Exploring the histories of health and deprivation in Britain, 1971–2011

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1. Introduction

Pervasive and persistent socioeconomic gradients in health which manifest geographically are well documented within Britain (Acheson, 1998; Macintyre et al., 2005; Marmot, 2010; Whitehead, 2014). Such gradients in health exist across the social spectrum, rather than there being a straightforward divide between those who are deprived and those who are not (ONS, 2014). Those in the most socioeconomically advantaged positions are found to have the best health, and conversely, those with the most deprived circumstances have the poorest health outcomes (Benzeval et al., 2014; ONS, 2014). This has been demonstrated for many health outcomes including cardiovascular disease and diabetes (Kavanagh et al., 2010), respiratory diseases (Elli
son-Loschmann et al., 2007) and low birthweight (Krieger et al., 2003). Despite targeted and substantial public health investments designed to reduce such inequalities, relative inequalities continue to widen as improvements in the least-deprived localities continue to be relatively larger than the improvements in the most deprived places (Marmot, 2010). Understanding inequalities not only at a single point in time but also across generations in a community or geographical location (Pearce et al., 2018) is key to illuminating the processes through which spatial inequalities are being maintained and how they might be successfully reversed.

In seeking to understand the influence of place on health, the role of deprivation is crucial. Area level deprivation may lead to disparities in health outcomes by shaping differential access to resources that can mitigate the risk of poor health outcomes (Bécaries et al., 2012). Areas are not static; their contextual and compositional characteristics change over time and in a related manner (Bernard et al., 2007; Gatrell and Elliott, 2009). Poor health outcomes may be the product of cumulative exposure to disadvantage, exposure during sensitive or critical periods in the life course, or both (Jivraj et al., 2019). Previous studies have demonstrated that the experience of people living in deprived areas can be very different (Macintyre et al., 1993).

Ecological research can allow for some impact of the aggregated effect on individual characteristics to be identified at the area level (Black, 2014). Many health outcomes vary in relation to a myriad of social, demographic and geographical factors, all of which display distinct patterns that imprint on the distribution of health. For example, the association between individual deprivation and health might also vary in relation to the aggregated socioeconomic profile of the population which evolves over time (Nazroo et al., 2007; Zhang et al., 2011). An ecological perspective within research is important; analysing individuals alone may ignore these patterns (Macintyre and Ellaway, 2003). Profiling changing demographic and socioeconomic characteristics of areas is vital for developing an understanding of the changing nature of deprivation and its impact upon changing health inequalities. There is a need for place-based approaches which recognise a life course perspective; that the relations between health and place are a set of interrelated processes operating simultaneously at various spatial and temporal scales (Lekkas et al., 2017; Pearce et al., 2018; Bambra et al., 2019).

Health status is multifaceted, with wide ranging mechanisms that characterise the complexity of neighbourhood environments and their influence on health. Such mechanisms are difficult to measure and have complex interactions (Macintyre et al., 1993). Consequently, assessing health change over time is complex and it is not possible to capture each of these facets in one study. Previous work has captured the diverse nature of the changing spatialities of health across Britain at a fine geographical scale (Dearden et al., 2019). Given the pervasive and persistent health gradient, profiling deprivation change and exploring how this is linked with changing health outcomes is an important next step. By measuring how levels of deprivation and poor health have changed in areas over several decades the analysis presented here provides a systematic assessment of the association between health status, deprivation and change.
2. Methodology

2.1. Consistent geographies

Studying how areas have changed over time is problematic due to inconsistencies in the definitions of geographical zones which often are not comparable over time. Removing issues of inconsistent boundaries through the use of gridded zones it is possible to generate directly comparable measures of areas to assess how they have evolved over time; allowing the interconnectedness of LLTI and deprivation to be identified. Expanding on previous work (see Dearden et al., 2019), this paper uses consistent 1 km$^2$ units to examine the changing spatial structure of poor health within Britain and explore how this is associated with changing deprivation.

It is acknowledged that areas, especially when exploring multifaceted concepts like health and deprivation, might ideally be identified in ways which are not constrained by administrative or otherwise arbitrarily drawn boundaries (Chatterton and Bradley, 2000). The utility of devising customised geographies of deprivation (Gockings and Martin, 2005; Haynes et al., 2007) has been demonstrated. Despite these approaches providing valuable insights, they are time-specific. Without taking a consistent geographical approach to produce comparable results over time it is not possible to assess the extent to which change in health status (LLTI) is associated with changing area characteristics (Norman et al., 2003). Gridded data are not constructed according to the population structure at any one time point (unlike, for example, output areas) and they arguably allow for a more natural representation of populations (Lloyd et al., 2017).

