Wellbeing, Space and Society 1 (2020) 100009

Contents lists available at ScienceDirect

Wellbeing, Space and Society

journal homepage: www.elsevier.com/locate/wss

Adverse conditions for wellbeing at the neighbourhood scale in England: Potential and challenges for operationalising indicators relevant to wellbeing in and of places

Sarah Curtis[a,*], Peter Congdon[b], Sarah Atkinson[a], Rhiannon Corcoran[c], Rosie MaGuire[d], Tessa Peasgood[e]

[a] Durham University, United Kingdom
[b] Queen Mary University of London, United Kingdom
[c] University of Liverpool, United Kingdom
[d] New Economics Foundation, United Kingdom
[e] University of Melbourne, Australia

1. Introduction

There is growing concern about inequality in wellbeing observed in populations of relatively high-income countries, including the United Kingdom. Action to address this issue is likely to involve interventions to improve conditions in communities as well as individual circumstances affecting wellbeing. These interventions may be designed to operate at local level, as well as at larger geographical scales. This brings into question what may be suitable geographical indicators to use to help operationalise policy and resource allocation intended to promote greater equality of wellbeing. This paper reports an example of research in England, designed to test small area indicators that are publicly available for governmental and non-governmental organizations and relevant for use in targeting and evaluating interventions aiming to reduce local inequalities in wellbeing.

This paper draws on an international literature on geographies of health and wellbeing (summarized below) showing that variation in wellbeing for individuals is likely to relate not only to individual and family characteristics but also to socio-economic and material living conditions in the communities where they live. It has been noted (Tunstall et al., 2004) that, in the health geography literature, some of the most robust evidence about these associations comes from longitudinal studies, although these are relatively unusual.

We report below a study carried out as part of a larger programme examining how 'community wellbeing' in the UK population can be understood, and might be improved and made more equal through action at the community level (Curtis et al., 2019a). The study draws self-reported wellbeing data collected in two waves of the longitudinal Understanding Society Survey, which follows a large sample of the population in the United Kingdom over time. We observed in our study sample that between these two survey waves, the average measure of individual wellbeing improved significantly, although this change was variable across the sample. In this research we examine the socio-geographical factors associated with this change. We focus particularly on whether relative change in individuals' self-reported wellbeing varied according to the level of neighbourhood disadvantage in the place where they were living, independently of characteristics of the individuals themselves. We also examine how perceptions of community social cohesion reported by survey respondents may operate as an intermediate factor in the relationships studied.

This research tests a measure of local area disadvantage, designed to reflect 'adverse context' for wellbeing, which we generated using selected domains from the Index of Multiple Deprivation 2010 - a composite indicator of local socio-economic inequalities (Department of Communities and Local Government 2011) - and also the Social Fragmentation Index 2011, based on the original developed by Congdon (Congdon, 1996). These indicators are intended to support research and planning in the public and independent sector in England. We explored their relevance as indicators of community conditions associated with relative change in wellbeing and we discuss their relevance for operationalising socio-economic planning to promote wellbeing. We also consider the international relevance of this English case study and the implications for future work in the growing field of research seeking to address the idea of 'wellbeing of (and in) places'.

1.1. Background: theories and evidence regarding the links between wellbeing and neighbourhood conditions

This paper is based upon the premise that 'wellbeing' can be conceptualised as a positive sense of one's current life experience including hedonic ideas of individual happiness and comfort, eudaimonic senses of usefulness and achievement and good relations with others (Ryan and Deci, 2001). The literature summarised below suggests that wellbeing of individuals making up the population in different geographical settings

* Corresponding author.
E-mail address: s.e.curtis@durham.ac.uk (S. Curtis).

https://doi.org/10.1016/j.wss.2020.100009
Received 6 April 2020; Received in revised form 5 August 2020; Accepted 16 November 2020
Available online 26 November 2020

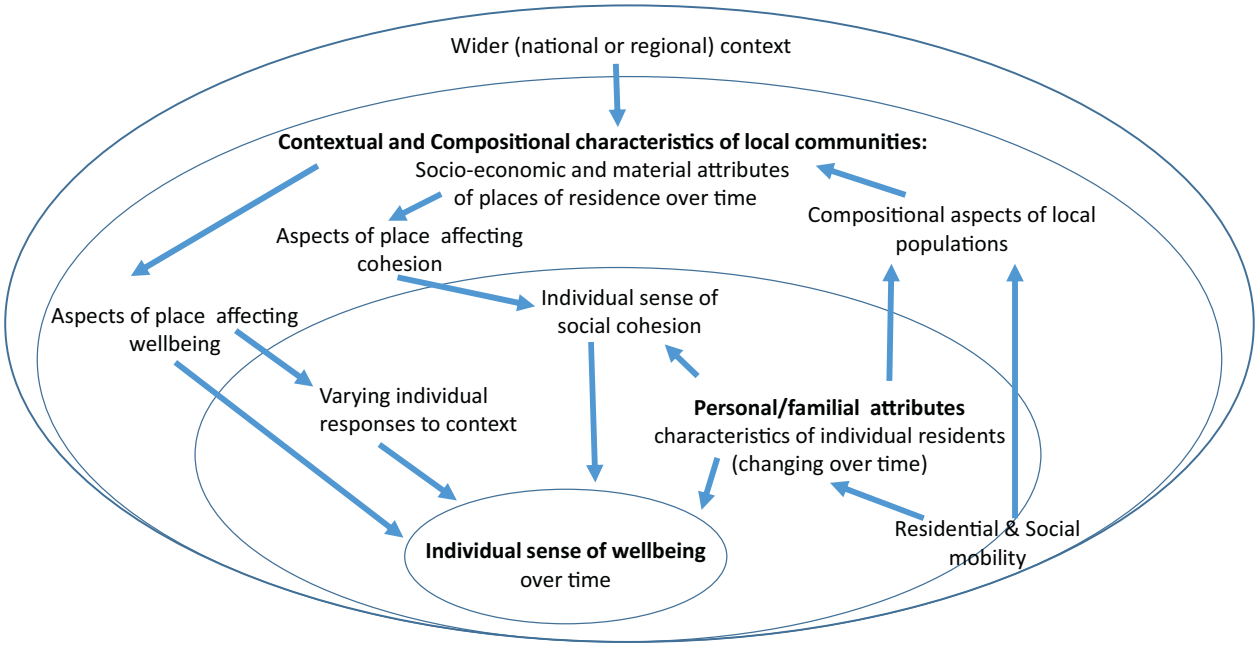

Fig. 1. Factors likely to be associated with individual sense of wellbeing: conceptual model drawing on previous research.

is likely to be associated both with their personal and familial attributes and with various aspects of neighbourhoods where they live.

Fig. 1 draws upon an extensive existing literature on geographies of wellbeing (Atkinson et al., 2012, 2020; Crooks et al., 2018; Williams, 2007). We also considered (though the word limit prevents a detailed review here) some of the broad conclusions from the literature on geographies of health inequality (e.g. (Jones and Moon, 1987; Duncan et al., 1998; Macintyre et al., 2002; Gatrell, 2002; Curtis, 2004; Curtis, 2010)). Fig. 1 represents the complex interplay of conditions described in the health geography literature as compositional and contextual determinants. Population differences in health and wellbeing between geographical areas are associated with combinations of 'compositional' factors (people with different attributes are unevenly distributed in space) and 'contextual' factors (local area attributes that are, at least to some degree, 'additional' to individual attributes, in that they influence wellbeing of residents in a community as a whole). Also, within a community, individuals with different characteristics may vary in their response to the local context (Cummins et al., 2007). Therefore, studies of socio-geographical inequality of health and wellbeing should consider the attributes of individuals living in areas as well as the community-wide conditions of the places where they are living. Moreover, it may be important to account for residential mobility of individuals between different local areas. Fig. 1 also points to wider scale determinants of wellbeing, operating at regional and national levels.

