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ARTICLE

Harnessing mobility data to capture changing work from home behaviours between censuses

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Abstract

This paper provides an analysis of working from home patterns in England using data from the 2021 Census to understand (1) how patterns of working from home (WFH) in England have shifted since the COVID-19 pandemic and (2) whether human mobility indicators, specifically Google Community Mobility Reports, provide a reliable proxy for WFH patterns recorded by the 2021 Census, providing a formal evaluation of the reliability of such datasets, whose applications have grown exponentially over the COVID-19 pandemic. We find that WFH patterns recorded by the 2021 Census were unique compared with previous UK censuses, reflecting an unprecedented increase likely caused by persistent changes to employment during the COVID-19 pandemic, with a clear social gradient emerging across the country. We also find that Google mobility in 'Residential' and 'Workplace' settings provides a reliable measurement of the distribution of WFH populations across Local Authorities, with varying uncertainties for mobility indicators collected in different settings. These findings provide insights into the utility of such datasets to support population research in intercensal periods, where shifts may be occurring, but can be difficult to quantify empirically.

KEYWORDS

census, COVID-19, England, Google, mobility, working from home

1 | INTRODUCTION

1.1 | Context

The 2021 UK Census was collected on 21 March 2021 during a period of unprecedented societal disruption caused by the COVID-19 pandemic and associated non-pharmaceutical interventions (Trasberg & Cheshire, 2021). These interventions included stay at home orders, limits on travel, and social distancing guidelines for out-of-home contacts (Deole et al., 2023; Institute for Government, 2022), as well as the closure of 'non-essential' businesses, and introduction of a furlough scheme to support workers temporarily prevented from working due to government restrictions (Clark, 2021).

For other employees, such as office workers, the UK government recommended working from home where possible, which was facilitated by remote working technologies (Al-Maroof et al., 2020; Song et al., 2022), and widely adopted by employers (Office for National Statistics, 2022). These changes to work from home (WFH hereafter) patterns are likely to persist beyond the end of the COVID-19 pandemic. Although the degree of this persistence remains unknown (Deole et al., 2023), previously published research has utilised a wide pool of novel data sources to quantify changes in mobility as a result of COVID-19 disruptions (Ballantyne et al., 2022; Gibbs et al., 2022; Rowe et al., 2023; Trasberg & Cheshire, 2021). This raises the question as to whether these mobility datasets can be an effective replacement for official statistics in the intercensal period.

The way that WFH patterns have changed in response to the COVID-19 pandemic is likely to have implications for the prosperity of cities and urban areas, requiring adaptations in planning and design to support their role in society. For example, an increase in remote working may create urban transportation challenges through modifications to typical commuting patterns, including expected declines in public transit ridership (Credit & Arnao, 2022). Furthermore, given the large body of work that has cited a decline in the economic vitality of inner cities and lower occupancy of office space during the pandemic (Rowe et al., 2023), there is further evidence to suggest their recovery is geographically uneven (Blundell et al., 2020), with ensuing implications for increasing levels of WFH in terms of the planning of residences and workplaces to provide suitable employment opportunities (Angel et al., 2022). Understanding these patterns, and how the WFH patterns measured in the census compare to novel mobility datasets, will help to inform future approaches to measuring WFH patterns and contribute to understanding of the economic and social impact of COVID-19.

1.2 | Measuring WFH behaviours—the decennial census

Conducted every ten years, the England and Wales Census provides a 'gold standard' for understanding the characteristics and distribution of the population (Catney et al., 2023), to a level that is unrivalled in other datasets, particularly when examining population migrations between decennial censuses (Lomax, 2022). The release of the latest 2021 Census provides opportunities for researchers and policy analysts (UK Data Service, 2021), particularly those who seek to understand how the population has changed over the last decade (Catney et al., 2023). However, the 2021 Census also represents a unique opportunity to better understand the impact of COVID-19 on the UK population (Catney et al., 2023). The need for granular insights about changing WFH behaviours remains particularly pertinent, as many argue that the 2021 Census provides a distorted snapshot of the population at an unrepresentative time (Savage, 2021). Scotland has even postponed their census for a year to minimise these uncertainties (Dorling, 2021).

Until the release of the 2021 Census, capturing reliable information on WFH during the COVID-19 pandemic was difficult, if not impossible, with the available sources of data (i.e., employers were not asked to report, nor does such granular employment data exist). The census records information about peoples' work and commuting behaviours, including small area statistics detailing the amount of people that work mainly at or from home. Historically, these employment statistics have been used to support transport planning and regional development (Coombes, 2002; Rae, 2017). However, because the 2021 Census happened during the COVID-19 pandemic, the census collected unique and concrete information about WFH behaviours in the English and Welsh populations. The census also allows an additional opportunity to validate much of the work concerning changes in mobility and WFH during the pandemic which were largely undertaken using new forms of (proxy) data (e.g., GPS derived mobility data). Such data were often used to accurately capture the mobility of populations during the pandemic by policy makers and researchers with little understanding of how accurate they were.

1.3 | Estimating WFH behaviours—Google Community Mobility Reports

Prior to the 2021 Census and in the context of WFH, human mobility data collected from technology service providers including Apple, Google, CityMapper, and Waze were used as a key resource for estimating travel activity, population redistribution, and evaluating the success of government restrictions. Epidemiologists and human mobility researchers used publicly available mobility indicators from commercial service providers to estimate the spread of COVID-19 infections, and to monitor adherence to stay-at-home orders (Badr et al., 2020; Bergman & Fishman, 2020; Jacobsen & Jacobsen, 2020; Trasberg & Cheshire, 2021). The national government and local governments in England also used these indicators to predict economic recovery following the lifting of pandemic restrictions (Greater London Authority, 2022; Office for National Statistics, 2021; Open Data Bristol, 2020). While these data provided valuable near-real-time measurements of behavioural changes, mobility data collected as a side effect of other commercial services include uncertainties in the data generation process regarding the size and representativeness of the sample of individuals from which these data were collected (Buckee et al., 2020; Grantz et al., 2020; Wesolowski et al., 2013). Research has identified biases in aggregated measures of mobility, relating to the demographics of users of certain applications which generate the data, as well as the negative biases for specific regions and locations where these data do not remain stable over time (Ballantyne et al., 2022; Coston et al., 2021; Dodge & Nelson, 2023). There is also evidence of variation in the relationship between aggregated human mobility indicators and the incidence of COVID-19 for data collected in urban and rural areas, likely reflecting varying qualities of data underlying aggregated measures (Kishore et al., 2022).

Despite the limitations and uncertainties inherent in aggregated measurements of human mobility, these data served as a crucial means of measuring responses to the COVID-19 pandemic, including adherence to social distancing measures and the transition to WFH. The timing of arrival and the rapid spread of infection meant that there was little official information available to guide government policy responses, or to understand rapid behavioural changes caused by successive government interventions (Grantz et al., 2020). To fill this informational gap, mobility data from technology service providers were used to measure near-real-time changes in WFH and other social distancing behaviours. While mobility data were a key source of information during the early pandemic, the degree to which such aggregated measurements of mobility correspond to those behaviours driving longer-term patterns of WFH is debatable. The extent to which these new forms of data can support research in the intercensal period remains unknown.

1.4 | Objectives and paper overview

We analysed geographical patterns of WFH recorded in the 2021 Census, and assess their relationship to the estimated number of WFH individuals derived from indicators of human mobility, collected by Google in different environmental settings. Additionally, we considered whether aggregated measures of human mobility can be used in the future to reliably predict WFH patterns. To do so, we pursued the following four objectives:

1. Explore the geography of WFH as recorded by the 2021 Census.
2. Assess the suitability of mobility data for triangulating WFH patterns reported in the 2021 Census.
3. Compare WFH changes presented by mobility data and census statistics, specifically in relation to the characteristics of Local Authority Districts (LADs).
4. Explore the potential to predict WFH patterns beyond the date of census data collection.