Fine-scale, spatially aggregated gridded data provide a novel perspective on health change over time and offer several advantages over irregular geographies for analyses of change. Several studies have utilised standard Census zones with counts reallocated from source zones to a common target geography (Norman et al., 2003; Norman, 2010; Norman and Darlington-Pollock, 2017). The gridded data utilised in this investigation were generated as part of the PopChange project (for more information see Lloyd et al., 2016 and Lloyd et al., 2017) which uses postcode densities to allocate parts of the populations of source zones (enumeration districts or output areas) to consistent 1km$^2$ grid cells. Using 1 km$^2$ sized grids provides a very fine geography allowing local detail in the relationship between health and deprivation to be explored, this size of cell allowed a reasonable level of detail in urban areas but without large numbers of (almost) empty cells in rural areas. 1 km$^2$ grid cells are also in-keeping with the Northern Ireland Census gridded outputs (Lloyd et al., 2017). Gridded data for Northern Ireland are not directly comparable to the PopChange data used here as they are direct outputs from the Census. For this reason, the focus in this paper is on Britain alone.

As grid cells have a constant size, their populations vary markedly. For this reason we experimented with a threshold approach which draws on the Northern Ireland Census grid square product (Shuttleworth and Lloyd, 2009). Fractions of people are possible in the PopChange estimates and only cells which are consistently populated at 0.5 persons and above across the study period (1971–2011) are included in the analysis. Gaps where there is no population present allow for a more natural representation of the spread of population across Britain; empty cells include, for example, large unpopulated areas in the highlands of Scotland. PopChange data are available from 1971 and although LLTI was not recorded in the Census until 1991; deprivation and demographic variables from 1971 are utilised to explore the cumulative impact of deprivation on health change over time.

2.2. Data

The Census is the key source of small area population data in Britain. Taking an ecological approach we examine the patterning and distribution of rates of self-reported Limiting Long-Term Illness (LLTI using Census-derived, gridded data PopChange population surface outputs for 1991, 2001 and 2011. Definitions of LLTI are not consistent across Censuses. Based on ONS guidelines (ONS, 2014), consistent groupings, dichotomised into ‘Limited’ or ‘Not Limited’ (expressed as a percentage of all people) were constructed, permitting comparisons between areas and across the Censuses of 1991, 2001, and 2011.

Previous research has identified a wide-range of factors from the social, economic and physical environment as influential to health status (WHO, 2010). These findings were used to inform the choice of explanatory variables utilised in this study. We seek to assess what characteristics explain LLTI rates, with a particular focus on how far area change over time in deprivation is important for changing health outcomes. In addition to variables which measure for different aspects of deprivation (introduced below), Census-derived demographic indicators including population density, age, ethnicity and country of birth were included in our analysis.

Quantifying the complexity of deprivation is a major challenge usually addressed through the use of composite indices. The Townsend Index (see Townsend et al., 1986) has been utilised widely in academic research as a measure of deprivation (Norman, 2015). The Townsend Index incorporates information on percentages of: unemployment, no access to a car or van, non-home ownership and household overcrowding (more than one person per room) and can be constructed using Census recorded variables for Britain. A summary index of deprivation allows the identification of deprived areas, but as a composite measure, does not permit the distinguishing of specific aspects of the residential environment which are most salient for health. A greater understanding of the interconnectedness of health outcomes and deprivation can be obtained by additionally unpicking the relative contributions of each of the Townsend Index component variables. Such an approach allows the identification of the extent to which different factors are important and how this changes across space and through time. The percentages of unemployed persons and households with more than one person per room (overcrowding) were logged (after addition of 1 to prevent logging zeros as the log of zero is not defined), this allows for the tendency of skewed distributions of these percentages. The four variables (two percentages and two logged percentages) were additionally converted to z scores (percentage-mean/standard deviation) and these were summed to derive Townsend deprivation scores. Positive values of the Index indicate areas with higher levels of deprivation while negative values indicate lower levels of deprivation (Townsend et al., 1988).

2.3. Multivariate regression

Using a multivariate regression approach allowed for an exploration of the relationship between health status (LLTI %) and potential explanatory variables. An Ordinary Least Squares (OLS) regression was implemented to study health by residential context, specified as:

\[ y_i = \beta_0 + \sum_{k} \beta_k x_{ik} + \epsilon_i \]

where \( y_i \) is the percentage of the population reporting LLTI for each grid cell \( i \), \( \beta_0 \) represents the intercept \( \beta_k \) is the parameter estimate for variable \( k \), and \( x_{ik} \) is the value of the \( k \)th variable for \( i \), and \( \epsilon_i \) is the error term. The underlying assumption of the global regression method is that the relationship under study is spatially constant. Thus, the estimated parameter from a global OLS model is spatially invariant. Due to differing compositional and contextual profiles of areas in reality, the relationship between the LLTI and independent variables is likely to vary across space. The spatial variation observed results from spatial autocorrelation in the variables of interest (Anselin, 1996). This spatial component is accounted for through the addition of a spatially lagged dependent variable model (denoted \( \rho \) implemented in GeoDa™ using the queen contiguity (QC) weighting scheme (Anselin et al., 2006). The spatially lagged dependent variable models include terms for
The model is specified as:

\[ z = X\beta + \rho Wz + \epsilon. \]