Considering inequalities in wellbeing more specifically, diverse community factors are also likely be relevant (Atkinson et al., 2012; Atkinson et al., 2020; Williams, 2007; Clark et al., 2018; Pearce et al., 2007; Gesler, 2005). Existing research evidence on the associations between wellbeing and community attributes was recently reviewed in detail by the present authors, as reported elsewhere (Atkinson et al., 2020). Here we focus especially on local variability in three groups of factors: social cohesion and disorder; wealth and economic conditions; housing and material living environments. These are aspects of community context that may be targeted through interventions designed to improve wellbeing, and they were identified as being of concern for a range of governmental and non-governmental stakeholders in preliminary consultations which prompted the analyses reported here (Quick and Seaford, 2014). Below, we summarise research demonstrating these relationships which is theoretically of particular relevance for the analyses reported here.

1.1.1. *Social cohesion, social disorder and wellbeing*

Spaces which are secure, integrative and inclusive, and which support capability and self-fulfilment operate in complex ways to influence wellbeing (Fleuret and Atkinson, 2007). For example, individuals' perceptions of neighbourhood cohesion reported at one point in time (wave 4 of the Understanding Society Survey) have been found to be associated with their self-reported sense of wellbeing (Li, 2016). Social cohesion is often conceptualised as a dimension of social capital, found to be relevant for the development of sustainable communities and for planning outcomes beneficial for health and wellbeing (Osborne et al., 2016). The pathways linking social cohesion and mental health and wellbeing are likely to be complex. Some authors suggest that social networks and social support are separate, though related, conditions that matter for health and wellbeing (Smith and Christakis, 2008). Community social cohesion may also relate to core network ties (Moore et al., 2011) and to social engagement and participation in one's community, which may be directly or indirectly beneficial for health and sense of wellbeing (Milton et al., 2012). Conversely, geographical indicators of social fragmentation (lack of social cohesion in local areas), are associated with health outcomes reflecting mental health, such as suicide and use of psychiatric care (Congdon, 1996; Curtis et al., 2006). These indicators also seem likely to be relevant for sense of wellbeing. A related theme in the literature on neighbourhood conditions and wellbeing concerns the significance of local levels of crime and disorder and perception of risks due to criminal or anti-social behaviour (Pearson and Breetzke, 2014; Tan and Haining, 2016; Wiseman, 2018). Equality of access and control of resources, viewed from a 'social assets' perspective, is another aspect of neighbourhood social capital that is theoretically important as the basis for 'resource based' social capital, which influences wellbeing (Bernard et al., 2007).

1.1.2. *Wealth and economic conditions*

In the literature considering health outcomes more generally, it is also well established that levels of socio-economic inequality (Wilkinson and Pickett, 2009) and one's sense of parity with others in

one's community (Okulicz-Kozaryn and Mazelis, 2017; Schneider, 2016) are important for health and wellbeing. International research demonstrates that these processes may operate over the long term, through the life course, as reported in a study from China (Mishra et al., 2014). Research also demonstrates associations between the work environment and wellbeing, suggesting that access to and the nature of employment opportunities, as well as social relations at work, may be important for individual's wellbeing (Burke, 2014; Conti-Ramsden et al., 2016; Flint et al., 2014; Gibb et al., 2014). Changing conditions in local labour markets, including employment levels, have also been shown in various studies to be relevant for mental health (Curtis et al., 2019b).

1.1.3. Housing and material living environments

Diverse attributes of the material living environment are likely to be important for individual wellbeing (Bilger and Carrieri, 2013; Schaeffner et al., 2018). The living environment influences aspects of social interaction and cohesion summarised above, since social spaces, and the opportunities for social interaction they create, are likely to be important for health and wellbeing (Cattell et al., 2008). The material quality of the built environment and related attributes such as noise, light levels, or 'navigability' of the environment (Cooper et al., 2008) may be relevant for wellbeing. Research also underlines the significance of ecosystem services for wellbeing (Ding and Nunes, 2014; Liu and Opdam, 2014; Maynard et al., 2015; Pope et al., 2018; Willis, 2015). Also, material housing conditions including housing quality (Smetcoren et al., 2014; Sowden and White, 2014), tenure (Badland et al., 2017) and affordability (Ratcliffe, 2015) are likely to be significant sources of variation in wellbeing. These may contribute to wellbeing through the experience of physical comfort and also the ways that social and psychological aspects of one's 'home' influence wellbeing (Foresight Mental Capital and Wellbeing Project 2008).

1.2. Aims of this study

The literature summarised above examines the complex relationships between individual and contextual determinants of wellbeing, highlighting especially links between wellbeing and local conditions including social cohesion, economic inequalities and material environments. We hypothesise that experiences of these community conditions may have 'cumulative' effects over the time, influencing how individuals' senses of wellbeing develop and contributing to related wellbeing inequalities. (As discussed below, it is also possible that more disadvantaged communities may have been most severely impacted by conditions of economic recession and austerity prevailing nationally during the period studied.) If individuals are residentially mobile between areas with different community conditions, this may alter their exposure to contextual factors associated with development of their wellbeing. We aimed to explore the evidence for such 'cumulative' effects by testing how community conditions in the person's local area relate to changes in their wellbeing over time.

Given international concern about how to target practical action designed to promote greater equality of wellbeing in the population, we also aimed to explore an approach by which publicly available socio-geographical indicators might be adapted to make them most relevant to strategies to promote improvement in and equality of wellbeing.

2. Materials and methods

We report below analyses of data from the Understanding Society Survey (USS), the largest longitudinal study of its kind in the UK (University of Essex 2017). The sampling method for the USS is explained in the guide to the USS (Kneis, 2018). It includes a diverse range of socio-demographic groups in the national population and is drawn from areas distributed across the country. The survey is therefore well suited to research such as that reported here, which investigates evidence for likely causal processes associated with variation and inequalities in the population. However, we note that it may not be suitable for precisely estimating descriptive statistics for the UK population as a whole. The USS includes weighting procedures designed to make data from the sample more statistically representative of the total UK population, but they were not applied in this study, since they are not applicable to the subset of respondents used for this analysis. Furthermore, other commentators (e.g. (Friedman, 2013; Solon et al., 2015)) suggest that sample weighting may not be appropriate for studies like this one, which are designed to explore relationships within a population sample, indicative of possible causal processes.

We analysed anonymized information for an effective sample of 17,298 USS members, comprising adults (aged over 16) living in England for whom the variables of interest (described below) were available. The main focus is on data from two survey waves which included measures of wellbeing (wave 4, collected 2012–14 and wave 7 collected 2015–17). These were linked to data on place of residence derived from the Index of Multiple Deprivation 2010 and the Index of Social Fragmentation 2011 (described below).

Our analyses were designed to address the following questions:

- Was relative change (between survey waves 4 and 7) in sense of wellbeing, reported by individuals in the USS, associated with measures of neighbourhood conditions in their place of residence, independently of their individual attributes, and controlling for their residential mobility between different types of area?
- Does sense of social cohesion (measured at wave 3) seem likely to be mediating variable in these relationships?

Fig. 2 is a diagrammatic summary of variables used in this study and the relationships between wellbeing and individual and local area conditions that were tested (shown as arrows marked '?'). The components of the model were measured and analysed as follows.

2.1. Outcome variables

The **'outcome' variable** of main interest in the analysis reported below is derived from USS data on individuals' self-reported wellbeing, recorded collected using the Short Warwick-Edinburgh Mental Wellbeing Scale (SWEMWBS) (Warwick Medical School 2013). This is reported in three USS survey waves to date, of which the two most recent observations are studied here (from survey waves 4 and 7) to examine how self-reported wellbeing changed over a period of about three years. The SWEMWBS is the sum of scores generated from responses to 7 survey questions that produces a scale ranging from 7 to 35, with higher scores indicating a more positive sense of wellbeing. The raw scores have been converted to a 'metric' version of the scale, which has been adapted to be Rasch compatible, and so better suited to normal linear regression modelling (Warwick Medical School 2013).

