Investigating people-place effects in the UK using linked longitudinal survey and administrative records

Project report

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Acknowledgements

We gratefully acknowledge funding and support from the Nuffield Foundation [grant number DLW/42989], in particular Alex Beer. The research benefited from comments and feedback received on findings presented in seminars held at University of Bristol, University of Manchester, University College of London and Department for Business, Energy and Industrial Strategy (BEIS), and during the peer-review process of our empirical research on the effect of neighbourhood deprivation on earnings and life satisfaction, now published in Urban Studies journal, see Knies et al. (2020a). Our particular thanks go to the members of our project advisory team, and to Min Zhang, who provided research assistance. The data processing would not have been possible without the support of the ESRC-funded Understanding Society project at the University of Essex [grant number ES/K005146/1] who allowed us to access the study respondents' postcodes in a secure setting that respects the privacy of the information.

The Nuffield Foundation is an independent charitable trust with a mission to advance social wellbeing. It funds research that informs social policy, primarily in Education, Welfare, and Justice. It also funds student programmes that provide opportunities for young people to develop skills in quantitative and scientific methods. The Nuffield Foundation is the founder and co-funder of the Nuffield Council on Bioethics and the Ada Lovelace Institute. The Foundation has funded this project, but the views expressed are those of the authors and not necessarily the Foundation. More information is available at www.nuffieldfoundation.org.

Executive Summary

There is a long history of research and increasing interest in the role of the place of residence in shaping peoples' economic and social life chances. This is explored particularly in the literature investigating the existence and importance of so-called 'neighbourhood effects': impacts on individual-level outcomes that can be attributed to differences in the neighbourhood context, which cannot be explained by past and present personal and family characteristics. Scholars have suggested more than a dozen mechanisms through which neighbourhood effects affect wellbeing. The early literature has focused on objective wellbeing outcomes (e.g., education, employment status, occupation, income, health, and crime). More recently, subjective wellbeing outcomes such as life satisfaction and other measures of quality of life have come into focus. Albeit, there is considerable disagreement between disciplines on whether neighbourhood effects exist and how important they are, the definition and measurement of neighbourhoods has been relatively unsystematic, and different methodological approaches have yielded different results. The prevailing view seems to be, however, that in the absence of real-world (quasi-) experimental evidence, large-scale longitudinal panel studies augmented with longitudinal geocoded microdata at very immediate scales afford the best opportunities to identify causal neighbourhood effects as they help overcome three paramount identification issues: that people choose the residential contexts to which they are then exposed (residential self-selection bias), that people's wellbeing is affected by local deprivation but that their wellbeing contributes to local deprivation at the same time (simultaneity bias), and that people are different - their residential choice and reaction to the neighbourhood context may be influenced by factors that have not been, or could not possibly be, measured (unobserved heterogeneity bias).

The "Investigating people-place effects in the UK" project provides new insights into the richness of empirical approaches to studying neighbourhood effects on individual wellbeing adopted in this interdisciplinary field of studies. It offers new empirical evidence for England and Wales on place effects on a range of subjective and objective wellbeing outcomes. For the empirical research, the project has innovatively combined longitudinal survey microdata from Understanding Society: the United Kingdom Household Longitudinal Study (UKHLS) with administrative data for very small geographies at multiple points in time, and various spatial scales of the neighbourhood. We also addressed the key identification issues that permeate

studies of neighbourhood effects by implementing a range of sophisticated panel data regression models and causal inference techniques.

The research centred around three key questions.

Does living in a deprived area affect individual wellbeing?

Much policy focus is placed on helping disadvantaged individuals living in disadvantaged areas. While it is intuitive to expect that local area conditions impact individuals' life chances as residing in structurally disadvantaged areas restricts the opportunities available to individuals, this is not the same as saying that local deprivation causes individual deprivation. The reality is more complex, because individuals living on the lowest incomes may only afford to live in the most deprived areas to start with, further contributing to local area deprivation. This distinction is crucial for policy aimed at improving individuals' objective and subjective wellbeing. Suppose we assume that the root of the problem (i.e., the cause) is the attractiveness or quality of the local area. In that case, the policy will focus on channelling resources into the most deprived neighbourhoods to improve them. While this indeed is a good thing, the investment may have the undesirable effect of making the area unaffordable to families on the lowest incomes, forcing them to migrate to yet more deprived areas. We find that the negative associations between neighbourhood deprivation and subjective and objective wellbeing are primarily due to non-random selection into neighbourhoods, not a genuine causal effect: More satisfied people and people who earn more money tend to live in and move to less deprived neighbourhoods. More specifically, we show that the selection bias is predominantly due to unobserved time-invariant individual characteristics such as soft skills and initiative, which can all be expected to be related to the probability to find a better job and to make the most of current circumstances however bleak they might be. By contrast, unobserved time-invariant neighbourhood characteristics (e.g., distance to amenities, physical environment) play a minor role.

At which spatial scale should resources be targeted to reduce inequalities in wellbeing arising from neighbourhood deprivation?

It is important for policies aimed at increasing population wellbeing to have realistic expectations of what may be achieved by targeting specific communities in need instead of individuals with wellbeing deficits. Even if there is no evidence of a social multiplier effect, disadvantaged places are home to a large number of disadvantaged individuals. When deciding which people or areas to target, ideally the geographical scale of policy interventions should coincide with the geographical scale at which the causal mechanism underlying the targeted problem(s) manifests. For example, initiatives to make the neighbourhood more walkable might be targeted at areas that are small enough to be face-to-face communities where social interactions between neighbours are likely to occur so that the perceived benefits (e.g., higher levels of physical activity, less noise and air pollution from motorised vehicles, increased social connections, as a result of pedestrian encounters) may be realised. We compare the role of neighbourhood deprivation across multiple scales, ranging from small areas with a minimum population size of 100 people to sites with a minimum population size of 10,000 people and show that deprivation matters at all scales of the neighbourhood. It is associated with reduced earnings, life satisfaction and health-related quality of life (albeit, the association is mainly explained by residential sorting, i.e., that people who earn more and who evaluate their life overall more positively tend to live in less deprived areas). For the health-related quality of life, deprivation in the smallest neighbourhoods of up to 3,000 people appears to matter the most.

Should policy-makers be more interested in reducing the impact of neighbourhood deprivation on subjective or objective wellbeing outcomes?

Subjective wellbeing is an important outcome for individuals and, increasingly, for policymaking. Yet, the bulk of the empirical neighbourhood effects literature has focused on objective wellbeing outcomes such as educational attainment or labour market success. Drawing on insights from the objective and subjective wellbeing research and adopting a modelling framework that works well across both types of studies, we show that the neighbourhood context may matter differently for life satisfaction and other quality of life measures than for objective outcomes. While the effect of neighbourhood deprivation on earnings is mostly accounted for by unobserved factors related to residential selection, we find some instances of statistically significant effects of neighbourhood deprivation on each of the three subjective wellbeing outcomes in models that account for residential selection. As many places are segregated along socio-economic lines, household income is an important factor in neighbourhood sorting, hence the association with earnings is not surprising. Moreover, good homes are difficult to come by and households in urgent need of housing may be forced to accept the first available option, which may be in less desirable neighbourhoods and impact their subjective wellbeing. While the results may be specific to our study and should not be generalised to the literature on neighbourhood effects overall, they invigorate calls for further studies of neighbourhood effects on subjective wellbeing.