2 | METHODS

2.1 | Measuring WFH behaviours from the decennial census

Census data were obtained for England for three decennial censuses (2021, 2011 and 2001), at Local Authority District level (LAD hereafter) to align with the geography of available mobility data (Google). In all years, the census has asked about travel to work behaviours, with people, who have fixed workplaces, answering what their primary method of travel to work is, from a range of options including 'driving a car or van', 'on foot', 'train' or 'work mainly at or from home'. For each year, the total number of people who answered 'work mainly at or from home' were extracted, and converted to a proportion of the total population in that LAD. This measure assumes a constant denominator by accounting for the number of people who reported this answer, relative to the total population in each LAD (Rae, 2017). However, a major challenge when working with longitudinal data at LAD level is local government restructuring (Lomax, 2022), which results in alterations to the size and boundaries of LADs. For example, prior to 2019, 'Dorset' comprised eight geographical areas that were merged into two, similarly Northamptonshire went from seven to two areas in 2021 (Office for National Statistics, 2023b). The effect of this was limited owing to unavoidable limitations in the aggregation of Google Community Mobility Reports to LAD level.

2.2 | Estimating WFH behaviours from Google Community Mobility Reports

Mobility data were obtained from Google Community Mobility Reports. These data were released between 15 February 2020 and 15 October 2022, describing changes in rates of mobility across different settings, and corresponding to LADs in England (Google, 2021). The sub-national units of aggregation were proprietary and defined by Google. However, researchers at the UK Office for National Statistics Data Science Campus created a lookup between the proprietary areas and recognised LADs (Office for National Statistics, 2023a). Despite this alignment, there were some unavoidable discrepancies between proprietary Google boundaries and 2019 LADs (Supporting Information Section 1: Appendix S1).

Data were collected from Google Maps users who opted into sharing their Location History with Google and allocated to six different settings: Residential, Workplaces, Transit Stations, Retail and Recreation, Grocery and Pharmacy, and Parks. Given the proprietary nature of such data, there are no publicly available metadata on the specific features of locations that comprised each setting. Also, the data comprised two different sets of human mobility measures. The first measures aggregate changes in the quantity of time that individuals spend in a Residential setting. The second set of indicators for other settings provide a count of the number of visitors to locations categorised as each setting. These two sets of measurements are not directly comparable because duration is bounded by the maximum length of a day, while the count of visitors is unbounded.

Mobility in each setting (e.g., Residential) and LAD (e.g., Camden) was reported as a relative change from baseline calculated in the four weeks prior to the release of the dataset, from 3 January to 6 February 2020 (Google, 2021). This choice of aggregation methodology prevents the disclosure of personally identifiable information, by obscuring information on the number of individuals contributing data to a specific measure. However, the use of a relative change from baseline (represented as a percentage) also raises challenges when comparing trends to the census WFH statistics, because Google mobility represents a change from a district- and setting-specific baseline which varies across districts.

2.3 | Comparison of census and mobility data WFH estimates

We modelled the relationship between the proportion of the population WFH as measured in the 2021 Census and the relative change in mobility measured by Google in individual LADs for different settings. Given that the census WFH data is a collection of estimates that represent the proportion of WFH individuals in the week prior to the census, we sought to extract a representative sample of the mobility data for comparison to the census. We therefore calculated the average weekday mobility within each setting in the four weeks prior to the date of the census, on the heuristic assumption that individuals reporting WFH patterns are more likely to work on weekdays than on weekends. This may introduce bias towards populations that regularly work on weekdays compared with those with variable working schedules. We provide the results of a sensitivity analysis of this assumption in Supporting Information Section 3: Appendix S1.

We then constructed a simple linear model (Equation 1) relating the proportion of WFH in each LAD as provided by the 2021 Census to the average relative change in activity in each setting as provided by the Google mobility data (see Equation 1). The purpose of this model is to provide an estimate of the change in the WFH proportion expected in individual LADs based on an observed change in mobility in a particular setting.

$$y = \text{Normal}\left(\alpha + \beta * x_k, \sigma\right) \tag{1}$$

where y is the proportion of WFH individuals in each LAD, α is the model intercept, and x_k is the relative change in mobility in setting k. β describes the model slope and σ is the standard deviation of the predictive distribution.

We fit each model in the Bayesian framework 'Stan' (Bürkner, 2022; Stan Development Team, 2023), specifying prior distributions for coefficients as simple normal distributions, Normal $(0, 1)$. The posterior predictive distribution is specified as a simple normal distribution truncated between 0 and 100. We assessed model convergence using the Gelman-Rubin statistic $(\hat{R}) = 1$ and bulk and tail effective sample sizes $> 10{,}000$ for each coefficient (Gelman & Rubin, 1992). Details of the model fitting and convergence diagnostics are provided in Supporting Information Section 4: Appendix S1.

2.4 | Comparison of WFH changes in mobility data and the census

To ascertain and confirm the nature of the relationship between census WFH statistics and Google mobility data, we considered how this translates into trends between individual LADs across England (see Section 3.4). For each LAD we calculated how WFH populations have changed from the 2001 Census to the 2021 Census, whilst for the Google mobility estimates we extracted the total difference in mobility on census day when compared with the same date in 2020. To unpack whether differences in WFH can be attributed to differences in socioeconomic characteristics between areas, additional ancillary datasets were used. Deprivation data for LADs (Ministry of Housing, Communities and Local Government, 2019) and the 2011 Local Authority rural–urban classification (Department for Environment, Food, & Rural Affairs, 2014) were joined onto the values of WFH for each LAD to enable exploration of differences in WFH behaviours between LADs with different characteristics.

2.5 | Forward projection of WFH estimates

After modelling and exploring the nature of the relationship between WFH estimates from the census and Google mobility data, we assessed whether the Google mobility data could be used to make viable predictions about future changes in WFH populations after the census date. As in Section 2.2, data in the four weeks prior to the census were used to fit the model. We then applied the model of mobility in the Residential setting fit according to the procedure in Section 2.3 to predict the WFH proportion in three time periods—three, six, and nine months after the census. We applied the model to the four-week average weekday mobility in areas Google labelled 'Residential'. There are no official data on WFH patterns beyond the census date. Therefore, it is not possible to assess the predictive validity of the model on time periods after the census. However, we highlighted areas where the model produces improbable estimates of WFH (such as LADs where WFH was much higher than reported in the census), indicating areas of instability in the model predictions, likely caused by variations in the quality of the Google mobility estimates.

3 | RESULTS

3.1 | Census 2021 WFH statistics

Figure 1 shows the proportion of people who identified as WFH in each census, where each dot corresponds to an individual LAD. What is apparent is that WFH behaviours remained relatively stable between the 2001 and 2011 Census, with LADs reporting an average value of 4.5% (2001) and 5.3% (2011) of the total population. This is different from those WFH behaviours reported in the 2021 Census, where an increase in the proportion of WFH is seen for all LADs, for example, the average value for LADs in 2021 was 14.7% (Figure 1). WFH trends are however most interesting when unpacking the geographical distribution of LADs. The majority of those LADs with the highest numbers of WFH can be found in London (e.g., Islington, City of London). Office for National Statistics (2021) described these differences as a result of differences in employment, specifically related to the types of occupations and industries found within London.

We examined how the level of deprivation in each LAD related to WFH, as previous research has demonstrated social inequalities in who could and could not WFH during (and after) the pandemic (Trasberg & Cheshire, 2021). The individual dots in Figure 1 were coloured by deprivation quintile. There is a clear deprivation gradient in WFH behaviour with more deprived LADs being more likely to experience lower prevalence of WFH, whilst WFH was more common in the least deprived LADs. Whilst this pattern occurs across the three censuses, the latest 2021 Census sees a widening of the distribution of WFH with an average increase of 12.8% for the least deprived quintiles compared with 8.2% for the most deprived quintiles. The exception to these patterns is London, where the links between deprivation and WFH become less clear. As discussed earlier, WFH was much more prevalent in London during the pandemic (Office for National Statistics, 2021), thus while some of the most deprived LADs in England can be found in London (e.g., Lambeth), these areas are still characterised by specific occupations and industries that were best suited to WFH during the pandemic, hence the high values in the 2021 Census. However, these differences in WFH populations between areas with differing industrial offerings remains difficult to empirically quantify, as suitable data at LAD level is absent, hindering efforts to explore the true nature of this relationship. The degree to which these changes are influenced by populations which are traditionally difficult to measure in the census (such as young men or students), those temporarily living in a secondary residence, is also unknown.