Our modelling approach seeks to examine relative change in the wellbeing outcome between waves 4 and 7. As the outcome variable in regression models, we therefore used the difference between the SWEMWBS scores at wave 7 and wave 4, with the SWEMWBS score at wave 4 also included in the models as a predictor.

For some of the models reported here, we have included data from the USS on individual perception of social cohesion in the persons' neighbourhood, measured at wave 3. This measure is based on a survey instrument used in the Project on Human Development in Chicago Neighborhoods (PHDCN) (University of Michigan 2020). As indicated in Fig. 2, some of our analytical models considered this as an outcome, but we also included it as a predictor of wellbeing. The measure of social cohesion is based on responses to four survey questions producing a score ranging from 4 – 20, which we have edited to avoid distortion due to a relatively small number of more extreme scores.

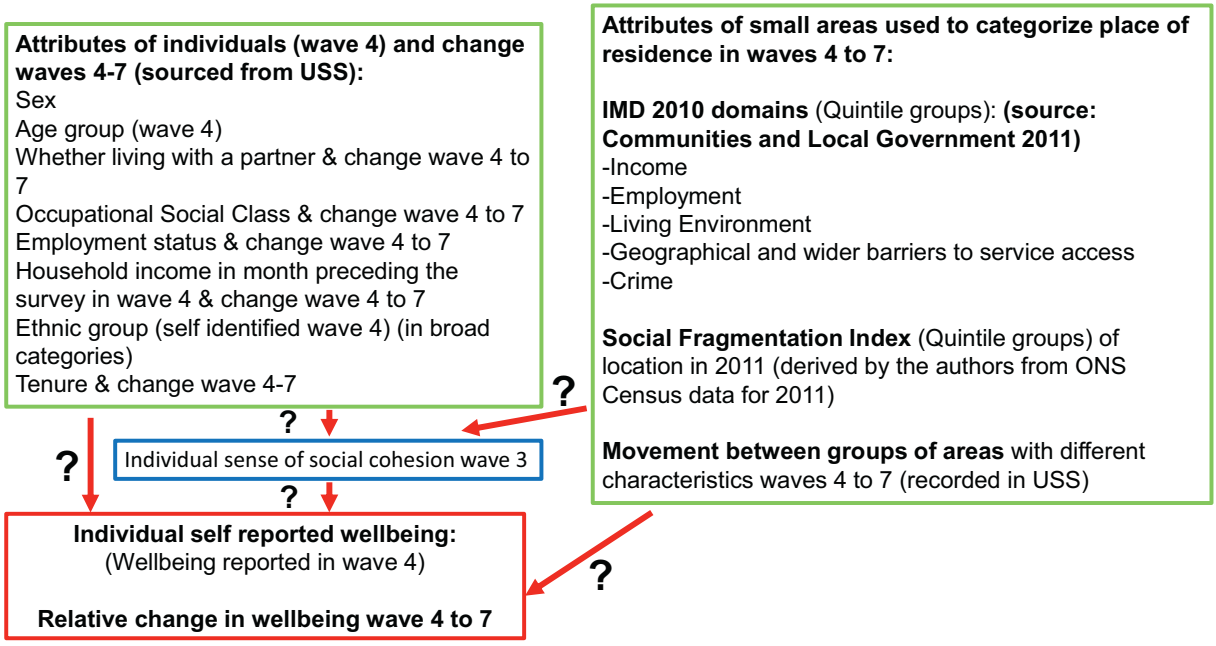

Fig. 2. Analytical model: individual and small area attributes relating to change in Wellbeing reported in USS waves 4 and 7.

2.2. Area indicators used as predictor variables

The predictor variables of primary interest relate to neighbourhood conditions in the places where the individuals were living. Places of residence are defined geographically for this research as Lower Layer Super Output Areas (LSOAs) created in 2011. LSOAs are small geographical zones (totalling 32,844 in England) with average populations of about 1500, for which population data from the census in 2011 and other administrative data are published. An approved researcher in our team was granted permission by the USS data governors, under 'special license', to analyse this information on residential location of individuals in the USS. In order to protect the confidentiality of individuals in the USS, the analysis was carried out in special facilities at the Scottish Centre for Administrative Data Research, Edinburgh University following the required security protocols. The analyses reported below examined the type of LSOA, but not the specific LSOA of residence for USS sample members.

We linked the USS study sample to publicly available data which classifies LSOAs in England according to different domains of the Index of Multiple Deprivation 2010 and also to an updated version of the Social Fragmentation Index (Curtis et al., 2019a; Congdon, 1996). The original IMD 2010 indicators were constructed by the Social Disadvantage Research Centre at the University of Oxford, and for this research they were sourced from an online platform provided by Communities and Local Government (Department of Communities and Local Government 2011).

We used data on six of the domains which make up the global Index of Multiple Deprivation 2010 (IMD2010) (measuring area conditions just prior to the dates when the individual USS data on wellbeing were collected). The domains included: the crime domain, relating to social cohesion; the income and employment domains that relate to wealth and economic conditions; and the domains measuring living environment and barriers to housing and services to reflect housing and material environment. Details of the components of these IMD2010 domains of disadvantage are shown in appendix Table A (supplementary information).

The 'global' IMD2010 indicator also includes two other domains that are not analysed in this study. The 'Education' domain of IMD2010 was omitted since it relates more particularly to educational disadvantage among children, rather than the adult population which is the focus of this research. The 'Health' domain was also excluded, since it does not directly measure socio-economic or material conditions and it includes information on mental health that might be confounded with the outcome variable on self-reported wellbeing.

We were also interested in aspects of social cohesion at community level (which is not currently represented in the Indices of Multiple Deprivation, except, arguably, in the 'crime' domain). We therefore also included information on the Social Fragmentation Index. This indicator was originally developed using 1991 census data (Congdon, 1996) and has subsequently been updated using decennial census data for 2001 and 2011 (Curtis et al., 2019a). This Social Fragmentation measure is treated in this analysis as a proxy indicator of conditions likely to be related to disadvantage in terms of lack of community social cohesion. In this study, we used a version based on population data from the 2011 census for Lower Super Output Areas (Curtis et al., 2019a). The components are proxy indicators for factors in local communities likely to be associated with lower levels of social interaction and lack of residential stability, which may contribute to social fragmentation at neighbourhood level (see Table A - supplementary material).

We categorised the study sample into quintile groups based on ranking by their LSOA of residence on each of the area indicators of interest described above. Quintile groups labelled 1 lived in areas that were least disadvantaged and those labelled 5 were in most disadvantaged areas. (This ranking convention is the inverse of the decile ranking of the IMD domains for LSOAs in datasets published by the Department of Communities and Local Government (Department of Communities and Local Government 2011).)

2.3. Controlling for individual characteristics

All the models we report below also incorporated **predictor variables** which are measures of **individual characteristics** reported in the USS that are likely to be associated with wellbeing, as frequently reported in the literature reviewed above. These are detailed in Table B (Supplementary Information). They measure: sex; age group, occupational social class at survey wave 4; whether the individual was socially mobile in terms of social class between waves 4 and 7; whether living with a partner and if this changed between waves 4 and 7; individual's

employment status and whether it changed between waves 4 and 7; housing tenure at wave 4 and whether this changed to outright ownership by wave 7; household income at wave 4; income change between waves 4 and 7; and ethnic group.

When these individual variables are included in the models, they serve to adjust our principal findings (regarding the associations between relative change in wellbeing and 'neighbourhood' conditions). By taking into account these various individual attributes relevant to wellbeing, we are able to examine more particularly how 'contextual' aspects of neighbourhood conditions relate to wellbeing. We note that these indicators of individual attributes may also relate to other individual characteristics that are not specifically included in our analyses, and may only be relevant for certain population groups (e.g. presence of dependent children in the household). We considered inclusion of information on individual health status, which has been reported as relevant to sense of wellbeing in other research, but decided not to include these indicators, since self-reported health status (especially mental health) and sense of wellbeing are likely to be so closely interrelated that they would produce confounding effects if both were included in the analytical models.

