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Not going out during the Covid-19 pandemic? A multilevel geographical analysis of UK Google Mobility Reports, February 2020–December 2021

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Abstract

The analysis reported in this paper uses Google Mobility Reports to understand subnational trends in population spatial immobility/mobility in the United Kingdom during 2020 and 2021. Using multilevel modelling, it analyses how spatial mobility changed through time in response to the strictness of government lockdown and the annual seasonal cycle of public holidays, and between places in terms of their population composition as measured by the shares of the highly-educationally qualified and the self-employed. The results show that there are no consistent differences between the nations of the United Kingdom; that time spent at home increased with the severity of lockdown; that the share of highly qualified was also a good predictor of staying at home; and that there were major effects from public holidays. The analysis did not explain all the variation between places and dates; it is suggested that this is because of randomisation of the data by Google and unmodelled factors such as tiered restrictions.

KEYWORDS
Covid, lockdown, spatial mobility

1 | INTRODUCTION

As the World Health Organisation declared Covid a pandemic in March 2020 the UK Government instructed people to stay at home wherever possible to limit the spread of the disease. This was part of a wide-ranging set of government measures that restricted social and spatial interactions for leisure, retail, and social/family events in the United Kingdom and also in other countries (e.g., Boterman, 2022; Drake et al., 2020; Ilin et al., 2021). They were necessary in the absence of medical and pharmaceutical interventions at the start of the pandemic and were still required into 2021 to maintain control of infections to give time for the effects of vaccines and new treatments to be felt across the population. Devolution of health responsibilities across the four UK countries led to differing restrictions at different times. Furthermore, varying occupational mixes and local/regional social conditions were considered to create differences in the possibilities for staying at home (Centre for Cities, 2020) and in the vulnerabilities to furlough and redundancies (Blundell et al., 2020) for cities, towns and for other smaller spatial units. The contribution of the paper is to describe and analyse in retrospect the geography of the increase in time spent at home during the Covid pandemic, before the arrival of the Omicron Wave. It explores variations between England, Scotland, Wales and Northern Ireland and then assesses them for a subregional geography for the whole UK using a multilevel approach where days (i.e., measurement occasions) are our Level 1 unit of observation and sub-regional places are the Level 2 units.

It begins by considering some literature in this new and emergent areas to set the context for the analysis. It then describes the Google Mobility Reports data and the other datasets that were combined with it to provide contextual variables. It also outlines the multilevel modelling strategy that was used. The main findings are then presented and discussed.

2 | REVIEW OF PANDEMIC RESPONSES

The socioeconomic impacts of Covid have been experienced unequally in the United Kingdom and it has been argued that this reflects longstanding patterns of (health) inequalities (Bambra et al., 2020). It is well known that people who are poorer, with pre-existing health conditions, from ethnic minorities, and resident in densely-populated neighbourhoods have been at greater risk of catching and dying from the disease (Basellini et al., 2021; Blundell et al., 2020; Drefahl et al., 2020; Harris & Brunsdon, 2021; Hughes et al., 2021) in various European contexts. Moreover, these inequalities translate into complex geographies as the disease spreads through the population (Feng, 2021). Part of the reason for these unequal outcomes might lie in other social and economic inequalities that influence the ability of people to stay at home during lockdowns, and also variations in household size and composition (Bambra et al., 2020).

The potential for these inequalities in staying-at-home was spotted early in the pandemic when assessments were made of differential abilities to adapt to working from home (OECD, 2020). Here, it was noted that large cities were most prone to the spread of Covid because of higher population density but it was also conjectured that other factors could help them manage lockdowns better than other types of location. This was their capacity to facilitate remote working and to reduce visits and time in workplaces; and also access to high-speed internet for other social interactions and online/digital shopping. In the United Kingdom, the OECD (2020, p. 3) identified London as having the greatest prospects for remote working and the North–East region the least. This was attributable to occupational mix in the labour market, and the extent to which some jobs demanded workers to be physically present to perform their tasks. Indeed, the Centre for Cities (2020) demonstrates a clear patterning in the estimated propensity of workers who could work from home for the labour markets of British cities and towns. As might be expected, they show that major cities such as Edinburgh, Leeds, Cardiff, Manchester and London have good prospects for home working as have the university cities of Cambridge and Oxford. These contrast with urban centres such as Doncaster, Sunderland, Blackpool, Newport and Barnsley, which have labour markets with fewer remote working prospects.

The analysis is taken further by Blundell et al. (2020). They note that some economic sectors were ordered to close, namely nonretail, hospitality, and leisure, and for these employees would be furloughed or made redundant. This will naturally reduce daily visits to workplaces by those occupied in these sectors; and there is a corresponding reduction in visits by consumers to retail and leisure settings which were closed. Additionally, workplace visits can also be reduced when workers in sectors that are not locked down can and choose to work from home. In this situation, Blundell et al. (2020) suggest that workers who are highly qualified (with degrees or higher) are better able to work from home as are those in high-income jobs, and with higher-skills (OECD, 2020). Key workers—doing valuable jobs that cannot be done remotely—such as in social care, retailing, manufacturing and assembly—have disproportionate shares of lower-qualified people (on average) and are often in lower income bands. There are thus good reasons to expect occupational and qualification differences between places to influence the extent to which people could stay at home during lockdown across the UK.

There are other institutional reasons to assume that there will be geographical differences across the UK in responses to lockdown. Health is a devolved matter across the four countries of the United Kingdom (Greer, 2016) and so were anti-Covid policies. This governance framework has permitted country divergences in the duration, timing and breadth of lockdown with differing policies for hospitality, leisure, mask wearing and recommendations for home working. Not only this, but as UK lockdown stringency changed through time, central government in England and Scotland applied geographically differentiated restrictions to cope with spatial hot-spots of infection (Gore et al., 2021). The prime example of this is the use of restriction tiers in the Autumn and Winter of 2020–2021 with different parts of Scotland and England in various lockdown levels (Brown & Kirk-Wade, 2021).

