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Estimating the social and spatial impacts of Covid mitigation strategies in United Kingdom regions: synthetic data and dashboards

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This study advances understanding of the broader social and spatial impacts of COVID-19 restrictive measures, particularly how they may have impacted individuals and households and, in turn, the geographic areas in which these individuals and households are concentrated. Data are combined and linked to a novel individual-level synthetic dataset and an interactive dashboard is developed to assist with the identification and understanding of the social and spatial impacts of restrictions. To illustrate the utility of this approach, the analysis focuses on the impact of three restrictions within a defined spatial area: Yorkshire and Humberside (UK). Results highlight the additive nature of restriction impacts and suggest areas that may have the least future resilience as policy priority areas. This approach is transferable to other regions and the use of the dashboard allows rapid consideration and communication of the social and spatial nature of inequalities to researchers, practitioners and the general public.

Keywords: COVID-19, pandemic, synthetic data, dashboard, inequality, urban, spatial
JEL Classifications: D10, I14, I31, R28

Introduction

On 11 March 2020, the World Health Organization (2020) declared COVID-19 a pandemic. Twelve days later, Prime Minister Boris Johnson addressed the United Kingdom (UK), requiring the public to stay at home with the exception of essential activities (Prime Minister's Office, 10 Downing Street, 2020). Almost two years later, as of early 2022, there have been over 300 million global cases of COVID-19 and an estimated 5.5 million deaths (John Hopkins University & Medicine, 2022). With each new variant comes renewed discussion around the appropriate extent of mitigation measures, such as work-from-home or school closures.

From the outset of the pandemic, governments, medical professionals and academics have worked to identify vulnerable groups so that prevention and mitigation measures could be implemented to minimise the spread of COVID-19 and the population-level impacts. Early insights were that age, ethnicity and underlying health conditions are significant contributors to increased risk of mortality from COVID-19 (Harris, 2020; National Health Service [NHS], 2021). In the UK, a range of measures were introduced periodically—and in combination—to reduce the spread of the virus, ranging from social distancing, use of face coverings, national lockdowns, geographical easings in the form of the tier system and many more. Despite these measures, no part of the UK has escaped the effects of COVID-19, though based on the Index of Multiple Deprivation, throughout the early months of the pandemic, the virus had a sustained and proportionally higher impact on the most deprived areas of England (Morrissey et al., 2021; Office for National Statistics [ONS], 2020a). These trends have been routinely reported in the media and academic settings since early 2020.

There are numerous definitions of 'vulnerability', many arising in a population health context (for example, Frohlich and Potvin, 2008). However, in the context of COVID-19, the Economic Social Research Council ([ESRC], 2020), defines it as 'greater risk of infection and/or adverse effects of social distancing measures'. As the pandemic has evolved, it has become increasingly apparent that, aside from the more obvious direct health impacts, COVID-19 has also contributed to economic and social crises, and that no single measure of vulnerability captures the full costs incurred by the disease (Davenport et al., 2020). Both the direct health burden arising from COVID-19 and the mitigation measures introduced to limit the spread of the virus have impacted society, including employment and social wellbeing, as well as the provision and quality of social care, activity levels and mental health (Her Majesty's Government, 2020). Mind (2020) warns that there will be a subsequent 'pandemic' resolving the mental health crisis that COVID-19 has caused, whilst the British Medical Association (2021) identified the large backlog of care as a pressure point that will result in future problems for months to come.[1] Taken together, this suggests a need to study the impacts of the virus itself, but also the associated restrictions and responses, and, in particular, their socially and spatially distributed effects.

This study was undertaken with the aim of advancing understanding of the broader social and spatial impacts of COVID-19 restrictive measures, especially how the restrictions introduced may have impacted individuals and households and, in turn, the geographic areas in which these individuals and households are concentrated. Yorkshire and the Humber was selected as a case study area, in order to illustrate the data requirements for investigating the social and spatial impacts of particular COVID-19 restrictions and the value of visualisation via a dashboard to communicate the geographies involved. A novel approach combining established and synthetic data is illustrated. Aside from identifying small areas of potentially high exposure to restriction impacts in the region, this research highlights examples of how current data collection and integration

efforts fall short of what would be necessary at scale for targeted and effective national policy development. There has recently been a transition from mapping the pandemic from a disease and health perspective to investigating the geography of other emerging impacts (Smith et al., 2020) and our research fits within this wider research agenda.

The remainder of the paper is structured as follows: the following section outlines the background to COVID-19 restrictions introduced in the UK and core features of the social and economic impacts of the pandemic. The case study area, data requirements and synthetic data are then described, alongside the interactive dashboard developed as part of the research. Subsequently, example results are demonstrated for a selection of restrictive measures applied through simulation and data analysis for the case study area. Finally, the value of the dashboard as a tool for communicating spatial impacts and decision support is described, with concluding remarks.

Background

Pandemic public health responses

In the aftermath of previous disease outbreaks such as influenza, swine flu and Ebola, the UK government had planning in place in the event of another pandemic (Department of Health and Social Care [DHSC], 2020a). Although these plans can and have been scrutinised, a range of fundamental components evolved as core elements of the COVID-19 pandemic response.

Initial COVID-19 restrictions were intended to reduce virus transmission dramatically and quickly. As more became known about how the virus spreads, the restrictions were adapted and tailored to the intensity and location of virus cases. For example, as evidence emerged that transmission via fomite was more difficult to control (for example, via cleaning regimes) and a lesser transmission route than aerosols, guidance on surface cleaning was reduced and guidance on ventilation increased. These changes exposed inequalities, such as whether people had access to ventilated environments at home or at work. Understanding of the virus has continued to evolve throughout the pandemic, leading to changes in policy responses and restrictions, with attendant shifts in the groups most affected by pandemic rules, such as 'stay at home' guidelines, furlough or school closures.

Previous research concerning vulnerabilities from the COVID-19 pandemic has concentrated on intersecting household level health and socio-economic characteristics. Mikolai et al. (2020), for example, focused on five main indicators of vulnerability: digital and connectivity, housing conditions, employment conditions, financial conditions and health indicators. Through the case study analysis presented here and the estimation of local-area impacts, the authors adopted a similar approach. This involved firstly identifying COVID-19 restrictions and potential vulnerabilities that each covered, then exploring these using a mixture of published data by geography, and simulated scenarios based on expected lifestyle changes. Table 1 provides representative examples of restrictions that have been implemented in England and the various populations impacted.