\(X\) is the matrix of independent variables, \(\beta\) are the parameters to be estimated, \(\rho\) is the spatial autoregressive coefficient, and \(W\) is the spatial weights matrix. A spatially lagged regression model is suitable where it is believed that the values of the dependent variable \(z\) are influenced directly by neighbouring values of \(z\). If \(\rho\) is zero, the model is equivalent to the standard OLS regression model (Lloyd, 2014). It is noted that the Akaike Information Criterion (AIC), log-likelihood and the Schwarz information criterion have been recommended as the proper means of comparison OLS and spatial regression results (Anselin et al., 2006). These model diagnostics, along with measures used to assess the significance of associations, are included in the analysis. Schwarz information criterion is a criterion for model selection among a finite set of models; the model with the lowest criterion value is preferred (Draper and Smith, 1998).

In order to fully explore the relationship of deprivation history on health status, several regression models, each exploring a different dynamic of this relationship over time were implemented. Firstly, separate regression models were executed for each time period (1991, 2001 and 2011) where the variable of interest and explanatory variables were exclusively associated with that year (for example, LLTI, unemployment and overcrowding, all for 1991). Variables were kept consistent between the models allowing comparability across time and identification of how persistent the effects of each variable over time are. Next, rates of explanatory variables for previous time periods were also incorporated into the models including variables which were available from 1971 to 1981 (for example, unemployment in 1981 being included in a model which seeks to explain LLTI in 1991). Changes between consecutive Census years were calculated for the same set of explanatory variables and included in the models. For example, Unemployment change between 2001 and 2011 was calculated as Unemployment rate in 2011 minus Unemployment rate in 2001. Additionally, change between non-adjacent years was calculated for any temporal combination for which data were available. For example, Unemployment change between 1981 and 2011 = Unemployment rate in 2011 minus Unemployment rate in 1981. Mapped residuals from multivariate models are also explored.

Initial variable choice was driven by existing work into the relationship between health and deprivation. Once relevant variables were selected and justified based on this theoretical approach they were obtained for every Census time period for which they were available. Change in these variables was then calculated as described above. An iterative stepwise selection process facilitated through IBM® SPSS Statistics 24 was then implemented in order to identify the temporal combination of variables to utilise. Variables were added according to which was most likely to result in the greatest increase in \(R^2\), beginning with the variable (in its most significant temporal format) which demonstrated the strongest association with LLTI rate. The remaining independent variables were then added into the model one at a time according to which one was most likely to lead to the greatest increase in \(R^2\); this was the variable which had the strongest partial correlation with the independent variable (LLTI rate separately in 1991, 2001 and 2011). Linear regression assumes that the data are normally distributed and that there is no correlation between the independent variables (collinearity) and variables included in this process met the selection criteria. Models which included the composite Townsend Index score and those which included the individual components of the indicator were generated separately.

### 3. Results

#### 3.1. Descriptive statistics of changes over time

Table 1 summarises LLTI rates, the Townsend Index score and its composite components at a national level showing how rates have changed over time. Deprivation is generally shown to have eased over the period due to downward trends in levels of lack of access to a car, household overcrowding and levels of unemployment. Fig. 1 displays long-term deprivation change between 1991 and 2011. Deprivation in most major urban areas including London, Birmingham, Liverpool, Manchester, Leeds, Glasgow and Edinburgh increased over this period. Urban areas were more deprived in 2011 than they were in 1991.

LLTI rates increased from 12.17% to 18.07% (1991–2011) with the majority of this increase occurring between 1991 and 2001; all constituent countries, and Britain as a whole, report a small decrease in LLTI rates between 2001 and 2011. Despite these trends, not all people within locations became less deprived or experienced reduced levels of LLTI, with gradients of deprivation and health largely persisting across Britain’s constituent countries. Fig. 2 displays the spatial patterning of change over time in LLTI rates (1991–2011) across Britain and reveals large decreases in the percentage share of LLTI in some urban centres especially in central London, Manchester, Leeds, Sheffield, Edinburgh and Cardiff, with small increases in LLTI in surrounding suburban areas during this period. Large increases in the percentage share of LLTI are predominantly found in cells which are in coastal locations including areas along the Lincolnshire coastline, the northern and south-western Scottish coast, areas along the coast of East Anglia and the coastline of south east England.