All this context suggests four research hypotheses. The first is that there will be statistically significant differences between the UK home nations in changes in time spent at home. The second is that there will be statistically significant variations between places within each of these countries in time spent at home. The third is that a substantial part of this variation will be accounted for by socio-economic conditions and the educational qualifications of residents within these places. The final hypothesis is that lockdown rules had a major effect on mobility but this was overlaid on the regular cycle of the working week and the yearly routine of public holidays. In this vein we also consider whether the example of Dominic Cummings (the then Prime Minister's chief political adviser) led to an emulation effect as the general population ignored lockdown rules too (BBC News, 2020).

3 | DATA AND METHODS

3.1 | Data

Six mobility domains were collected and made available by Google; *retail_and_recreation*, *grocery_and_pharmacy*, *parks*, *transit_stations*, *workplaces* and *residential*. The main dependent variable we consider is time spent at home[1]. This is to give a focus on spatial immobility as most people spend most of their time at home whenever they are not

[1]In full, *Residential_percent_change_from_baseline*.

other active in the other five mobility domains. In addition, we consider changes in workplace visits and transit use as minor focuses—presenting the results in the appendix as further context. The data are freely available to download from Google Mobility Reports and are based on location histories captured by users of Google applications on mobile devices with a Google account (and have opted to keep location histories switched on). Random perturbations are added to preserve privacy and these data have been compiled and aggregated by Google for the United Kingdom and 130 other countries (Hu et al., 2021; Ilin et al., 2021). Additionally, information for certain dates or some places can be suppressed for reasons of privacy. Google published these mobility data during the Covid-19 pandemic principally to support the work of public health consultants and have indicated that they would cease to publish new reports from Autumn 2022 onwards (Google LLC, n.d). They provided limited detailed information about data capture and representativeness, but the data has been used by the ONS and in other academic publications (e.g., ONS, 2022; Cot et al., 2021; Drake et al., 2020).

The Google Mobility Reports data show "…how visitors to (or time spent in) categorised places change compared to our baseline days. A baseline day represents a *normal* value for that day of the week. The baseline day is the median value from the 5-week period January 3—February 6, 2020" (Google LLC, n.d). It is important to note that each day is measured against the median for the equivalent baseline day. Thus, Sundays are compared with Sundays, Mondays with Mondays, and so on. The outcome variable is thus relative to these fixed benchmarks. A possible shortcoming is that January and February are not representative of the entire year because of seasonality (Toger et al., 2020) but with this caveat, the data are robust. The data series used for this paper ran from February 15, 2020 to December 10, 2021.

The Tier 1 geography defined by Google was selected from the United Kingdom country reports for 2020 and 2021 and downloaded as a CSV file. There were 151 areas across the UK, 86 in England, 32 in Scotland, 22 in Wales and 11 in Northern Ireland. The full list is available in Table A1 (Supporting Information: Appendix 1) by country. As mentioned earlier, Google suppress information for some places or dates to safeguard confidentiality. For time spent at home, three Level 2 places are not included in the analysis—the Orkney Islands, the Shetland Islands and Na-hEileanan an Iar, for workplace visits there are data for all Level 2 units, and for transit only one Level 2 unit is excluded.

We have examined the geography used by Google in the mobility reports, and it does not fit explicitly into the European Nomenclature of Territorial Units for Statistics (NUTS) hierarchy, nor does it conform in a simple way to the statistical geographies generated by the three UK national statistical agencies. In fact, it appears to be an ad hoc combination of NUTS III council areas in Northern Ireland and metropolitan counties, council areas and ceremonial counties in other parts of the United Kingdom which was chosen by Google on the basis that they claim that it was relevant to public health professionals. There is the possibility of looking at smaller spatial scales in England only (e.g., the London Boroughs within Greater London) but this would be to forfeit the chance for consistent UK-wide analysis as the coarser higher-level geography is only available in Northern Ireland, for instance. We have thus opted to use these hybrid 'Google geography units' as a UK-wide common spatial denominator. Moreover, there is more missing data for dates and places for the lower-level Google geography, another reason to use the coarser all-UK geography.

Given the variables discussed in the review as differentiating the ability to stay at home for cities and regions, data were obtained from the NOMIS Local Authority Profiles (NOMIS, n.d.) on the population aged 16–64 with NVQ4+ qualifications and the percentage of self-employed workers (who in some cases might be assumed to be more vulnerable). For Northern Ireland data were obtained from the Northern Ireland Neighbourhood Information Service (NINIS, n.d.). For qualifications, the workforce proportion with NVQ4+ qualifications and the self-employed percentage for 2018 was sourced from the Labour Force Survey (NOMIS, n.d.). These were conceived as level-2 variables in the multilevel analysis design as described below.

To understand how staying at home changed through time, temporal indicator variables were created and included in models as fixed effects. Dummy variables were made for Christmas 2020, the Easter weekends of 2020 and 2021, the May Day and late May Bank Holidays of 2020 and 2021, the late August Bank Holidays of 2020, and 2021 New Year's Eve and New Year's Day 2020/21. Additionally, the additional New Year and St Andrew's Day (November 30th) Bank Holidays in Scotland in 2020 and 2021 were included as were St Patrick's Day (March 17th) in Northern Ireland and the July Boyne Bank Holiday in 2020 and 2021. These dummy variables were set to one when bank holidays occurred; and specifically, for example, in the case of St Andrew's Day and the Boyne Bank Holiday, the respective dummies were only applied to areas in Scotland or Northern Ireland where these holidays applied (UK Government, 2022).

To these were added the general UK Covid Stringency Index sourced from the University of Oxford (Hale et al., 2021). This was chosen, rather than the separate national indices, on the basis that with UK-wide media there was considerable spill over between different jurisdictions of health messages, and also because of the problems in sourcing data to include tiered restrictions as fixed effects. These differences will however be captured in the random parts of the models. Country differences in mobility within the United Kingdom were modelled by a series of dummies set to one when measurement occasions were located in areas in Scotland, Wales, or Northern Ireland, whilst England was used to represent the base category. The daily Central England Temperature (CET) was included as a measure of seasonality and the yearly cycle of weather was sourced from the United Kingdom Meteorological Office (Parker et al., 1992). Of course, there is considerable weather diversity across England on the same day, let alone the whole UK, so although this is a measure that is correlated to a greater or lesser extent with local temperatures across the whole country it does not provide precise information on local conditions. This variance in mobility can be modelled by the country dummies and Level 2 variation between the hybrid 'Google geography units'. A 'day of the week' series of dummies were also created with Saturday set as the base category. This was to explore/model the effects of different days of the week on mobility. Finally, a 'Cummings dummy' was set to one for the last week of May and the first week of June 2020 when the press coverage of his ill-conceived trip to Barnard Castle was at its height (BBC News, 2020). The reason for this was the argument made at the time that this behaviour eroded public support for the lockdown and it was thus thought of interest to see if this applied to workplace and other types of visit. These were modelled as level-1 (day varying) variables in the analysis design.