The **modelling approach** used to examine factors associated with change in wellbeing is an ordinary least squares regression. The individuals considered in this analysis were distributed across a total of 9120 LSOAs, with on average less than 2 individuals per LSOA. This meant that multi-level modelling of 'area effects' was not appropriate in this study. (We discuss below the potential to extend this research using other types of model which examine effects of spatial clustering and processes operating at larger scales.)

Stages of analysis are detailed in Figure A (Supplementary information). These involved:

- Measuring change in self-reported wellbeing (the outcome);
- Preliminary modelling to examine the relationship between wellbeing change, individual attributes, and each of the area predictor variables considered;
- Generating a composite score for area disadvantage relevant to wellbeing (combining the different area predictors) for each person's place of residence;
- Testing whether the area disadvantage score predicted change in wellbeing between waves 4 and 7 of the USS survey, controlling for individual attributes;
- Testing whether the composite area disadvantage score predicted individual sense of neighbourhood cohesion at wave 3, controlling for individual characteristics;
- Modelling to test whether sense of cohesion was likely to act as a mediating variable in the association between area disadvantage and individual wellbeing.

We report the results of the regression models including the regression 'coefficients' for predictor variables, which are 'beta' coefficients showing the 'strength' and 'direction' of the association with the outcome, as well as the 't-statistic' as a measure of variability in the 'beta' coefficient across cases, and the 95% confidence interval for the 'beta' coefficient likely to apply in the wider population from which the sample was drawn. The 'P' value reported in the results shows the statistical significance of the beta coefficient reported. In the report below, we follow the common convention by considering associations with a P value of less than 0.05 (5%) as being 'significant', as they are unlikely to occur by chance.

3. Findings

3.1. Average change in self-reported wellbeing

Preliminary analyses showed that the mean wellbeing score for the sample as reported in wave 7 was significantly higher (23.2; 95% confidence interval: 23.1 - 23.2) than at wave 4 (22.6; 22.5 - 22.6), suggesting on average improvement in sense of wellbeing over time in the sample as a whole. (This may partly reflect the aging of the cohort over time, as discussed below.) The findings reported below show how change in wellbeing varied amongst the sample studied in relation to the predictor variables considered.

3.2. Associations of wellbeing change with individual attributes

Table 1 shows that several individual characteristics of the sample members are associated with relative wellbeing change. Compared with those who were aged 60–69 in wave 4, wellbeing improved less among those aged under 50 years, who would have still been middle-aged by wave 7. This finding is consistent with many studies which show that wellbeing tends to be more positive for those in older age groups compared with younger adults. Differences between men and women are not statistically significant after controlling for other variables in the models presented. However, in a preliminary analysis (not reported in detail here) in which wellbeing score in at wave 7 was predicted only by sex and age group, we found that, allowing for age differences, women had significantly lower levels of wellbeing than men. This suggested that both sex and age group should be retained in the models as 'control' variables,

We also show in Table 1 how relative change in wellbeing related to socio-economic characteristics of individuals. Wellbeing scores improved more for those who:

- Were living with a partner (either a spouse or unmarried) at both waves or at wave 7 (as compared to not living with a partner at either time point);
- Were in receipt of a relatively high household income in the month prior to interview at wave 4 (controlling for relative change in income by wave 7);
- Were outright owners of their homes at wave 4, or became outright owners by wave 7 (as compared with those who were tenants both time points);
- Were upwardly mobile between social classes between waves 4 and 7;
- Identified as members of ethnic groups defined here as 'Asian' or 'Black', as opposed to 'White British' or other 'White' ethnic groups.

Results reported in Table 1 also show that relative change in wellbeing was significantly lower for those who were:

- Unemployed in waves 4 and 7, compared with those employed at both time points;
- In social class 2, as compared to class 1 at wave 4.

3.3. Associations of wellbeing change with separate area indicators and generating a composite area disadvantage score

The relationships of principle interest in this paper are those between change in wellbeing and characteristics of the individuals' places of residence, after controlling for the associations with individual variables reported above. The preliminary results, shown in Table C (Supplementary Information) and summarized in Fig. 3, show how change in wellbeing between waves 4 and 7 related to ranking on separate domains of area deprivation at wave 4, and to change in deprivation ranking on these domains, due to residential migration, by wave 7 (after controlling for individual variables).

Fig. 3 illustrates the beta coefficients from the models reported in Table C, showing how wellbeing change was associated with area ranking on each domain at wave 4. The statistically significant relationships (represented in darker shading), indicate how change in individual wellbeing differed between those in quintile group 1 and those in other (more 'deprived') quintile groups. Ranking on each of the different domains of area deprivation showed some significant associations with

Table 1

Regression model predicting change in wellbeing (SWEMWBS) wave 4–7 with pedictors including: wellbeing at wave 4, individual attributes, quintile category of Index of area disadvantage for place of residence in wave 4, and whether the person moved between LSOAs in different categories wave 4–7, dependant variable: change in wellbeing (SWEMWBS) wave 4–7.

Predictor Variable (reference for categorical variables)	category	Coefficient	Standard Error	t	*P*>|t|	95% Confidence Interval	
SWEMWBS wellbeing score at wave 4		−0.461	0.008	−60.2	<0.001	−0.476	−0.446
Sex (male)	female	−0.067	0.057	−1.16	0.245	−0.179	0.046
Age group (years) wave 4	16–19	−0.447	0.236	−1.89	0.058	−0.909	0.015
(60–69)	20–29	−0.414	0.178	−2.32	0.020	−0.764	−0.065
	30–39	−0.530	0.168	−3.16	0.002	−0.858	−0.202
	40–49	−0.498	0.163	−3.06	0.002	−0.817	−0.179
	50–59	−0.299	0.161	−1.85	0.064	−0.615	0.018
	70+	−0.184	0.109	−1.69	0.091	−0.397	0.030
whether living with a partner							
(not living with a partner at wave 4 or wave 7)	living with a partner waves 4 & 7	0.251	0.074	3.42	0.001	0.107	0.396
	not with partner wave 4, with partner wave 7	0.347	0.159	2.18	0.029	0.035	0.659
	lived with partner wave 4, not at wave 7	−0.434	0.169	−2.56	0.011	−0.766	−0.101
Occupational Social class wave 4							
(Class I) (Management & Professional)	Class II (Intermediate)	−0.332	0.111	−2.99	0.003	−0.550	−0.114
	Class III (small employers and own account)	−0.053	0.129	−0.41	0.683	−0.307	0.201
	Class IV (lower supervisory & technical)	−0.032	0.150	−0.21	0.831	−0.326	0.262
	Class V (semi-routine & routine)	−0.151	0.099	−1.52	0.130	−0.346	0.044
	Unclassified (Inapplicable)	−0.176	0.158	−1.11	0.266	−0.486	0.134
Change in social class wave 4 to 7							
(no change)	upwardly mobile wave 4 to 7	0.272	0.132	2.05	0.040	0.012	0.531
	downwardly mobile wave 4 to7	0.213	0.149	1.43	0.153	−0.079	0.505
	inapplicable (unclassified)	−0.183	0.173	−1.06	0.291	−0.521	0.156
housing tenure wave 4							
(rented/other)	owned outright	0.420	0.088	4.78	<0.001	0.248	0.592
	owned with mortgage	0.044	0.080	0.55	0.582	−0.113	0.201
Change in homeownership wave 4 to 7							
(no change)	became outright owner	0.243	0.117	2.07	0.038	0.013	0.472
gross HH income in last month at wave 4 (quintiles)							
(quintile 1- lowest)	quintile 2	0.331	0.093	3.57	<0.001	0.149	0.514
	quintile 3	0.283	0.101	2.82	0.005	0.086	0.480
	quintile 4	0.469	0.108	4.34	<0.001	0.257	0.681
	quintile 5 (highest)	0.526	0.116	4.54	<0.001	0.299	0.753
Relative change in income waves 4–7							
(quintile 1 greatest fall in income)	quintile 2	−0.050	0.091	−0.55	0.580	−0.229	0.128
	quintile 3	−0.210	0.094	−2.24	0.025	−0.393	−0.026
	quintile 4	−0.151	0.094	−1.62	0.106	−0.335	0.032
	quintile 5 (greatest increase in income)	0.128	0.098	1.31	0.191	−0.064	0.319
employment status waves 4 to 7							
(employed waves 4 & 7)	unemployed at wave 4 and 7	−0.486	0.186	−2.61	0.009	−0.850	−0.121
	became unemployed/retired wave 4 to 7	−0.051	0.197	−0.26	0.795	−0.436	0.334
	Not employed wave;employed by wave 7	0.258	0.179	1.44	0.149	−0.092	0.609
	retired	0.416	0.219	1.9	0.058	−0.014	0.847
ethnicgroup	'Asian' ('Indian', 'Pakistani', 'Bangladeshi', 'Chinese', 'other Asian')	0.854	0.120	7.12	<0.001	0.619	1.089
('White British/Irish')	'Black' ('Black African', 'Caribbean',' Black other')	1.019	0.167	6.09	<0.001	0.691	1.348
	'mixed/other' ('white' & 'black' or 'Asian' 'Arab' 'other')	−0.047	0.193	−0.24	0.808	−0.426	0.332
Area disadvantage Score quintile for place of residence in wave 4							
(lowest quintile - least deprived)	Quintile II	−0.099	0.088	−1.12	0.262	−0.271	0.074
	Quintile III	−0.119	0.089	−1.34	0.180	−0.293	0.055
	Quintile IV	−0.259	0.091	−2.83	0.005	−0.438	−0.079
	Quintile V (most deprived)	−0.317	0.098	−3.22	0.001	−0.509	−0.124
Residential Mobility - area disadvantage quintile in wave 7 compared with wave 4							
(no change in quintile group of LSOA)	Quintile group in wave 7 less deprived than wave 4	0.125	0.128	0.98	0.329	−0.126	0.377
	Quintile group in wave 7 more deprived than wave 4	−0.207	0.110	−1.89	0.059	−0.422	0.008
constant		10.950	0.276	39.72	<0.001	10.410	11.491
Number of observations	17,298						
R-squared	0.180						
Adjusted R-squared	0.178						