Recommendations and future avenues for research

The findings from this project allow making several recommendations for different groups of users, notably scholars and policymakers. One of the key implications of our findings for policymaking is that targeting resources specifically on neighbourhoods characterised by high levels of deprivation may not be an efficient way to improve residents' wellbeing compared to targeting individuals or households in need irrespective of where they live. Moreover, the latter may also be more effective for social justice or social equity purposes because it targets individuals and households directly instead of discriminating by neighbourhood context. Improvements in wellbeing may be achieved through policies that, for example, increase long-term employment opportunities available to disadvantaged individuals, develop regional labour markets through better connected and more affordable transport networks, or raise skill levels. This conclusion is not, of course, an appeal for policymakers to dismiss any neighbourhood-basis for policy intervention: given the strong correlation between neighbourhood deprivation and concentration of disadvantaged groups, local targeting can still be effective in reaching large numbers of people in need.

Although our results may not be generalised to other indicators of deprivation, the key recommendation for researchers working on neighbourhood effects is that it is important to address identification challenges, specifically, endogeneity bias resulting from residential self-selection. In our empirical results, the neighbourhood effect on all outcomes and at all scales was significantly reduced when we considered various sources of residential selection bias. Ideally, the residential choice should be modelled simultaneously with the effect of local deprivation on individual wellbeing, which remains very difficult to implement empirically due to data limitations. It is possible, however, to get a handle on residential selection bias drawing on auxiliary information provided in many of the studies we have reviewed, be it by selecting samples of the population that may be hypothesised to have had less choice over where to live or by making use of the panel nature of many individual and spatial data sources.

Despite improvements in the availability of geocoded information at small scales and increased accessibility of geographical locator variables for members of longitudinal studies such as Understanding Society, the number of studies exploiting such opportunities is surprisingly low. A possible explanation is that the definition of much-used indicators such as the Index of Multiple Deprivation and its constituent domains change over time, thus preventing analysts from disentangling the various sources of change, observed or unobserved. Regarding the scale at which such neighbourhood indicators should be computed, our results suggest slight variation in the effect of neighbourhood deprivation across scales. Still, it is neighbourhood scales below the threshold of 3,000 people where results become marginally statistically significant for some outcomes. More research is needed to throw further light on which scale matters for which outcome, and why. It may be a mere coincidence that this is the average population size of the so-called lower super output areas in key neighbourhood statistics for the UK. For Britain, the absence of longitudinally harmonised one-dimensional indicators such as the average income or the unemployment rate at this scale is notable. Currently, small area income estimates from administrative data are only available at the MSOA level (which may refer to too large an area to uncover social interaction effects that rely on close contact with neighbours) and the bi-annual time series uses different boundaries across time (Office for National Statistics, 2020). Longitudinally harmonised indicators may be produced centrally and consistently-through-time from administrative records. They could then be made available, for example, as special licence data with longitudinal studies (such as those supported through the longitudinal studies enhancement resource CLOSER, see www.closer.ac.uk.

1. Introduction

There is a long history of research and increasing interest in the role of the place of residence in shaping people's economic and social life chances, explored in particular in the literature investigating the existence and importance of so-called 'neighbourhood effects': impacts on individual-level outcomes that can be attributed to differences in the neighbourhood context, and which cannot be explained by past and present personal and family characteristics. Scholars have suggested more than a dozen mechanisms through which neighbourhood effects affect wellbeing. The early literature has focused on objective wellbeing outcomes (e.g., education, employment status, occupation, income, health, and crime). More recently, subjective wellbeing outcomes such as life satisfaction and other quality of life have come into focus. Albeit, there is considerable disagreement between disciplines on whether neighbourhood effects exist and how important they are, the definition and measurement of neighbourhoods has been somewhat unsystematic, and different methodological approaches have yielded different results. The prevailing view seems to be, however, that in the absence of real-world experimental or quasi-experimental evidence large-scale longitudinal panel studies augmented with longitudinal geocoded microdata at very immediate scales afford the best opportunities to identify causal effects as they help overcome identification issues relating to residential self-selection bias, simultaneity bias, and unobserved heterogeneity.

This report provides new insights into the richness of empirical approaches to studying neighbourhood effects on individual wellbeing adopted in this interdisciplinary field of studies. It provides new empirical evidence for England and Wales on the presence of place effects on a range of subjective and objective wellbeing outcomes. For the empirical research, the "Investigating people-place effects in the UK" project has innovatively combined longitudinal survey microdata from Understanding Society: the United Kingdom Household Longitudinal Study (UKHLS) with administrative data for very small geographies at multiple points in time, and various spatial scales of the neighbourhood, while the key identification issues that permeate studies of neighbourhood effects have been addressed by implementing a range of panel data regression models and causal inference techniques.

In this report we present the purpose, methodology and findings of the substantive work packages of the project (Parts 2-4) followed by an overall summary of the research, the lessons learned and next steps (Part 5). The first work package was concerned with conducting an in-depth review of the empirical neighbourhood effects literature focussing specifically on how empirical estimation challenges have been addressed and making sure to capture the latest developments in this area. The review formed an essential element of the project as its findings informed the empirical analyses. In particular, the literature review has guided the choices to be made when constructing the longitudinal database of neighbourhood indicators (i.e., which variables, boundaries and spatial scales were included), which we describe in Part 3 of the report, and when choosing the wellbeing outcomes and econometric estimators to be implemented to address the main identification challenges in the empirical analyses, which we describe in Part 4. The main conclusions, limitations and avenues for future research are provided in Part 5.

2. Reviewing the Empirical Evidence on Neighbourhood Effects

Do neighbourhood effects exist and how important are they? According to a number of high impact reviews of the neighbourhood effects literature in the social sciences that were published around the turn of the millennium (see, e.g., Dietz, 2002; Durlauf, 2004; Friedrichs et al., 2003; Ellen and Turner, 1997; Lupton, 2003), the answer may well vary by which scientific discipline the research is routed in. Different disciplines tend to opt for different research designs, focus on different outcomes and pay more or less attention to empirical estimation challenges such as residential selection bias, unobserved heterogeneity, and reverse causation. If such identification challenges are not addressed, the measured association between neighbourhood and individual outcomes is likely to be erroneous, undermining any causal claims made.

Improvements in access to high-quality observational data linked with spatial information mean opportunities to address the paramount econometric estimation challenges abound. To get a better overview of the latest most promising approaches to identify causal effects, in the spirit of our interdisciplinary research project, before launching into our own empirical investigations of neighbourhood effects for key wellbeing outcomes in British society, we undertook a detailed review of the existing literature.

2.1 Searching studies and extracting information – how it was done

Our aim was to provide an assessment of the empirical literature across disciplinary boundaries and covering a wide range of wellbeing outcomes. Initial searches on ‘neighbourhood effects’ in titles and abstracts across a number of prominent online databases suggested that reviewing all suggested papers would be unwieldly, however.[1] To reduce the complexity of the task and to minimise the possibility of bias in deciding which research to review and what information to extract, we therefore defined strict protocols for both the search (see **Figure 1**) and information extraction (see **Table 1**).