4 | METHOD

A multilevel approach was used (Goldstein, 2010; Gould et al., 1997). Level 1 units were measurement occasions and identified by date, running from 15/02/20 to 10/12/21, and Level 2 were the hybrid Tier 1 Google geography units listed in Appendix 1. The reasons for this were to explore/model geographical variations between the Level 2 units and to account for the clustering of dependent variables (i.e., mobility outcomes) within these units. The main theme of the analysis was to explore between and within unit variance, and to examine how far it can be 'explained' by the Level-2 contextual variables described above and the time-varying variables of lockdown stringency, holidays and festivals, and the seasonal rhythms. The explanatory variables are fully described in Supporting Information: Table A2 in the Appendix.

A series of hierarchical two-level measurement occasion nested within-places models which includes both fixed-effect dummy terms that relate specifically to measuring occasions distinguishing particular nations, days of the week and bank holidays, together with random 'intercepts' (i.e. means) allowed to vary between places, can be estimated and written thus:

$$y_{ij} = \beta_0 x_{0ij} + \beta_1 x_{1ij} + \beta_n x_{nij} + (\mu_{0j} x_{0ij} + \varepsilon_{0i} x_{0i})$$

Where:

y is the response variable and included here as residential, transit, or workplace visits;

i a subscript denoting individual measurement occasions—that is specific dates during the pandemic (level-1 units);

j a subscript denoting a specific hybrid Google area;

n a subscript denoting the last *nth* variable;

x_0 the constant;

x_1 a predictor measured either on a ratio-scale (e.g., Stringency Index) or included as a dummy binary variable (e.g., a particular bank holiday such as May Day);

β_0 the estimated intercept term;

β_1–β_n the estimated fixed-effect model terms associated with predictor variables;

ε_0 the level-1 random terms associated with specific measurement occasions;

μ_0 the level-2 random terms relating to hybrid Google areas.

The analysis uses the MLwiN software package (Rasbash et al., 2013). It starts by estimating a null model to capture Level 2 and Level 1 variance without any explanatory variables. Following this, the country dummies are entered into the analysis to estimate whether there are statistically significant differences between the UK nations. After this, the Level 2 contextual variables of the percentages of the working age population with NVQ4+ qualifications[2] and in self-employment are included with the main interest being in the reduction in Level 2 variances between places. Then the Level 1 variables beginning with the UK Stringency Index, the CET, the holiday dummies, and the Cummings Effect are entered into the model. Finally, the incremental modelling approach concludes by retaining all the terms previously entered in the model and adding the days-of-the-week dummies.

5 | RESULTS

We begin by presenting descriptive statistics that explore the residential outcome variable (eg staying at home) and then its relationship with the NVQ4+ contextual variable. Table 1 considers changes in time spent at home aggregated and averaged across the 151 Level 2 units. Everywhere recorded an increase with an average growth of just over 10 percentage points (pp), with the smallest increase in Moray at just under 7 pp and the largest in Wokingham—the home of the University of Reading—at nearly 16 pp. In considering these places, the highest increases are in cities and commuter areas which often have universities. The places with the lowest increases tend to be rural or more peripheral. This does not contradict the expectations noted earlier by the OECD and the Centre for Cities and may even go some way to confirming them. Figure 1 compares the place with the largest change (Wokingham) with the smallest (Moray). Through the study period, the growth over time (relative to the benchmark) spent at home varies in phase according to lockdown restrictions and seasonal/date effects (such as holidays) but there is a consistent differential between the two areas and the two lines never cross. They appear to respond to the same stimuli but at different relative levels. Figure 2 takes the analysis a little further by considering average change between places over the whole period of the analysis, comparing it with the proportion of the workforce with NVQ Level 4+ qualifications. There is overall a positive relationship—the greater the share of qualified people, the higher the change in time spent at home. It is by no means a perfect relationship but the coefficient of determination (R^2) at 0.46 indicates that nearly half of the variation between places is 'explained' by the educational composition of the population. This accords well with the type of places identified in Table 1 with very large/small changes in staying at home and also with the literature on what responses might

[2]Defined as having at least Licentiateship, Higher Professional Diploma, SVQ/NVQ level 4, Level 4 vocational awards, https://www.cityandguilds.com/qualifications-and-apprenticeships/qualifications-explained/qualification-comparisons.

TABLE 1 Top ranking areas for largest and smallest changes in changes from benchmark in staying-at-home (averaged across the Tier 1 geography).

	Changes in time at home, benchmark = 100
Minimum	6.96
Maximum	15.87
Mean	10.41
Standard deviation	1.81
Number	148
Largest change 10 areas	Smallest change 10 areas
Wokingham (largest)	Moray (smallest)
Edinburgh	Pembrokeshire
Reading	North–East Lincolnshire
Greater London	Dumfries and Galloway
Windsor and Maidenhead	Fermanagh and Omagh
Surrey	Argyll and Bute Council
East Renfrewshire Council	Rutland
Bristol City	Gwynedd
East Dunbartonshire	Ceredigion
West Berkshire	Isle of Anglesey

Source: Google LLC (n.d).

be expected to lockdown restrictions. It suggests, however, that there is considerable variation between places and this is explored more systematically in the modelled coefficients in Table 2 which presents the results from five multilevel models of increasing complexity.

