in mobility over the course of the lockdown in Figure 3 and Figure 4. Also, we revealed that the lowest mobility reduction before the lockdown and the continuation of high levels of mobility recovery throughout the lockdown occurred in low-income areas in disadvantaged local authorities in Northern England. In contrast, a greater mobility reduction and marginal bounce back over time were indicated in high-income areas with excellent health-related accessibility and a relatively high proportion of self-employed, particularly in Inner London.

Table . Characteristics of change in mobility during lockdown by clusters.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Characteristics | G1  (45 LTLAs) | G2  (96 LTLAs) | G3  (105 LTLAs) | G4  (69 LTLAs) | National level  (315 LTLAs) |
| Mobility level on the first day of lockdown | -67.1% | -57.7% | -44.2% | -36.2% | -47.7% |
| Minimum level of mobility | -88.5% | -82.6% | -75.4% | -67.3% | -78.4% |
| Maximum reduction | 21.4% | 24.9% | 31.2% | 31.1% | 30.7% |
| Mobility level on the last day of lockdown | -75.0% | -64.7% | -51.8% | -40.0% | -57.1% |
| Mobility recovery | 15.3% | 21.7% | 31.3% | 40.6% | 27.2% |
| Net reduction in mobility | 11.8% | 12.2% | 17.2% | 10.4% | 19.6% |

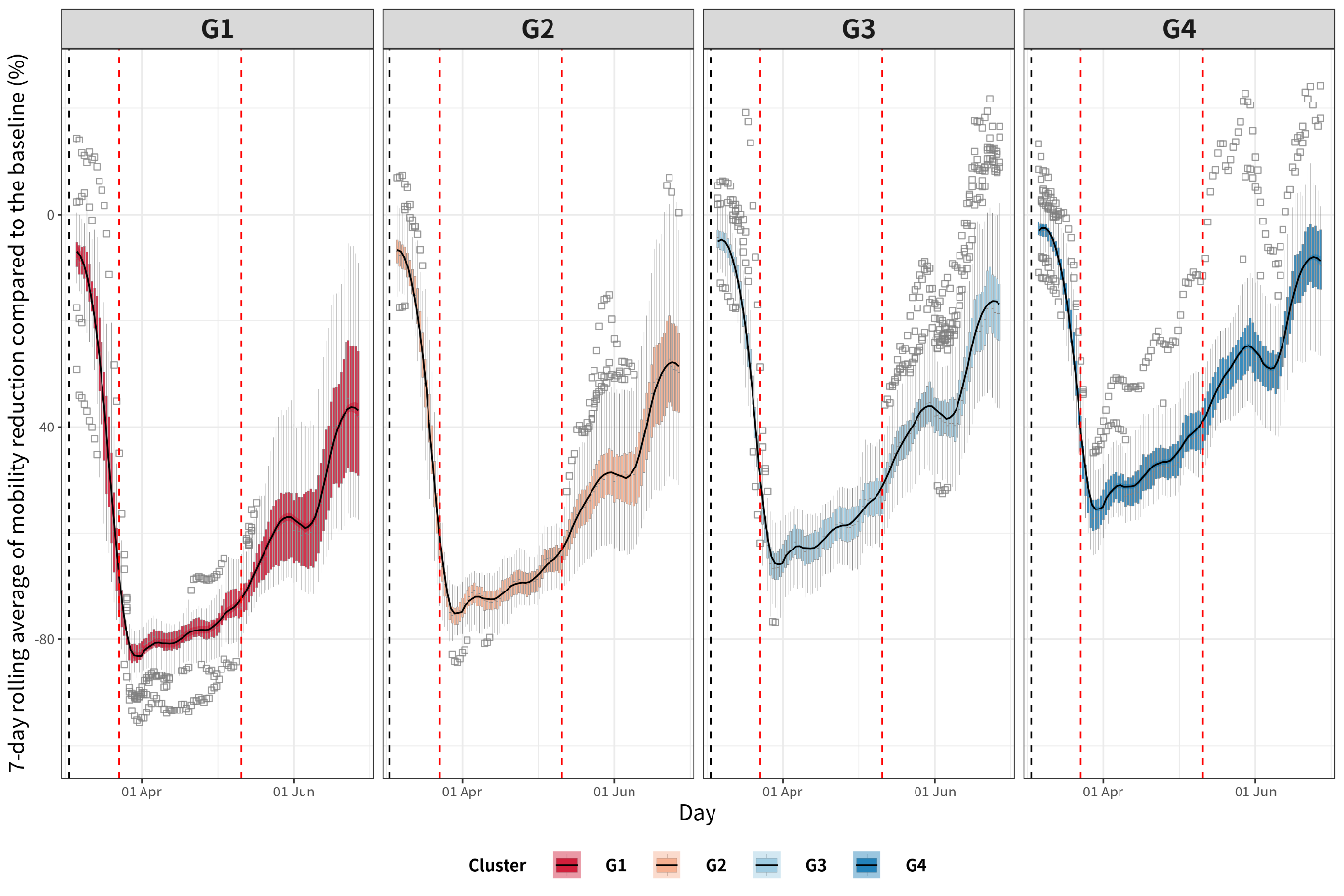


Figure . Trajectories of mobility between clusters.