Foundational reviews of the neighbourhood effects literature in the fields of economics, sociology, human geography and epidemiology and a small number of hand-picked empirical studies that offered a fresh approach to addressing some of the challenges facing the research

[1] In their commentary about the most promising lines of enquiry in neighbourhood effects research van Ham and Manley (2012) noted that a Google scholar search on ‘neighbourhood effects’ returned more than 17,000 results; when we conducted our search less than a decade later (10 June 2019) the figure amounted to ~667,000.

informed the protocol. The eligibility criteria assured that we would review papers that are most relevant for the research we envisaged to do with the Understanding Society data. In practice that meant that our review does not include any of the rich research that focuses on specific sub-populations such as children, elderly or minority ethnic groups; studies that focused on the general population living in a range of neighbourhoods in specific urban or metropolitan areas were included.[2]

Figure 1. Literature search protocol and screening outcomes

Identification

Identification of study characteristics through inspection of review studies and of exemplary empirical research: Buck (2001); Dietz (2002); Diez Roux and Mair (2010); Durlauf (2004); Ellen and Turner (1997); Friedrichs et al. (2003); Kingdon and Knight (2007); Knies (2007); Knies (2012); Sampson et al. (2002); van Ham and Manley (2012); Brännström (2004).

Identification of studies through database online search: ISI Web of Knowledge, JSTOR (Journal Storage), and Google Scholar[a]: Studies published between 1st Jan 2002 and 9th Feb 2018[b]. Title includes combination of keywords "neighbourhood effect(s)"[c] AND any of the following: "income", "earnings", "employment", "unemployment", "happiness", "life satisfaction", "self-rated health", "self-reported health", "health", "well(-)being".
Total number of studies identified: 684

Screening

Screening of titles and abstracts for eligibility: Quantitative empirical analysis, focused on the general population, not specific sub-groups, Published in English, Full-text must be available.
Total number of studies eligible for detailed review: 91

Notes: [a] After pre-testing the search terms in all three online search engines, we chose Google Scholar for its coverage of all types of literature and disciplines. [b] For some thesis chapters and working papers we could identify a peer-reviewed article after this cut-off date. In this case, we used the peer-reviewed version. [c] We allowed for British and American English spelling.

Regarding the outcomes studied, we did not include research that focuses on subjective evaluations of one's financial situation or on one's objective markers of health. For example, studies that examined the outcome "Would you say your health in general is poor, fair, good, very good or excellent?" or summary scores from the General Health Questionnaire (GHQ) or the Short Form Health Questionnaire (SF-12 or SF-36) were included, but studies that examined respondent's objective health status ("Have you been diagnosed with cancer?") were

[2] We did not identify any studies that focused on specific rural areas, which is intriguing considering that a large share of the population lives in rural areas or small towns rather than metropolitan or urban areas and we may expect some aspects of socio-economic disadvantage to exacerbate in rural contexts.

not included. Note that if a study focused on multiple outcomes all results relating to the outcomes that were in scope were extracted but none of the results relating to out-of-scope outcomes.

Table 1. Study dimensions extracted from selected research papers

Study dimension	Detail recorded
Study information	Author(s), year, title, journal, discipline
Wellbeing outcome	Detailed description, and coded to four broad categories: Employment (incl. unemployment), Income (incl. earnings), *Life satisfaction* (incl. happiness), *and Self-rated health* (incl. self-reported health). [a]
Neighbourhood effect	Detailed description of the nature of the neighbourhood effect mechanism(s) studied, and coded to Galster (2012)'s four main types (i.e., social interactive, environmental, geographical and institutional).
Neighbourhood indicator	Detailed information about the information used to capture the neighbourhood effect, including the type of neighbourhood data used.
Neighbourhood definition	Detailed information about how the neighbourhood is operationalised, covering whether the boundaries are respondent-defined or administrative, the spatial scale, and any socio-economic or demographic descriptors of the place and its people.
Identification strategy	Detailed information about the method applied to address residential selection bias, and coded to eleven types of strategies ranging from attempts to capture residential selection bias through observed individual and neighbourhood characteristics to fully modelling residential selection.

Notes: [a] Subjective wellbeing outcomes highlighted in *italics.*

We entered study parameters of all research studies eligible for review into Excel for posterior analysis in Stata and deposited the database in an open data depository so others may benefit from it, see Knies et al. (2020b). Overall, the database contains information about 311 neighbourhood effects, defined as a result for a specific outcome, using a specific neighbourhood definition, a specific neighbourhood characteristic and investigating a specific mechanism.

2.2 Approaches to identifying neighbourhood effects – what we find

Our literature review database of "Neighbourhood effect studies of subjective and objective wellbeing (2002-2018)" (Knies et al., 2020b) makes it possible to explore and synthesise the empirical literature on neighbourhood effects from different perspectives. In our review, we concentrated on how neighbourhood effect studies of income, employment, life satisfaction, and self-rated health have defined and conceptualised the neighbourhood effect, set out to identify the potential mechanisms underlying the effect, and addressed the main estimation challenges impeding this line of research.

2.2.1 Neighbourhood effects by main discipline and wellbeing outcome

To set the scene, we report the overall number of studies and neighbourhood effects studied by main discipline and wellbeing outcome (**Table 2**). A split by discipline is important for context: Economists are known to focus their analysis on empirical identification challenges and tend to study objective wellbeing outcomes while subjective wellbeing outcomes tend to be studied mostly by health researchers, who publish more rapidly, and rarely address empirical identification challenges (Diez Roux and Mair, 2010).

Table 2. Number of wellbeing outcomes examined, by discipline

Wellbeing outcome	Economic Sciences	Geographical Sciences	Health Sciences	Social Sciences	Total
Employment	12	8	0	3	23
Income	16	25	0	14	55
Health	5	1	158	21	185
Life satisfaction	14	9	6	19	48
Total	47	43	164	57	311

Source: Knies et al. (2020b). Own analyses.

In our review, 52.7% of the 311 effects are from studies in health sciences (N=164). This represents 70.4% of the recorded subjective wellbeing outcomes (N=233). All health sciences studies focused on subjective wellbeing. Other sciences have studied a greater range of outcomes with objective outcomes making up 76.7% of outcomes studied in geography (N=33), 69.6% in economics (N=29), and 29.8% in sociology, social and public policy (referred to here as Social Sciences, N=40).

2.2.2 Neighbourhood effect mechanisms studied

Scholars have suggested more than a dozen mechanisms through which the neighbourhood context may affect individual wellbeing. To gauge which specific causal mechanisms have been studied - if any - and how this varies across different outcomes (and disciplines), we adopted Galster (2012)'s categorisation which differentiates between four different types of mechanisms:

- Social interactive: social contagion, collective socialisation, social networks, social cohesion and control, competition, relative deprivation, and parental mediation;

- Environmental: exposure to violence, physical surroundings, and toxic exposure;
- Geographical: spatial mismatch of jobs and workers and a lack of quality public services;
- Institutional: stigmatisation, local institutional resources, and local market actors.

While identifying the specific pathway to neighbourhood effects appears essential for the design of effective public policies, this is not an easy thing to do. In particular, many of the effect mechanisms may be expected to produce the same empirical result – an issue coined ‘observational equivalence’ problem by Dufour and Hsiao (2008). For example, area deprivation may affect earnings negatively because of the lack of well-paying jobs (i.e., a geographical effect), too much competition may reduce the reservation wage (i.e., a social interactive effect), or the workers’ skills may be lower due to poorer training (i.e., an institutional effect) and a more restricted social network (i.e., another social interaction effect).

Previous reviews have found that only a few studies have tried to investigate specific mechanisms by laying out a particular set of hypotheses associated with carefully defined neighbourhood-level indicators. The majority of studies are said to have used broader ‘catch-all’ measures of local area deprivation and looked at ‘catch-all’ effects of neighbourhood disadvantage (see, e.g., Friedrichs et al., 2003). Our review of the more recent literature shows that studying a ‘catch all’ neighbourhood effect is still quite prevalent in neighbourhood research but it is by no means the dominant approach (see **Table 3**).