The following sections explore the three main categories of restrictions considered in this analysis, all of which have potential to generate a range of social and economic impacts:

Shielding

Shielding was quickly introduced at the start of the pandemic to reduce infection risk amongst those most susceptible to the disease (Kemp et al., 2020). There are approximately 4 million people on the shielding list in England, with 1.7 million of these being added nearly a year into the pandemic in February 2021 (British Heart Foundation [BHF], 2021). The call to shield was primarily based on a range

Table 1. *Example restriction measures for England and their potentially disparate demographic impacts.*

Type	Restriction	Result	Impacted groups	Implementation
Demographic	Shielding	Isolation encouraged for the clinically extremely vulnerable and extreme caution recommended for the clinically vulnerable.	Those with specific health issues that place them at high risk from coronavirus. Additionally, those with further health issues and/or aged 70 or over. Often requires external support from family, friends, volunteer groups or local government.	Since the start of the pandemic, with relaxation of shielding measures suggested in line with the lowest levels of national restriction.
Social	Social distancing	Social interaction dramatically reduced. Limits on close contact mean it is impossible for people to continue normal behaviours and socialisation skills (Koci et al., 2021).	Everyone. However, as the size of groups who can interact has changed, different social and household structures (for example, single-person households or two multi-generational households) have been differentially affected.	Since the start of the pandemic, with relaxation of the distance required based on the presence of other mitigating actions (for example, masks).
Economic	NHS Test and Trace Support Payment Scheme	Up to £500 made available to eligible individuals on low income, should they be positive for COVID-19 or have to isolate due to being in contact with an infected person.	Low-income isolating individuals.	In place since September 2020. Expected to cease in early 2022.
Geographical	Household interaction only allowed outside in private spaces	Movement and social interaction reduced partially, influenced by availability and quality of greenspace.	12% have no private or shared garden space, with Black individuals four times as likely as white people to have no private area and 8% of over 65s with no private outdoor space (ONS, 2020b)	On and off, in line with national lockdown rules.

of underlying health issues, although those at moderate risk also include individuals aged 70 or older, even if they have no underlying medical conditions (NHS Digital, 2021a). The extreme nature of shielding—for example, staying at home unless absolutely necessary or using online services—was not-compulsory (BHF, 2021). Throughout the various national lockdowns and tier systems the guidance on shielding has also changed, being most strictly applied until 31 July 2020, with, for example, supplies of basic food delivered to the home on request through the national shielding service until that date. The national shielding programme formally ended on 15 September 2021, with no further advice on shielding provided after that time.

Even under the most relaxed shielding advice, rapidly introduced guidance of this type is likely to have psychological impacts on individuals and those they live with. A survey by Blood Cancer UK (2020) showed that over half of the individuals surveyed, who were shielding due to a blood cancer, reported struggles with their mental health. These individuals were likely to have prolonged changes to their lifestyle even as the majority of societal COVID-19 related restrictions were eased. An approximate measure of shielding can be replicated by identifying small area patterns of

ailing individuals from the census and using localised thresholds of the percentage shielding, as reported on NHS Digital's (2021b) open data set 'Shielding Patient List'.

Limited household interaction

Despite the disruptive changes that COVID-19 restrictions involved, households comprising more than one person were able to maintain some form of face-to-face social interaction, even if these interactions did not reflect their pre-pandemic relationships. The absence of these face-to-face interactions for single occupancy households can impact these individuals' mental wellbeing (Leng et al., 2021). To allow close contact between these isolated individuals and help combat loneliness without removing social distancing for all, 'support bubbles' were introduced in June 2020 (DHSC, 2020b; Gullard, 2020; Leng et al., 2021). The criteria for support bubbles subsequently expanded to include additional household types, such as multiple occupancy households where all but one individual required continuous care due to disability (DHSC, 2020b).

Data on the uptake of support bubbles is extremely scarce. There are many factors that might prevent households from forming a 'support bubble'. These include individuals where there is no appropriate household to join up with, anxieties or being unable to set up a bubble due to shielding. As any estimate of UK bubble uptake would be entirely conjecture, this analysis assumes that all single-person households experienced increased isolation and exclusion in comparison to their multiple-person household counterparts.

Furlough

The furlough scheme was a key economic policy response throughout the COVID-19 pandemic, enabling businesses to continue supporting their employees with reduced salaries. This promoted a continuation of the workforce and dampened economic impacts, mitigating the potential for mass redundancies and unemployment. Concerns were expressed at the time that furlough may only postpone mass redundancies until the point at which the COVID-19 Job Retention Scheme eventually ended (in practice, September 2021) (Beatty and Fothergill, 2021). In the first lockdown, 33% of employees in older industrial Britain were furloughed (Beatty and Fothergill, 2021). This proportion is in line with UK-wide values, with 30% of the workforce furloughed during the peak in May 2020 (Her Majesty's Treasury, 2020). The arts, entertainment and recreation industry experienced the lowest percentage of usual trading of all ONS defined industry groups (ONS, 2020c). This corresponds with the industry having the greatest average furlough figures throughout the pandemic (ONS, 2020c). In addition, research shows that females were more likely to stop working, either temporarily on furlough, or permanently (Blundell et al., 2020). Although primarily initiated by the employer, one study found mothers were also more likely than fathers to initiate the decision to take up the furlough scheme (DELVE Initiative, 2020).

Impacts

The impacts of COVID-19-related measures will vary across different population groups and different time scales, depending on the type of impact generated (Davenport et al., 2020; Smith et al., 2020). Researchers proposed that as a result, exit strategies should have an economic and public policy focus in addition to the more researched health focus (Anderson et al., 2020). This broader focus can only be achieved if we understand the spatial and social disruptions that COVID-19 restrictions have had. It is also widely conjectured that Covid has had an unequal impact on an *already unequal* society (The Health Foundation, 2020). Providing seemingly aspatial restrictions with a spatial footprint highlights places that will need additional support as the transition takes place to living with the virus in the longer term.

Data and methods

One of the challenges for this research was to bring together diverse data sets to understand the social and spatial impacts of COVID-19 on a defined population. To address this, it was necessary to consider how individual-level restrictions could be mapped onto population characteristics, in order to derive local geographies of pandemic rules. Exploring the spatial variation of COVID-19 impacts allows policy makers, charities and researchers to make informed decisions on how to replan and future proof urban spaces for the longer term with an endemic COVID-19 virus.

To understand and mitigate COVID-19 restriction-related isolation and exclusion, we propose that research must be carried out at a small-area level, or it will be impossible to observe detailed impacts. For example, school closures will affect neighbourhoods with high densities of children more than neighbourhoods with low densities. This is a minimal threshold for the impact of school closures, given that closures affect not only children but also parents, carers and of course, their places of employment. Reaching the additive, multilayered effects of different types of restrictions requires rich data at a household level, which can then be aggregated to higher spatial resolutions to communicate disparate impacts and support targeted local policies. Alongside household level data, further data is needed at the neighbourhood or small area level—for example, on land-use and greenspace availability. Although useful from a policy perspective, the City or Local Authority levels are too large a data collection unit for calculating local pandemic effects.