The Null Model has only the constant and this coefficient, closely reflects the mean increase in time spent at home. Most (around 93%) of the variance is at Level 1 with just under 7% at Level 2 between places[3]. This indicates that there is far more day-to-day variability than there is between different places. The variance at Level 1 and at Level 2 is statistically significant[4]. Model 1 adds fixed effects for the United Kingdom countries. Only the coefficient for Wales is negatively (and statistically) significant (tested using Wald tests), suggesting that the increase in time spent at home was on average less relative to England. The Level 2 variance is reduced by the addition of the country dummies but remains statistically significant[5]. Model 2 adds more Level 2 explanatory variables—the NVQ Level 4+ and the percentage self-employed (SEPC). NVQ4+ is associated with more time spent at home and SEPC with less time. Wald tests show both to be statistically significant as is the Level 2 variance. However, there is a large fall in the Level 2 variance from the Null Model which amounts to a 69% decrease; these two variables therefore seem to model much of the difference between places with the remaining random components attributable to policy differentials (eg tiered restrictions), omitted variables such as local events, and the random noise introduced into the data by Google to safeguard privacy.

Model 3 add the Stringency Index and CET variables recorded for Level 1 measurement occasions. These show their expected signs and are statistically significant as indeed are all the fixed effects in the model. As lockdown measures become more restrictive the time spent by people increases; as the weather gets warmer, it decreases as some/many people were able to spend their time elsewhere outside. The Level 2 variance hardly changes but the Level 1 variance associated with measurement occasion unsurprisingly falls by nearly 51% from its base in the Null Model. Experimentation by adding the Stringency Index and CET separately indicates that the overwhelmingly largest part of the fall in Level 1 variance is attributable to the harshness of the lockdown and government policy. This shows that the lockdown worked across the UK in modifying the average stay-at-home behaviour of the population. Model 4 assesses the impact of including festivals and holidays such as Christmas, Easter and other Bank Holidays, plus the Cummings effect dummy term. All the fixed effects are statistically significant apart from the 2020 August Bank Holiday, the St Andrew's Bank Holidays of 2020 and 2021, and St Patrick's Day in 2021. Generally, there is a greater likelihood of staying at home relative to the benchmark at these holidays but the effect is larger for some than for others. For instance, there is a large effect for Easter 2020—not only was this a holiday time but it was also at the height of the first lockdown when fears were at their greatest. Likewise, the August Bank Holiday effect was negative (and insignificant) in 2020 and positive in 2021. The Eat Out to Help Out scheme was running in Summer 2020 and lockdown had been in part lifted so this might offer a tentative explanation. There is no evidence that the Cummings dummy variable was associated with people breaking lockdown. In fact, it is positively related to people staying at home. Finally, Model 5 adds dummy terms for days-of-the-week. All the fixed effects apart from the late May Bank Holiday in 2021 and the St Andrew's Day Bank Holiday 2020 are statistically significant. The most noteworthy feature of this model is that all the coefficients for the working week are positive—the population is more likely to stay at home relative to the benchmark from Monday through to Friday. This is just as expected. There is a big fall in the Level 1 variance—a decrease of 75% from the Null Model base—but there remains statistically significant Level 1 and Level 2 variance indicating that although the models describe well the day-on-day changes and the between-place variations in time spent at home, there remain unmodelled factors. At Level 2 this might include omitted variables like local tiered restrictions (which we do not model and which thus remain captured by the random part of the model) and local weather events.

[3]This is calculated as a proportion of the sum of the level 1 and level 2 variation: (44.2/(3.2 + 44.2))*100.

[4]Comparing the ratio of estimate to its standard error (the pseudo Z-test) and also checking using a more exacting Wald test (Goldstein, 2010).

[5]Improvements in model fit were tested using change in deviance, number of extra parameters (degrees of freedom) and a chi-square test. Each model modification resulted in statistically significant improvement in model fit (indicated by bold font for 'Change' in (Table 2).