Table 3. Number of wellbeing outcomes examined, by causal mechanism

Wellbeing outcome	Neighbourhood effect mechanism					Total
	Catch-all	Social interactive	Environ-mental	Geographical	Institutional	
Employment	15	2	0	2	4	23
Income	33	21	0	0	1	55
Health	45	51	72	3	14	185
Life satisfaction	11	24	13	0	0	48
Total	104	98	85	5	19	311

Source: Knies et al. (2020b). Own analyses.

Overall, about a third of the 311 neighbourhood effects studied in the 91 reviewed studies are ‘catch-all’ effects (N=104). Examples are Roy et al. (2012)’s study of the effects of neighbourhood ethnic composition and neighbourhood income on self-rated health and life satisfaction, and Plum and Knies (2019)’s study of the effect of local unemployment on the springboard effect of low pay.[3] Although the studies separate out different aspects of the neighbourhood context, the analysis is unspecific as to whether social interactive, environmental, geographical or institutional mechanisms underpin the identified neighbourhood effect. While 24% (56 out of 233) of neighbourhood effects on subjective wellbeing were of this type, this figure amounts to 61.5% (48 out of 78) of neighbourhood effects on objective wellbeing.

Thirty-one percent of the studied neighbourhood effects classify as social interaction effects (N=95). Papers on self-rated health focused mainly on the benefits of social cohesion and trust as well as the importance of local associational ties (e.g., Bjornstrom, 2011; Bjornstrom and Kuhl, 2014; Bjornstrom et al., 2013; Maass et al., 2016; Moore et al., 2010). A group of studies focused on whether neighbourhood income matters for life satisfaction, identifying multiple distinct effect mechanisms within the social interactions group of effects. Kingdon and Knight (2007), researching communities in South Africa, found empirical evidence consistent with the hypothesis that higher levels of income in the most immediate neighbourhood promotes wellbeing, as richer neighbours provide social insurance (i.e., an institutional mechanism). The authors go on to show that at greater neighbourhood scales, neighbours compete over resources and price-out each other implying a negative effect of neighbourhood income on life satisfaction. This social interaction mechanism has also been studied as a relative deprivation effect in sociological research by Knies (2007), Knies et al. (2008) and Dittmann and Goebel (2010). While social interaction mechanisms have been studied across all disciplines and outcomes, they were most prominent in studies of neighbourhood effects on life satisfaction, where they represent 50% (24 out of 48) of the effects studied.

The breakdown by type of mechanism for each wellbeing outcome also reveals that environmental mechanisms are prominent mechanisms explored in neighbourhood effects on self-rated health (Ozdamar, 2016; e.g., Cremonese et al., 2010) but absent from the research examining effects on employment and income. Institutional and geographical mechanisms, on the other hand, have received some traction in studies of employment and income but not in life satisfaction.

[3] Our review included the previous version, published as Plum and Knies (2015).

2.2.3 Neighbourhood indicators studied

We were interested to see whether there are any prevailing neighbourhood-level indicators to identify the specific types of neighbourhood effects. The word clouds presented in **Figure 2** illustrate the richness of indicators used. The bigger and bolder the indicator label appears, the more often the indicator has been used to investigate the respective neighbourhood effect mechanism.

Figure 2. Word clouds of indicators used to capture neighbourhood effects, by effect mechanism

a) Catch-all mechanisms

b) Social-interactive mechanisms

c) Institutional mechanisms

d) Environmental mechanisms

Source: Knies et al. (2020b). Own analyses. For full list and frequencies, see Knies and Melo (2021), Table A8.

We can see that a few indicators stand out. Various indicators of local context are used to study 'catch-all' effects, ranging from more complex composite measures of neighbourhood disadvantage and deprivation indices (e.g., Andersson et al., 2007; Galster et al., 2015; Hedman and Galster, 2013; Reijneveld, 2002; Wong et al., 2009) to less complex markers of the neighbourhood income distribution (e.g., mean, median, poverty line). These types of indicators are not exclusive to any one of the effect mechanisms, however. They are also used to capture social interactive effects and institutional effects. Similarly, indicators used to capture environmental effects seem to stand out as they use perceptions of the physical space and perceptions of the environment. However, we also found such indicators used to capture institutional effects. Overall, no clear patterns emerged.

2.2.4 Neighbourhood scales and conceptualisation

Our literature review shows that the geographical conceptualisation of neighbourhood varies significantly across studies, particularly when we differentiate between the wellbeing outcomes under focus (see **Table 4**).

Table 4. Definition of neighbourhood by wellbeing outcome

Neighbourhood definition	Wellbeing outcome				Total
	Employment	Income	Health	Life satisfaction	
Respondent-defined	0	0	73	14	87
Administrative unit	23	55	112	34	224
… by source					
census	18	26	45	13	102
(external) community survey	0	0	51	10	61
registers	5	29	10	2	46
geo-marketing data	0	0	6	9	15
Total	23	55	185	48	311

Source: Knies et al. (2020b). Own analyses.

There were two types of neighbourhood definitions; those that use administrative boundaries and those that use respondent-defined 'boundaries'. Seventy-two percent (224 out of 311) of the reviewed neighbourhood effects have defined neighbourhoods on the basis of administrative reporting units available in national census, register or micro-marketing products, either to link to population characteristics at these scales or to aggregate community survey data at these scales. The remainder are studies in which survey respondents describe their neighbourhood, often without referring to geographical boundaries. Intriguingly, this approach was very common in the literature focussing on self-rated health (39.5%) and life satisfaction (29.2%) but absent from studies that examined neighbourhood effects on income or employment. Moreover, while some studies used such community survey data to predict area characteristics at the scale of administrative units such as census districts (e.g., Browning and Cagney, 2002; Franzini et al., 2005; Shields et al., 2009), this too is not an approach we observed in the objective wellbeing studies.

A small number of effects refer to bespoke neighbourhood definitions (N=8). The bespoke neighbourhood approach combines the use of very small pre-defined administrative units with the concept of placing the respondent (or rather the administrative unit into which his or her home falls) at the centre of the neighbourhood. Bolster et al. (2007) constructed bespoke neighbourhoods by aggregating neighbouring UK Census 1991 enumeration districts based on a series of population thresholds (i.e., 500 to 10,000 people) as well as distances (i.e., 200 to 2,000 metres), while Hedman et al. (2015) use individual-level administrative records grouped into 100x100 metre squares to construct bespoke neighbourhoods based on population thresholds. The studies test for the presence and intensity of neighbourhood effects at different scales and find that neighbourhood effects are more marked at smaller scales. Interestingly, the approach was absent from the literature focusing on subjective wellbeing.

The in-depth review also revealed great variation across studies in terms of the size of the neighbourhood units (see **Table 5**). Overall, we identified five neighbourhood size clusters:

- Very small: Areas with below 500 people on average
- Small: Areas with sizes of around 1,000-3,500 people on average
- Intermediate: Areas with approximate population sizes of around 4,000-8,000 people on average (e.g., US Census tracts)
- Large: Areas with 10,000 -20,000 people on average
- Very large: Areas with significantly more than 20,000 people on average (such as local authority area level or Public Use Micro Areas in US studies).

Table 5. Size of neighbourhood by wellbeing outcome (among administrative units)

Neighbourhood size	Wellbeing outcome				Total
	Employment	Income	Health	Life satisfaction	
very small	3	3	24	16	46
small	8	23	37	11	79
intermediate	11	5	36	6	58
large	0	8	9	0	17
very large	0	16	6	2	24
Total	23	55	112	34	224

Source: Knies et al. (2020b). Own analyses.