In the following section we detail the case-study area selected to illustrate the analysis. The individual-level synthetic data set used, and the additional data sets linked, are then presented, along with a brief discussion of data challenges encountered. Finally, details of the visualisation tool, an interactive dashboard, are given. The developed dashboard focuses on social, economic and other impacts by small scale geographies, emphasising the equity implications of virus mitigation measures. Ivanković et al (2021) provide a descriptive assessment and appraisal of a sample of 158 COVID-19 dashboards from 53 countries. Whilst nearly all dashboards reported epidemiological indicators and the majority gave health system management indicators, indicators of social and economic impact and behavioural insights were the least reported (4.4% and 1.3%, respectively). This research serves to help fill that gap.[2]

Study area

Yorkshire and the Humber, within the North of England (UK), was chosen as a suitable site for identifying areas of isolation and exclusion that could be generated by COVID-19 restrictions (Figure 1). It is an area with an assortment of high-resolution data available and a diverse range of settlement types from dense urban city spaces to National Park areas. The area also encompasses a variety of socio-economic groups and characteristics (Figure 2). Due to data availability, we focus on developing estimates at the MSOA level (Middle-layer Super Output Areas). These are English Census areas with an average of 10,000 residents, usually within 2000–6000 households (Office for National Statistics, 2022). There are 692 MSOAs within Yorkshire, which each include between 2116 and 6127 households, with an average of 3364. Figure 2 highlights the Local Authority Districts of key cities in the study area (Bradford, Hull, Leeds and Sheffield); as an economically and socially diverse area, we specifically focus on Bradford for additional discussion.

Deprivation is captured by the English Index of Multiple Deprivation (IMD), which provides a score based on aspects including local education, economic and living environment statistics (Ministry of Housing, Communities & Local Government, 2020). Local areas are ranked according to their deprivation at a national scale, where the highest ranks indicate the most deprived areas in the country.[3] We use the national rankings as a point of comparison in this study.

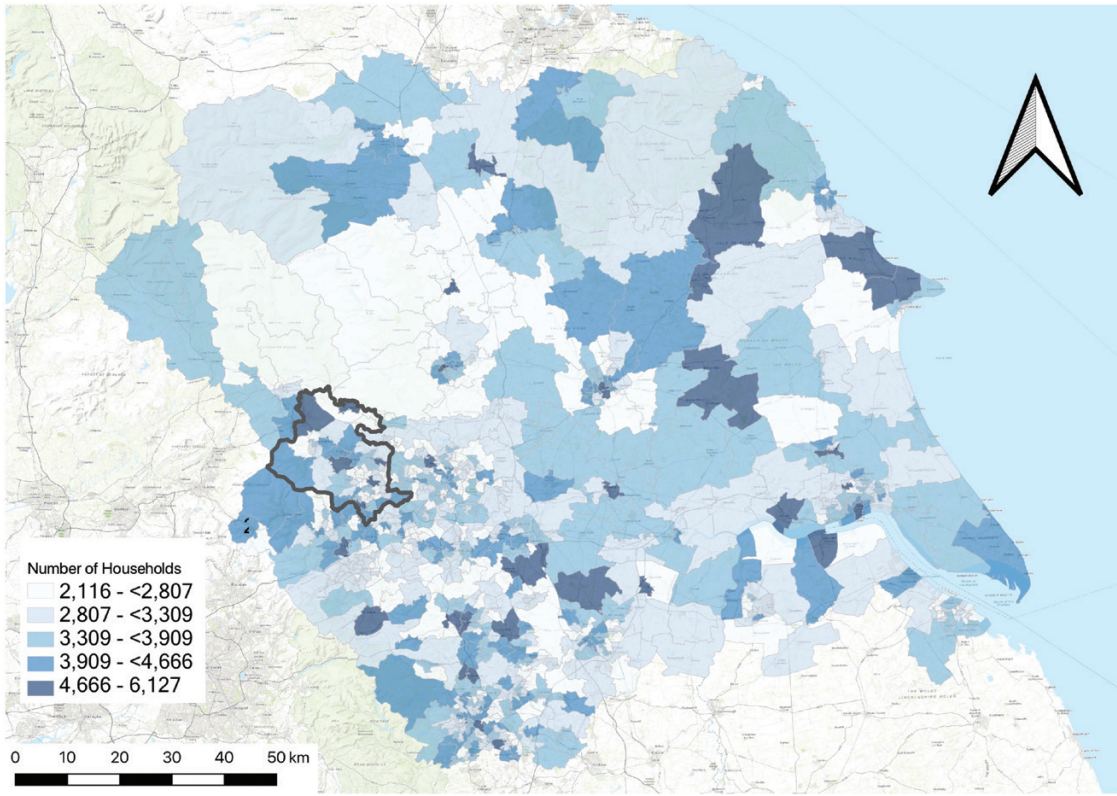

Figure 1. *Yorkshire and the Humber study area MSOAs (Bradford Local Authority highlighted).*

As in many cities, the most deprived areas in Bradford (Figure 2, reflected by high IMD ranks/small numbers) are located in particular pockets of the city, with many directly adjacent to more affluent areas. A specific example is Girlington in Bradford, which borders a wealthier leafy suburb and a private school. The underlying sources of these juxtapositions are complex and historical, often tied to industrial change, quality of housing stock and local land-use. Local topographies have also influenced patterns of settlement, accessibility and distribution of resources.

Constructing the picture: data sources

To investigate the small-area level impacts of COVID-19 measures, an individual-level synthetic dataset was employed to build variables of interest. Synthetic data are artificially generated data that reflect the statistics and relationships contained within a real dataset. Using synthetic data allows for detailed predictions and estimates to be made whilst preserving anonymity. Use of a synthetically generated data set also helps resolves challenges related to data limitations—in particular, where no suitable data exist at the necessary geographical scale. Part of the novelty in this study is the combination of established data and synthetic data to explore impacts that would be difficult to identify with readily available data alone. The Synthetic Population Estimation and Scenario Projection Model (SPENSER) produces synthetic populations with a number of attributes drawn from the UK Census (Lomax et al., 2022). See Table 2 for the variables of interest for this study.