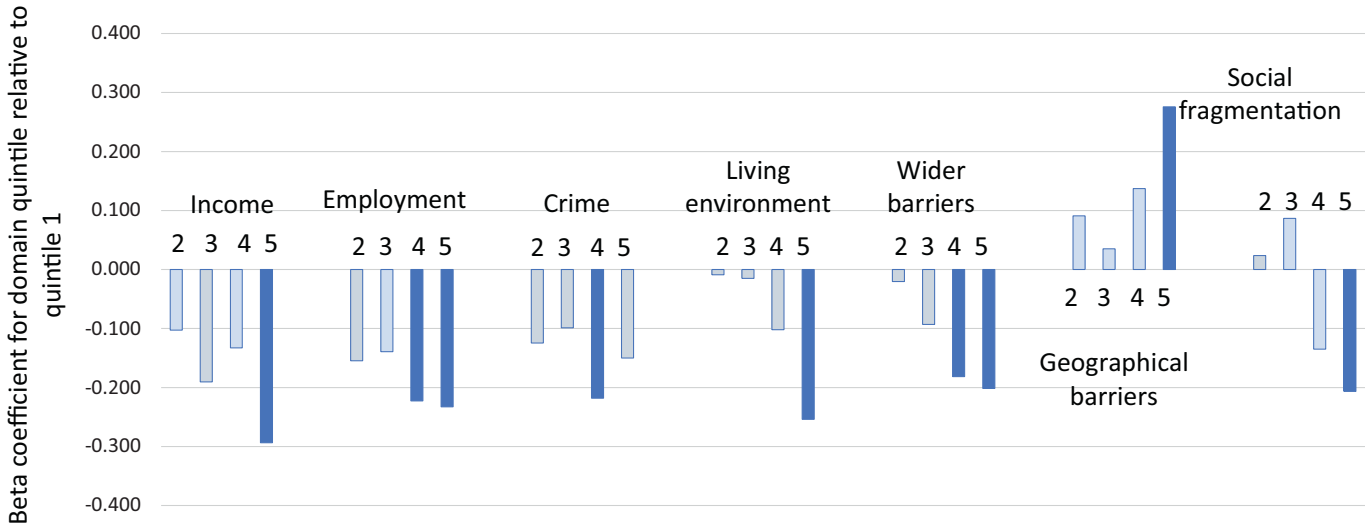

Fig. 3. Diagram of b coefficients from regression models shown in Table C illustrating the relationship between change in wellbeing waves 4 to 7 and different domains of deprivation for place of residence in wave 4 (after controlling for other factors. For each indicator of deprivation the coefficients are shown for the association with quintiles 2,3,4 and 5, as compared with quintile 1 (least deprived). The dark shaded bars show coefficients indicating statistically significant associations with wellbeing change.

change in wellbeing (represented in darker shading in Fig. 3). For most domains, individuals living in areas ranked in more 'deprived' quintiles showed significantly lower improvement in wellbeing (Fig. 3; Table C: Models 1–5 and 7). However, for one domain, relating to 'geographical barriers' of low access to services, wellbeing improved more for those in the most 'deprived' areas (Fig. 3; Table C: Model 6). This probably reflects better wellbeing outcomes in more remote rural areas.

Based on these results, we constructed a composite area disadvantage score in which deprivation due to geographical barriers carries a negative weighting, while the other area deprivation indicators are all treated as positive components of disadvantage. We categorized the study sample into quintiles by this indicator of disadvantage in their area of residence.

3.4. Testing whether the area disadvantage score predicted change in wellbeing between waves 4 and 7 of the USS survey

Table 1 shows the association with the composite score of area disadvantage, controlling for individual variables. Compared with those who at wave 4 lived in an LSOA grouped in quintile 1 (least disadvantaged areas in England), those in quintiles 4 and 5 (more disadvantaged areas) had less positive change in wellbeing outcomes. Mobility between quintile categories of the composite area disadvantage score seemed not to have had a very significant relationship with change in wellbeing, although those whose ranking in terms of area disadvantage had shifted to more disadvantaged quintiles by wave 7 showed less improvement in wellbeing at the 10% probability level. (Also, in Table C, models 2 and 4 suggest that those who moved to areas which were less deprived in terms of employment levels and living environment showed significantly greater improvement in wellbeing.)

3.5. Models including perception of local social cohesion

Table 2 shows that the individual measure of perceived social cohesion at wave 3, considered as an outcome, was also significantly related to the composite area disadvantage ranking, with those living in more deprived areas showing significantly worse perceptions of social cohesion in their neighbourhood. In Table D (Supplementary Information), we see that when individual perception of social cohesion is included as a predictor in the model predicting change in wellbeing, the association between change in wellbeing and area disadvantage becomes less significant than in Table 1. This suggests that sense of neighbourhood cohesion may be a mediating variable contributing to the link between area disadvantage and change in wellbeing.

4. Conclusions

4.1. Discussion of findings

Other authors have commented on the need to critically assess how the components of Indices of Multiple Deprivation should be interpreted in terms of their policy relevance (Deas et al., 2003; Niggebrugge et al., 2005). To our knowledge, these indicators have not been extensively tested for their relevance for policy with respect to change in wellbeing in the population. Our analysis responds to a recognized need for further research on the links between area conditions and individual wellbeing; for example, Oguz calls for 'further research on area effects' [(Oguz, 2014), p. 44].

The analyses reported here involved preliminary testing of different components of the Index of Multiple Deprivation (2010) and also the Social Fragmentation Indicator (2011) in terms of their association with change in wellbeing. On the basis of these preliminary analyses, we constructed a composite indicator of area disadvantage which was designed to be particularly relevant to inequalities in wellbeing. This was found to be significantly and negatively associated change in wellbeing, after controlling for individual attributes and residential migration between different types of area. For most of the components examined, wellbeing improved less over the period studied for those who were in more disadvantaged areas. However, we also found that the 'Housing – Geographical Barriers' sub domain of the IMD2010 index, measuring varying access to services, shows the reverse relationship, suggesting that more remote rural areas with relatively poor access to services have some advantages for wellbeing. For some area indicators considered here we also found that 'upward residential mobility', from more disadvantaged areas to less disadvantaged parts of England, was associated with more positive changes to wellbeing over the period.