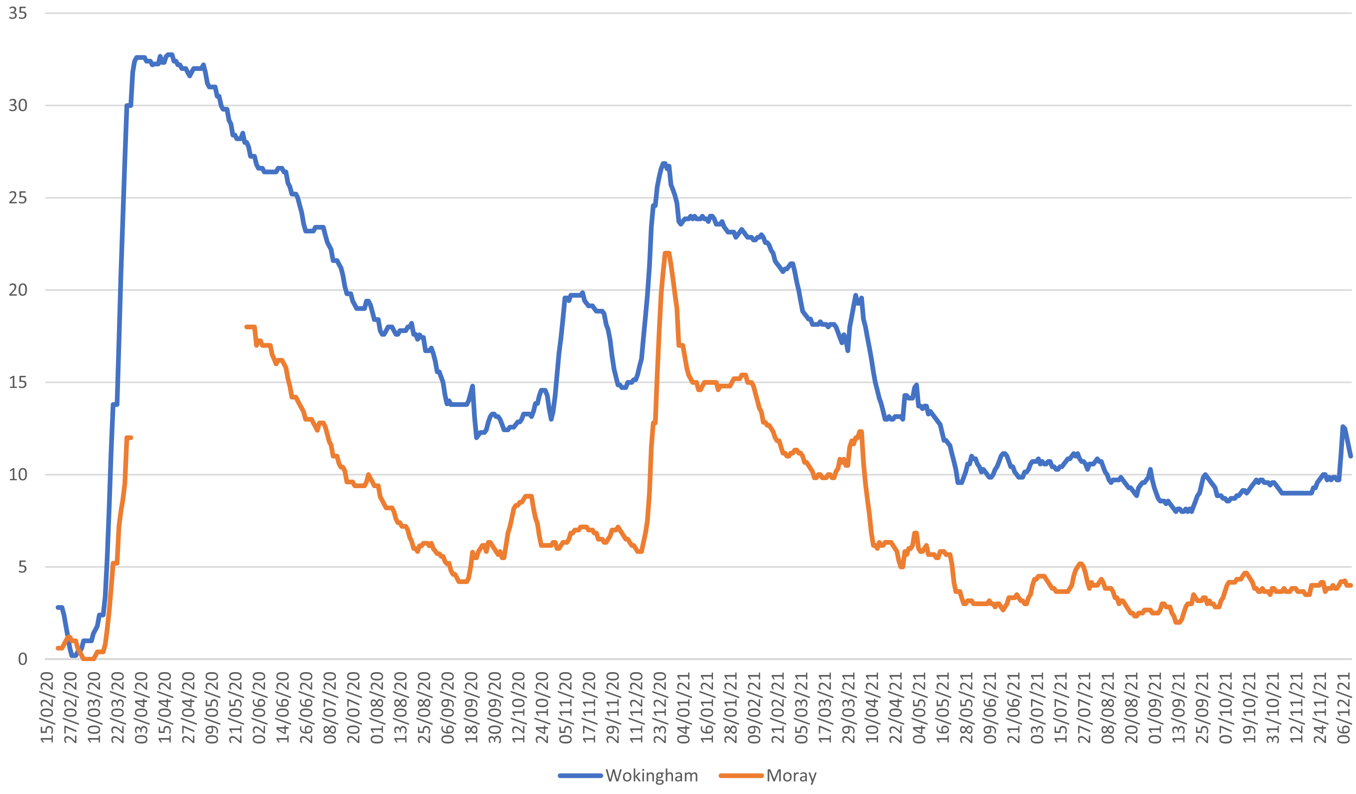

FIGURE 1 Wokingham and Moray—staying at home deviation from benchmark, 7-day average, 15/02/20–10/12/21.

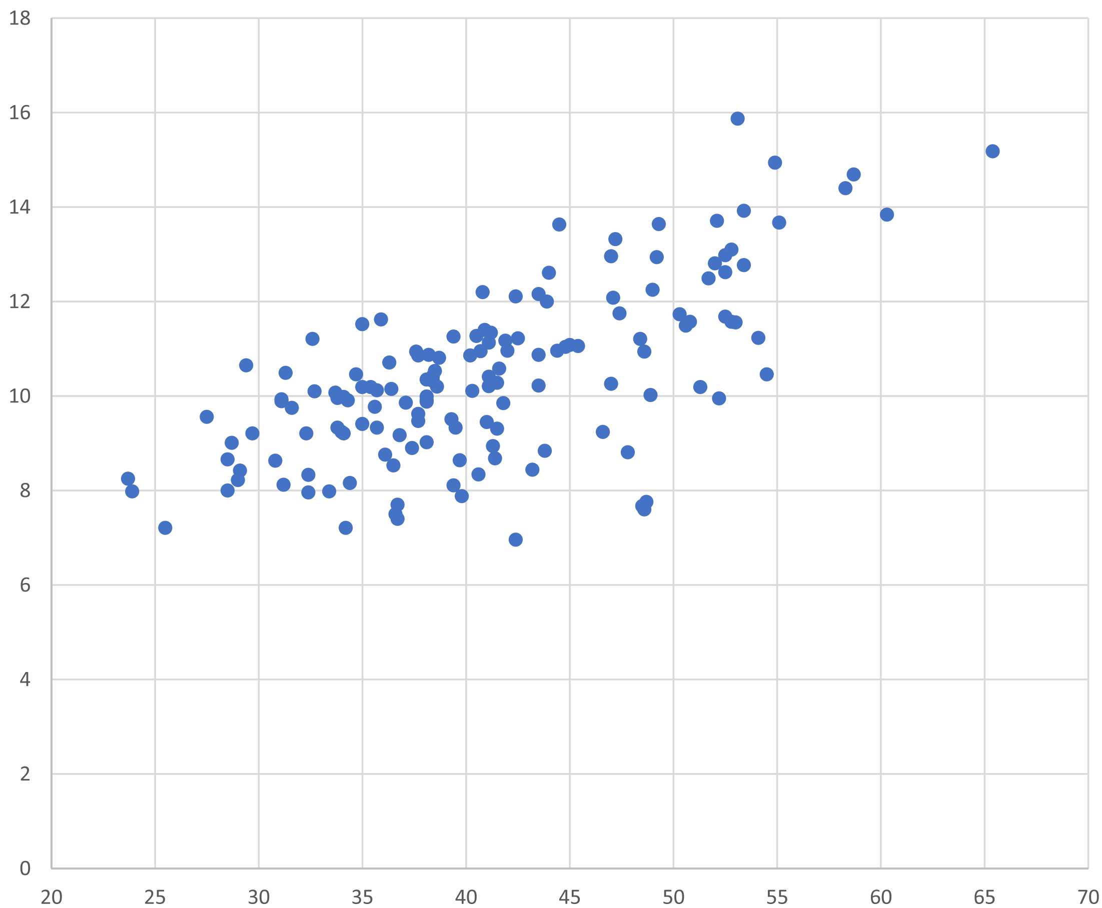

FIGURE 2 Residential (staying at home) deviation from baseline (y-axis) by percentage NVQ4 + qualifications or higher (x-axis) by place.

TABLE 2 Model coefficients – dependent variable time spent at home.