Note: Using 7-day rolling average mobility levels, temporal trend estimated by using local polynomial regression function (with span *s*=0.2), and dotted lines highlighted the important days; black – baseline (3 March 2020), and red – 2020 Spring lockdown period in England.

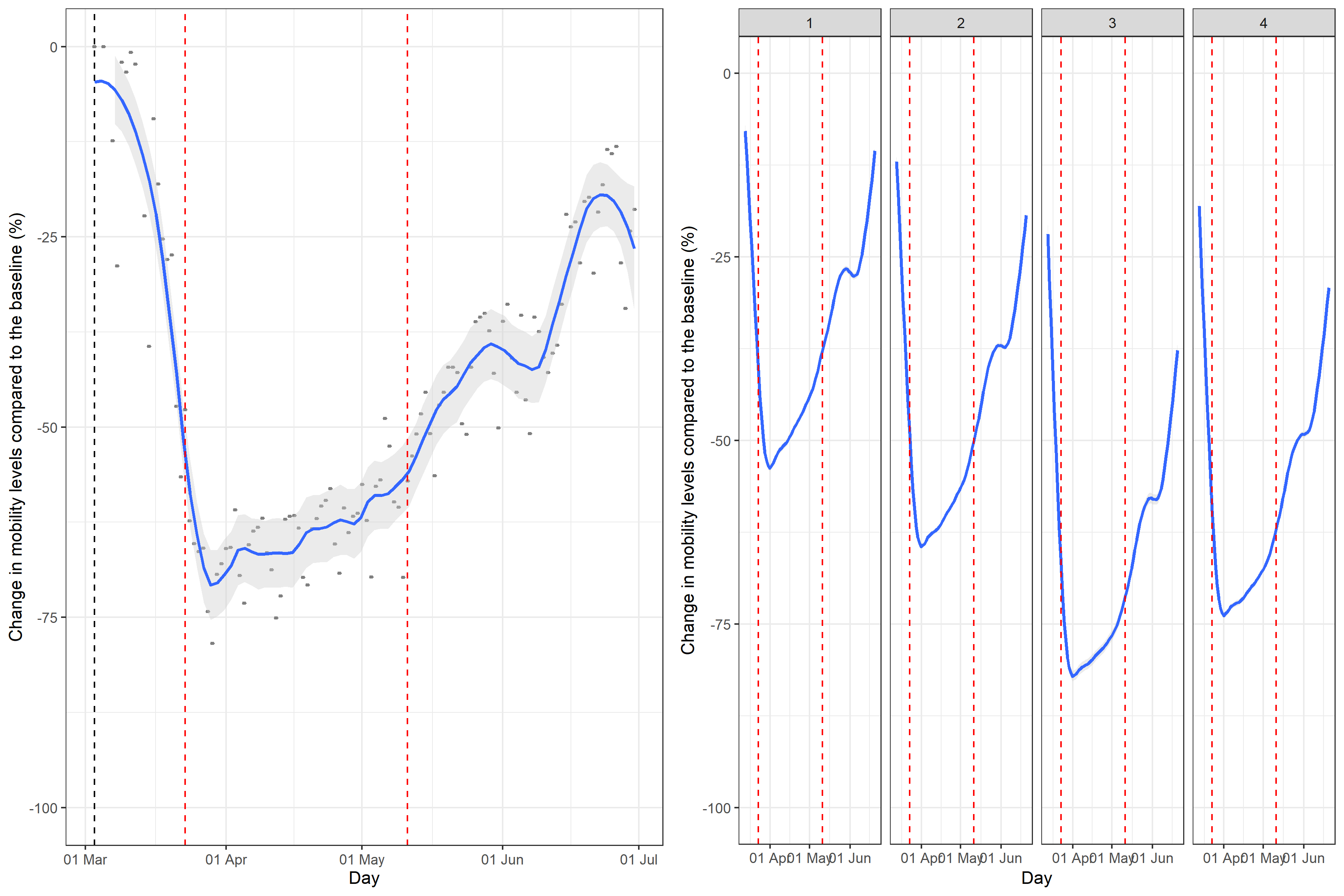


Figure . Trajectories of mobility reduction in England; national level (left), and differences in temporal trend between clusters (right).