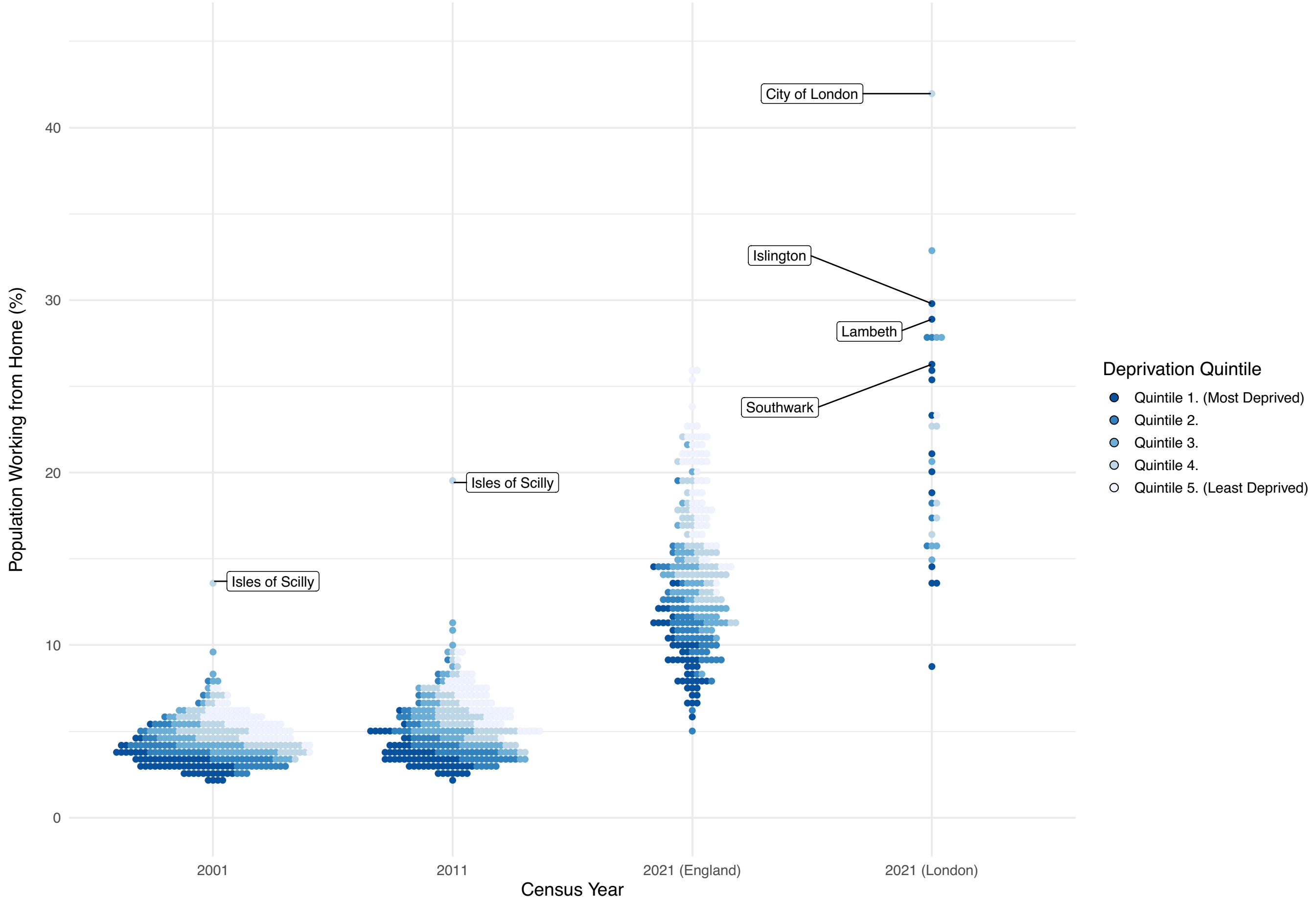


FIGURE 1 Historical changes in working from home (WFH), as defined by the census. Local Authority District (LAD) WFH populations across the previous three censuses and specifically in London for 2021, coloured by deprivation quintile to highlight the social gradient of WFH.

Figure 2 displays the absolute change in WFH for each LAD across England, highlighting that all LADs have experienced an increase in the WFH proportion. However, this increasing trend is spatially heterogeneous (Figure S1). Inner city London has seen the largest growth in WFH, with City of London LAD recording the highest increase in 2021 (33%). There are also higher values surrounding London, appearing to reflect commuting patterns into London (Office for National Statistics, 2020). LADs adjacent to other major cities have also experienced larger increases in WFH, such as South Cambridgeshire, St Albans, Trafford and Warwick. By contrast, many rural areas across Cornwall and Devon, East of England and the North of England experienced smaller increases in their WFH population. Such trends are likely related to the mix of employment types and occupations within these areas (e.g., farming, manufacturing), which could not be easily modified to be suitable for WFH.

3.2 | Human mobility and the timing of the 2021 Census

Figure 3 presents Google mobility data for different settings between February 2020 and October 2022. The data show an abrupt response to the first national lockdown interventions, with an increase in the amount of time users spent in Residential areas and a decrease in the number of visits to all other settings. This pattern is repeated in the two subsequent lockdowns (introduced in late 2020 and early 2021). While the second and third lockdowns were less stringent than the first national lockdown, they resulted in clear behavioural responses that are reflected in the Google data. The subnational trends in the Google mobility data mask variations in the level of activity across LADs (Figure S2). Broadly, the national pattern of decreased activity during periods of lockdown interventions are reflected across LADs; however, there are notable differences in the degree to which activity was reduced in Residential settings in the first lockdown