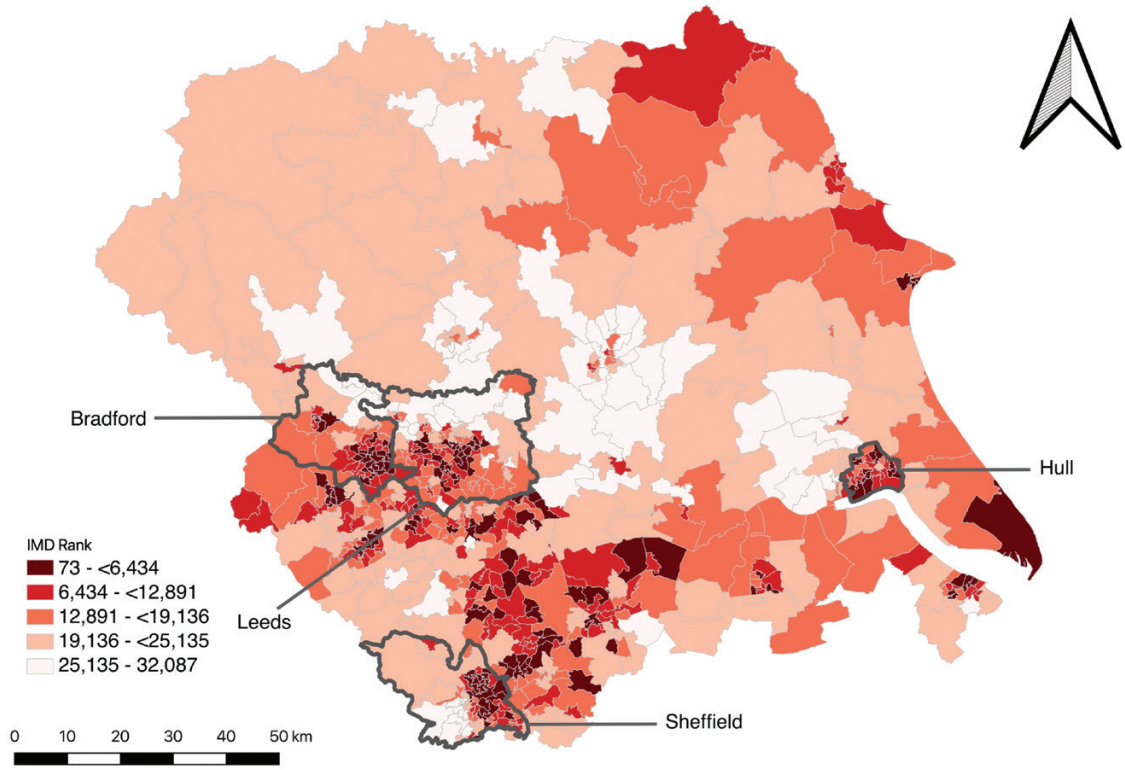

Figure 2. *Variation in the Index of Multiple Deprivation (IMD) across the study area, by MSOA. Smaller numbers/higher ranks indicate more deprived areas, relative to all areas in England.*

Table 2. *Variables across the two SPENSER population files that were utilised in this research. Middle Layer Super Output Area (MSOA, minimum population 5000) and Output Area (OA, postcode clusters).*

Household data (MSOA)	Individual data (OA)
Household ID	Household ID
Output Area	Person ID
Household size	Middle Layer Super Output Area
Household reference person's ID	Age

SPENSER uses an approach termed Iterative Proportional Fitting (IPF) to reweight microdata and area level counts from the 2011 Census of Population for England and Wales to create a micro-level synthetic dataset for the entire population. To achieve this, four steps are implemented: (i) estimate the individual population from 2011 Census; (ii) estimate the household population from 2011 Census; (iii) simulate the baseline population and households forward to 2020; and (iv) assign individuals to households to provide consistency between files. Synthetic individuals are placed in households and are attributed demographic (age and sex for each individual), socioeconomic (based on the socioeconomic status of the household's reference person) and housing condition variables according to the individual and household estimates from the 2011 Census (see Spooner et al., 2021 for an applied example). Further details on SPENSER can be found in Lomax et al. (2022).

For our study, SPENSER data exists as two files, one reporting household information at Middle Layer Super Output Area, (MSOA, minimum population 5000) and the other containing information at the Output Area level (OA, clusters of individual household postcodes and the smallest unit reported in the UK national census). The two can be joined by a 'Household ID'. Overall, there were 5,522,023 individuals across 2,434,505 households in the study area. As a result of SPENSER's complex data generating process for individual and household level populations, a very small number of households were not populated with individuals. These empty households were removed from the study population, resulting in the final synthetic population being assigned to 2,327,774 households.

While suitable for the case study adopted here, this approach is not without challenges and involves a high computational burden where applied for extensive geographic areas. Hence the limited scope of the present study.

Additional variables were incorporated from other data sets to enable exploration of the restrictions, as detailed below:

Shielding

Shielding was identified through a combination of ill-health data and known proportions of the population to be shielding. Firstly, MSOA level ill-health obtained from the 2011 census was used to identify a representative proportion of the population in each MSOA who identified as having their day-to-day activities severely limited due to a long-term health problem or disability. These proportions were applied in four age categories (0–15, 16–49, 50–64 and 65 and over) to improve the representativeness of the patterns assigned to the synthetic population. At the time of analysis, 4.83% of the North-East and Yorkshire region population were on the shielding register (NHS Digital, 2021b). A random 4.83% of all individuals classed as having limiting poor health were then identified as the synthetic population who would experience the effects of shielding. The remaining individuals who had been identified as in poor health were returned to the healthy population subset and were all marked as unimpacted by shielding measures. We may expect some variation in results if a different 4.83% sample were taken, however without detailed health data on who comprised the shielding population, it would be challenging to sample in a more representative way.

Furlough

The identification of a furloughed population drew on supplementary 2011 census data. Here, the proportion of individuals in each Middle Layer Super Output Area (MSOA) who worked in: (i) Accommodation and food service activities; (ii) Arts, entertainment and recreation; and other service activities; and (iii) Wholesale and retail trade; repair of motor vehicles and motorcycles industries, were identified. An average of 61.3% of those in the accommodation and food service activities industry, 67% of those in arts, entertainment and recreation and 13.8% of those in wholesale and retail trade were then identified, in line with ONS sector comparisons of furlough data (2020d). These three illustrative industries were selected as they represent the two industries with the largest proportion of the workforce furloughed, and the industry that employs the most individuals, respectively.

Support bubbles

Using the household size variable in the SPENSER synthetic data (Table 2), single-person households could easily be identified by extracting the households that had a size of one. Due to the absence of English 'support bubble' uptake data, all single-person households were judged to be harmfully affected by this social distancing measure. All other households were considered not to be as adversely impacted by limited household interaction, regardless of the number of people in their household.

Visualising the picture: dashboard design

With an identified set of COVID-19 restrictions for exploration, and a simulated population for the case study area, the final aspect of the research was the development of a visualisation tool—an interactive dashboard—for the outputs generated, which had the capacity to reflect the geographies of impacts at high resolution. Wissel et al. (2020) describe a dashboard as a place where accessible information can be presented in a way that provides easy granular assessment. This type of tool is particularly useful for research where the spatial distribution of the outcomes is significant and may not be apparent from tabular presentation.

Dashboards also allow for complex information to be displayed in a way that a broad audience, such as the general public, can understand (Pellert et al., 2020). Throughout the pandemic, dashboards showing interactive maps of cases and mortality have received high traffic. A number of interactive dashboards were developed as part of early communications efforts, displaying live COVID-19 case rates. Dashboards displayed COVID-19 data at a variety of spatial scales, although a few were utilised more nationally and internationally. Examples include the John Hopkins COVID-19 Dashboard (John Hopkins University & Medicine, 2022) and the UK Government's Coronavirus Dashboard (Public Health England, 2021). Similarly, the British Red Cross (2021) developed an interactive dashboard showing vulnerable groups with unmet needs. This dashboard demonstrates that presenting information about the *impact* of COVID-19 restrictions and measures in a similar manner would allow for the interrogation of complex layers of information in an accessible format.