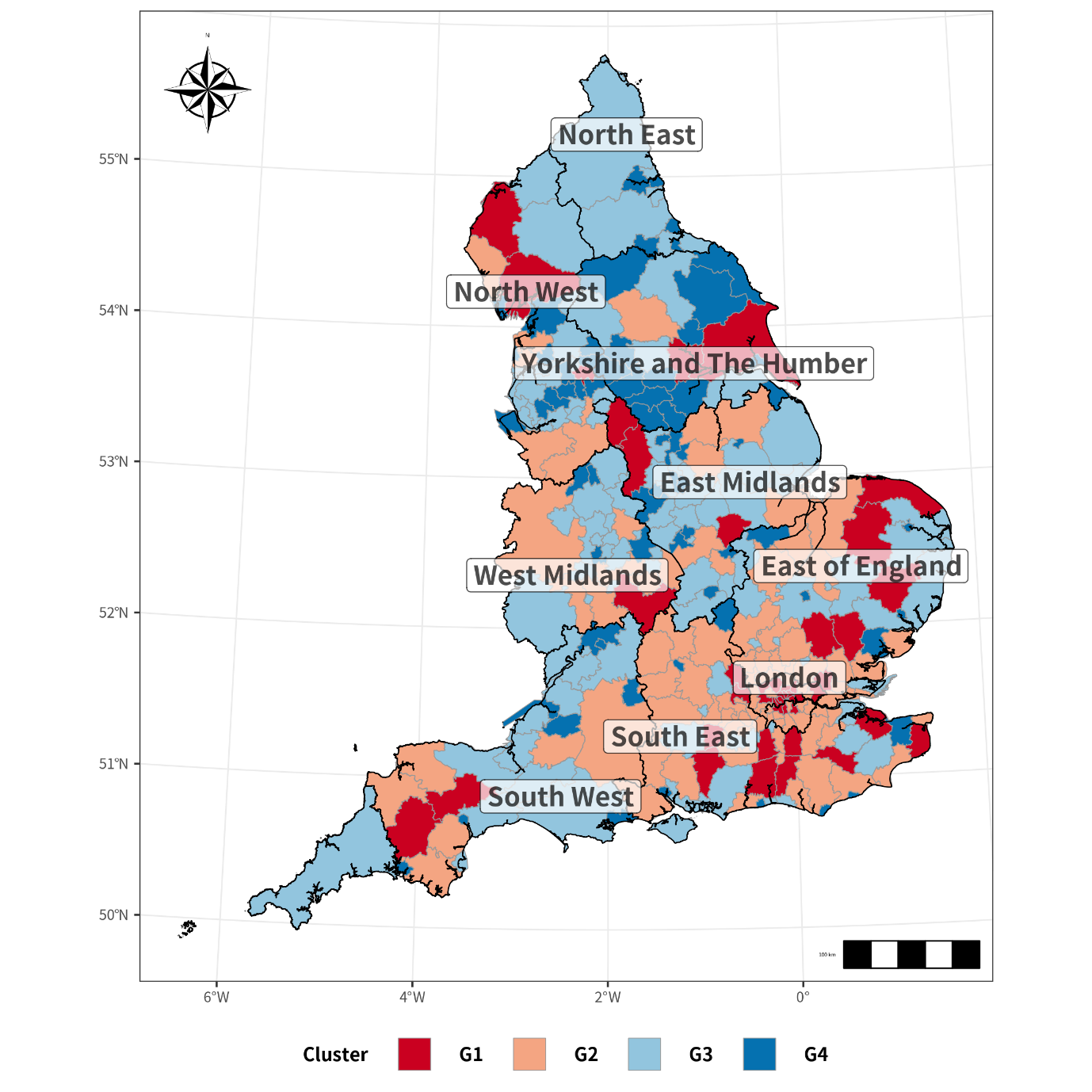


Figure . Spatial distribution of clusters (*k*=4).

## Differences in the association with socioeconomic characteristics

In the following analysis, we deployed the classification model to examine the significant factors that help us to interpret the clusters identified through the time-series clustering analysis. MLR LASSO is applied to assess the effects of socioeconomic characteristics between clusters, which grouped into similar trajectories of mobility reduction during the lockdown. MLR LASSO can take advantage of reducing the dimension of input features or variable selection. Some socioeconomic characteristics might be irrelevant to explain that interpreting trajectories of mobility over time. It also outperformed to eliminate the redundant collinear features to avoid multicollinearity (Gao et al., 2020). In MLR LASSO, estimated coefficients yielded the penalised coefficients for the standardised variables. A positive or negative sign is indicated as the direction of the relationship. MLR LASSO has no built-in model for ranking the model predictors (Abdel Majeed et al., 2018). Thus, the relative feature importance (RF) can be used to rank the importance of selected features according to their magnitude of MLR LASSO resulting coefficients, and it gave each feature a rank from 0 to 1 to estimate using *caret* package for R (Kuhn, 2008).

The model estimation results provided the estimated coefficients for selected factors between clusters. All explanatory variables were normalised to the range of [0,1] prior to model fitting. The best , penalty parameter, was selected by 10-fold cross-validation (CV). Seventeen factors remain through the embedded feature selection process in MLR LASSO. The share of high-income households, self-employed workers, and households with one vehicle were the most effective variables for the classification, yet the estimated coefficients varied between clusters (see Figure 6). The positive coefficients for the share of high-income households and self-employed workers were observed in G1 and G2. Based on the sign of coefficients, it can be inferred that those local authorities with particularly high levels of affluent populations and self-employed workers (are more likely to be low earners in London). Conversely, negative coefficients were indicated in G3 and G4 that high-income households and self-employed workers were negligible. In addition, the positive coefficients for the share of households with one vehicle were observed in G2 and G4, while negative coefficients were indicated in G1 and G3.

Table 3 details the estimated coefficients for selected factors correlated with the classification of generated clusters. It was generally classified as G4, where the share of households with more than three vehicles, self-employed workers, and people in the lower middle class (i.e., social grade C1) were substantially lower. In contrast, G1 was more likely located in the local authorities; the share of high-income households, cumulative COVID-19 infection rates before the lockdown, and minority ethnic groups were comparatively high. Among the remaining clusters, high levels of the share of middle-income households, and more than three bedrooms in the house were more likely classified as G3. At the same time, G2 was more likely located in local authorities; the share of high-income households, lower middle class, and Black African were relatively higher.