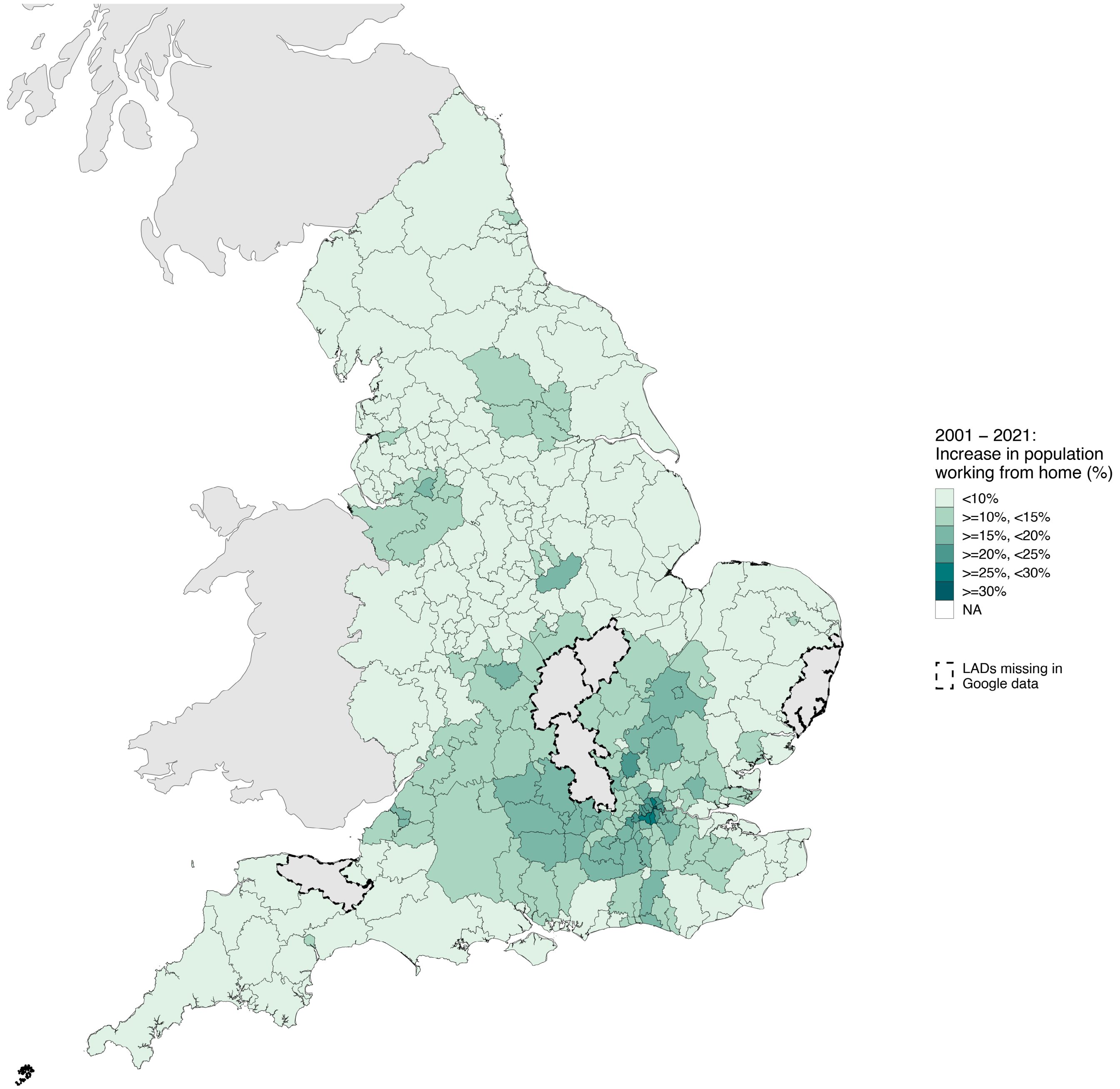


FIGURE 2 Change in working from home (WFH) populations for Local Authority Districts (LADs) across England. The percentage increase in population WFH in LADs between the 2011 and 2021 censuses.

period. For example, the increase in Residential activity varied between 23% and 42% during the height of the first national lockdown, and between −90% and −61% for Workplace activity. This heterogeneity, though reduced, also exists around the census date, when the change in Residential activity varied from 6% to 11% and Workplace mobility varied from −41% to −1% (Table S2).

3.3 | Modelling census WFH using Google mobility data

We modelled the relationship between the proportion of WFH individuals in each LAD and the average change in weekday mobility activity in individual settings in the four weeks preceding the census date. First, we explored the correlation between the proportion of WFH individuals in LADs and change in mobility in each setting (Figure S3), finding

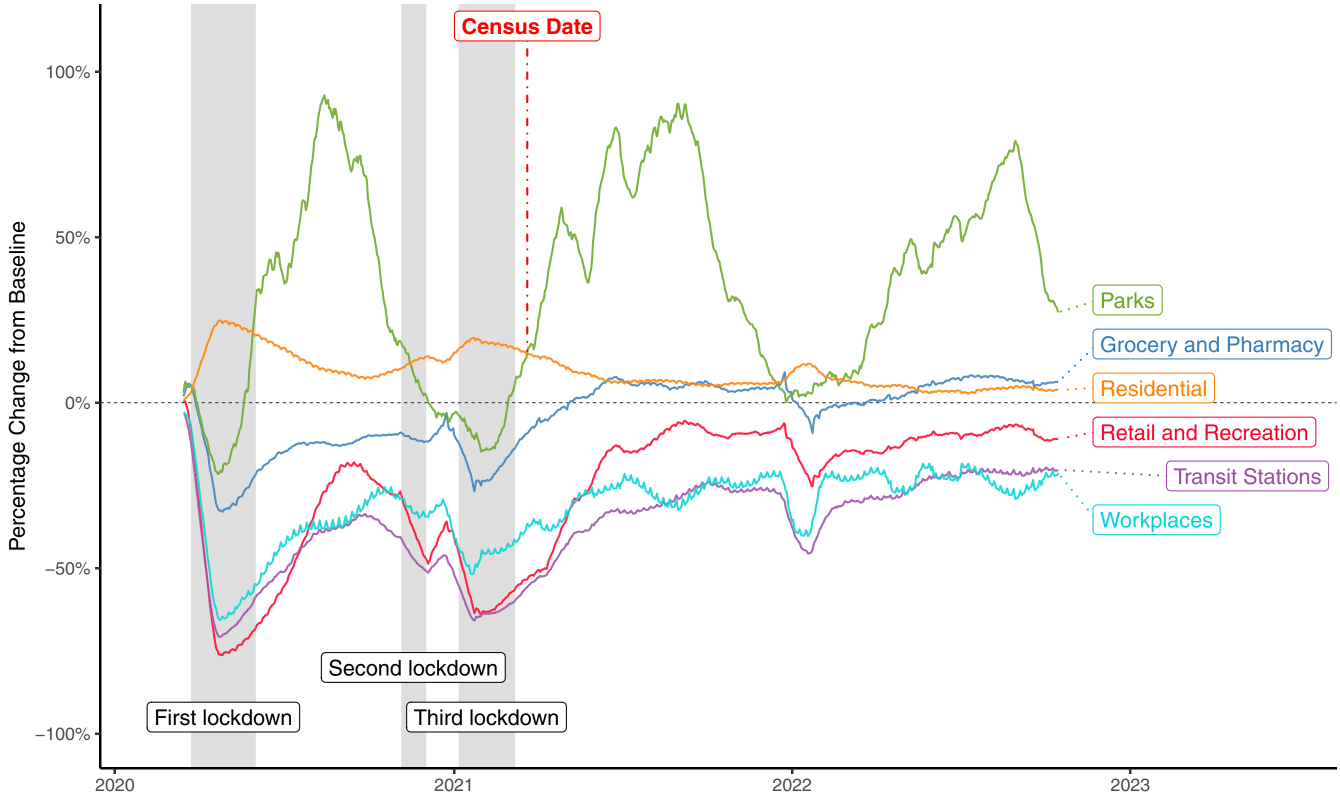


FIGURE 3 Mobility indicators in different settings. Change in mobility indicators in different settings relative to the census data. Mobility indicators have been smoothed with a 30 day moving average for display. Shaded areas indicate the timing of national lockdown interventions in England. The first and third lockdowns were ended in phases. The end of both shaded areas indicates the date of the beginning of phased reopening of schools: first lockdown 1 June 2020, third lockdown 8 March 2021.

that activity in the Residential and Workplace settings was highly correlated with the proportion of WFH individuals ($R=0.93$ for the Residential setting and $R=0.86$ for the Workplace setting). Mobility in other settings (Transit Stations, Grocery and Pharmacy, and Retail and Recreation) had moderate association with the proportion of WFH individuals (R between 0.35 and 0.53). Mobility changes in parks had no relationship with WFH ($R=-0.07$). We also found that certain indicators had high covariance, meaning that they tended to be correlated with one another. Comparing the correlation of mobility change in the Residential, Workplace, and Transit Stations settings with each other, we found that all comparisons had a minimum correlation of $R=0.63$.

We then modelled the relationship between the change in mobility activity in each setting and the proportion of WFH individuals (Figure 4). We found clear relationships between the changes in activity in the Residential and Workplace settings and the proportion of WFH individuals in LADs. Our model identified a model slope of 1.41 for Residential activity and −0.53 for Workplace activity (Figure S4, Table S3). These values indicate the amount of change expected in the WFH proportion resulting from a 1% change in mobility in each setting. Our model predicted relationships for all other settings between −0.32 and −0.23, except for the Parks setting, which was not able to predict any variation in WFH proportion based on changes in mobility. Mobility in the Grocery and Pharmacy setting also appeared to have a predicted relationship similar to other settings (Retail and Recreation, Transit Stations) largely due to a small number of outliers.