#### 3.2. Multivariate regression

The regression coefficient estimates for OLS and spatially lagged models at each time point are reported in Table 2 and Table 3. When the components of the Townsend Index are included individually in the models, a greater understanding of the interconnectedness of LLTI and deprivation was achieved. Increased \(R^2\) values were obtained in comparison to those models that alternatively included a composite Townsend score. The \(R^2\) values for all three study periods demonstrate that the model fit improved when a spatially lagged dependent variable was incorporated. Incorporation of a spatial lag element results in around 80% of the variation explained in comparison to 57% or less in each of the models that do not include a spatial element. This suggests that use of spatial regression approaches is beneficial. The decrease in AIC for the spatial lag model relative to OLS suggests that the spatial lag model is beneficial, with the smallest AIC value across all study time points reported for the spatial lag model. Constituent variables were deliberately chosen for their association to the subject matter under study, however, variance inflation factors (VIFs) did not exceed the threshold of 10. Therefore, there is no indication that multicollinearity biased the results (Belsley et al., 2004).

A reduction in LLTI prevalence, associated with increased numbers of people born outside of the UK, is reported consistently over all models and is shown to have increased in strength across time. The better health of this group relative to the UK-born is likely to be associated with the ‘healthy migrant effect’; the positive selection of migrants in terms of health (Wallace and Kulu, 2014). As might be expected, Table 2 reveals a strong association between LLTI and age and the effect size of both included age coefficients is broadly constant over time. A positive relationship is observed between LLTI and percentage of residents aged 65 and over with a 0.43% increase in LLTI per one unit increase in the proportion of older residents reported for 2011 (OLS model) and similar in previous years. In contrast, an increase in the number of 0–14 year olds is associated with decreasing LLTI rates. The direction of the coefficient estimates regarding age groups are expected given well-established research on the association of morbidity and older age.
With regards to the Townsend Index score inputs, unemployment is shown to matter significantly for health, with reduced employment levels linked to an increase in prevalence of LLTI. Furthermore, unemployment is shown to have increased in effect size over time. The work of Cooper et al. (2015) suggests that individuals who experience unemployment for more than a short period of time have an increased risk of adverse health outcomes. Overcrowding is negatively associated with LLTI in 1991, but positively associated in 2001 and 2011. The areas with the largest increases in overcrowding between 1991 and 2001, and between 2001 and 2011 have larger non-White ethnic groups, and also greater numbers of people born outside of the UK – both of which have younger age profiles than those who are White and also UK-born. Ethnic group and country of birth are controlled for in the model which suggests LLTI is positively associated with overcrowding for some ethnic groups (and for some national origins), but not for others.

Table 1: Descriptive statistics of key variables.

<table>
<thead>
<tr>
<th></th>
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<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Limiting Long Term Illness (Limited %)</td>
<td>-</td>
<td>-</td>
<td>12.17</td>
<td>18.41</td>
<td>18.07</td>
<td>-6.24 (-0.34) 5.90</td>
</tr>
<tr>
<td>Mean Townsend Index Score</td>
<td>1.56</td>
<td>0.79</td>
<td>0.42</td>
<td>-1.28</td>
<td>-1.32</td>
<td>-1.70 (-0.04) -1.74</td>
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<td>Unemployed (%)</td>
<td>4.08</td>
<td>10.50</td>
<td>9.29</td>
<td>5.34</td>
<td>6.67</td>
<td>-3.95 1.33 -2.62</td>
</tr>
<tr>
<td>Not Owner-Occupied (%)</td>
<td>51.67</td>
<td>44.34</td>
<td>33.94</td>
<td>31.71</td>
<td>35.88</td>
<td>-2.23 4.17 1.94</td>
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<tr>
<td>No Car or Van Access (%)</td>
<td>49.02</td>
<td>39.48</td>
<td>33.35</td>
<td>27.47</td>
<td>26.08</td>
<td>-5.88 -1.39 -7.27</td>
</tr>
<tr>
<td>Overcrowding (%)</td>
<td>7.21</td>
<td>4.34</td>
<td>2.22</td>
<td>1.88</td>
<td>1.99</td>
<td>-0.34 0.11 -0.23</td>
</tr>
<tr>
<td>Aged 65 and over (%)</td>
<td>13.25</td>
<td>15.03</td>
<td>15.85</td>
<td>15.86</td>
<td>16.53</td>
<td>0.01 0.67 0.68</td>
</tr>
<tr>
<td>Aged 14 and under (%)</td>
<td>24.08</td>
<td>20.59</td>
<td>19.17</td>
<td>18.79</td>
<td>17.57</td>
<td>-0.38 -1.22 -1.60</td>
</tr>
<tr>
<td>Non-UK born (%)</td>
<td>6.40</td>
<td>6.70</td>
<td>7.30</td>
<td>8.90</td>
<td>13.40</td>
<td>1.60 -11.80 6.10</td>
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<tr>
<td>Not-White (%)</td>
<td>-</td>
<td>-</td>
<td>5.90</td>
<td>8.70</td>
<td>14.00</td>
<td>2.80 5.30 8.10</td>
</tr>
</tbody>
</table>

Author’s calculations using PopChange data derived from Office for National Statistics and National Records Scotland data. Britain-level percentages of total population or households (derived from grids) and Townsend scores. Scores are given for cells with >0.5 persons or households for all variables for the specific census year.