The observed range of population sizes was immense. The typical or average population size for the neighbourhoods ranged from eight households (i.e., housing blocks in a German micro-marketing data set, see Dittmann and Goebel (2010)) to 125,000 people (i.e., those living in the same district, the largest of three spatial aggregations considered by Kingdon and Knight (2007)). Public Use Micro Areas from the US census were an example of neighbourhood units that have a population size of over 100,000 (Levanon, 2014; Luttmer, 2005). The vast majority of evidence on neighbourhood effects relates to neighbourhoods that had very small or small population sizes, however.

The subjective wellbeing research tended to use smaller spatial scales than the objective wellbeing research. In particular, the greater part of life satisfaction research uses very small (45.7%) and small (31.4%) scales, whereas health-related research has a relatively higher use of intermediate (32.1%) scales, while also making a great use of very small (21.4%) and small (33%) scales. By contrast, objective wellbeing research uses larger scales: While the research studying employment is characterised by using intermediate (50%), followed by small (36.4%) and very small (13.6%) scales, the most frequent neighbourhood scale in the research focussing on income was ‘small neighbourhoods’ (41.8%) but very large neighbourhoods were also prominent (29.1%).

2.2.5 Methods used to address empirical identification challenges

Next, we present which approach to address residential selection bias has been adopted for the 311 neighbourhood effects reported across the 91 studies in our review. To account for the fact that many studies examined multiple neighbourhood effects using the same framework, we report statistics at the neighbourhood effect-level by outcome, and statistics at the study-level by discipline (**Table 6**).

Residential selection bias was not addressed in 59 out of 91 studies (64.8%), corresponding to 226 out of 311 (72.7%) of the studied neighbourhood effects. Not addressing residential selection bias seemed particularly common in neighbourhood effects on health (93.9%). However, when we exclude subjective wellbeing studies that do not use the term ‘neighbourhood effect’ in the title or abstract, the figure drops significantly (to 58.5%; 24 out of 41) putting studies of health in the same ballpark as studies of income (60%) and life satisfaction (57.9%). At the study-level, one in ten studies in health and economics, and two in ten studies in geography and social sciences have not addressed selection bias.

Regarding the specific approaches taken to address residential selection bias, there is great heterogeneity in approaches across different wellbeing outcomes and no clear patterns emerge. The only exception is that studies on health have adopted only two out of the six methods: Two studies accounted for selection bias using observed characteristics (Xiao et al., 2017; O'Campo et al., 2015). Another group drew on information from randomised experiments (Fauth et al., 2008; Ludwig et al., 2013; Turney et al., 2006).

Table 6. Methods used to address residential selection bias in neighbourhood effects on wellbeing, by wellbeing outcome

Method used[(1)]	Number of neighbourhood effects by outcome				Total
	Employment	Income	Health	Satisfaction	
[0] Bias not addressed	6	33	160 (24)	27 (5)	226 (68)
[1] Controls for observed characteristics [(2)]	4	0	8	4	16
[2] Fixed effects/ correlated Random effects [(3)]	1	14	0	14	29
[3] Instrumental variables	3	3	0	0	6
[4] Propensity score matching	4	0	0	0	4
[5] Residential choice modelling	0	3	0	0	3
[6] Randomized experiment	5	2	9	1	17
Total [1-6]	17	22	25	21	85
Total [0-6]	23 (23)	55 (55)	185 (41)	48 (24)	311 (143)
Method used[(1)]	**Number of studies by discipline**				**Total**
	Econ.	Geog.	Health	Soc.	
[0] Bias not addressed	3 (2)	7 (3)	39 (5)	10 (4)	59 (14)
[1] Controls for observed characteristics [(2)]	2	1	4	3	10
[2] Fixed effects/ correlated Random effects [(3)]	4	3	0	2	9
[3] Instrumental variables	2	2	0	0	4
[4] Propensity score matching	2	0	0	0	2
[5] Residential choice modelling	0	1	0	0	1
[6] Randomized experiment	3	0	0	3	6
Total [1-6]	13	7	4	8	32
Total [0-6]	16 (14)	14 (9)	43 (8)	18 (10)	91 (41)

Notes: ( ) The figure excludes neighbourhood effects from studies that do not have the word 'effect' in the title. These are studies in health that were identified using less stringent search terms to identify further subjective wellbeing studies eligible for review.
(1) A number of studies combined approaches. We report the method with the highest value.
(2) Neighbourhood effects estimated using models that include individual, family background and/or neighbourhood variables specifically to address residential selection bias.
(3) Covering individual, family and/or neighbourhood-level effects.
Source: Knies et al. (2020b). Own analyses.

Life satisfaction and income studies make heavy use of fixed effects identification strategies, additionally relying also on sample restrictions to drill down to a specific causal effect (e.g., Knies, 2012; Luttmer, 2005). To isolate the exogenous effect of neighbourhood influences, these studies restrict the analysis to cases for whom the residential choice may be assumed to be exogenous. We have not tagged this strategy as a separate approach as it coincided with other methods. Examples of this approach include use of sibling data (Vartanian and Buck, 2005); young adults still residing with at least one parent (Dujardin et al., 2009); social renters (van Ham and Manley, 2010); individuals reporting to prefer to move/stay in current neighbourhood (Clark and Drinkwater, 2002; Knies et al., 2008; Knies et al., 2016; Plum and Knies, 2015).

A number of studies used instrumental variables (IV). They all focus on employment or income. The IV technique requires finding variables (i.e., instruments) that influence the choice of residential location, but do not affect individual wellbeing other than through the endogenous neighbourhood effect. Finding valid instruments is notoriously difficult, which explains the paucity of studies adopting this method. Furthermore, the validity of instruments can be context-specific and dependent on the wellbeing outcome under study. Examples of instruments used include the number of children and their gender mix in the household (Dujardin and Goffette-Nagot, 2010)[4]; interactions between variables referring to individual–partner ethnic combination, number of children, partner income, and proportion of males in the household (Hedman and Galster, 2013)[5]; cell-based instruments (Bauer et al., 2011)[6]; and deep time lags of the neighbourhood attribute of interest (Melo, 2017). The IV method is sometimes combined with other methods, namely individual fixed effects models (Hedman and Galster, 2013), hedonic house price control function (Bauer et al., 2011), or the estimation of a system of equations (Dujardin and Goffette-Nagot, 2010).

Other identification strategies were rare. Two studies (i.e., Calavrezo and Sari, 2012; Cheng and Smyth, 2015) have used propensity score matching to measure the effect of living in a

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[4] The idea is that both the number of children and the gender mix of children are part of the criteria for allocating households to social housing and there is a positive correlation between the presence of social housing in neighbourhoods and neighbourhood deprivation. On the other hand, we would not expect the number of children and the gender mix of children to affect individual wellbeing outcomes.

[5] The rationale behind these variables is that they affect neighbourhood income mix in a given year but not the individual's income – the objective wellbeing outcome - earned during that year.