3.4 | Comparison of census and mobility change

In order to evaluate whether new forms of data can effectively capture underlying population changes between censuses, we directly compared WFH behaviours, as recorded by the census and Google mobility data. From Section 3.3, Google mobility data appear to align closely with census WFH estimates. However it is also important to consider whether

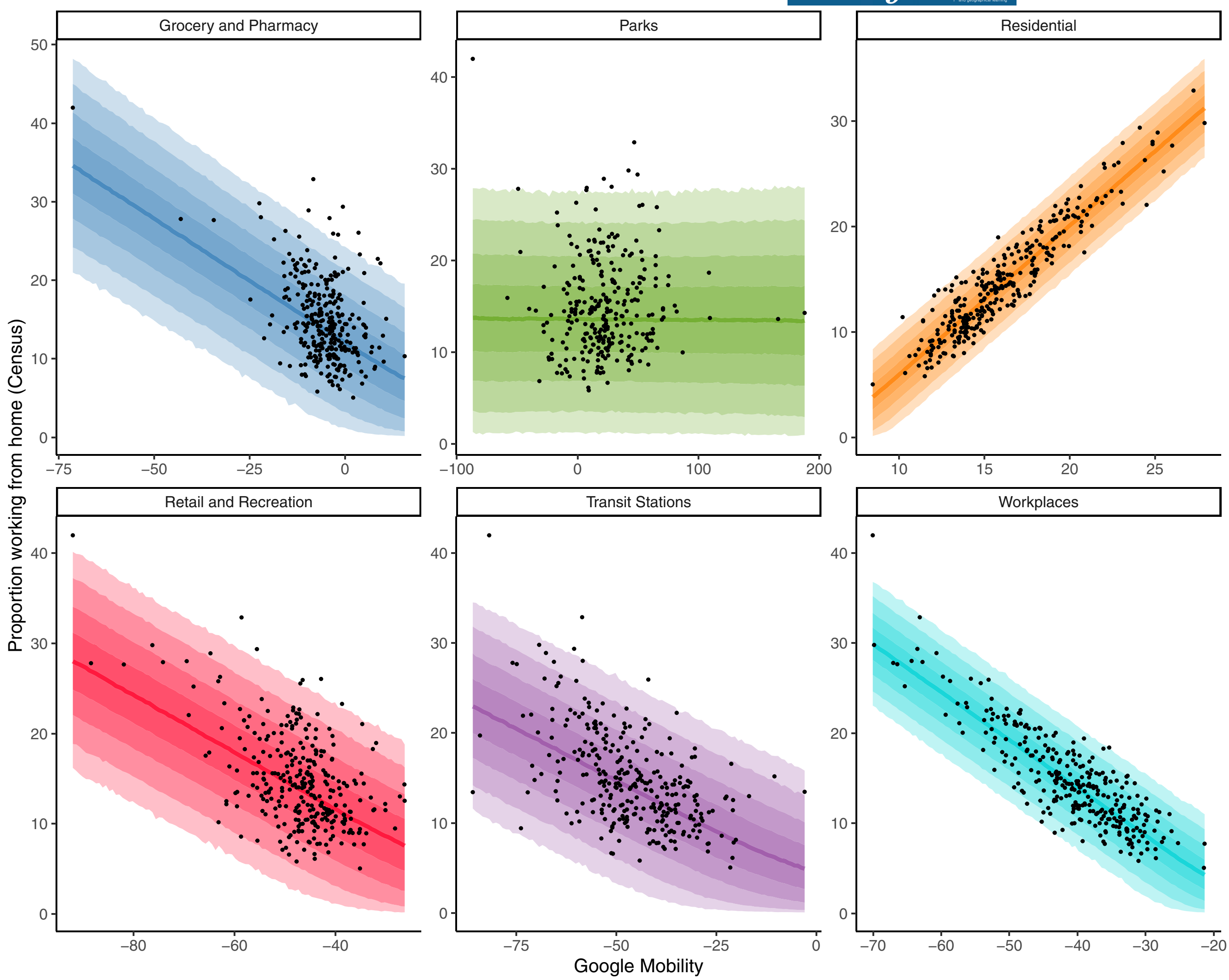
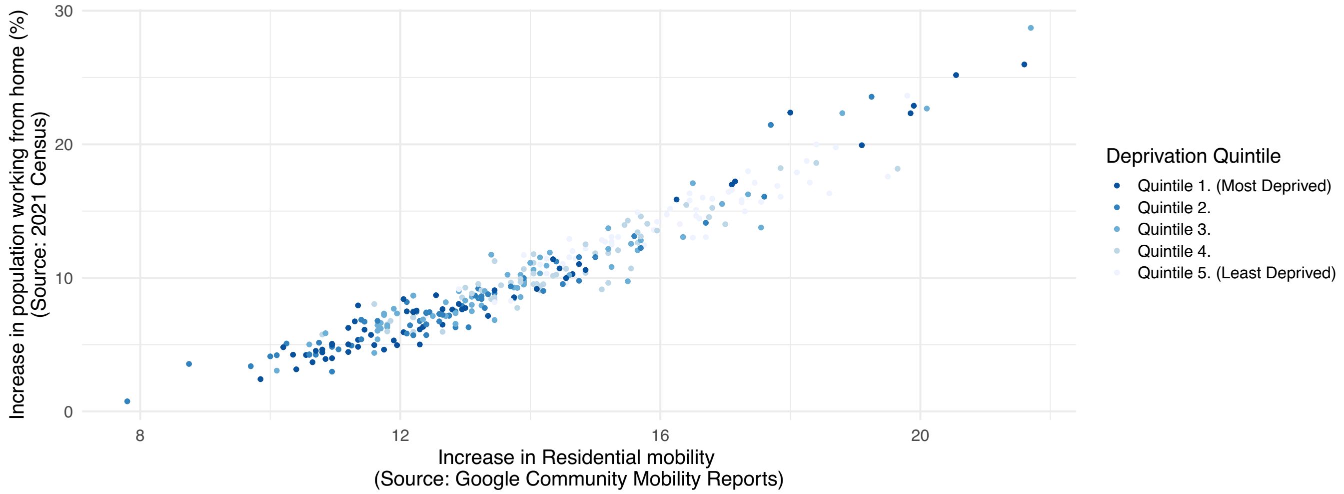


FIGURE 4 Predictions of working from home (WFH) using mobility in different settings. The predicted relationship between the proportion of individuals WFH in Local Authority Districts (LADs) and Google mobility in different settings. Shading indicates 99%, 95%, 80% and 50% credible intervals for regression models for each setting.

changes in WFH in both mobility data and the census were closely associated with the social and demographic characteristics of LADs, to highlight possible explanations for differences in WFH across LADs. Figure 5 demonstrates that increases in WFH as derived from the 2021 Census and Google mobility data (see Section 2.4 for calculation of change) followed a linear pattern as in Figure 4; the LADs in England that experienced the greatest uplifts in WFH from the 2011 Census were also those to experience the greatest uplifts in time spent in residential areas when compared with pre-pandemic levels. However, there are interesting differences when relating such changes to patterns of material deprivation and rurality. For example, it appears that the least deprived and most urbanised LADs across England were those to experience the greatest uplift in WFH, whilst those more deprived and mainly rural LADs were those that experienced the smallest. There remains a question about the recording of Residential activity in rural areas and its impacts on these trends, given existing literature illustrating the urban bias of mobility datasets (e.g., Ballantyne et al., 2022). However, by presenting the change this way, accounting for both the 2021 Census and Google mobility estimates, the impact of such bias appears to be minimal, as WFH changes in mobility data are closely associated with census changes. Furthermore, this also provides support for the use of mobility data as a proxy for population mobility (Rowe et al., 2023), as we have been able to evidence a strong relationship between the 2021 Census and Google Community Mobility Reports for examining the geographies of WFH. Our findings therefore suggest that new forms of data have the potential to generate new insights in the intercensal period.