– data not available.

Fig. 1. Townsend Index score change 1991-2011.
Author’s calculations using PopChange data derived from ONS and NRS data. Scores are given for cells consistently populated with >0.5 persons or households across all census years (1971–2011).

Fig. 2. LLTI (%) change 1991–2011.
Author’s calculations using PopChange data derived from ONS and NRS data. % change given for cells consistently populated with >0.5 persons or households across all census years (1971–2011).

(Gould, 2009).

Table 2

<table>
<thead>
<tr>
<th>Variable (%)</th>
<th>OLS</th>
<th>SLQC</th>
</tr>
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<tbody>
<tr>
<td>1991 LLTI</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aged 65 and over 1991</td>
<td>0.15*</td>
<td>0.08*</td>
</tr>
<tr>
<td>Not UK Born 1991</td>
<td>-1.18*</td>
<td>-0.48*</td>
</tr>
<tr>
<td>Unemployment 1981</td>
<td>0.41*</td>
<td>0.13*</td>
</tr>
<tr>
<td>Aged 0-14 1991</td>
<td>-0.10*</td>
<td>0.06*</td>
</tr>
<tr>
<td>Overcrowding change 1981-1991</td>
<td>0.06*</td>
<td>-0.01*</td>
</tr>
<tr>
<td>Unemployment change 1981-1991</td>
<td>-0.07*</td>
<td>0.02*</td>
</tr>
<tr>
<td>2001 LLTI</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aged 65 and over 2001</td>
<td>0.46*</td>
<td>0.26*</td>
</tr>
<tr>
<td>No Car or Van 2001</td>
<td>0.15*</td>
<td>0.10*</td>
</tr>
<tr>
<td>Not UK Born 2001</td>
<td>-1.95*</td>
<td>-0.72*</td>
</tr>
<tr>
<td>Unemployment 1981</td>
<td>0.25*</td>
<td>0.32*</td>
</tr>
<tr>
<td>Unemployment change 1981-2001</td>
<td>-0.14*</td>
<td>-0.03*</td>
</tr>
<tr>
<td>Aged 14 and under change 1991-2001</td>
<td>-0.12*</td>
<td>-0.06*</td>
</tr>
<tr>
<td>Aged 65 and over change 1991-2001</td>
<td>-0.02*</td>
<td>0.03*</td>
</tr>
<tr>
<td>2011 LLTI</td>
<td></td>
<td></td>
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<tr>
<td>Aged 65 and over 2011</td>
<td>0.48*</td>
<td>0.29*</td>
</tr>
<tr>
<td>No Car or Van 2011</td>
<td>0.18*</td>
<td>0.11*</td>
</tr>
<tr>
<td>Not UK Born 2011</td>
<td>-2.26*</td>
<td>-0.87*</td>
</tr>
<tr>
<td>Unemployment 2001</td>
<td>2.76*</td>
<td>1.08*</td>
</tr>
<tr>
<td>Unemployment change 2001-2011</td>
<td>1.42*</td>
<td>0.60*</td>
</tr>
<tr>
<td>Aged 14 and under change 2001-2011</td>
<td>-0.12*</td>
<td>-0.07*</td>
</tr>
<tr>
<td>Aged 65 and over change 2001-2011</td>
<td>-0.11*</td>
<td>-0.06*</td>
</tr>
</tbody>
</table>

3.3. Residuals

The improved model fit when a spatially-lagged variable is incorporated suggests that the spatial dimension is an inherently important aspect of the relationship between LLTI prevalence and deprivation. Variables included in the model are likely to have highly localised impacts, which cannot be specified in a global model. The residuals from the global regression have been explored to enable the identification of areas where the global model fails to explain a large proportion of the variation. Fig. 3 displays the mapped residual values from 2011 LLTI global regression (Model 2b).