4.2. Limitations and scope for further analysis

We acknowledge certain caveats with respect to these results. These include the fact that we have not been able to analyse the whole USS survey sample, which affects the extent to which the results reflect the

Table 2
Regression model predicting sense of social cohesion score (CoHSc) at USS survey wave 3, with predictor variables representing individual attributes and area disadvantage score of place of residence at wave 4 dependent variable = sense of cohesion score at wave 3 of USS survey.

Predictor Variable (reference for categorical variables)	category	Coefficient	Standard Error	T	$P>\|t\|$	95% Confidence Interval	
Sex (male)	female	0.071	0.016	4.44	<0.001	0.040	0.103
Age group (years) wave 4	16–19	−0.297	0.057	−5.20	<0.001	−0.409	−0.185
(60–69)	20–29	−0.237	0.038	−6.27	<0.001	−0.311	−0.163
	30–39	−0.099	0.034	−2.88	0.004	−0.167	−0.032
	40–49	−0.098	0.033	−2.98	0.003	−0.162	−0.033
	50–59	−0.079	0.031	−2.53	0.012	−0.141	−0.018
	70+	0.112	0.031	3.63	<0.001	0.052	0.173
whether living with a partner							
(not living with a partner at wave 3)	living with a partner at wave 4	0.068	0.017	4.07	<0.001	0.035	0.101
Occupational Social class wave 4							
(Class I) (Management & Professional)	Class II (Intermediate)	−0.064	0.030	−2.11	0.035	−0.123	−0.004
	Class III (small employers and own account)	0.039	0.036	1.09	0.276	−0.031	0.108
	Class IV (lower supervisory & technical)	−0.033	0.041	−0.80	0.426	−0.113	0.048
	Class V (semi-routine & routine)	−0.088	0.026	−3.33	0.001	−0.140	−0.036
	Unclassified (Inapplicable)	−0.110	0.033	−3.34	0.001	−0.175	−0.046
gross Household income in last month at wave 4 in quintiles							
(quintile 1: lowest income)	quintile 2	0.014	0.025	0.55	0.579	−0.035	0.063
	quintile 3	−0.001	0.026	−0.03	0.976	−0.053	0.051
	quintile 4	0.087	0.028	3.12	0.002	0.032	0.141
	quintile 5 (highest income)	0.127	0.029	4.37	<0.001	0.070	0.184
Employment status wave 3							
(employed)	unemployed	−0.019	0.044	−0.42	0.674	−0.105	0.068
	Retired	0.128	0.039	3.30	0.001	0.052	0.204
	Other	0.016	0.033	0.48	0.628	−0.048	0.080
ethnic group							
('White British/Irish')	'Asian' ('Indian', 'Pakistani', 'Bangladeshi', 'Chinese', 'other Asian')	0.146	0.033	4.38	<0.001	0.081	0.211
	'Black'; ('Black African', 'Caribbean', 'Black other')	0.010	0.046	0.21	0.836	−0.081	0.100
	'mixed/other' ('white'& 'black' / 'Asian' / 'Arab', 'other')'	−0.035	0.054	−0.64	0.519	−0.140	0.071
Housing tenure at wave 4							
(rented/other)	outright owner	0.167	0.024	6.91	<0.001	0.120	0.214
	owned with mortgage	0.161	0.022	7.36	<0.001	0.118	0.204
Area disadvantage Score quintile for place of residence in wave 4							
(lowest quintile - least deprived)	Quintile II	−0.097	0.024	−3.94	<0.001	−0.145	−0.049
	Quintile III	−0.262	0.025	−10.61	<0.001	−0.310	−0.214
	Quintile IV	−0.422	0.025	−16.71	<0.001	−0.472	−0.373
	Quintile V (most deprived)	−0.629	0.027	−23.22	<0.001	−0.682	−0.576
Ordered probit regression							
Number of observations =	17,298.000						
LR chi2(29) =	1707.630						
Prob > chi2 =	<0.001						

English population generally. Also, it is possible that those who were residentially mobile may be less well represented in the sub-sample from the USS analysed here, since they may have been more difficult to track over time, and some may have moved across borders to other parts of Britain during the period. We have classified area conditions quite crudely (in quintile categories), partly to ensure that there is no risk of disclosure of sensitive information about location for members of the USS sample. Some of the components of the IMD2010 are sourced from data which predate USS wave 4, so that area conditions may have changed for some areas by wave 4 when wellbeing was first recorded.

For this study, we have used data for lower layer super output areas to measure neighbourhood conditions. These spatial units are widely used in research to inform planning and policy in the UK. We note, however, that these are not necessarily fully representative of spatial zones which reflect the extent of communities in terms of social organization and functions (Kwan, 2012). We also note that some authors have suggested that analyses of 'area effects' of community conditions may vary according to the geographical scale of analysis (Schuurman et al., 2007) and the degree of clustering of small areas with similar attributes (Rae, 2009).There may be scope to extend the analyses reported here using techniques such as Geographically Weighted Regression (GWR) (Fotheringham et al., 1998; Ha, 2019; Czarnota et al., 2015) or Bayesian Geographically Weighted Regression (Subedi et al., 2018). However, in order to be theoretically justified, such applications would need to be informed by an extension of the research reported here to consider the likely impact of regional as well as national processes. Permission has not been granted for this study to use grid references for LSOA of residence for USS sample members (linkage is permitted only for specifically approved data relating to these area units). Therefore, GWR was not feasible for the analysis reported here.

4.3. Implications of our findings for policy and further research

In general terms, our findings add further support to other research reviewed above by showing that change in wellbeing is not only associated with individuals' personal or family attributes, but also with the type of residential community environment. Community context is therefore relevant for the development of wellbeing, considered over time. This seems to support the case for interventions aiming to change local conditions in order to improve wellbeing in the population and reduce wellbeing inequalities.

We also provide an original contribution to the field by showing how area conditions at the local level are associated with relative change in wellbeing. It seems from our results that the general improvement in wellbeing over the 3–4 year period studied, observed in the study sample as a whole, tends to have been diminished, or even reversed, among those living in more disadvantaged areas. This association is significant after controlling for individuals' personal attributes and their residential mobility between local areas which ranked differently in terms of area disadvantage. Our findings are consistent with the idea that cumulative exposure to relatively disadvantaged conditions may be detrimental to the development of sense of wellbeing, even over a rather short period. However, this finding also raises further questions about the underlying causal processes that may be involved. We note that residents in the most deprived parts of England may have been among those most severely affected by the 'aftershocks' of the 'great depression' which started in 2008, including reductions in public spending on welfare benefits and community services associated with austerity programmes introduced in Britain during the period of recovery from recession, as covered by this study (Bambra, 2019). Our findings suggest that lower levels of social cohesion may be associated with these effects of austerity, perhaps due to reduced public spending on community support. Thus, we would also acknowledge that contextual conditions at a broader geographical scale, not specifically examined in this study, may have been operating variably in local areas, in ways associated with the aspects of community disadvantage that we have reported on here. This raises questions about the associations between local community disadvantage and broader scale socio-economic processes, which would be interesting to explore in more detail in future research.

To implement social and environmental interventions promoting wellbeing, international governments need to have access to validated indicators to help identify the places where these interventions are likely to be most needed and the aspects of local environments that might need to be targeted by these interventions. Our study confirms that indicators of the type considered here are likely to be useful to help to plan social policy initiatives relating to wellbeing in England. Collective action aiming to improve wellbeing and reduce inequality in wellbeing may have the greatest impact if it is targeted towards effectively improving wellbeing in local areas that are relatively disadvantaged in terms of the composite area disadvantage score presented here. We also note that components of this disadvantage score suggest diverse aspects of the wider determinants of wellbeing that might need to be prioritised in action that aims to improve wellbeing by changing conditions in places. Our findings are therefore important in terms of debates about operationalising ideas about wellbeing and place.