[6] The cell-based method controls for correlation between individual unobservable characteristics and neighbourhood characteristics by instrumenting for each individual's observed neighbourhood attributes with the average neighbourhood attributes of all observationally identical individuals. For more details on the method, see Bayer and Ross (2006).

deprived neighbourhood on individual wellbeing. The logic behind the method is similar to that of regression adjustment in that they control for the characteristics of individuals that make them more or less disposed to receiving a given treatment (here: living in a deprived neighbourhood), and then compare outcomes between individuals with similar or equal propensity scores but different treatment status.[7] One study has modelled residential choice and neighbourhood effects simultaneously (van Ham et al., 2018).[8]

2.3 Conclusions and recommendations

We have presented a detailed review of 91 studies that examined 311 neighbourhood effects, on four individual wellbeing outcomes: employment, income, life satisfaction and self-rated health. The review focused on an assessment of how much progress has been made, since publication of a number of literature reviews in the late 1990s and early 2000s, in addressing issues relating to the identification of specific neighbourhood effect mechanisms, the definition of neighbourhood and its spatial scale, and the identification of causal versus correlational effects. We could not review all neighbourhood effect studies published since 2002, but by adopting a strict screening and review protocol designed to lead us to the studies most relevant to our planned research of contemporary neighbourhood effects on prominent subjective and objective wellbeing outcomes we achieved a manageable sample of studies to review.[9]

We find that neighbourhood definitions and effect mechanisms in the research continue to be quite vague but there is a rise in studies using smaller-scale and more nuanced indicators. Social interactive neighbourhood mechanisms were the most commonly studied mechanism through which neighbourhood impacts are said to transpire.

The key finding from this review is that although neighbourhood effect research is an interdisciplinary field of study that shares common identification challenges, the challenges are addressed in clearly disciplinary ways. A significant number of studies do not address

[7] The validity of this approach relies on two fundamental assumptions: the conditional independence assumption and the overlapping support assumption.
[8] The data requirements for this type of modelling are immense. The analysis was restricted to the area of one metropolitan area in the Netherlands to restrict the number of neighbourhoods in individuals' choice set.
[9] For reviews focused on health outcomes more generally we refer the Reader to Diez Roux and Mair (2010); Jivraj et al. (2019) provide a detailed review of the long-term impact of neighbourhood disadvantage on mental health. Galster and Sharkey (2017) focus on the vast literature on the effects of segregation while Nieuwenhuis and Hooimeijer (2016) focus on educational outcomes. A great deal of the latter two literatures overlap with the equally vast literature focused on outcomes for ethnic minorities. We could not locate a recent review of the ethnicity and place literature but note that a great deal of British neighbourhood studies focus on issues pertaining to ethnic inequalities (Platt et al., 2020).

residential selection bias whilst claiming to look at causal neighbourhood effects. This malpractice is less common in health and economic studies than in sociological and geographical studies. It is difficult to quantify how much progress has been made as we do not have a comparable reference for early studies. At best, we may consider as a reference the review studies that state, for example, that the majority of studies looked at ‘catch-all’ neighbourhood effects. This implies that at least more 50% of early studies adopted this approach. We would then argue that in respect to testing specific mechanisms there has been quite a bit of progress as the respective figure among the more recent studies we reviewed is 30%. However, among the studies that tested specific mechanisms many did still not pay a great deal of attention to testing alternative hypotheses (which is problematic because of the observational equivalence problem).

Greater availability of spatial and temporal data has allowed methodological improvements across all disciplines - for example, studies of health and place are no worse than other discipline studies at overselling correlational associations as neighbourhood effects, unfortunately though this does not appear to have spurred greater collaboration among scholars with different disciplinary backgrounds: There are still too many studies around that make undue causal claims and which do not make use of the rich auxiliary data we know are available in the individual survey data and which could help get a handle on residential selection bias. To some extent, this lack of interdisciplinary approach is an outcome from the still prevalent organisation of universities in discipline-based departments as well as the generally higher reputation of discipline-specialised journals. Making the study of neighbourhood effects truly multi- and interdisciplinary is therefore likely to require more ambitious and structural changes to the approach to the production of scientific knowledge and its relevance for public policy design.

3. Creating a Database of Longitudinally Harmonised, Scalable Neighbourhood Characteristics

3.1 Introduction

Our review highlighted that there is little consensus about which geographical scales are important for wellbeing (also see Petrović et al., 2019). Empirically, the matter of 'which scale matters' may be approached by conducting parallel analyses of a particular outcome using neighbourhood indicators measured at different scales (Andersson and Musterd, 2010; Galster, 2005), and by additionally considering multiple outcomes where the effect of the neighbourhood may be expected to transpire at different scales. A number of British studies have adopted such a multi-scale approach, comparing the importance and intensity of neighbourhood effects at bespoke neighbourhood scales ranging from the nearest 500 to 10,000 people based on information for "Enumeration Districts" (EDs) of the 1991 UK census (Buck, 2001; Bolster et al., 2007; Johnston et al., 2004a; Johnston et al., 2004b; Propper et al., 2005). At the time, these bespoke neighbourhoods offered context measures at much more immediate scales than was available from public data depositories[10] and all aforementioned studies suggested that the neighbourhood impact was greater the more immediate the neighbourhood context was measured - yet we have seen no further applications using the bespoke census data for 1991.

Our ambition for this research project was to advance the British neighbourhood effects research also by incorporating neighbourhood dynamics in the empirical models, thereby venturing down an important but as yet underexplored avenue of neighbourhood effects research (van Ham and Manley, 2012). Are improvements in the neighbourhood socio-economic status as important to increasing wellbeing as are deteriorations to decreasing it? In Britain as elsewhere, the bulk of the neighbourhood effects research has measured neighbourhood characteristics at only one point in time precluding answers to this question; this is true for studies that looked at contemporaneous neighbourhood effects (Knies et al., 2020b) and for studies that used long runs of cohort or panel data linked to spatial aggregate

[10] "Enumeration Districts" (EDs) were the smallest areal units for which information from the 1991 census geography was principally available. There were 106,865 English 1991 EDs, with an average of 420 persons and 175 households. ED boundaries did not follow any rules regarding homogeneity of the population or housing. EDs nest within wards, the next smallest census areal unit. Wards vary widely in population size (~4,500 residents on average), but tend to be of similar population sizes within a single local government area. For further information see Martin (2006). To our knowledge, no social survey has released geographical locator variables to facilitate data linkage at the ED scale. The most widely used geographical scale for neighbourhood context analyses was the ward level.

data (Jivraj et al., 2019). One of the obstacles facing this research path is that neighbourhood boundaries change over time, which means that we cannot disentangle the effect of the boundary change from the genuine effect of the change in neighbourhood context. Moreover, measurement of spatial features may also change over time. E.g., the much-used Index of Multiple Deprivation has been released in 2000, 2004, 2007, 2010, 2015 and 2019 cannot, however, be treated as a time series because of changes in area boundaries, population sizes and in the information used to construct the indicators (such as eligibility for income maintenance support in the income domain). At best, a neighbourhood's rank position may be compared over time using these indices and all neighbourhoods that experienced boundary changes may be discarded.

To better track stability and change in neighbourhood conditions and to do so for areal units that may be perceived as neighbourhoods, the 2001 UK census saw the introduction of new census geographies. So-called output areas (OA) replaced the EDs as the smallest reporting units. OA boundaries were delineated based on spatial proximity, natural boundaries as well as homogeneity of dwelling type and tenure so that aggregations to areas of around 600 households (~1,500 people, so-called Lower Super Output Areas, LSOAs) would refer to localities that local people conceive as neighbourhoods[11]. LSOAs became the core reporting unit to monitor neighbourhood wellbeing; they are "substantially smaller and more internally homogenous than the geographies that have been relied upon by many previous studies, enhancing our ability to uncover evidence of neighbourhood processes operating within local communities" (Sutherland et al., 2013: 1055-1056).