Lastly, Figure 7 illustrates how RF emphasised the relative contributions of each feature to predict the clusters and how much each feature explains the output variance of MLR LASSO. In this case, the substantial explanatory variables are plotted against their relative importance from 0 to 1. The top 5 features for each cluster are described as follows:

* G4: Share of households with more than three vehicles (0.64), self-employed workers (0.26), more than three bedrooms in the house (0.23), cumulative COVID-19 mortality rates before lockdown (0.20), and percentage Black Caribbean (0.19).
* G3: Share of medium-income households (0.38), social grade C1 (0.25), high-income households (0.23), more than three bedrooms in the house (0.25), households with one vehicle (0.04), and self-employed workers (0.02).
* G1: Share of self-employed workers (0.71), households with one vehicle (0.35), cumulative COVID-19 infection rates before lockdown (0.24), high-income households (0.19), and percentage Other Black (0.12).
* G2: Share of high-income households (0.47), percentage Black African (0.43), households with more than three vehicles (0.39), more than three bedrooms in the house (0.30), and Hospital density per 1,000 population (0.15).

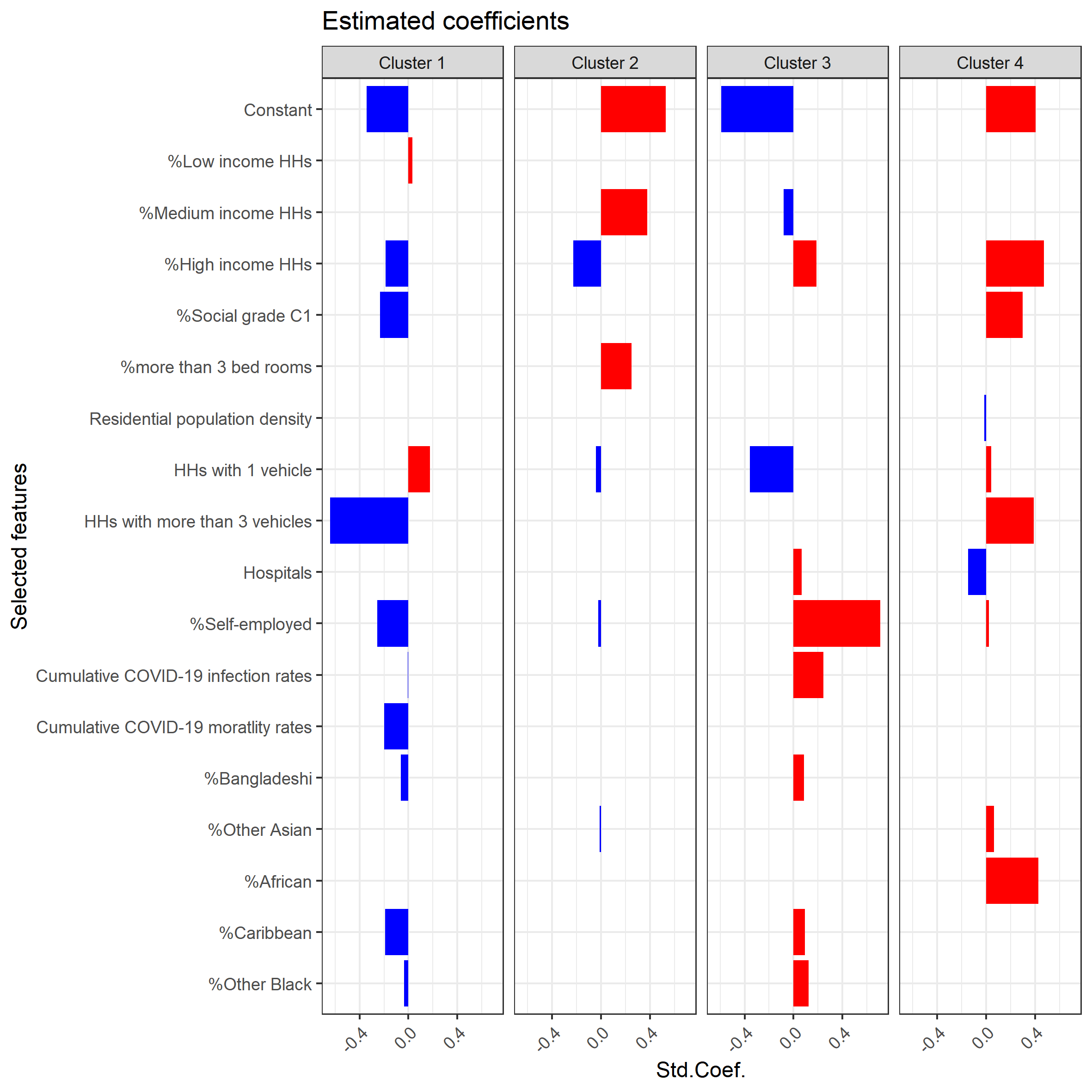


Figure . Estimated coefficients of explanatory variables to predict the clusters.