The dashboard is designed to clearly display a combination of variables within the study area, both as a research tool and as a prototype for policymakers to explore the data. Each of the COVID-19 restrictions detailed above was applied to individuals or households, as appropriate, in order to create a count for numbers of households impacted by each restriction combination. These can all be visualised within the dashboard, which was coded using R Shiny (https://shiny.rstudio.com).

Results and discussion

Main findings

By assigning households to scenarios and displaying them visually, it is possible to identify how the potential impacts of different lockdown restrictions are distributed spatially and which local areas are mostly heavily affected.

Figure 3 presents the geography of those potentially impacted by the reduced social interaction restriction. This restriction is not inherently spatial, but because there is a geography associated with single-person households, some areas were likely more affected by this restriction than others. For example, more densely populated urban areas, represented by the smaller polygons, contain more residents living on their own. Indeed, single-person households have a distinct rural/urban split, with the highest numbers of households in city centres and large towns—in this case Bradford, Leeds, Hull and Sheffield. There is additionally a slight increase in single-person households in the large rural areas towards the north of the study area. The numbers affected by this restriction are also considerably higher than any other measures included here, with up to 3430 households impacted in some urban localities, compared to just 748 affected by shielding measures (Figure 4).

The spatial impacts of the shielding restriction (Figure 4) are less demonstrably urban. Although there are clusters of higher numbers in both Hull and Sheffield, Leeds appears to be less affected. Meanwhile, pockets of impact emerge in coastal locations, as well as in a stretch of MSOAs located between Sheffield and Leeds. The geography of the shielding

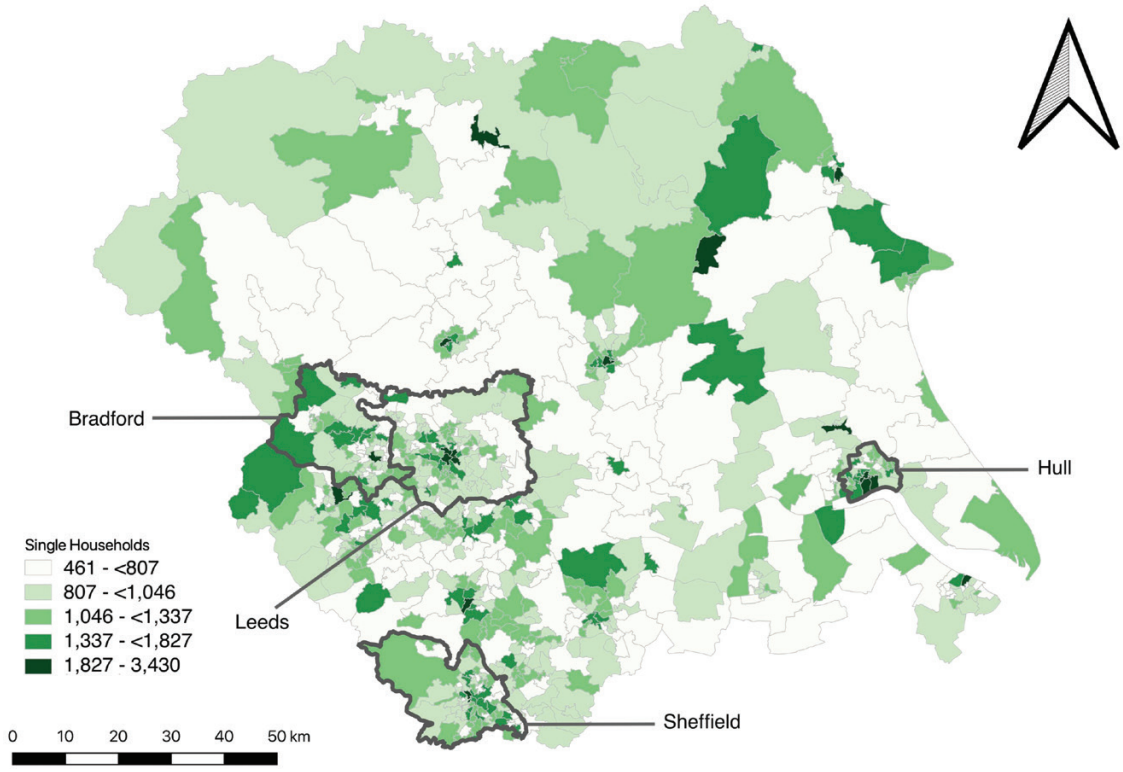

Figure 3. *Estimated impacts of reduced social contact restriction at the MSOA level.*

population exemplifies how pre-existing inequalities, both social and spatial, may be reinforced when pandemic restrictions are disproportionately aimed at particular demographic sub-groups, such as those already suffering ill health.

Households affected by furlough (Figure 5) display an interesting geography, with higher rates at the geographical extremities: both highly urban (the smallest polygons) and highly rural (the largest polygons) contain households within the top two bands. Interpretation of furlough scheme impacts is difficult. On one hand, furlough is an improvement over complete loss of income or unemployment, likely providing important support to areas with a concentration of workers affected by (or benefitting from) the programme. On the other hand, lighter covered areas—those with fewer households affected by the scheme—may include areas with concentrations of workers in industries that were relatively robust to pandemic disruption, but also areas with workers in more informal industries that were affected but not covered by the furlough scheme.

When multiple restrictions are combined, the differential impacts on urban areas become even starker, particularly for the conurbations surrounding Leeds, Bradford and Sheffield. Figure 6 shows the total additive count of impacts for all households in each MSOA, as different households are impacted by multiple restrictions. These emerging patterns appear to be explained by locations of single-person households. The geography of impacts is comparable to that of deprivation (see Figure 2), with the numbers impacted highest towards the urban centres in the South, followed by the