The spatial patterning displayed in Fig. 3 demonstrates the complexity of the relationship between LLTI prevalence and deprivation. It is clear that a global model fails to adequately assess how modelled relations vary spatially. The model fits very well in some areas of Britain but explains substantially less of the variance of poor health in others. Fig. 3 highlights key localities where large over (less than 2) and under (greater than 2) predictions are distributed across the study area. Exploring the socioeconomic context and composition of areas with particularly high or low residual values can provide valuable information for understanding the localised relationship between deprivation and health inequalities explicitly. Former industrial centres of northern England including Newcastle upon Tyne, Middlesbrough, Sunderland, Sheffield and Liverpool display large under predictions, indicating that the model does not explain LLTI rates well in these areas. Similarly, mill towns in Lancashire and Yorkshire also display larger residual values. Fig. 3 also reveals large residual values across much of Scotland and in former coal-mining areas, especially in south Wales and northern England including Grimsby, Morecambe and Rhyll. Areas where the model reports residual values which over-predict LLTI outcomes are predominantly large rural areas; Cumbria, parts of north Wales, Devon and Cornwall, and areas of Northumberland. This could be the result of scale effects as these are...
large areas which have large input zones, which may be heterogeneous and could indicate that the model is more generalised in areas with low population densities. Although this problem might be solved by introducing interactions in terms of contextual covariates, it is unlikely that we can identify and utilise all contextual factors as operational variables in ecological studies.

The $I$ coefficient developed by Moran (1950) has been implemented to provide an indication of the degree of spatial concentration in the residual values from the OLS regression model (2011). The Moran’s $I$ coefficient value generated was 0.70 and statistically significant ($p < 0.001$). It indicates a strong degree of positive association; small areas with similar residual values tend to occur next to each other. This further confirms spatial variation in the variables that explain the presence of poor health across Britain. The Moran’s $I$ coefficient value for the same year reduced markedly ($I = 0.21$) when generated for the residuals of the spatial lag model, indicating that much of the underlying spatial structure is accounted for.

Fig. 4 displays the spatial lag model residuals (2011 model). Less apparent spatial patterning in the model residuals is evident, however, some clear spatial structure remains. Former industrial centres, particularly those with a mining heritage including south Wales, Flintshire and Durham, continue to report large under predictions. It is also evident that London remains heterogeneous with small residual values in central London and larger values on the outskirts. Within London area characteristics are likely to change rapidly across space, therefore a different model may be required to fully explain health inequalities. One possibility would be a local regression model which would help unpick the spatial patterning specifically in London and hint at additional variables which could be included in an expanded model.

3.4. Exploring change over time

We next investigate the exploration of long-term patterning of small-area deprivation and its association to health patterning. Variables were again selected using an iterative stepwise selection process and analysis was repeated including the components of the Townsend Index separately and then as a composite score. The variance inflation factors (VIFs) did not exceed the threshold of 10; providing no indication that multicollinearity is biasing the results (Belsley et al., 2004). Model fit improved when using the four constituent components of the Townsend Index rather than the composite score. When lag effects through both space (as represented by $\rho$) and time (achieved through the use of consistent data and inclusion of variables from previous time points) were incorporated the model fit also improved.

The underlying demography of areas was important at each time point. Rates of being born outside of the UK were associated with LLTI prevalence at each time period. This is an effect which appears to have a strong spatial association and has strengthened over time as the percentage of non-UK born residents within Britain has increased. The age structure was also important. The percentage of young individuals (aged 14 or younger) was consistently negatively associated with LLTI reflecting that most chronic conditions are unlikely in younger populations (Chandola et al., 2007; ONS, 2014). However, contradictory associations were also observed in older populations (other than in 1991). The overall percentage of older populations was positively associated to LLTI rates, however changes between periods were negatively associated, suggesting that larger increases in older populations improved health in small areas.

Unemployment rates at the previous Census time point are
consistently reported to explain more LLTI prevalence than unemployment rates pertaining to the Census year under investigation. The effect size of unemployment is especially pronounced when a spatial lag is incorporated, indicating that localised economic factors are important for health. This is further highlighted by the persistent inclusion of unemployment change in the models. The length of time between the year of focus and the year which unemployment (or change in unemployment) relates to, the strength of the coefficient and the direction of the relationship between LLTI and unemployment change (%) are period-specific. Across the study period the unemployment rate rose sharply between 1971 (4.08%) and 1981 (10.9%) then fell until 2001. Consequently, when change in unemployment rate is positive this is associated positively with LLTI rate, and when unemployment change is negative, this has a negative association with LLTI. This relationship is most obvious in 2001 when unemployment in Britain had decreased by 5.16% from its 1981 high. This change variable (unemployment change 1981–2001) had a greater effect on LLTI rates in 2001 than change in unemployment only over the 1991 to 2001 period. Between 2001 and 2011 unemployment rates increased by 1.33% and this is associated with an increase in LLTI rates.