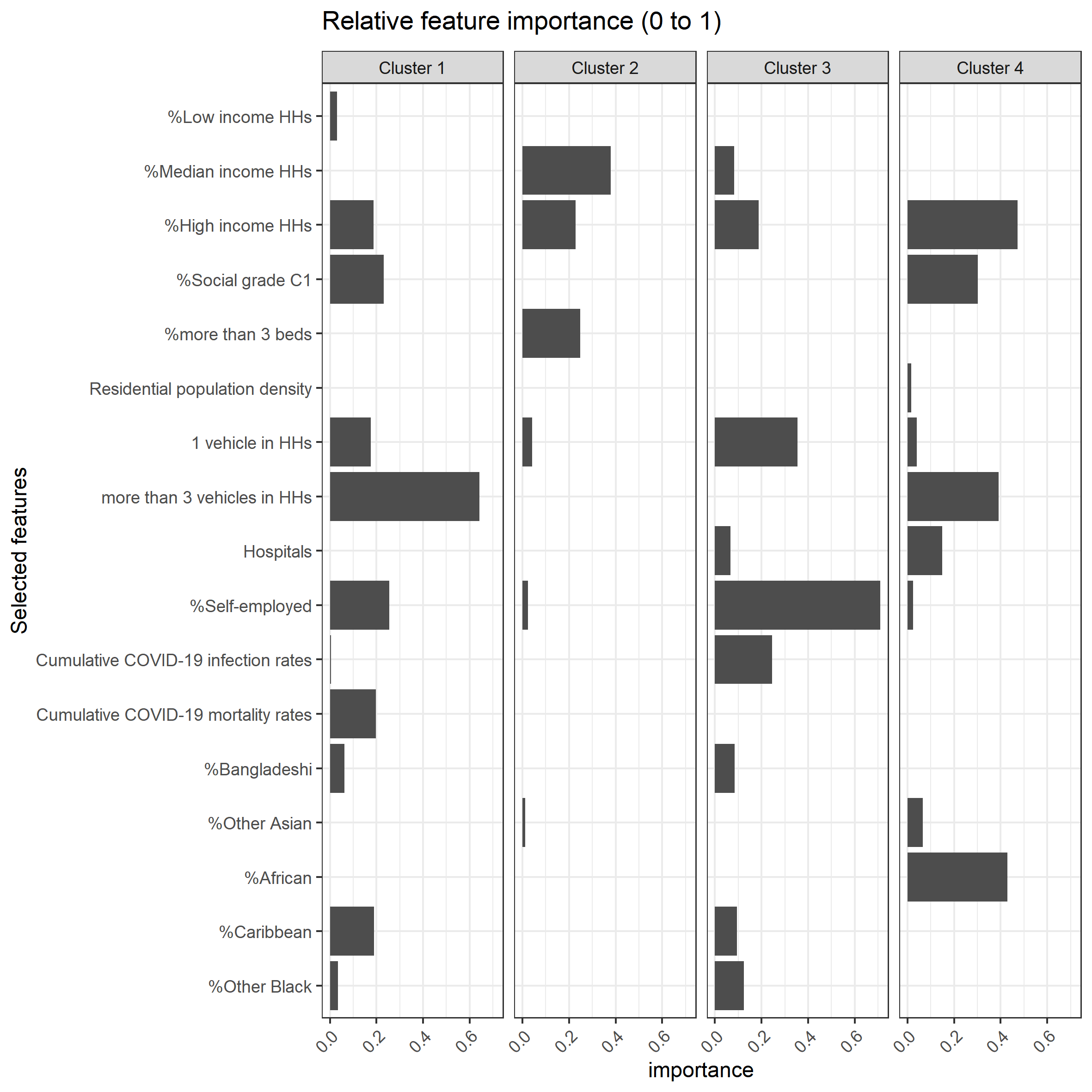


Figure . Ranking the relative feature importance to predict the clusters.

Table . Descriptive statistics of socioeconomic status by clusters.