	Null Model	S.E.	Model 1	S.E.	Model 2	S.E.	Model 3	S.E.	Model 4	S.E.	Model 5	S.E.
Response	Residential		Residential		Residential		Residential		Residential		Residential	
Fixed part												
Cons	**10.413**	**0.148**	**10.665**	**0.189**	**5.158**	**0.532**	**−9.274**	**0.514**	**−9.161**	**0.514**	**−12.254**	**0.566**
Scotland			−0.117	0.376	**−1.909**	**0.247**	**−1.691**	**0.236**	**−1.663**	**0.237**	**−2.278**	**0.261**
Wales			**−1.117**	**0.419**	**−0.723**	**0.248**	**−0.523**	**0.237**	**−0.480**	**0.237**	**−1.161**	**0.262**
Northern Ireland			−0.854	0.560	**−1.298**	**0.330**	**−1.289**	**0.316**	**−1.271**	**0.316**	**−1.605**	**0.350**
NVQ4 +					**0.191**	**0.012**	**0.193**	**0.011**	**0.193**	**0.011**	**0.192**	**0.012**
SEPC					**−0.215**	**0.033**	**−0.202**	**0.032**	**−0.201**	**0.032**	**−0.233**	**0.035**
Stringency Index							**0.254**	**0.001**	**0.248**	**0.001**	**0.242**	**0.001**
CET							**−0.012**	**0.000**	**−0.012**	**0.000**	**−0.014**	**0.000**
Christmas 2020									**4.730**	**0.218**	**4.856**	**0.168**
New Year's Eve 2020									**7.272**	**0.370**	**5.278**	**0.287**
New Year's Day 2021									**14.327**	**0.370**	**12.936**	**0.286**
Easter 2020									**10.290**	**0.259**	**11.396**	**0.200**
Easter 2021									**0.902**	**0.191**	**2.512**	**0.148**
May Day 2020									**14.060**	**0.439**	**12.727**	**0.339**
May Day 2021									**8.843**	**0.369**	**7.631**	**0.286**
Late May BH 2020									**5.970**	**0.445**	**4.250**	**0.344**
Late May BH 2021									**1.003**	**0.369**	−0.044	0.286
August BH 2020									−0.453	0.374	**−2.147**	**0.290**
August BH 2021									**2.307**	**0.368**	**0.704**	**0.285**
St Andrew's Day 2020									0.672	0.369	−0.502	0.286
Scottish August BH 2020									**−1.609**	**0.377**	**−2.692**	**0.292**
Scottish New Year BH 2021									**2.766**	**0.370**	**1.545**	**0.286**
St Andrew's Day 2021									−0.188	0.368	**−1.953**	**0.285**
Sctottish August BH 2021									**2.388**	**0.369**	**1.248**	**0.286**
St Patrick's Day 2020									**6.261**	**0.372**	**4.427**	**0.288**
St Patrick's Day 2021									−0.573	0.369	**−2.533**	**0.286**
Boyne BH 2020									**2.967**	**0.379**	**1.859**	**0.294**
Boyne BH 2021									**−7.705**	**0.494**	**−1.853**	**0.382**
Cummings									**5.166**	**0.145**	**5.648**	**0.112**
Sunday											**−1.897**	**0.047**
Monday											**5.344**	**0.045**
Tuesday											**5.793**	**0.044**

(Continues)

TABLE 2 (Continued)

	Null Model	S.E.	Model 1	S.E.	Model 2	S.E.	Model 3	S.E.	Model 4	S.E.	Model 5	S.E.
Wednesday											**6.169**	**0.044**
Thursday											**6.028**	**0.044**
Friday											**5.463**	**0.044**
Random Part												
Level: ID2 Area												
Var(Cons)	**3.168**	**0.38**	**2.990**	**0.36**	**0.982**	**0.12**	**0.929**	**0.11**	**0.937**	**0.11**	**1.165**	**0.14**
Level: ID1												
Var(Cons)	**44.148**	**0.21**	**44.148**	**0.21**	**44.149**	**0.21**	**21.734**	**0.1**	**19.938**	**0.09**	**11.836**	**0.06**
Units: ID2 Area	148		148		148		148		148		148	
Units: ID1	90,076		90,076		90,076		90,076		90,076		90,076	
Estimation:	IGLS		IGLS		IGLS		IGLS		IGLS		IGLS	
−2*loglikelihood:	597,351.43		597,343.06		597,188.66		533,443.16		525,689.55		478,822.17	
Change	n/a		**8**		**155**		**63,745**		**7754**		**46,867**	

Note: All estimates set in bold are statistically significant ($p < 0.05$).

In the Appendix, results are presented in Supporting Information: Tables A3 and A4 for workplace visits and for transit station visits to give context for the residential results. The same incremental results (Null Model, Models 1–5) are presented as for residence but for the sake of time, these will not be discussed in the text in the same sequential way. Instead, just the main features of the results will be highlighted. Looking first at workplace in Supporting Information: Table A3, it is important to note that the Null Model shows a decline of just over 32% in the time spent in workplaces over the analytical period. There are no statistically significant national differences when only these terms are modelled but in the final Model 5 Scotland and Northern Ireland differ significantly from England in having a higher proportion of workplace visits. Increased Stringency has its expected sign; as it increases, workplace visits declines. There are large negative and statistically significant effects for holidays through the year and also on week days. These are larger than those noted for residence but accord well with working practices and the weekly routine. Considering the random part of the model, there is more between-place and between-date variability than for residence but the addition of NVQ4+ and the percentage self-employed reduces the between-place Level 2 variance by about 70% as was the case for residence and the inclusion of the day and holiday dummies reduces the between-date Level 1 variance also by about 66% (a little less than was the case for the residential models). Despite, the final Model 5 shows that the Level 2 and 1 variances remain statistically significant indicating that there are unmodelled factors. In summary, the workplace fixed-effect results are consistent with those for residence and differ only in minor detail, and although the random part of the model indicates greater variability roughly the same amount is explained by the final Model 5.

In Supporting Information: Table A4, the transit models are presented. Again, the Level 2 and Level 1 variances are greater than for residence. It is noteworthy for this domain that the random variances are larger and that the models are less successful in explaining these variances. In contrast to residence and workplace, only 34% of the Level 2 between-place variance is accounted for in Model 5 although 60% of the between-date Level 1 variance is modelled (but less than for workplace and residence). With regard to between-place variance it makes sense since transport infrastructure (and particularly public transport) differs markedly across the UK. Moreover, NVQ4+ and the percentage self-employed is less self-evidently related to transport although they show their expected signs and are statistically significant. The fixed effects show there are no consistent country differences across the UK apart from a statistically significant positive coefficient for Scotland in Model 5. It is interesting to note that Stringency has a significant negative effect and that CET has a significant positive effect—people get around more in better weather! There are some differences in the holiday fixed effects from residence; in some cases, these are large and negative effects especially for the Winter and early Spring holidays but in the Summer but on some days such as the August Bank Holiday and St Patrick's Day there are large positive coefficients. These make sense as people travel to parks, beaches and parades on these days if the weather is good and lockdown is less restrictive. Once again, the results look consistent with those for residence and for workplace.