From an international perspective, this study also suggests a research process which might be applied in other national settings (depending on availability of relevant survey and small area data), with scope for international comparisons to explore whether similar aspects of area disadvantage are relevant to individual experience of wellbeing in other settings.

Within the limits of this paper, we have not been able to explore all aspects of personal and geographical conditions which may affect wellbeing, and a number of further research questions could be explored. For example, since this paper is particularly concerned with local socio-economic and environmental factors likely to influence wellbeing, we have not included indicators relating to medically defined health conditions in the analysis as possible predictors of sense of wellbeing. Further research might explore, in particular, whether individuals who developed physical health problems during the study period might show less improvement in wellbeing compared with others. While wellbeing should not be interpreted as simply the inverse (or absence) of mental illness, it may be closely related to experience of illness. As such, analyses including indicators of individual mental health are likely to raise issues of complex intercorrelations in regression models.

Our findings underline broader theoretical issues regarding the ways we consider wellbeing of and in places. The statistical models we have presented suggest that contextual conditions in one's local place of residence are important for wellbeing independently of individual attributes, and these might be considered as aspects of wellbeing of places. However, there are also several aspects of individuals' personal characteristics considered here which might reflect the diversity of individual wellbeing determinants operating within different places. There is scope to explore further how individual and area conditions interact, and the relevance of relational approaches to studying how place relates to wellbeing.

Our research also illustrates the special value of longitudinal studies (such as the Understanding Society Survey in the British context). The study reported here illustrates the relevance of a growing field of international research which takes a longitudinal perspective to discover how individuals' experiences of place over the life course impacts on wellbeing. The potential for such research will be further enhanced as more consistently defined longitudinal data on small areas become available, allowing us to explore in more detail the associations with lifecourse of place.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This paper is based on research carried out as part of the What Works for Wellbeing: Communities project, funded by the Economic and Social Research Council.

This paper includes results derived from data released under 'special license' as output from the UK Data Service, the original data creators and copyright holders of data sets from the Understanding Society Survey, which have been used in the form specified in information accompanying the data set or notified to the user. Understanding Society is an initiative funded by the Economic and Social Research Council and various Government Departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex, and survey delivery by the National Centre for Social Research and TNS BMRB. The research data are distributed by the UK Data Service.

We gratefully acknowledge help and advice provided by the managers of the Understanding Society Survey at the University of Essex, the UK Data Service, and the Administrative Data Centre at University of Edinburgh. The authors are responsible for the findings and interpretation reported here.

We are also most grateful to Professor Wil Gesler for his comments on an early draft of this paper which have helped us to develop the text.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.wss.2020.100009.

References

Atkinson, S., Bagnall, A.-.M., Corcoran, R., South, J., Curtis, S, 2020. Being well together: individual subjective and community wellbeing. J. Happiness Stud. 21, 1903–1921.
Atkinson, S., Fuller, S., Painter, J., 2012. Wellbeing and Place. UK: Ashgate, Farnham.
Badland, H., Foster, S., Bentley, R., et al., 2017. Examining associations between area-level spatial measures of housing with selected health and wellbeing behaviours and outcomes in an urban context. Health Place 43, 17–24.
Bambra, C., 2019. Health in Hard Times. Policy Press, Bristol, UK.
Bernard, P., Charafeddine, R., Frohlich, K.L., et al., 2007. Health inequalities and place: a theoretical conception of neighbourhood. Soc. Sci. Med. 65, 1839–1852.
Bilger, M., Carrieri, V., 2013. Health in the cities: when the neighborhood matters more than income. J. Health Econ. 32, 1–11.
Burke, J., 2014. An economic appraisal of the 'wellbeing through work' service. Br. J. Occup. Ther. 77 126-126.
Cattell, V., Dines, N., Gesler, W., et al., 2008. Mingling, observing, and lingering: everyday public spaces and their implications for well-being and social relations. Health Place 14, 544–561.
Clark, A., Fleche, A., Layard, R., et al., 2018. The Origins of happiness: the Science of Wellbeing Over the Lifecourse. USA: Princeton University Press, Princeton.
Congdon, P., 1996. The incidence of suicide and parasuicide: a small area stud. Urban Stud. 33, 137–158.
Conti-Ramsden, G., Durkin, K., Mok, P.L.H., et al., 2016. Health, employment and relationships: correlates of personal wellbeing in young adults with and without a history of childhood language impairment. Soc. Sci. Med. 160, 20–28.
Cooper, R., Boyko, C., Codinhoto, R., 2008. The effect of the physical environment on mental wellbeing. State-of-Science Review: SR-DR2. London: Government Office for Science Academia https://www.academia.edu/455653/Mental_Capital_and_Wellbeing_and_the_Physical_Environment.
Crooks, V., Andrews, G., Pearce, J., 2018. Routledge Handbook of Health Geography. London: Routledge.
Cummins, S., Curtis, S., Diez-Roux, A.V., Macintyre, S., 2007. Understanding and representing 'place' in health research: relational approaches. Soc. Sci. Med. 66 (2), 1825–1838.
Curtis, S., 2004. Health and Inequality: Geographical Perspectives. London: Sage.
Curtis, S., 2010. Space, Place and Mental Health. UK.: Ashgate, Farnham.
Curtis, S., Congdon, P. & Atkinson, S., Corcoran, R., Macguire, R., Peasgood, T. (2019a) Individual and local area factors associated with self reported wellbeing, perceived social cohesion and sense of attachment to one's community. What works for wellbeing technical report: social fragmentation. London. What works wellbeing: places and communities. The evidence Quarter, Albany house,Westminster, London, SW1H 9EA: What Works Centre for Wellbeing. https://whatworkswellbeing.org/wp-content/uploads/2020/02/120919-Social-Fragmentation-full-report.pdf (Accessed November 2020).
Curtis, S., Copeland, A., Fagg, J., et al., 2006. The ecological relationship between deprivation, social isolation and rates of hospital admission for acute psychiatric care; a comparison of London and New York City. Health Place 12, 19–37.
Curtis, S., Pearce, J., Cherrie, M., et al., 2019b. Changing labour market conditions during the 'great recession' and mental health in Scotland 2007-2011: an example using the Scottish longitudinal study and data for local areas in Scotland. Soc. Sci. Med. 227, 1–9.
Czarnota, J., Wheeler, D.C., Gennings, C., 2015. Evaluating geographically weighted regression models for environmental chemical risk analysis. Cancer Inf. 14, 117–127.
Deas, I., Robson, B., Wong, C., et al., 2003. Measuring neighbourhood deprivation: a critique of the index of multiple deprivation. Environ. Plan. C Gov. Policy 21, 883–903.
Department of Communities and Local Government, 2011. The English Indices of Deprivation 2010. London: Department of Communities and Local Government.
Ding, H., Nunes, P., 2014. Modeling the links between biodiversity, ecosystem services and human wellbeing in the context of climate change: results from an econometric analysis of the European forest ecosystems. Ecol. Econ. 97, 60–73.
Duncan, C., Jones, K., Moon, G., 1998. Context, composition and heterogeneity: using multilevel models in health research. Soc. Sci. Med. 46, 97–117.
Fleuret, S., Atkinson, S., 2007. Wellbeing, health and geography: a critical review and research agenda. N. Z. Geogr. 63, 106–118.
Flint, E., Cummins, S., Wills, J., 2014. Investigating the effect of the London living wage on the psychological wellbeing of low-wage service sector employees: a feasibility study. J. Public Health (Bangkok) 36, 187–193.
Foresight Mental Capital and Wellbeing Project (2008). Final project report. The Government Office for Science, London. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/292450/mental-capital-wellbeing-report.pdf. (Accessed November 2020).
Fotheringham, A.S., Charlton, M.E., Brunsdon, C., 1998. Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis. Environ. Plan. A 30, 1905–1927.
Friedman, J. (2013) Tools of the trade: when to use those sample weights. World bank group, https://blogs.worldbank.org/impactevaluations/tools-of-the-trade-when-to-use-those-sample-weights Accessed July 2020.
Gatrell, A., 2002. Geographies of Health. Oxford: Blackwell.
Gesler, W., 2005. Therapeutic landscapes; an evolving theme. Health Place 11 (4), 295–297.
Gibb, K., Osland, L., Pryce, G., 2014. Describing Inequalities in Access to Employment and the Associated Geography of Wellbeing. Urban Stud. 51, 596–613. https://www.icpsr.umich.edu/icpsrweb/content/NACJD/guides/phdcn/index.html. Accessed November 2020.
Ha, H., 2019. Using geographically weighted regression for social inequality analysis: association between mentally unhealthy days (MUDs) and socioeconomic status (SES) in US counties. Int. J. Environ. Health Res. 29, 140–153.
Jones, K., Moon, G., 1987. Health, Disease and Society: An Introduction to Medical Geography. London: Routledge & Kegan Paul.
Kneis G. (editor) 2018 Understanding society the UK household longitudinal study waves 1-8, User Guide. University of Essex, Colchester, Essex https://www.understandingsociety.ac.uk/sites/default/files/downloads/documentation/mainstage/user-guides/mainstage-user-guide.pdf (Accessed November 2020).
Kwan, M.-P., 2012. How GIS can help address the uncertain geographic context problem in social science research. Ann. GIS 18, 245–255.
Li, Y., 2016. Social mobility, social network and subjective wellbeing in the UK. Contemp. Soc. Sci. 11, 222–237.
Liu, J., Opdam, P., 2014. Valuing ecosystem services in community-based landscape planning: introducing a wellbeing-based approach. Landsc. Ecol. 29, 1347–1360.
Macintyre, S., Ellaway, A., Cummins, S., 2002. Place effects on health: how can we conceptualise, operationalise and measure them? Soc. Sci. Med. 55, 125–139.
Maynard, S., James, D., Davidson, A., 2015. Determining the value of multiple ecosystem services in terms of community wellbeing: who should be the valuing agent. Ecol. Econ. 115, 22–28.
Milton, B., Attree, P., French, B., et al., 2012. The impact of community engagement on health and social outcomes: a systematic review. Commun. Dev. J. 47, 316–334.
Mishra, V., Nielsen, I., Smyth, R., 2014. How does relative income and variations in short-run wellbeing affect wellbeing in the long run? Empirical evidence from China's Korean minority. Soc. Indic. Res. 115, 67–91.
Moore, S., Bockenholt, U., Daniel, M., et al., 2011. Social capital and core network ties: a validation study of individual-level social capital measures and their association with extra- and intra-neighborhood ties, and self-rated health. Health Place 17, 536–544.
Niggebrugge, A., Haynes, R., Jones, A., et al., 2005. The index of multiple deprivation 2000 access domain: a useful indicator of public health. Soc. Sci. Med. 60, 2743–2753.
Oguz S. (2014) Exploring personal well-being and place. London. Office of National Statistics. https://www.researchgate.net/publication/271191317/download (Accessed November 2020).
Okulicz-Kozaryn, A., Mazelis, J.M., 2017. More unequal in income, more unequal in wellbeing. Soc. Indic. Res. 132, 953–975.
Osborne, C., Baldwin, C., Thomsen, D., 2016. Contributions of social capital to best practice urban planning outcomes. Urban Policy Res. 34, 212–224.
Pearce, J., Witten, K., Hiscock, R., et al., 2007. Are socially disadvantaged neighbourhoods deprived of health-related community resources. Int. J. Epidemiol. 36, 348–355.
Pearson, A.L., Breetzke, G.D., 2014. The association between the fear of crime, and mental and physical wellbeing in New Zealand. Soc. Indic. Res. 119, 281–294.
Pope, D., Tisdall, R., Middleton, J., et al., 2018. Quality of and access to green space in relation to psychological distress: results from a population-based cross-sectional study as part of the EURO-URHIS 2 project. Eur. J. Public Health 28, 35–38.
Quick, A., Seaford, C. (2014) Talking wellbeing: engaging people in the wellbeing policy making process . London, New Economics Foundation. https://neweconomics.org/uploads/files/5426bba63177f07215_11m6bqg6f.pdf (Accessed November 2020).
Rae, A., 2009. Isolated entities or integrated neighbourhoods? An alternative view of the measurement of deprivation. Urban Stud. 46, 1859–1878.

