

# Changes in the time-space dimension of human mobility during the COVID-19 pandemic

**Keywords:** *Mobility, Radius of Gyration, Mobility Synchronisation, LBS Data, COVID-19*

## Extended Abstract

The society produces digital records of, for example, the places we visit, the products we buy, and the people we call. These digital records proved valuable in studying different aspects of human behaviour [1]. Here, we leverage Location Base Service (LBS) data from mobile phone users to study how citizen mobility patterns have been affected during the COVID-19 pandemic in the UK. Assessing the effects of the mobility restriction policies on daily routines relies on investigating the relationship between space and time-based population mobility patterns. We employ the radius of gyration [2] to gauge the span of the urban movement (spatial dimension). We also define mobility synchronisation as a time metric that quantifies the co-temporal occurrence of the daily mobility motifs [4] – i.e. leave/return home from work happens periodically at the same time (temporal dimension). Combining these space and time metrics, we can estimate the effect of the mobility restrictions on the population. Using the radius of gyration (Fig. 1 A orange), we could identify that the effect of the first lockdown was more significant than the others in changing the spatial characteristics of citizens' movement. Among the reasons that could lead to this result, we can mention more strict policies adopted in the first lockdown and the lockdown duration [5, 6]. However, further investigation is needed to obtain more evidence to support these hypotheses. In contrast to the spatial dimension of mobility, the results indicate that the temporal (Fig. 1 A green) one was more impacted during the second lockdown when more flexible mobility restriction policies were enforced. After the first lockdown, we argue that people who could not work from home were allowed to leave home and work in the office as long as they respected social distancing rules [5, 3]. The results also indicate that the two lockdowns affected the synchronisation of people's movement differently (Fig. 1 B). The mobility synchronisation displays a recovery latency compared to the gyration radius. Furthermore, how we respond to mobility restriction measures is interwoven with the characteristics of the geographical space, such as income groups, economic activities, and population density. In particular, we focus on disentangling how the population density in terms of rural-urban classification and the different socio-economic groups have adjusted their routine to comply with the mobility restrictions imposed. We observed that the radius reduction was slightly more significant in rural areas than the urban ones. In contrast, the decrease in synchronisation levels was more notable in urban areas than rural ones. We noticed that high-income groups displayed a more considerable reduction in the radius and synchronisation than the low-income groups. We also studied the differences concerning the duration and the type of trips. Fig. 1 B illustrates that high-income groups have the most reduction in the duration of their work-related trips. While Fig. 1 C depicts that rural areas presented the greatest increase in park trips compared to the baseline year of 2019. In summary, the analysis of the spatial dimension of human mobility coupled with the insights from the study of the time dimension allows us to characterise the impact of *stay-at-home* policies on the population of different areas/socioeconomics. These differences suggest that each group experiences, in a particular way, the emergence of asynchronous mobility patterns primarily due to mobility restriction policies and the ascension of

new habits (e.g. home office and home education). In summary, the analysis of the spatial dimension of human mobility coupled with the insights from the study of the temporal dimension allows us to characterise the impact of policies such as *stay-at-home* and school closures on the population of different areas/socioeconomics. These differences suggest that each group experiences, in a particular way, the emergence of asynchronous mobility patterns primarily due to the enforcement of mobility restriction policies and the ascension of new habits (e.g. home office and home education).

## References

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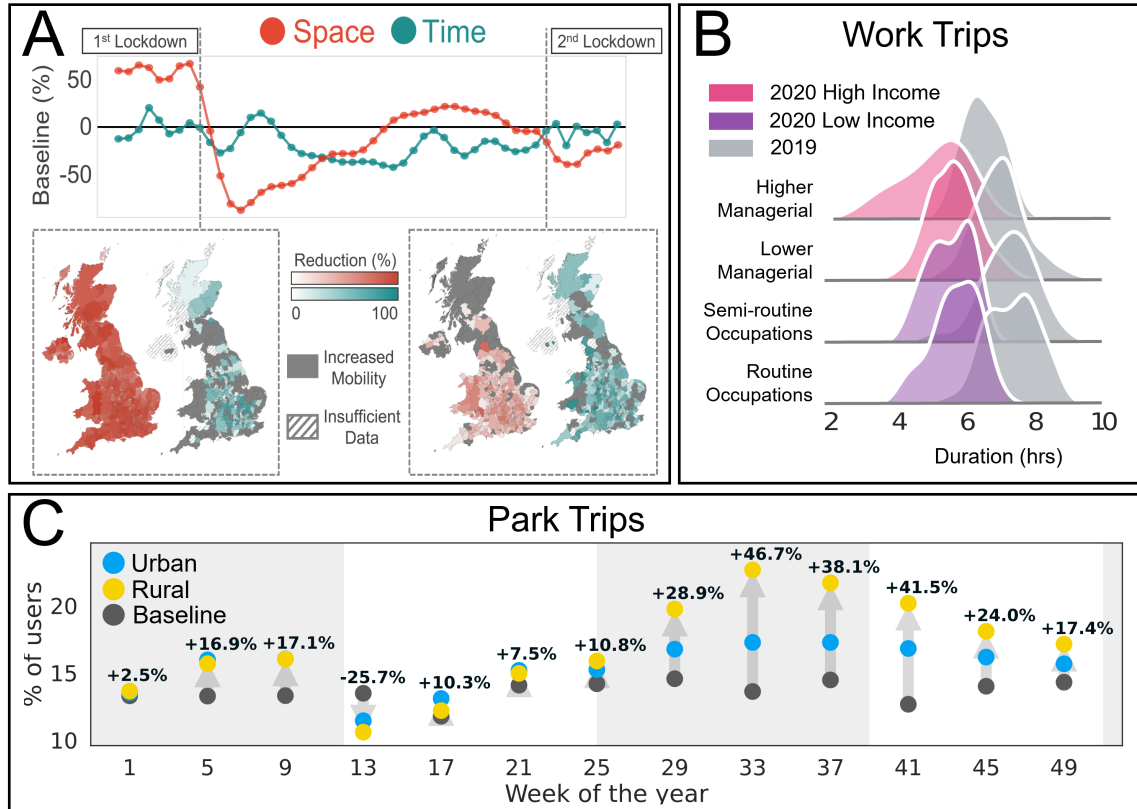


Figure 1: Changes in mobility patterns during the COVID-19 pandemic. (A) illustrates the mobility difference over time and for the first two English national lockdowns measured with mobility synchronisation (time) and the radius of gyration metrics (space). (B) looks at the mobility related to the duration of work-related trips before (2019) and during the pandemic (2020). Using the NS-SEC classification, we show the different behaviour of income and socioeconomic groups. Lastly, (C) depicts the differences in the number of trips to green spaces such as parks compared to the baseline year of 2019. Note that in this case, we group the local authorities according to their level of urbanisation.