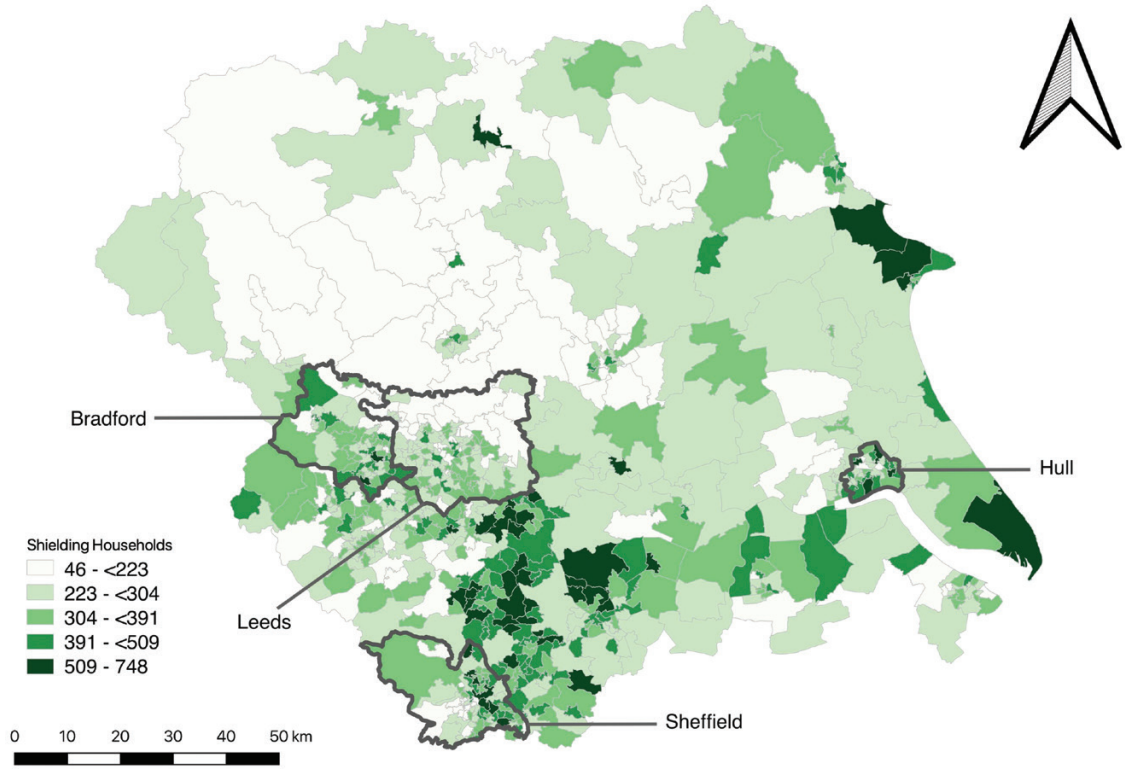

Figure 4. *Estimated impacts of the shielding restriction at the MSOA level.*

rural areas in the North-East. In the latter case, this may be partially driven by households affected by furlough. This finding suggests that those living in more deprived areas may also be more vulnerable to both social and economic impacts of these lockdown restrictions.

To investigate further, we home in on Bradford, an area of disparate wealth and deprivation, with more than 10 years difference in life expectancy and an expectation of 20 years fewer healthy years of life for children born in some parts of the city region, compared to others (Bradford Institute for Health Research, 2019).

At this scale, it is evident that the numbers affected by this combination of restrictions vary a great deal across the city (Figure 7). The patterns of impacts and the IMD are broadly similar, although the geography of pandemic restriction impacts is often more concentrated than the larger clusters of higher deprivation ranked areas. This suggests that, just as pandemic restrictions may have had additive impacts on local inhabitants, for some places, higher pre-existing levels of deprivation may have contributed yet another challenge to local wellbeing. Whether measured in terms of IMD (Figure 7, left) or COVID-19 restriction impacts (Figure 7, right), less vulnerability is seen north of Bradford, towards the more affluent rural areas. This may be partly due to each restriction tending to impact different household characteristics, which are themselves more prevalent in different areas (Figures 3–5). Notably, there are differences in those more vulnerable to economic or social restrictions, such as those shielding or in single person households, who may experience greater isolation because of

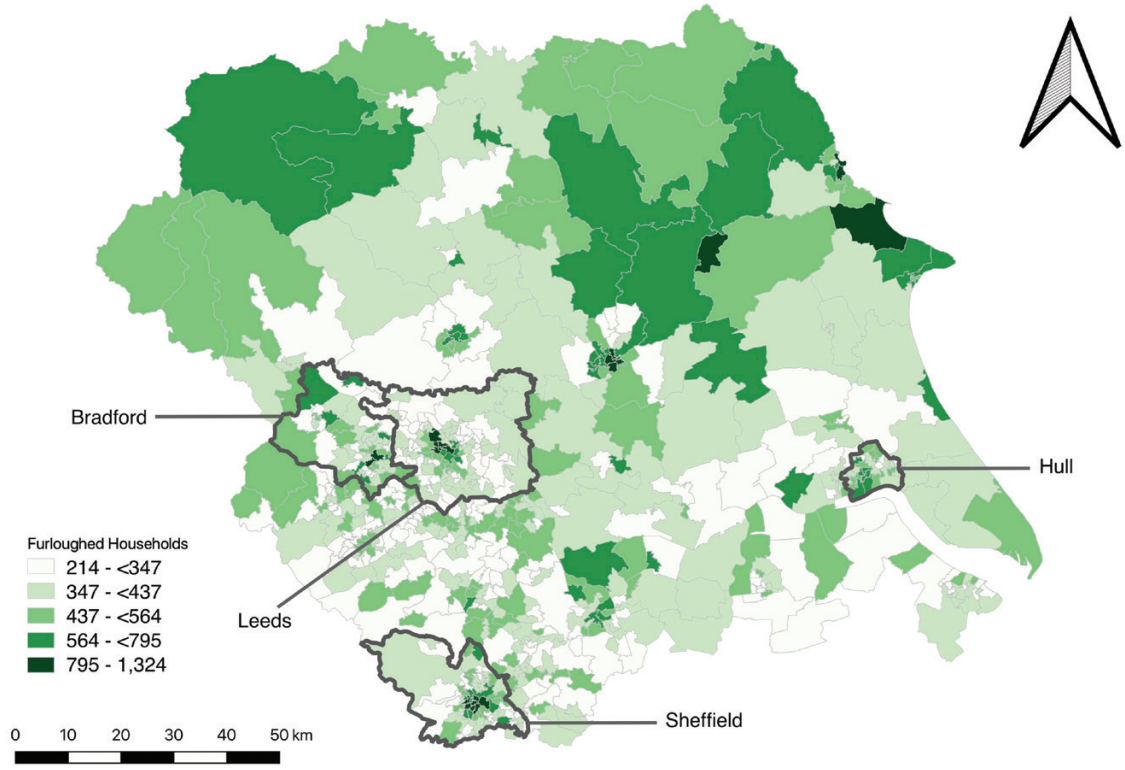

Figure 5. *Estimated impacts of furlough at the MSOA level.*

limited household mixing, compared to those who live with others or do not have to shield. This indicates a need to consider restriction impacts individually, as well as in combination.

While the combination of different restrictions reveals a mixed geography, the spatial inequalities observed for each measure demonstrate the social and economic vulnerabilities of different sectors of the population. This highlights the need for complex multi-channel data to understand (blanket) policy impacts, such as national restrictions. One key finding is the relatively high prevalence of single-person households, particularly in urban areas, suggesting that additional support may be necessary in these places. Urban/rural disparities in numbers of those shielding may also have consequences for where social support is needed, while those affected by furlough—which is more unevenly spread across the study area—show both urban and rural economic vulnerabilities.