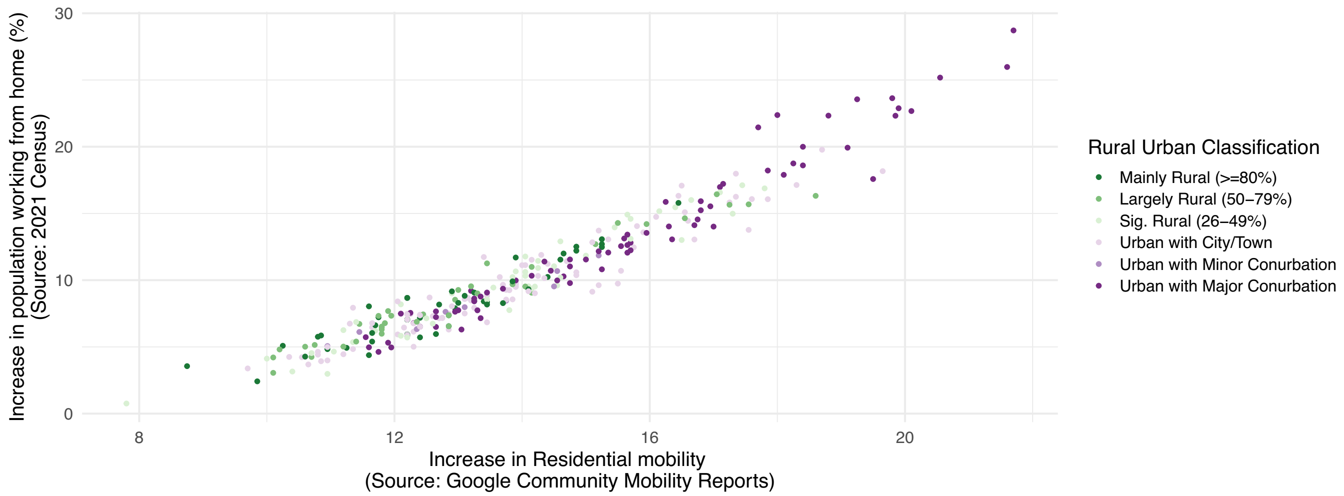


FIGURE 5 Comparing working from home (WFH) changes between the 2021 Census and Google Community Mobility Reports. Change in WFH is calculated for each Local Authority District (LAD), with change from 2011 to 2021 used for census estimates (top), and change from census date and same date in 2020 used for Google mobility (bottom). LADs are coloured by deprivation decile and rural urban classification to highlight area characteristics associated with greater increases.

3.5 | Forward projection of WFH patterns

Using the model from Section 3.3 of the relationship between WFH proportion and change in time spent in residential areas, we predicted the WFH proportion in each LAD three, six and nine months after the census date (Figure 6). In the first prediction, three months after the census, the model predicted far higher WFH proportions than measured in the census. Many predictions were >5% compared with 10–20% in the census WFH data (Figure 1). Over time, the model predictions decreased, likely reflecting a relative decrease in the proportion of WFH. However, considering the data recorded in the census and the magnitude of changes in WFH patterns over the decades between 2001, 2011 and 2021, we consider that, while the predicted direction of change in WFH may be accurate, the magnitude of these changes was likely erroneous. The model used for prediction was fit for a specific period (coinciding with the date of the census) and does not account for seasonal and random variations in the mobility data. These findings show that, while at a single time point, Google mobility may be indicative of the relative differences in the WFH proportion across LADs, the data include temporal variations that do not consistently reflect WFH behaviours over time. These variations must be accounted for before these data can be used to reliably project WFH patterns beyond the census, suggesting that the potential of mobility data to supplement official statistics in the intercensal period might not be so certain.

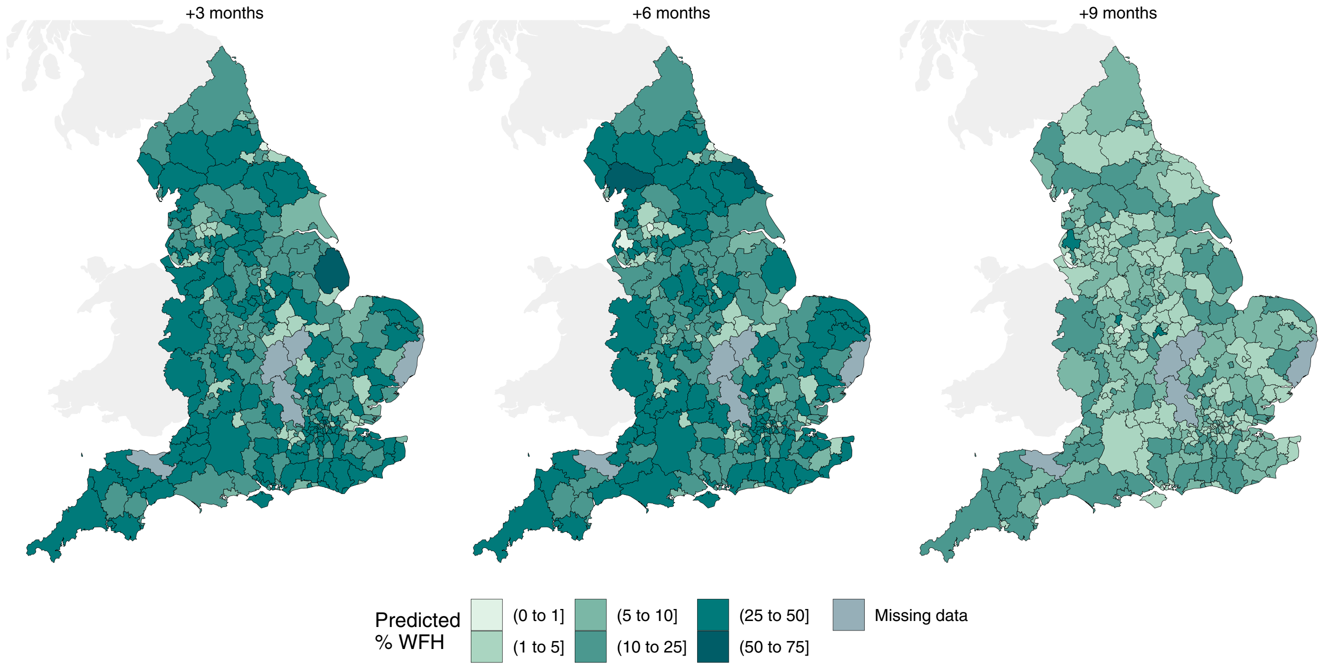


FIGURE 6 Prediction of working from home (WFH) proportion beyond the census. Predicted WFH proportion in individual Local Authority Districts (LADs) 3, 6 and 9 months after the 2021 Census.

4 | DISCUSSION

This paper has provided an overview of how WFH patterns in England have changed relative to previous censuses, how WFH patterns were influenced by the COVID-19 pandemic, and how novel forms of data can be used to estimate WFH patterns. These insights have contributed new knowledge about the potential of new forms of data to capture changes in the characteristics and behaviours of the population between censuses. First, we presented an overview of the geography of WFH in England, noting the significant growth of WFH in the 2021 Census compared with 2001 and 2011. We also highlighted interesting variations in the change in WFH, particularly in London. Second, we considered whether Google mobility data could be used to triangulate trends observed with the 2021 Census, finding a clear correspondence between census WFH data and activity in Residential and Workplaces reported by Google Community Mobility Reports. Third, we examined the changes in WFH in relation to the socio-demographic characteristics of LADs, identifying significant growth in WFH for the least deprived LADs across England, a trend that is less clear for London, where WFH populations remained high. Finally, we considered the predictive potential of Google mobility data, finding that the data were sufficient to predict the direction of change in WFH after the census, but that estimates of the magnitude of these changes were likely not credible. This reflects the limitations of the modelling framework used in this paper, and invites further research to account for seasonal variations in mobility data while predicting WFH patterns.