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| --- | --- | --- | --- | --- | --- | --- | --- |
| Domains | | Variable | G1 | G2 | G3 | G4 | National level |
| Mean (Std.) | Mean (Std.) | Mean (Std.) | Mean (Std.) | Mean (Std.) |
| Socioeconomic | **Income** | **Share of households in lowest household**  **income quintile at national level** | **0.16 (0.02)** | **0.17 (0.02)** | **0.19 (0.03)** | **0.17 (0.02)** | **0.17 (0.02)** |
| **Share of households in median household**  **income quintile at national level** | **0.22 (0.02)** | **0.23 (0.02)** | **0.22 (0.02)** | **0.21 (0.02)** | **0.22 (0.02)** |
| **Share of households in top household**  **income quintile at national level** | **0.17 (0.05)** | **0.17 (0.05)** | **0.14 (0.04)** | **0.24 (0.07)** | **0.19 (0.07)** |
| Education and skills | Share with no qualifications | 0.21 (0.04) | 0.24 (0.04) | 0.25 (0.05) | 0.19 (0.05) | 0.22 (0.05) |
| Share of non-English speakers | 0.07 (0.07) | 0.04 (0.04) | 0.06 (0.05) | 0.11 (0.12) | 0.06 (0.07) |
| **Occupation** | Share of Social Grade AB  (upper middle class) | 0.35 (0.07) | 0.3 (0.06) | 0.27 (0.05) | 0.37 (0.07) | 0.32 (0.07) |
| **Share of Social Grade C1**  **(lower middle class)** | **0.24 (0.03)** | **0.23 (0.03)** | **0.21 (0.03)** | **0.23 (0.04)** | **0.23 (0.03)** |
| Share of Social Grade C2  (skilled working class) | 0.2 (0.04) | 0.23 (0.03) | 0.23 (0.03) | 0.18 (0.05) | 0.21 (0.04) |
| Share of Social Grade DE  (semi-skilled working class and non-working) | 0.14 (0.04) | 0.16 (0.04) | 0.19 (0.05) | 0.14 (0.04) | 0.16 (0.05) |
| **Housing type** | Share of social rented housing | 0.15 (0.06) | 0.15 (0.05) | 0.18 (0.06) | 0.18 (0.09) | 0.16 (0.06) |
| **Share of dwellings with ≥3 bedrooms** | **0.63 (0.07)** | **0.65 (0.06)** | **0.6 (0.06)** | **0.56 (0.15)** | **0.62 (0.09)** |
| Accessibility | **Residential density** | **Resident population density**  **(1,000 inhabitants per km2)** | **0.01 (0.01)** | **0.01 (0.01)** | **0.01 (0.01)** | **0.03 (0.04)** | **0.01 (0.02)** |
| **Car availability** | Share of households with 0 vehicle | 0.19 (0.08) | 0.21 (0.07) | 0.27 (0.07) | 0.28 (0.19) | 0.23 (0.11) |
| **Share of households with 1 vehicle** | **0.42 (0.03)** | **0.42 (0.02)** | **0.44 (0.02)** | **0.4 (0.04)** | **0.42 (0.03)** |
| Share of households with 2 vehicles | 0.29 (0.07) | 0.28 (0.05) | 0.23 (0.05) | 0.24 (0.12) | 0.27 (0.07) |
| **Share of households with ≥3 vehicles** | **0.03 (0.01)** | **0.02 (0.01)** | **0.01 (0.01)** | **0.02 (0.02)** | **0.02 (0.01)** |
| Clinical capacity and Allowed premises | **Hospitals (per 1,000 inhabitants)** | **0.27 (0.11)** | **0.29 (0.16)** | **0.26 (0.15)** | **0.33 (0.2)** | **0.28 (0.15)** |
| Parks (per 1,000 inhabitants) | 22.87 (10.32) | 22.89 (11.82) | 21.61 (10.54) | 25.5 (10.95) | 22.97 (10.98) |
| Activity commitment | **Economic activity** | Share of part-time workers  in the resident population aged 16-74 | 0.14 (0.01) | 0.15 (0.01) | 0.14 (0.01) | 0.13 (0.03) | 0.14 (0.02) |
| Share of full-time worker  in the resident population aged 16-74 | 0.4 (0.04) | 0.39 (0.03) | 0.38 (0.04) | 0.39 (0.04) | 0.39 (0.04) |
| **Share of self-employed workers**  **in the resident population aged 16-74** | **0.11 (0.02)** | **0.1 (0.02)** | **0.08 (0.02)** | **0.13 (0.02)** | **0.1 (0.03)** |
| Population Health | General health status | Share of population in good health | 0.83 (0.03) | 0.81 (0.03) | 0.8 (0.03) | 0.83 (0.02) | 0.82 (0.03) |
| Share of population in fair health | 0.12 (0.02) | 0.14 (0.02) | 0.14 (0.02) | 0.12 (0.02) | 0.13 (0.02) |
| Share of population in bad health | 0.05 (0.01) | 0.05 (0.01) | 0.06 (0.01) | 0.05 (0.01) | 0.05 (0.01) |
| Perceived risk of COVID-19 | **Infection rates** | **Cumulative COVID-19 reported cases**  **per 100,000 population before lockdown** | **15.72 (12.14)** | **11.29 (7.04)** | **9.49 (8.57)** | **24.6 (19.65)** | **14.11 (12.40)** |
| **Mortality rates** | **Cumulative COVID-19 reported deaths**  **per 100,000 population before lockdown** | **1.25 (1.44)** | **0.93 (1.26)** | **0.61 (0.81)** | **1.83 (1.87)** | **1.08 (1.39)** |
| Ethnic composition | White | Percentage of the residential population  that identified as White British | 0.88 (0.14) | 0.93 (0.08) | 0.9 (0.09) | 0.82 (0.2) | 0.89 (0.13) |
| Mixed/multiple groups | Percentage of Mixed (joint) and  Multiple ethnic groups | 0.02 (0.01) | 0.01 (0.01) | 0.02 (0.01) | 0.03 (0.02) | 0.02 (0.01) |
| Indian | Percentage Indian | 0.02 (0.04) | 0.02 (0.03) | 0.02 (0.04) | 0.03 (0.05) | 0.02 (0.04) |
| Pakistani | Percentage Pakistani | 0.01 (0.03) | 0.01 (0.03) | 0.02 (0.04) | 0.01 (0.02) | 0.01 (0.03) |
| **Bangladeshi** | **Percentage Bangladeshi** | **0 (0.01)** | **0 (0.01)** | **0 (0.01)** | **0.02 (0.05)** | **0.01 (0.02)** |
| Chinese | Percentage Chinese | 0.01 (0) | 0 (0) | 0.01 (0.01) | 0.01 (0.01) | 0.01 (0.01) |
| **Other Asian** | **Percentage Other Asian** | **0.02 (0.02)** | **0.01 (0.01)** | **0.01 (0.01)** | **0.02 (0.03)** | **0.01 (0.02)** |
| **African** | **Percentage Black African** | **0.02 (0.03)** | **0.01 (0.01)** | **0.01 (0.01)** | **0.03 (0.04)** | **0.01 (0.02)** |
| **Caribbean** | **Percentage Black Caribbean** | **0.01 (0.02)** | **0 (0.01)** | **0 (0.01)** | **0.02 (0.03)** | **0.01 (0.02)** |
| **Other Black** | **Percentage Other Black** | **0 (0.01)** | **0 (0)** | **0 (0)** | **0.01 (0.01)** | **0 (0.01)** |
| Other ethnic groups | Percentage of any other ethnic group | 0.01 (0.01) | 0 (0) | 0.01 (0.01) | 0.02 (0.02) | 0.01 (0.01) |

*Notes*: Variables in bold (i.e., 17 selected features) have been included in the classification model below at least in one cluster.