6 | CONCLUDING DISCUSSION

It is worth reflecting on what these results mean for the hypotheses outlined at the start of the paper. The first hypothesis was that there would be statistically significant differences between the UK home nations. The evidence for this is qualified—when nation only is modelled, there are no statistically significant differences of Scotland, Northern Ireland and Wales from England. However, when other variables are taken into account some country differences do emerge as highlighted earlier. The second hypothesis was that there would be statistically significant between-place variations in behaviour. This is true for the residence domain (and also for the workplace and transit domains where there is more variance). This shows that there was a subnational geography in the response of the population to government lockdown restrictions. The Level 1 between-measurement date variance is far larger, however, and is the greatest contributor to the total variances that are modelled. The third hypothesis was that between-place differences in educational qualifications and socioeconomic conditions (as proxied by the percentage self-employed) could account for a substantial portion of the Level 2 between-place variance. This is shown to be the case with just these two variables accounting for 75%, 70% and 34% of the variance for residence, workplace and transit respectively. The fourth hypothesis concerned the effectiveness of lockdown policies. The models show that the Stringency Index was always statistically significant and operated in the expected direction. This demonstrates that government lockdown policies were observed by the population and that they worked albeit with differences between places.

The models also show that holidays and religious festivals have major and strong effects on different aspects of spatial (im)mobility, and that the greatest changes in behaviour were observed on week days with very large proportions staying at home, learning online and the economic active working at home depending on their type of occupation. The 'Cummings effect' was statistically significant but not in the expected direction perhaps because it was masked by other factors that were driving spatial (im)mobility. Finally, the full models still left unexplained variance at Level 1 and at Level 2 due to omitted variables. Although the models are effective they do not fully account for day-to-day and between-place variations in the outcome variables.

Finally, there are a number of reasons that might explain this observation. First, and most simply, the spatial mobility of populations is highly variable with lots of randomness and varies on a daily and seasonal basis (Toger et al., 2020). Additionally, Google added an undisclosed random component to the data to safeguard privacy. We might therefore, for instance, question the degree to which the period in January and February 2020 selected by Google as their baseline reference point for measuring was typical of the whole year. Ideally, alternative yardsticks would be desirable by which, for example, March days in the pandemic could be compared with pre-pandemic March days but even if these data were available questions of typicality and elements of randomness would remain—was, March 13, 2019, for instance, a day with particularly harsh weather whereas March 13, 2020, was very benign and sunny? Was there a rail strike? Was there a big football match? To start to address this theme of benchmarks, longer runs of runs of data are required as it is necessary to understand temporal variability on a daily, weekly, monthly and seasonal basis to get a better grasp of variations from the 'normal'. Nevertheless, the Google Mobility Report data have been widely used by academics (Drake et al., 2020; Paez, 2020; Sulyok & Walker, 2020) to study the mobility impact of Covid and the January-February 2020 benchmark does give a fixed starting point that makes analysis possible and so is better than nothing. Second, there might be omitted variables that if included could model the variances more effectively. At Level 2, for example, the addition of average income, unemployment, or a place typology might add something, as might the addition of local happenings such as sports attractions or small spatial scale weather events such as thunderstorms, despite the power of the two variables used. Furthermore, a Treasury analysis (using Google Mobility Reports) showed that the impact of tiered restrictions at different stages of the pandemic, with differing local levels of restriction and lockdown, also led to uneven changes in mobility at a subnational spatial scale (Treasury, H.M., 2021). Our analysis, whilst not rejecting this, caveats it. The amount of Level-2 variance explained by NVQ4+ and SEPC leaves, for the residence domain, no more than about 30% unmodelled. Some of this is attributable to Google's randomisation of the data, some to other omitted variables. This implies that the greatest possible maximum of the difference explained by the tiers is around 30% and it may be less given the other factors we note. In Models 4 and 5 there are terms for major holidays and days of the week and here it is difficult to imagine what else could improve this part of the model especially given the complexities of this UK-wide data set.

It is also worthwhile reflecting on the use of 'Big Data' generated datasets such as the Google Mobility Reports for geographical research on spatial mobility and indeed other topics. In this regard, this analysis has highlighted two problems. The first concerns the metadata that are available to describe and explain the data. Unlike quantitative datasets generated by national statistical agencies or by higher education, which normally have full data dictionaries, variable descriptions, and methodological descriptions, and are lodged with bodies such as the UK Data Service, the amount of supporting material for Google Mobility Reports is scant. Furthermore, there is no dedicated help service to answer user queries. This means that more needs to be taken on trust than otherwise would be the case in using data like these. The second is a reflection on the spatial units used by Google to release the data. This does not match to the UK statistical geographies and Google provide no unique numeric area codes to allow easy data set linkage to these geographies. To overcome this meant creating codes, working with several different UK statistical geographies to extract data, and then careful manual checks; a far lengthier task than normal. There is thus a case for a unified and coordinated geographical approach to spatial data that spans Big Data providers such as Google, retail organisation, mobile phone companies and national statistical organisations whose data are being increasingly used to study the behaviour of populations. A second issue is that the spatial units selected by companies such as Google may not be the optimum for some academic analyses which might ideally require larger, smaller, or different-shaped units. In this particular instance it seems that the geography was selected with public health considerations in mind and with privacy protection also as an important element. Nevertheless, datasets like Google Mobility Reports offer the opportunity to research topics that cannot be investigated using more traditional datasets, have been used (as we earlier noted) by academics and government, and will be increasingly used in the future as the sources of population data develop and diversify.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in Google Mobility Reports at https://support.google.com/covid19-mobility/answer/9824897?hl=en%26ref_topic=9822927 and also these following sources: Covid-19 Government Response Tracker, 2022, https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker; NINIS (n.d.), https://www.ninis2.nisra.gov.uk/public/Home.aspx; NOMIS (n.d.), https://www.nomisweb.co.uk/reports/lmp/la/contents.aspx.

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REFERENCES

Bambra, C., Riordan, R., Ford, J., & Matthews, F. (2020). The COVID-19 pandemic and health inequalities. *Journal of Epidemiology and Community Health*, *74*. https://doi.org/10.11136/jech-2020-214

Basellini, U., Alburez-Gutierrez, D., Del Fava, E., Perrotta, D., Bonetti, M., Camarda, C. G., & Zagheni, E. (2021). Linking excess mortality to mobility data during the first wave of COVID-19 in England and Wales. *SSM-Population Health*, *14*. https://doi.org/10.1016/j.ssmph.2021.100799

BBC News. (2020). *Dominic Cummings: What is the scandal about?* Retrieved March 14, 2022, from https://www.bbc.co.uk/news/uk-52811168

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

Boterman, W. (2022). Population density and SARS-CoV-2 pandemic: Comparing the geography of different waves in the Netherlands. *Urban Studies*. Advance online publication. https://doi.org/10.1177/0042098022108716

Brown, J., & Kirk-Wade, E. (2021). Coronavirus: A history of English lockdown laws. *Research Briefing 9068, [online]*. House of Commons Library.