The dashboard prototype

Visualisation tools, such as the dashboard presented here (Figure 8), are a useful tool for locating vulnerable communities and regions, and may allow for informed allocation of resources during crisis times, as well as interventions to improve support and resilience in strategic locations. Dashboards offer an appealing medium for communicating complex spatial information quickly and intuitively to a broad range of audiences. In addition, the interactive functionality of dashboards offers an advantage over static maps, allowing users to shift geographies and restriction combinations, thus facilitating a variety of comparisons.

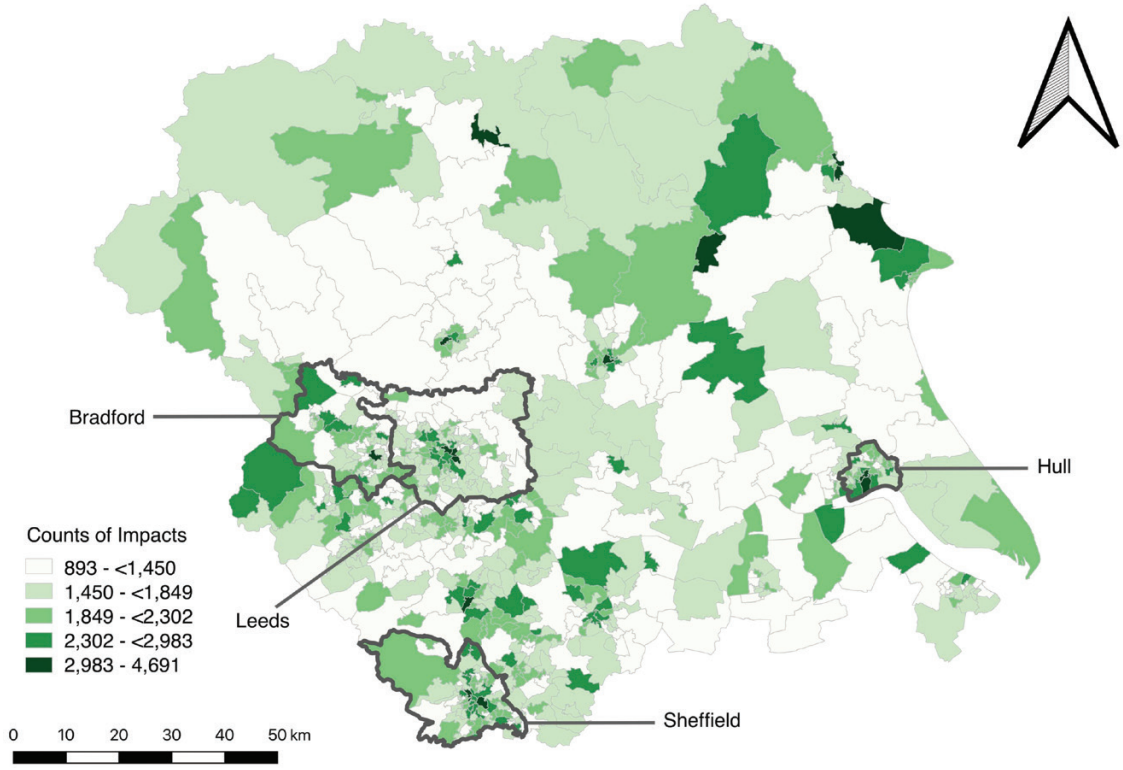

Figure 6. *Additive impacts of all three restrictive measures at the MSOA level.*

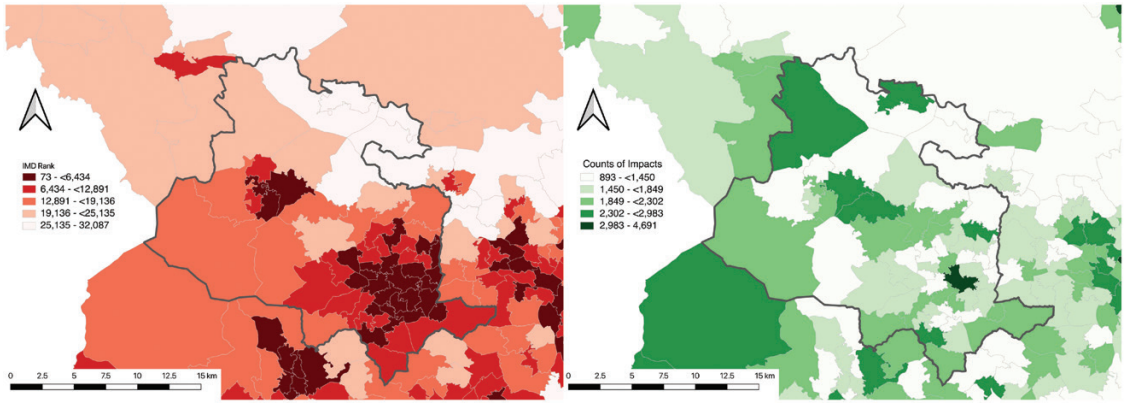

Figure 7. *Comparison of the Index of Multiple Deprivation (IMD) (left) and numbers affected by all three restrictions (right) in the Bradford area at the MSOA level.*

In the dynamic context of the pandemic, the clear communication of policy and data has been essential for public information, engagement and cooperation. Outreach has had several intended audiences, including the public, researchers and local policy makers.

Moreover, the identification and illustration of geographic variations supported and justified local governments and public health authorities in making informed decisions regarding local restrictions. This is particularly pertinent for identifying, and intervening to support, vulnerable populations.

The dashboard interface shown in Figure 8 (prototype available at: https://isolationpostcovid.azurewebsites.net) highlights several important components of impactful data visualisation. The provision of interactive mapping capability is, naturally, the main focus of the dashboard, however, clear definitions of pandemic restrictions also serve to remind viewers of the range of potential impacts and how these might be experienced locally. Moreover, clear explanations of underlying data and estimation of restriction impacts are integral to dashboard development.

Conclusions and limitations

This research makes two main contributions to the existing literature on COVID-19 impacts. First, we demonstrate the feasibility and importance of estimating local-area impacts of pandemic restrictions. Estimates such as these will be fundamental to ensuring wellbeing in the post-covid city. In addition, just as there is a fine-grained geography to vulnerability to illness, so too is there an associated geography of impacts to households and individuals from mitigation strategies, however necessary they may have been. Developing tools to estimate the social and spatial effects of restrictions, whether conceptual, methodological or visual, contributes to the existing range of approaches to understand how the COVID-19 pandemic has affected people and places. Moreover, the approach outlined here can provide insights on the spatial articulation of a variety of social and economic shocks, not just COVID-19.