Table . Estimated coefficients of explanatory variables to classify clusters.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Domains | | Variable | G1 | G2 | G3 | G4 |
| Constant | | | -0.59 | 0.41 | 0.53 | -0.34 |
| Socioeconomic | Income | Share of households in the lowest household  income quintile at the national level |  |  |  | 0.03 |
| Share of households in median household  income quintile at the national level | 0.38 | 0.38 | 0.38 |  |
| Share of households in top household  income quintile at national level | -0.23 | -0.23 | -0.23 | -0.19 |
| Occupation | Share of Social Grade C1 (lower middle class) |  |  |  | -0.23 |
| Housing type | Share of dwellings with ≥3 bedrooms | 0.25 | 0.25 | 0.25 |  |
| Residential density | Resident population density  (1,000 inhabitants per km2) |  |  |  |  |
| Accessibility | Car availability | Share of households with 1 vehicle | -0.04 | -0.04 | -0.04 | 0.18 |
| Share of households with ≥3 vehicles |  |  |  | -0.64 |
| Clinical capacity and Allowed premises | Hospitals (per 1,000 inhabitants) |  |  |  |  |
| Activity commitment | Economic activity | Share of self-employed workers in the resident  population aged 16-74 | -0.02 | -0.02 | -0.02 | -0.26 |
| Perceived risk of COVID-19 | Infection rates | Cumulative COVID-19 reported cases per 100,000  resident population before lockdown |  |  |  | -0.01 |
| Mortality rates | Cumulative COVID-19 reported deaths per 100,000  resident population before lockdown |  |  |  | -0.20 |
| Ethnic composition | Bangladeshi | Percentage Bangladeshi |  |  |  | -0.06 |
| Other Asian | Percentage Other Asian | -0.01 | -0.01 | -0.01 |  |
| African | Percentage Black African |  |  |  |  |
| Caribbean | Percentage Black Caribbean |  |  |  | -0.19 |
| Other Black | Percentage Other Black |  |  |  | -0.03 |
| Model criteria information | | | | | | |
| AICc (Akaike's Information Corrected Criterion) | | -222.91 | | | | |
| BIC (Bayesian information criterion) | | -161.18 | | | | |

# Discussion

People make new daily decisions, which are rendered into their mobility behaviours, travelling between locations to carry out their daily activities. Pandemic has forced us to adapt to the *new normal* in our daily lives, the ways of working from home and homeschooling during waves of infection and government-mandated stay-at-home orders, lockdowns and social distancing, and longer-term impacts likely to outlast the COVID-19 pandemic. People have started to see new ways to restore activities differently in their everyday lives, such as relying on the internet for shopping (Mouratidis & Papagiannakis, 2021). However, on the one hand, people make journeys by walking or cycling to increase physical activity levels through active transport activity (Beck & Hensher, 2020).

In this vein, we examined changes in mobility over time using long-term mobile phone data, and then we demonstrated different trajectories of mobility in a spatially uneven manner using time-series clustering analysis. We quantified similarities according to changes in mobility throughout the initial phases of the lockdown by the mobility metric. It allows us to demonstrate the distinctive effects of socioeconomic and demographic factors between generated clusters. Whilst previous literature has highlighted examining spatio-temporal mobility patterns as an early observation in the pandemic. We believe this is the first study that seeks to unfold trajectories of mobility in view of the prolonged pandemic, and uncover its existence explicitly linked to socioeconomic status.

The results confirmed mobility reductions in the early stage of the pandemic, and the continuation of reductions following the national lockdown. However, mobility began to rise when the lockdown lifted. People start to go back to normal life (Sun et al., 2020), and more people will want or need to move more with the support of warmer weather, tiredness of staying at home, and cost-of-living issues in a pandemic, recognised as *Quarantine Fatigue* (Zhao et al., 2020). Pan et al. (2020) observed that people tend to practice less social distancing immediately when they indicated decreasing in the perceived risk of COVID-19. The evidence of post-lockdown mobility recovery appeared in line with England’s up-to-date general reopening of retail shops and public-facing businesses in the post-lockdown period (i.e., 15 June 2020).