Much of the British neighbourhood research has relied on neighbourhood characteristics at the LSOA level. But it would seem reasonable to expect many different scales to be important for individual wellbeing: neighbourhoods, due to variations in peer groups, social organisations, and social networks; political jurisdictions, due to variation in health, education, recreation, and safety programs; and metropolitan areas, due to providing locations of employment of various types and skill requirements (Galster, 2005). In particular, we may expect social interaction effects to operate at smaller scales than the 1,500 people in the LSOA, for example,

[11] Generally, neighbourhood definitions fall into four broad categories: Those that focus on a) homogenous areas regarding demographic and housing characteristics, b) shared identity among residents, social and/or political organisation, c) housing sub-markets in which individual units are substitutes; or d) simply small areal units that do not have any of the aforementioned socially structured characteristics (Megbolugbe et al., 1996). While EDs fall into the fourth category, the new OAs combine elements of the first and second categories.

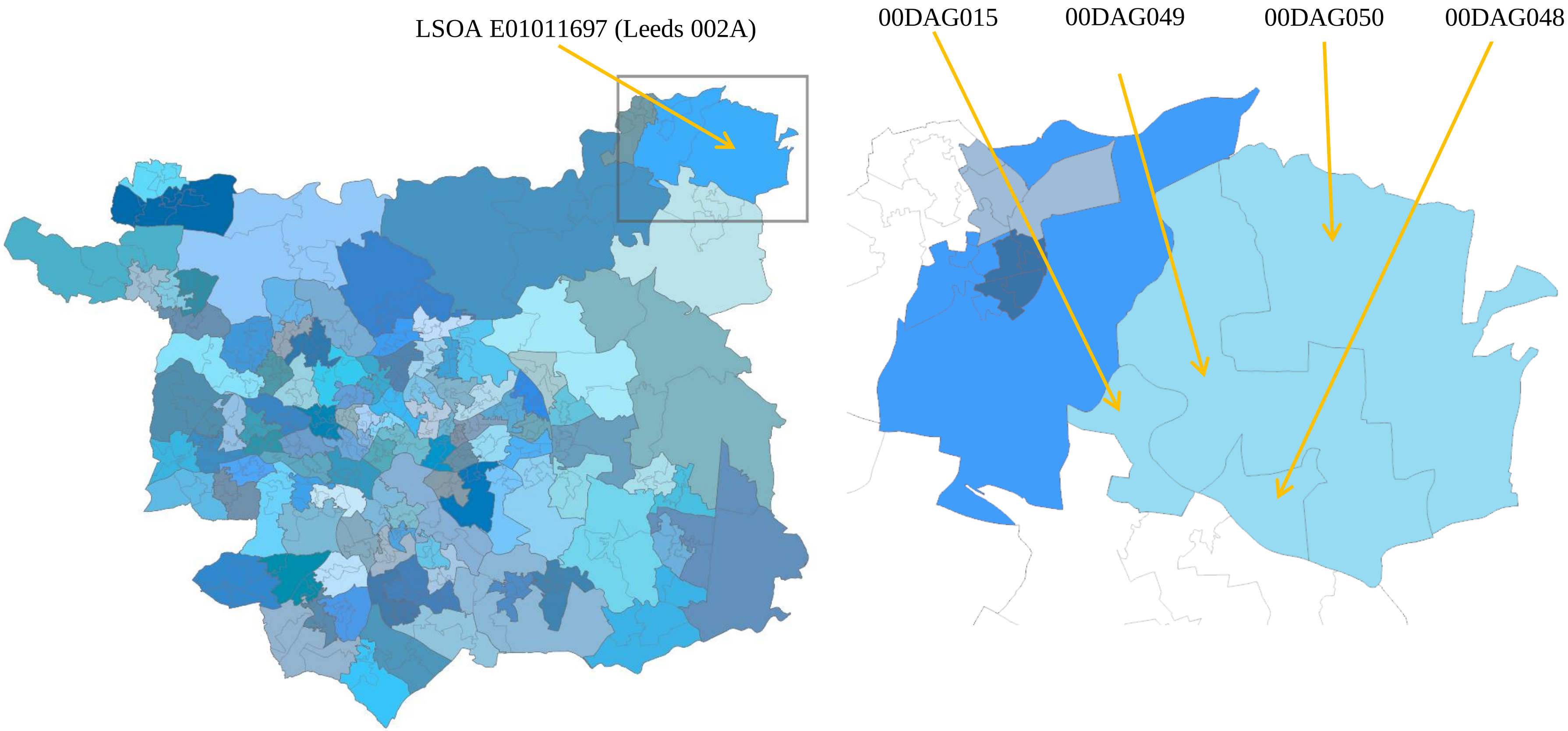
since "150-250 people can maintain (the) close, personal interaction", and "400 to 600 can maintain (the) more casual form(s) of interaction" (Talen, 2019) which underpin effects based on (possible) interacting with others. By contrast, when examining institutional effects that may manifest through local council policies or geographical effects such as labour market competition, neighbourhoods defined at broader spatial scales may be more relevant (Andersson and Musterd, 2010; Petrović et al., 2019). For our project, we therefore set out to create bespoke neighbourhoods based on the OA geographies used in the 2001 and 2011 UK census and to then produce a database of neighbourhood characteristics at these bespoke scales.

3.2 Methodology

We only describe the basic features of our approach here, for a more detailed description of the approach, see technical appendix in Knies et al. (2020a) on our project website. We base our bespoke neighbourhoods on the physical distance between the population-weighted centroid of the postcode and the population-weighted centroid of OAs in the 2001 census (OA01). OAs have a minimum population of 100 residents, are socially homogeneous in terms of household tenure and dwelling type, and are defined by clear boundaries such as major roads (Office for National Statistics, 2019). OAs are nested within greater geographical units. Firstly, neighbouring OAs with similar socio-demographic make-up and building characteristics are grouped into LSOAs that have a minimum population size of 1,000 residents (and are considered to resemble neighbourhoods by local experts involved in the revision of census boundaries). At the next level, the most similar neighbouring LSOAs are grouped into Middle Layer Super Output Areas (MSOA) that have a minimum population size of 5,000 residents. OA, LSOA and MSOA are nested within Local Authority Districts (LAD).

Our algorithm respects the nested structure of census geographies. In **Figure 3** we illustrate how this works using the LAD of Leeds as an example. Overall, Leeds had 108 MSOAs in the 2001 Census, each comprising four to six LSOAs, each comprising of two to ten OAs. For example, the MSOA E02002331 (also known as Leeds 002; bright blue area in the grey square in the top right corner of **Figure 3**, left panel) contains four LSOAs. For example, the LSOA E01011697 (Leeds 002A) comprises of four OAs (00DAG050, 00DAG015, 00DAG048, and 00DAG049; see area highlighted in light blue in **Figure 3**, right panel).

Figure 3. Illustration of the nesting structure of 2001 Census output areas using Leeds local authority



LSOA boundaries within MSOAs
LAD Leeds in focus

OA boundaries within LSOAs
MSOA E02002331 (Leeds 002) in focus

The bespoke area algorithm for any postcode in the OA 00DAG015 first includes all OAs from the postcode's own LSOA (E01011697, area highlighted in light blue), then identifies which OA from outside the own LSOA but inside the own MSOA (i.e., any of the coloured areas numbered 1, 2 or 3) is the nearest. All OAs from this area will then be included in sequence of distance, then the next area is identified and all its OAs are included, and so on until all OAs in its own MSOA (E02002331/Leeds 002) have been included. The process is then repeated to include any OAs from the areas that are shadowed out.