Our analysis shows that WFH has increased with the spread of WFH technologies during the COVID-19 pandemic as well as the adoption of flexible working schedules by many employers (Office for National Statistics, 2021). While our results show that the increase in WFH persisted into 2021, beyond the severe disruption of the first national lockdown, there remain significant questions about how this trend will develop in the future. Our modelling results indicate that WFH is likely to have decreased after the census date, but without validation data we cannot be certain of the accuracy of this prediction. If the rate of WFH in England remains elevated, this will likely influence how local communities will adapt to lower levels of commuting, which may limit the economic activity brought by office workers in central business locations, while increasing economic activity in more residential areas. The increased quantity of WFH may also have impacts that vary by socio-demographic characteristics such as deprivation. As we show in this paper, higher levels of WFH outside of London are associated with lower socioeconomic deprivation. If WFH remains elevated in low deprivation areas, this may reinforce regional inequalities. In contrast, UK national government planning is currently focused on decreasing such persistent regional disparities and it is plausible that the new geography of WFH may complicate efforts to respond to longer-term structural inequalities (Blundell et al., 2020; Department for Levelling Up, Housing and Communities, 2022).

Whilst our paper has demonstrated the interesting associations between new forms of data and the census in examining the geographies of WFH in England, this analysis has limitations that must be considered. First, for new sources of data to directly replace the census, reliable sources of mobility data are needed at high geographical resolutions for comparison with census estimates on a range of different topics (e.g., population distribution, housing, ethnicity). This is particularly necessary as in Section 3.1 we suggested that differences in WFH populations between LADs are likely to be related to the types of industries and employment available in those areas, something we cannot empirically assess without more granular mobility data. Also, exclusion of some English LADs due to discrepancies between Google and census LAD boundaries meant that we were unable to ascertain the nature of these relationships for missing LADs (e.g., Northamptonshire), and for other countries such as Wales and Scotland, due to a lack of suitable mobility and/or census data. It is also important to note that use of census data describing the 'method of travel to work' might not capture movement of specific workers who do not have a fixed workplace (e.g., construction workers), thereby affecting direct comparability with Google mobility reports, something which could be investigated by future research.

There are also limits to the Google mobility data, including the calculation of mobility change relative to a baseline which removes information on the different quantities of activity across districts, and obscures information on the sample size contributing to each indicator. Additionally, the mobility data contain variations which may represent changes in user behaviour, rather than changes in activity (such as a lack of device usage around the holiday period in 2022). There is also an absence of public information on the social and demographic characteristics of Google maps users, or the types of individual behaviours represented by the Location Histories used to calculate aggregated measures of mobility. Our choice to calculate the average change in weekday mobility may further bias our estimates of mobility towards individuals with regular work on weekdays, which may bias mobility estimates towards certain socio-demographic groups. Finally, given the inclusion of two types of mobility measures in Google Community Mobility Reports, each measure cannot be compared across all settings. A valid comparison of each measure would require that both measures were captured in the same settings. Intuitively, we expect that time spent in residential areas will be more predictive of WFH patterns, making it impossible to assess whether duration spent in residences is a better measure of WFH behaviours compared with the number of visits to residences.

Perhaps the most important question this paper answers is whether new forms of data, such as mobility data from providers like Google, can offer robust statistics in the intercensal period. As we have shown, through examination of the spatial and temporal trends of increasing WFH behaviours during the pandemic, and over the last three censuses, Google mobility data appears to provide a meaningful proxy measurement of WFH behaviours at the time of the census. This is an important finding since it suggests that these new forms of data can capture underlying population changes. At a time when the future of the UK census is being reviewed, these data may offer valuable population insights at a significantly lower cost compared with the census (Lansley & Cheshire, 2018). With sufficient validation, aggregated measures of human mobility could supplement, augment or even replace official statistics (especially if combined with other administrative and survey data), and support research at a greater temporal resolution, instead of every 10 years. However, as demonstrated in Section 3.5, this is not yet feasible as forecasts of WFH behaviours beyond the census period proved unsuccessful. More work is needed to better understand the implicit uncertainties within these novel datasets, such as the lack of transparency regarding the characteristics of the individuals represented by the data, and how this sample changes over time (Buckee et al., 2020). Whilst our research demonstrates that new forms of data are not yet ready to replace the census, it provides evidence that these data still have a role to play, especially in intercensal periods where changing trends are not known or visible. This invites future research which can more accurately characterise and resolve the limitations of mobility data, thereby allowing their use to measure a range of social behaviours traditionally measured by the decennial census (Rowe et al., 2023).

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DATA AVAILABILITY STATEMENT

This study relies on publicly available data sources. The datasets used in this study are referenced in the bibliography.

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REFERENCES

Al-Maroof, R.S., Salloum, S.A., Hassanien, A.E. & Shaalan, K. (2020) Fear from COVID-19 and technology adoption: The impact of Google meet during coronavirus pandemic. *Interactive Learning Environments*, 31, 1293–1308. Available from: https://doi.org/10.1080/10494820.2020.1830121

Angel, A., Cohen, A., Dalyot, S. & Plaut, P. (2022) Impact of COVID-19 policies on pedestrian traffic and walking patterns. *Environment and Planning B: Urban Analytics and City Science*, 50, 1178–1193. Available from: https://doi.org/10.1177/23998083221113332

Badr, H.S., Du, H., Marshall, M., Dong, E., Squire, M.M. & Gardner, L.M. (2020) Association between mobility patterns and COVID-19 transmission in the USA: A mathematical modelling study. *The Lancet Infectious Diseases*, 20(11), 1247–1254. Available from: https://doi.org/10.1016/S1473-3099(20)30553-3

Ballantyne, P., Singleton, A. & Dolega, L. (2022) Using unstable data from mobile phone applications to examine recent trajectories of retail Centre recovery. *Urban Informatics*, 1(1), 21. Available from: https://doi.org/10.1007/s44212-022-00022-0

Bergman, N.K. & Fishman, R. (2020) Correlations of mobility and Covid-19 transmission in global data. *MedRxiv*, 2020, 05.06.20093039. Available from: https://doi.org/10.1101/2020.05.06.20093039

Blundell, R., Costa Dias, M., Joyce, R. & Xu, X. (2020) COVID-19 and inequalities. *Fiscal Studies*, 41(2), 291–319. Available from: https://doi.org/10.1111/1475-5890.12232

Buckee, C.O., Balsari, S., Chan, J., Crosas, M., Dominici, F., Gasser, U. et al. (2020) Aggregated mobility data could help fight COVID-19. *Science*, 368(6487), 145–146. Available from: https://doi.org/10.1126/science.abb8021

Bürkner, P.-C. (2022) *Brms: Bayesian regression models using* '*Stan*' (2.18.0). Available from: https://cran.r-project.org/web/packages/brms/brms.pdf [Accessed 11th September 2022].