We also indicated the voluntary mobility reduction before government-mandated lockdowns. Xiong et al. (2020) suggested that people might be acting more actively when they perceived the threat to COVID-19, such as the rise of daily new COVID-19 cases and deaths where they are living. As a result, *Spontaneous mobility reduction* is quantified before lockdown measures have been introduced to suppress the mobility. People start to practice voluntary social distancing, in terms of self-regulation in the early stage of the pandemic (Khataee et al., 2021) depending on their ability to isolate and risk aversion on mobility. In overview, lockdown measures were effective for restricting people’s everyday mobility, but only in the short term (J. Kim & Kwan, 2021). It is, however, a *nuclear option* that is “causing substantial collateral damages to society, the economy, trade and human rights” (Haug et al., 2020, p. 1309). Although the risk of new and more transmissible variant of the virus and the threat of second waves, people's mobility levels soon recovered throughout lockdown by considering people willing to socialise again and return to normality. It is plausible that the limited effectiveness of lockdown measures, even though travel restrictions and interventions to protect lives and communities under the lockdown. It is not a failure of policy but too late to contain the epidemic. People forecasted the ongoing and future situations cautiously in the wake of COVID-19 before social distancing policies were widely implemented. It might be making them regulate their social contacts and practice voluntary social distancing, which accounts for voluntary mobility reduction before the lockdown.

# Conclusions

This paper has sought to provide rigorous evidence that trajectories of mobility change under the lockdown, and contribute to the methodological development to characterise trajectories of mobility coping with socioeconomic and demographic factors. The research was founded on the integration of novel data and data mining techniques. In detail, employing longitudinal perspective to explore changes in mobility by using mobile phone data spanning seven months. And then, Clustering analysis and classification model were chosen to collect similar trajectories of mobility and find the significant factors to predict the clusters, respectively. Two main conclusions can be drawn.

First, people’s everyday mobility has been changed, and it could be the clear evidence of the effectiveness of government interventions in times of the pandemic. In England, mobility levels already falling about 50% compared to the pre-pandemic in the early stage of the pandemic (i.e., the first day of lockdown). Mobility levels continuously declined towards 80% (i.e., 7-day on lockdown) but soon bounced back up to 50% over the course of the national lockdown. Easing lockdown supported the mobility recovery so that mobility levels returned to normal in the post-lockdown period. However, the trajectory of mobility reduction under the lockdown is not the same extent. Group heterogeneity in trajectories of mobility change was exhibited throughout time-series clustering analysis. It revealed differences in the recovery of mobility levels during the lockdown between generated clusters. The finding that areas with the greatest reduction in mobility levels before the government-mandated lockdown and marginal recovery during the lockdown have been observed in Inner London. In contrast, areas with the lowest reduction in mobility and rapid mobility bound back can be found in North West, and Yorkshire and the Humber.

Second, people’s mobility levels have been influenced by government interventions, but it was also coupling with the individual ability to restrict everyday mobility (Lee et al., 2021). Unsurprisingly, high-income workers mainly were working from home, and felt to adapt successfully to the new normal (Office for National Statistics, 2021). Racial and ethnic minorities and poor people lived in crowded conditions and generally worked in essential industries (Huang et al., 2021). Additionally, Lou et al. (2020) found that stay-at-home orders did not significantly reduce low-income work trips. Thus, it is vital to demonstrate the effects of socioeconomic and demographic factors to predict the patterns of temporal evolution of mobility level in pandemic times. Our classification model, MLR LASSO, has examined the significant factors and assessed the importance of selected features between clusters. As a result, income, employment and accessibility are quantified as the most effective domains. Subsequently, housing type, perceived risk of COVID-19 (before the lockdown), and BAME (Black, Asian and minority ethnic) variables were also selected.

# Availability of data and materials

All source R code and data necessary for the replication of our results and figures are available at <https://github.com/wondolee/covid19-eng-lockdown>.

# Credit authorship contribution statement

Won Do Lee: Conceptualisation, Data Curation, Methodology, Formal analysis, Writing-Original draft preparation. Matthias Qian: Data Curation, Writing-Reviewing and Editing. Tim Schwanen: Conceptualisation, Writing-Original draft preparation, Supervision, Writing-Reviewing and Editing.

# Declaration of competing interest

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

# Acknowledgement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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1. Paper prepared for submission to the [*Journal of Sustainable Cities and Society.*](https://www.journals.elsevier.com/sustainable-cities-and-society) [↑](#footnote-ref-2)
2. Transport Studies Unit, School of Geography and the Environment, University of Oxford. [↑](#footnote-ref-3)
3. Saïd Business School, University of Oxford. [↑](#footnote-ref-4)
4. Anonymised mobile phone location data provided by a large British mobile phone company. [↑](#footnote-ref-5)
5. At least two percent of the population has been sub-sampled from the users of a large British mobile phone provider, stratified by the 317 Lower Tier Local Authorities in England. *City of London* and *Hackney* are combined due to small population sizes, and *Cornwall* and *Isles of Scilly* as well. [↑](#footnote-ref-6)
6. The computation of home region of users exploits the night-time location when users are most likely to be at home. Home region detection followed three steps: a) filter observations from 10 pm to 6 am, b) finding the most common cell phone tower used at night-time, c) dropping users with fewer than 30 night-time observations per month. Each cell phone tower is assigned to its Lower Tier Local Authority area according to its location. [↑](#footnote-ref-7)
7. Nearest-neighbour or Single-linkage Method ("single"), Furthest-neighbour or Complete-linkage Method ("complete"), Average-linkage Method ("average"), McQuitty’s Method ("mcquitty"), Metric Methods; Centroid Sorting Method (“centroid”), Gower’s Median Method ("median"), Ward’s method (“ward.D", "ward.D2"). [↑](#footnote-ref-8)