For other constituent components of Townsend, only overcrowding did not exhibit consistent associations across the study period. No car or van was positively associated with LLTI. The effect size remained fairly consistent over each time point despite large increases in ownership from 50% in 1971 to 75% by 2011. Results demonstrate that at all time points the size of the effect of ‘Not Owner Occupied’ was small.

4. Discussion

The work presented here is one of the most detailed investigations of small area change in inequalities in health relating to changing deprivation histories for Britain. Using novel gridded population data for 1971 to 2011, we have been able to unpick the relative contributions of unemployment, no car or van ownership, non-home ownership and overcrowding. Results show that when lag effects through both space (as measured by γ) and time (consistent data, previous time points included in model) are considered, deprivation and demographic characteristics explain a large proportion of LLTI variation. This has allowed greater understanding of the relationship between health and deprivation, as well as an exploration of how these associations have varied across space and time. Changing definitions of overcrowding in the Scottish census between 1971 and 1981 have resulted in exaggerated decreases of this variable over time and help to explain why it was selected for inclusion in the 1991 model but excluded in models for other years.

We find consistent evidence across all of our models that small area deprivation, as measured though multiple materialistic dimensions, is positively associated with poor health. Material position and its effect over the lifetime of place plays a key role in determining life chances and health outcomes, with cumulative effects of deprivation known to produce poorer outcomes (Cummins et al., 2007). The role of neighbourhood deprivation was demonstrated to interact with an area’s local spatial and historical context. Several cities and regions contained worse health than our model predicted. Departures at a local level suggest specific deprivation histories are important and require further investigation. Materially deprived groups have been shown to disproportionately experience poor social circumstances (Macintyre et al., 1993). Rosenberg (2014) suggests that the systematic unequal distribution of power, prestige and resources among groups in society operates to exclude certain groups from the material living and working conditions, opportunities for consumption of health promoting goods and services, and chances of social participation that can contribute positively to well-being. The inequalities that exist in the distribution of income, employment, skills, education and housing are systematically associated with social disadvantage and marginalisation (Macintyre, 2007; Marmot, 2010; WHO, 2010).

Given that unemployment as a whole has fallen in Britain over the study period, an increased influence of being unemployed on LLTI prevalence is reported over the same period. We also observe the enduring effect of historical unemployment rates. The lasting effects of deindustrialisation have produced regionally concentrated falls in the demand for labour, most notably in northwest and northeast England and south Wales (Mactaggart et al., 2016). Results suggest that areas which have legacies of unemployment and deindustrialisation such as the coal mining areas of south Wales, Northumberland and Durham have an especially localised relationship with poor health where deprivation is strongly correlated with poor health. Localised economic and social factors may act over time to particularly amplify the effects of unemployment in the production of local rates of LLTI. High levels of socioeconomic deprivation, underinvestment in human or social infrastructure and services, and limited labour market opportunities contribute to social exclusion, poor health and reduced well-being (Berkman and Glass, 2000; Riva et al., 2011; Mactaggart et al., 2016). The quality and type of labour market opportunities is an important consideration for unequal health outcomes. Labour market changes have been accompanied by a decline in the number of full-time and permanent roles and a rise in flexible, precarious employment with limited or no employment or welfare rights (MacInnes et al., 2013). Skill mismatches that result in overall job dissatisfaction can be associated with negative health implications (Mactaggart et al., 2016), especially if the employment does not provide financial resources sufficient to relieve financial pressures (Cooper et al., 2015). Given the change over time element of this work variable selection was necessarily limited to those that permitted comparisons through time. However, this structural inequality has been shown to affect health through disadvantaged material living conditions, discrimination, dominance hierarchies and violence (Berkman and Glass, 2000).

The complex and spatially sensitive relationship observed between poor health and deprivation could also suggest that hidden unemployment has been an important factor in the self-reporting of limiting conditions within some areas of Britain (Bambra and Garthwaite, 2015). It has been suggested that the benefits system and the employment services within Britain have diverted people away from unemployment benefits and onto sickness benefits, occurring most prevalently in areas of highest unemployment where jobs are hard to find and occupational ill health is highest (Møller et al., 2013). In a situation of abundant employment opportunities, these ‘hidden unemployed’ individuals could reasonably be expected to participate in the labour market, however, their illness is considered ‘limiting’ when employment opportunities are scarce (Møller et al., 2013). Deindustrialised regions are characterised not only by overall economic decline, but also deteriorating environmental conditions and social disruption (Riva et al., 2011). This has subsequently hindered regeneration and development of new economic pathways. Consequently, such areas are prone to the effects of broader changes in the national labour markets and international economy (Mactaggart et al., 2016). In a study of social capital in north east England, Tiffin et al. (2005) found evidence of associations between life-course deprivation and poorer mental health outcomes for men, with those who had downward socioeconomic trajectories found to report significantly poorer mental health. Men who experience reduced economic circumstances, perhaps through the loss of skilled and semi-skilled jobs that occurred in the north east during the 1980’s and 1990s, may have suffered from loss of role and identity and self-esteem, that could have had an impact on their perceived mental health (Tiffin et al., 2005). Both ‘social drift’ and ‘social causation’ mechanisms have been postulated to produce he association between downward social class trajectory and poor health outcomes.