Second, we demonstrate the potential for synthetic data methods to help fill in the gaps, where existing data provision is concerned. By linking the SPENSER individual and household data with existing data at larger geographical scales, we provide estimates of numbers and types of households affected under different scenarios. Emphasising the geography of the disparate effects of different scenarios is a strength of the dashboard, which, unlike static maps or tabular results,

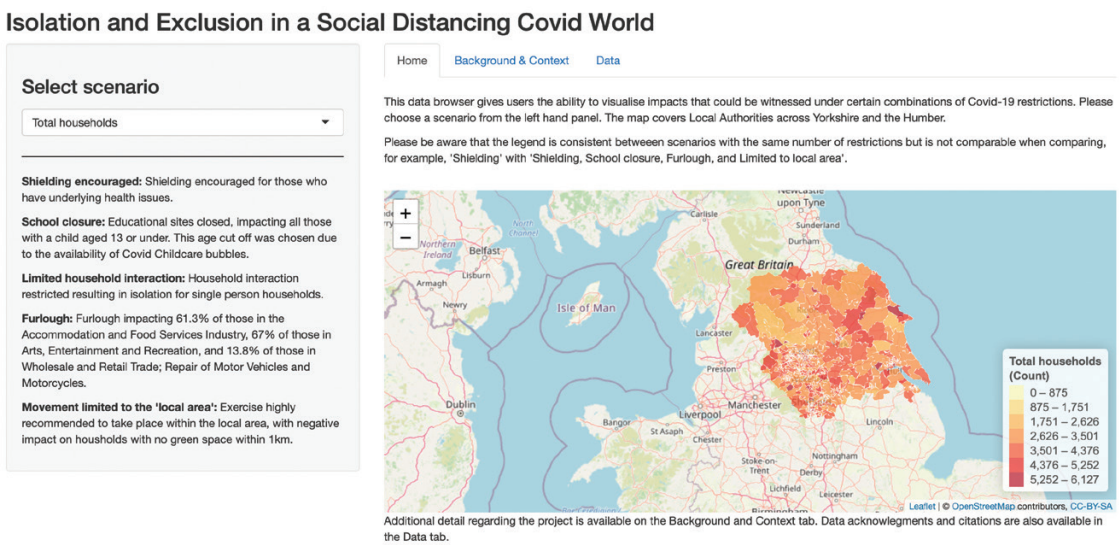

Figure 8. *COVID-19 Restriction Dashboard Interface.*

intuitively conveys the uneven nature of pandemic restriction impacts.

There are a number of challenges to estimating the local effects of pandemic-related government restrictions, giving rise to limitations to this research. One general challenge is the amount of high-resolution empirical data required to explore the impacts directly. Small-area data with good geographic coverage and accuracy are difficult to obtain. Our solution has been to combine published, established data at a national or regional scale with a high spatial resolution synthetic population: SPENSER. Some variables were completely non-existent—for example, any UK-wide data on the uptake of the support bubble. These support bubbles were intended to mitigate against the social isolation caused by extensive social distancing and stay-at-home rules, which limited single-person household social interaction, so knowledge from this data would have enhanced the analysis further. As an illustration, some data is available for New Zealand, where, in the strictest of four COVID-19 alert levels, the uptake of similar support bubbles was thought to be 18.6% (Long et al., 2020). New Zealanders have since been able to expand their bubbles, with a reported 47.6% doing so, but the expectation is that this value is higher (Long et al., 2020). Equivalent data for the UK does not exist. Continued investment in methods to generate high-quality synthetic data for a variety of applications, such as employed here, is recommended—but even these require more input data than is currently available.

Unlike support bubble data, ONS furlough data by industry type can be used as a proxy for capturing the impact of furlough. However, these ONS values are national and are not disaggregated geographically. Certain job types have a distinct geography (for example, seaside tourism), but this geography cannot be easily derived from the furlough data—we apply national-level figures to the local area data.

There are other important data limitations. For example, the assumption that all single-person households have been equally impacted by reduced household interaction is a big one, although it still serves to make a valuable point about the geography of social isolation as a result of pandemic restrictions. Taking up a COVID-19 support bubble will have mitigated the impact of this restriction, but, as noted, relevant data to evidence this are unavailable. Additional detail on the uptake of support bubbles might support understanding of whether different types of single-person households (for example, young professionals or retired elderly) have differing likelihoods of taking up a support bubble. The geographical distribution of these different household types would likely change the geography of households impacted by this measure.

Interpreting household-level impacts from these figures requires high-quality input data. For this illustrative case study, we employed proxy values for certain restrictions and made assumptions for others. This is not ideal and highlights one of the chief limitations to ascertaining *who* and *where* has been most impacted by the range of COVID-19 mitigation strategies put in place in England during the pandemic. As data sets become more detailed, or as additional social and spatial inequalities come to light, our estimates can be updated and these changes can be reflected in the dashboard.

Finally, scaling up this work to a wider geography—the whole of England, for example—offers benefits, but also challenges. Expanding this work nationally (or perhaps internationally, with the necessary relevant cultural alterations) could be hugely insightful, helping to draw out broader inequalities. Viewing patterns at a larger geography could assist in assessing whether impacts from COVID-19 measures match current inequalities such as the North-South divide. Unfortunately, the larger the geography across which the analysis extends, the more likely that computational issues arise.

In summary, from the case study based on Yorkshire and the Humber, we conclude that the combination of synthetic data approaches and interactive dashboard development is viable and informative, but would be further strengthened by the availability of more complete data (such as the uptake of social bubbles). Most importantly, the use of the simulated micro-population has been foundational to the estimates presented in this research and this approach is transferable to other parts of the UK and (potentially) other national contexts—although the conditions for transferability would include an established simulated population, information on area characteristics and sufficient pandemic data. We recommend the continued collection of a wide range of impact data in the medium and longer-term to allow temporal modelling of inequalities. The nature and extent of COVID-19 related inequalities may only become truly apparent over time and as cities, suburbs and rural communities adapt towards more resilient futures.

Endnotes

[1] Although the majority of the impacts of COVID-19 restrictive measures are negative, it should be noted that some unanticipated positive impacts have also arisen. Examples are as follows: some individuals who suffer from physical and mental health problems may have found it easier to participate in work, social and other activities from the comfort of their own homes; some businesses have announced long-term plans to retain flexible home working lifestyles; 63.3% of British shoppers are shopping regularly at local, specialised stores, with the majority keen to continue this habit post-pandemic (Barclaycard, 2021); and instances of influenza were significantly lower in 2020, as some of the COVID-19 related measures helped hold other viruses at bay (Servick, 2021).

[2] For readers with further interest in dashboards, foundational definitions of dashboard are covered in works by Stephen Few. Discussion of governance issues can be found in Kitchin et al. (2015).

[3] As IMD estimates are provided at Lower-layer Super Output Area (LSOA) level, a spatial unit smaller than MSOA, we present the mean ranking for each MSOA. To emphasise relative inequalities in deprivation, we use the national rankings as a point of comparison in this study, where, nationally, 1 is the most deprived and 34,743 the least. For our study area, the lowest-ranked, or least deprived, area is 32,087.

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