Centre for Cities. (2020). *How will Coronavirus affect jobs in different parts of the country*? Retrieved March 3, 2022, from www.centreforcities.org/blog/how-will-coronavirus-affect-jobs-in-different-parts-of-the-country/

Cot, C., Cacciapaglia, G., & Sannino, F. (2021). Mining Google and Apple mobility data: Temporal anatomy for COVID-19 social distancing. *Scientific Reports*, *11*(1), 4150. https://doi.org/10.1038/s41598-021-83441-4

Drake, T. M., Docherty, A. B., Weiser, T. G., Yule, S., Sheikh, A., & Harrison, E. M. (2020). The effects of physical distancing on population mobility during the COVID-19 pandemic in the UK. *The Lancet Digital Health*, *2*(8). https://doi.org/10.1016/S2589-7500(20)30134-5

Drefahl, S., Wallace, M., Mussino, E., Aradhya, S., Kolk, M., Brandén, M., Malmberg, B., & Andersson, G. (2020). A population-based cohort study of socio-demographic risk factors for COVID-19 deaths in Sweden. *Nature Communications*, *11*(1), 5097. https://doi.org/10.1038/s41467-020-18926-3

Feng, Z., (2021). *Spatiotemporal pattern of COVID-19 mortality and its relationship with socioeconomic and environmental factors in England, Unpublished presentation, British Society for Population Studies, September 2021*.

Goldstein, H. (2010). *Multilevel Statistical Models* (4th edition.). Wiley.

Google, L. L. (n.d.). *Google COVID-19 Community Mobility Reports*. Retrieved January 17, 2023, from https://www.google.com/covid19/mobility/

Gore, A., Bimpson, E., Dobson, J., & Parkes, S. (2021). *Local Government Responses to the COVID-19 Pandemic in the UK: A thematic review. Working Paper #3—International Geographical Union Commission on Geography of Governance Project: "Local Government Response Towards Covid-19 Pandemic: A Worldwide Survey and Comparison"*.

Gould, M., Jones, K., & Moon, G. (1997). Guest editorial. *Environment and Planning A: Economy and Space*, *29*, 581–584.

Greer, S. L. (2016). Devolution and health in the UK: Policy and its lessons since 1998. *British Medical Bulletin*, *118*, 16–24. https://doi.org/10.1093/bmb/ldw013

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, *5*, 529–538. https://doi.org/10.1038/s41562-021-01079-8

Harris, R., & Brunsdon, C. (2021). Measuring the exposure of Black, Asian and other ethnic groups to COVID-infected neighbourhoods in English towns and cities. *Applied Spatial Analysis and Policy*, *15*, 621–646. https://doi.org/10.1007/s12061-021-09400-8

Hu, T., Wang, S., She, B., Zhang, M., Huang, X., Cui, Y., Khuri, J., Hu, Y., Fu, X., Wang, X., Wang, P., Zhu, X., Bao, S., Guan, W., & Li, Z. (2021). Human mobility data in the COVID-19 pandemic: Characteristics, applications, and challenges. *International Journal of Digital Earth*, *14*(9), 1126–1147. https://doi.org/10.1080/17538947.2021.1952324

Hughes, J., Ijpelaar, J., McAuley, R., Shuttleworth, I., & Lowry, E. (2021). *Covid-19 Deaths in Wave One: Analysis of Equality Group, Healthand Socio-demographic Characteristics*. NISRA.

Ilin, C., Annan-Phan, S., Tai, X. H., Mehra, S., Hsiang, S., & Blumenstock, J. E. (2021). Public mobility data enables COVID-19 forecasting and management at local and global. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-92892-8

NINIS. (n.d.). Retrieved January 17, 2023, from https://www.ninis2.nisra.gov.uk/public/Home.aspx

NOMIS. (n.d.). Retrieved January 17, 2023, from https://www.nomisweb.co.uk/reports/lmp/la/contents.aspx

OECD. (2020). *Capacity for remote working can affect lockdown costs differently across places*. Retrieved March 2, 2022, from https://www.oecd.org/coronavirus/policy-responses/capacity-for-remote-working-can-affect-lockdown-costs-differently-across-places-0e85740e/

Office for National Statistics (ONS). (2022). *Statistical bulletin, Economic activity and social change in the UK, real-time indicators*. Retrieved September 16, 2022, from https://www.ons.gov.uk/economy/economicoutputandproductivity/output/bulletins/economicactivityandsocialchangeintheukrealtimeindicators/latest#data

Paez, A. (2020). Using google community mobility reports to investigate the incidence of COVID-19 in the United States. *Transport Findings*. https://doi.org/10.32866/001c.12976

Parker, D. E., Legg, T. P., & Folland, C. K. (1992). A new daily central england temperature series, 1772-1991. *International Journal of Climatology*, *12*, 317–342.

Rasbash, J., Browne, W., Healy, M., Cameron, B., & Charlton, C. (2013). *MLwiN Version 2.29*, *Centre for Multilevel Modelling*. University of Bristol.

Sulyok, M., & Walker, M. (2020). Community movement and COVID-19: A global study using google's community mobility reports. *Epidemiology and Infection*, *148*. https://doi.org/10.1017/S0950268820002757

Toger, M., Shuttleworth, I., & Östh, J. (2020). How average is average? Temporal patterns in human behaviour as measured by mobile phone data—or why chose Thursdays. *arXiv preprint arXiv*:2005.

Treasury, H. M. (2021). *Budget 2021*, *Protecting the Jobs and Livelihoods of the British People*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/966868/BUDGET_2021_-_web.pdf

UK Government. (2022). *UK bank holidays*. Retrieved March 14, 2022, from https://www.gov.uk/bank-holidays

SUPPORTING INFORMATION

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

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