Catney, G., Lloyd, C.D., Ellis, M., Wright, R., Finney, N., Jivraj, S. et al. (2023) Ethnic diversification and neighbourhood mixing: A rapid response analysis of the 2021 census of England and wales. *The Geographical Journal*, 189(1), 63–77. Available from: https://doi.org/10.1111/geoj.12507

Clark, H. (2021) *Examining the end of the furlough scheme*. Available from: https://commonslibrary.parliament.uk/examining-the-end-of-the-furlough-scheme/

Coombes, M. (2002) *Travel to work areas and the 2001 census*. Newcastle University. https://api.semanticscholar.org/CorpusID:162553431

Coston, A., Guha, N., Ouyang, D., Lu, L., Chouldechova, A. & Ho, D.E. (2021) Leveraging, Administrative data for bias audits: Assessing disparate coverage with mobility data for COVID-19 policy. *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*, 173–184. Available from: https://doi.org/10.1145/3442188.3445881

Credit, K. & Arnao, Z. (2022) A method to derive small area estimates of linked commuting trips by mode from open source LODES and ACS data. *Environment and Planning B: Urban Analytics and City Science*, 50, 709–722. Available from: https://doi.org/10.1177/23998083221129614

Deole, S.S., Deter, M. & Huang, Y. (2023) Home sweet home: Working from home and employee performance during the COVID-19 pandemic in the UK. *Labor Economics*, 80, 102295. Available from: https://doi.org/10.1016/j.labeco.2022.102295

Department for Environment, Food & Rural Affairs. (2014) *2011 local authority rural urban classification*. Department for Environment, Food & Rural Affairs. Available from: https://www.gov.uk/government/statistics/2011-rural-urban-classification-of-local-authority-and-other-higher-level-geographies-for-statistical-purposes

Department for Levelling up, Housing and Communities. (2022) *Levelling up the United Kingdom*. GOV.UK. Available from: https://www.gov.uk/government/publications/levelling-up-the-united-kingdom

Dodge, S. & Nelson, T.A. (2023) A framework for modern time geography: Emphasizing diverse constraints on accessibility. *Journal of Geographical Systems*, 25, 357–375. Available from: https://doi.org/10.1007/s10109-023-00404-1

Dorling, D. (2021) *Census 2021 will reveal how a year of lockdowns and furlough has transformed the UK*. The conversation. Available from: http://theconversation.com/census-2021-will-reveal-how-a-year-of-lockdowns-and-furlough-has-transformed-the-uk-157337

Gelman, A. & Rubin, D.B. (1992) Inference from iterative simulation using multiple sequences. *Statistical Science*, 7(4), 457–472. Available from: https://doi.org/10.1214/ss/1177011136

Gibbs, H., Waterlow, N.R., Cheshire, J., Danon, L., Liu, Y., Grundy, C. et al. (2022) Population disruption: Observational study of changes in the population distribution of the UK during the COVID-19 pandemic. *Wellcome Open Research*, 7, 243. Available from: https://doi.org/10.12688/wellcomeopenres.18358.1

Google. (2021) *Overview—Community mobility reports help*. Available from: https://support.google.com/covid19-mobility/answer/9824897?hl=en&ref_topic=9822927

Grantz, K.H., Meredith, H.R., Cummings, D.A.T., Metcalf, C.J.E., Grenfell, B.T., Giles, J.R. et al. (2020) The use of mobile phone data to inform analysis of COVID-19 pandemic epidemiology. *Nature Communications*, 11(1), Article 1. Available from: https://doi.org/10.1038/s41467-020-18190-5

Greater London Authority. (2022) *Coronavirus* (*COVID-19*) *mobility report*. *London datastore*. Available from: https://data.london.gov.uk/dataset/coronavirus-covid-19-mobility-report

Institute for Government. (2022) *Timeline of UK government coronavirus lockdowns and restrictions*. Institute for Government. Available from: https://www.instituteforgovernment.org.uk/data-visualisation/timeline-coronavirus-lockdowns

Jacobsen, G.D. & Jacobsen, K.H. (2020) Statewide COVID-19 stay-at-home orders and population mobility in the United States. *World Medical & Health Policy*, 12(4), 347–356. Available from: https://doi.org/10.1002/wmh3.350

Kishore, N., Taylor, A.R., Jacob, P.E., Vembar, N., Cohen, T., Buckee, C.O. et al. (2022) Evaluating the reliability of mobility metrics from aggregated mobile phone data as proxies for SARS-CoV-2 transmission in the USA: A population-based study. *The Lancet Digital Health*, 4(1), e27–e36. Available from: https://doi.org/10.1016/S2589-7500(21)00214-4

Lansley, G. & Cheshire, J. (2018) Challenges to representing the population from new forms of consumer data. *Geography Compass*, 12(7), e12374. Available from: https://doi.org/10.1111/gec3.12374

Lomax, N. (2022) Internal migration: Census data as a gold standard for insight and visualisation. *Journal of Maps*, 18, 543–550. Available from: https://doi.org/10.1080/17445647.2022.2046655

Ministry of Housing, Communities and Local Government. (2019) *English indices of deprivation 2019*. GOV.UK. Available from: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2019

Office for National Statistics. (2020) *Travel to work areas (Dec 2011) BGC in United Kingdom*. Available from: https://geoportal.statistics.gov.uk/datasets/ons::travel-to-work-areas-dec-2011-bgc-in-united-kingdom-1

Office for National Statistics. (2021) *Economic activity and social change in the UK, real-time indicators*. Available from: https://www.ons.gov.uk/economy/economicoutputandproductivity/output/bulletins/economicactivityandsocialchangeintheukrealtimeindicators/29july2021

Office for National Statistics. (2022) *Is hybrid working here to stay?* Office for National Statistics. Available from: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/ishybridworkingheretostay/2022-05-23

Office for National Statistics. (2023a) *Google-mobility-reports-data*. Data Science Campus. Available from: https://github.com/datasciencecampus/google-mobility-reports-data

Office for National Statistics. (2023b) *Local government restructuring*. Available from: https://www.ons.gov.uk/methodology/geography/ukgeographies/administrativegeography/ourchanginggeography/localgovernmentrestructuring

Open Data Bristol. (2020) *Mobility data COVID-19*. Available from: https://opendata.bristol.gov.uk/explore/dataset/google_mobility_data/

Rae, A. (2017) The geography of travel to work in England and Wales: Extracts from the 2011 census. *Applied Spatial Analysis and Policy*, 10(4), 457–473. Available from: https://doi.org/10.1007/s12061-016-9196-0

Rowe, F., Calafiore, A., Arribas-Bel, D., Samardzhiev, K. & Fleischmann, M. (2023) Urban exodus? Understanding human mobility in Britain during the COVID-19 pandemic using meta-Facebook data. *Population, Space and Place*, 29(1), e2637. Available from: https://doi.org/10.1002/psp.2637

Savage, M. (2021) *Emergency census in 2026 'needed to show true picture of UK'*. The observer. Available from: https://www.theguardian.com/uk-news/2021/mar/14/danny-dorling-emergency-census-2026-true-state-uk

Song, Y., Lee, S., Park, A.H. & Lee, C. (2022) COVID-19 impacts on non-work travel patterns: A place-based investigation using smartphone mobility data. *Environment and Planning B Urban Analytics and City Science*, 50, 642–659. Available from: https://doi.org/10.1177/23998083221124930

Stan Development Team. (2023) *Stan modeling language users guide and reference manual* (2.21.0). Available from: https://mc-stan.org

Trasberg, T. & Cheshire, J. (2021) Spatial and social disparities in the decline of activities during the COVID-19 lockdown in greater London. *Urban Studies*, 60, 1427–1447. Available from: https://doi.org/10.1177/00420980211040409

UK Data Service. (2021) *Census 2021/2022 could be the most important census in decades*. UK Data Service. Available from: https://ukdataservice.ac.uk/2021/03/12/census-2021-2022-could-be-the-most-important-census-in-decades/

Wesolowski, A., Eagle, N., Noor, A.M., Snow, R.W. & Buckee, C.O. (2013) The impact of biases in mobile phone ownership on estimates of human mobility. *Journal of the Royal Society Interface*, 10(81), 20120986. Available from: https://doi.org/10.1098/rsif.2012.0986

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Figure S1. Comparison of Local Authority Districts' work from home proportions to the national average for 2011 and 2021.
Figure S2. Google mobility in Local Authority Districts.
Figure S3. Correlation plots for Google mobility in different settings.
Figure S4. The posterior distributions of regression model mobility coefficients in different settings.
Table S1. Inconsistencies between Google-defined districts and Local Authority Districts.
Table S2. The distribution of mobility activity across LADs.
Table S3. Coefficient estimates and credible intervals.
Table S4. Sensitivity analysis of regression results.
Table S5. Regression model convergence diagnostics.

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