5. Conclusions

This work offers a new level of insight into the changing health and deprivation profiles of small areas in Britain. Comparison of area populations over time allows changes in population health status and
progress towards targeted reductions in health inequalities to be assessed. Findings from this investigation have allowed us to ‘set the scene’ for spatial health change and its relationship with deprivation change presenting a fine-grained exploration of changes over time. When lag effects through both space and time are considered, deprivation and demographic characteristics explain a large proportion of LLTI variation. The analysis provides a rich picture of the changing variation of health inequalities in Britain. Results demonstrate that economic inequalities play a significant role in the divergent health profiles of different places and that the long-term socioeconomic history of local areas is especially salient for population health.

The finding that area histories, particularly in relation to employment opportunities, continue to have an important influence on health status, has implications for the ways in which widening health inequalities are approached and how appropriate interventions, aimed at reducing inequalities across Britain, are applied. Results demonstrate that the extent to which area history is found to matter for health changes through time, with a spatial sensitivity to this relationship implied by the findings. Exploring the spatial patterning of relationships between LLTI and deprivation in further detail through a spatial modelling approach is necessary but was not possible within the confines of this already analysis intensive work. Although the pervasiveness of the influence of material and social circumstances in determining health outcomes is recognised, the challenge of disentangling the causal mechanisms by which these determinants exert themselves on inequalities through a myriad of biological, behavioural, environmental and psychosocial pathways is subject to ongoing research. An explicitly spatial approach which incorporates area histories and explores how health at one point in time is influenced by conditions at a previous time point can offer a more complete understanding.

This analysis is the first to explore long-term change in health inequalities and deprivation in Britain at a very fine scale using consistent small area data. The potential for understanding long-term health and deprivation change offered through the use of a comparable census data set has been highlighted by the novel findings presented here. There are, however, some caveats about the results and their interpretation that need to be considered. There are concerns about using aggregate level data to make generalisations about people and places, however, the purpose of this work was to provide a geographically rich analysis that was consistent over time which has been achieved through Census data. The grid cells utilised are small and so generalisations have been minimised. The analysis uses quite broad categories such as White/non-White. Of course the categories could have been sub-divided and there are likely to have been considerable differences between subsets of the groups used here. As the study is based on Census-derived data, the analysis is restricted to broad 10-year periods and variables that have been recorded in the Census. Whilst the indicators used are believed to be as time-robust as possible, changes to their relevance within society may have occurred over time. Such changes are likely to have been consistent across Britain, however, results should be interpreted with careful consideration of this and in light of wider changes which may have impacted on these variables. For example, the “right to buy” policy instigated by the Conservative government in the 1980s has been shown to have increased levels of home ownership (Disney and Luo, 2014). Further, results obtained reflect the deprivation measures used here. Increased levels of deprivation observed here are driven by increased overcrowding which is a key component of our measure, other studies utilising different deprivation measures may report different spatial patterning. Nevertheless, the study holds several considerable advantages and presents important conclusions about how changes in deprivation are associated with changes in LLTI. The significance of deprivation for health may change depending on geographical contexts.

Although the pervasiveness of the influence of material and social circumstances in determining health outcomes is recognised, the results identify important associations between health and deprivation but do not provide understanding as to why these patterns are observed. The descriptive analysis presented in this work is pertinent to understanding why the spatial patterns observed matter for health inequalities and provides a valid and useful starting point for teasing out potential causal mechanisms. Interpretation of the results presented here should consider this. It was not possible to find data on an exhaustive list of social, economic, political and cultural factors that was available over a suitable time period and may determine health outcomes within a specific area. For example, migration is an important process that, through the sorting of individuals in terms of their health, contributes to growing polarisation and inequality in health patterning (Boyle and Norman, 2010). A natural extension to the initial findings presented would be to use areal interpolation weighting methods to convert additional variables, such as migration data or subjective health measures (hospital admissions records), into a gridded format. Such an approach would provide insights into factors linked to health that are missing from this work but important for understanding how local particularities may mediate relationships, offering a more complete representation of the geographies of health needs and inequalities in Britain.

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Appendix 1

Appendix Fig. 1. Region locations in Britain.
Appendix Fig. 2. Location of key areas in Britain.
The centre of place names are positioned on the centre of the location they relate to.

References

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