Ratcliffe, A., 2015. Wealth effects, local area attributes, and economic prospects: on the relationships between house prices and mental wellbeing. Rev. Income Wealth 61, 75–92.
Ryan, R.M., Deci, E.L., 2001. On happiness and human potentials: a review of research on hedonic and eudaimonic well-being. Ann. Rev. Pscyhol. 52, 141–166.
Schaeffner, D., Irvin, L.H., Smith, H.H., 2018. Insights in public health: the built environment and health: how the places we live, work, and play shape our wellbeing. Hawai'i J. Med. Public Health A J. Asia Pac. Med. Public Health 77, 146–147.
Schneider, S.M., 2016. Income inequality and subjective wellbeing: trends, challenges, and research directions. J. Happiness Stud. 17, 1719–1739.
Schuurman, N., Bell, N., Dunn, J.R., et al., 2007. Deprivation indices, population health and geography: an evaluation of the spatial effectiveness of indices at multiple scales. J. Urban Health 84, 591–603.
Smetcoren, A., De Donder, L., De Witte, N., et al., 2014. Influence of housing quality on feelings of wellbeing and neighbourhood integration. Gerontologist 54, 63–64.
Smith, K.P., Christakis, N.A., 2008. Social networks and health. Annu. Rev. Sociol. 34, 405–429.
Solon, G., Haider, S.J., Wooldridge, J.M., 2015. What are we weighting for. In: Journal of Human Resources, 50. University of Wisconsin Press, pp. 301–316.
Sowden, S., White, M., 2014. High-rise health: a qualitative study of the effect of social housing improvements on the health and wellbeing of residents in high-rise flats. Lancet 384 76-76.
Subedi, N., Zhang, L., Zhen, Z., 2018. Bayesian geographically weighted regression and its application for local modeling of relationships between tree variables. iForest 11 542-522.
Tan, S.-Y., Haining, R., 2016. Crime victimization and the implications for individual health and wellbeing: a Sheffield case study. Soc. Sci. Med. 167, 128–139.
Tunstall, H., Shaw, M., Dorling, D., 2004. Places and health. J. Epidemiol. Commun. Health 58, 6–10.
University of Essex, 2017. Institute for social and economic research, NatCen social research, kantar public. Understanding Society: Waves 1-7, 2009-2016. [data collection], 9th Edition UK Data Service. SN: 6614 doi:10.5255/UKDA-SN-6614-10.
University of Michigan (2020) Project on human development in chicago neighborhoods, institute of social research, University of Michigan, USA. https://www.icpsr.umich.edu/icpsrweb/content/NACJD/guides/phdcn/index.html. (Accessed November 2020).
Warwick Medical School (2013). The Warwick-Edinburgh mental wellbeing scales – WEMWBS. https://warwick.ac.uk/fac/sci/med/research/platform/wemwbs (Accessed November 2020).
Wilkinson, R., Pickett, K., 2009. The Spirit Level: Why More Equal Societies Almost Always Do Better. London: Penguin.
Williams, A., 2007. Therapeutic Landscapes. UK: Ashgate, Farnham.
Willis, C., 2015. The contribution of cultural ecosystem services to understanding the tourism-nature-wellbeing nexus. J. Outdoor Recreat. Tour. Res. Plan. Manag. 10, 38–43.
Wiseman, P., 2018. Hate crime and the community: place and wellbeing. J. Appl. Res. Intell. Disabil. 31, 489–490.