3.2.1 Dealing with boundary changes

Britain experienced substantial population and housing stock growth between 2001 and 2011, and this has prompted a number of boundary changes to OAs, LSOAs and MSOAs. To allow researchers getting a handle on these changes, the ONS provides look-up files for the 2001 and 2011 geographies that include an indicator for which units were merged, split or changed in a more complex way.[12] We used the information on merges to aggregate the 2001 units so they refer already to the new 2011 boundaries before running the nearest neighbour algorithm. Following this we used the cumulative population in the now longitudinally harmonized OA01, and flagged the nearest OA01s needed to cross the minimum population threshold of 500, 1,000 (1k), 2,000 (2k) to 10,000 (10k) neighbours.

3.3 Characteristics of bespoke neighbourhoods

Having defined the OA01 involved in each bespoke area, we can flexibly attach characteristics at the 2001 or 2011 OA scales to each bespoke neighbourhood and compute aggregate statistics.[13] **Table 7** reports population size statistics. Bespoke neighbourhoods in 2011 had a population size that was comparable to that in 2001 – judging by the 25th percentile, median and 75th percentile values – but the minimum and maximum values indicate greater heterogeneity and an overall increase in the neighbourhood population sizes across the board. This is true for each bespoke neighbourhood scale. Note that our two smallest units nevertheless have considerably smaller typical population sizes in both census years than the smallest units that had been produced for the 1991 Census based on enumeration districts (see, e.g., Buck, 2001).

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[12] Note that boundary changes are relatively scarce. Less than 3% of OAs experienced them and most changes are merges and splits.
[13] For OA01 that were split in 2011, this involves aggregating information from the 2011 census so they refer to the 2001 boundaries instead. Note that this approach can only be used with count data, not with qualitative data such as neighbourhood classifications.

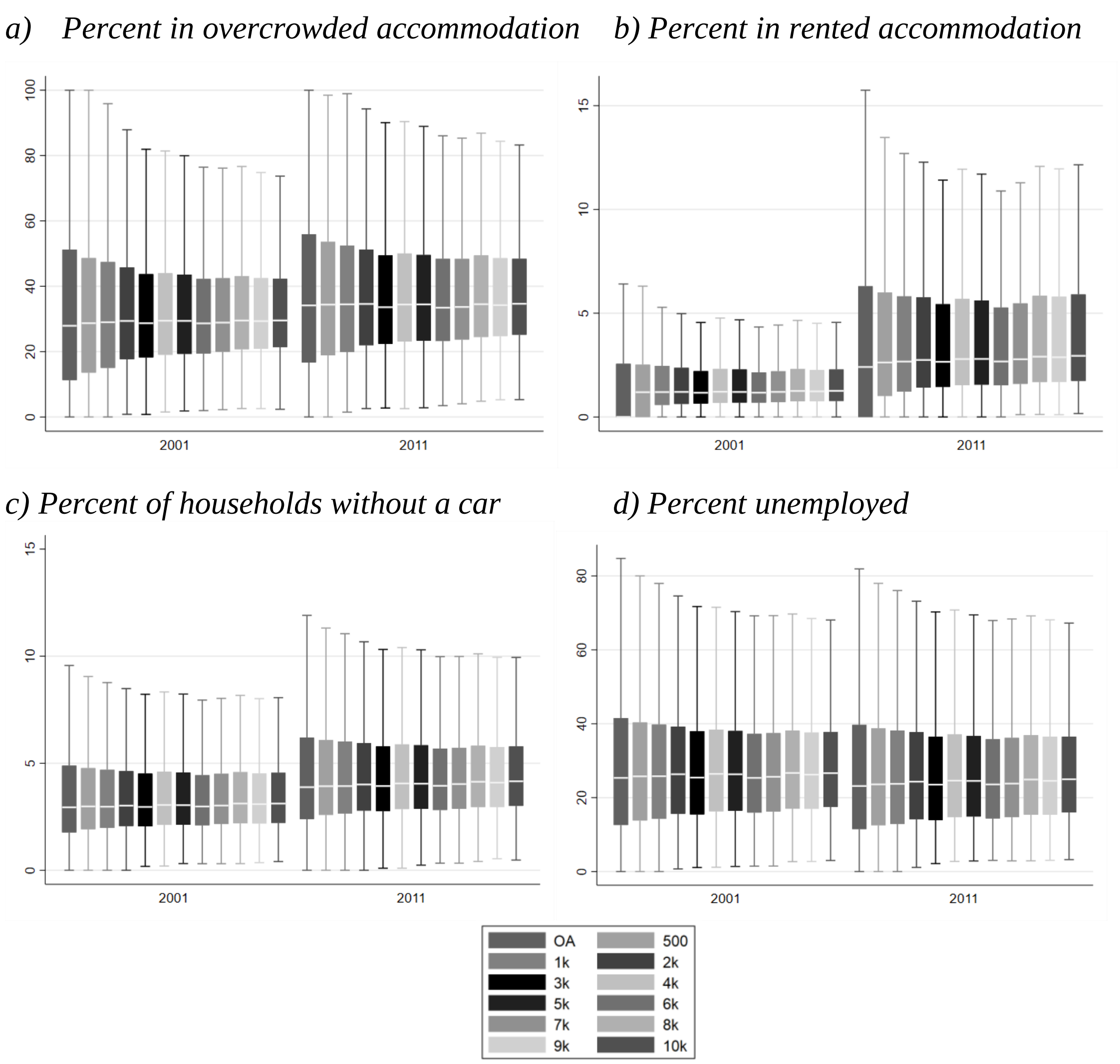
Table 7. Characteristics of bespoke neighbourhoods in 2001 and 2011: Population size

	2001					2011				
Spatial scale	**min**	**p25**	**median**	**p75**	**max**	**min**	**p25**	**median**	**p75**	**max**
OA	101	263	298	334	4,156	99	274	313	363	9,801
Bespoke 500	501	568	620	684	4,520	150	587	655	758	14,051
Bespoke 1k	1,001	1,084	1,163	1,230	4,520	259	1,128	1,224	1,345	15,504
Bespoke 2k	2,001	2,075	2,145	2,222	5,912	994	2,132	2,269	2,471	16,803
Bespoke 3k	3,001	3,075	3,152	3,231	6,026	1,750	3,154	3,329	3,593	17,931
Bespoke 4k	4,001	4,073	4,148	4,226	7,753	2,774	4,174	4,392	4,724	20,220
Bespoke 5k	5,001	5,077	5,151	5,230	7,753	3,816	5,195	5,461	5,856	21,047
Bespoke 6k	6,001	6,076	6,153	6,230	8,669	4,845	6,221	6,516	6,965	22,091
Bespoke 7k	7,001	7,074	7,149	7,228	10,132	5,809	7,250	7,596	8,119	25,695
Bespoke 8k	8,001	8,075	8,151	8,230	10,701	6,781	8,298	8,689	9,284	28,920
Bespoke 9k	9,001	9,076	9,151	9,228	13,099	7,763	9,336	9,764	10,431	30,682
Bespoke 10k	10,001	10,074	10,150	10,229	13,298	8,650	10,369	10,838	11,560	31,398

Source: Bespoke neighbourhood characteristics for longitudinally harmonised OA01 characteristics. Based on 2001 and 2011 census for England and Wales. Sample restricted to areas that do not include any complex boundary changes. Bespoke areas for postcodes observed in Understanding Society, waves 1-6.

Figure 4 shows Box-Whisker plots for the four constituent characteristics of the Townsend Deprivation Index, the key measure of neighbourhood socio-economic disadvantage that we will use in our empirical investigation: the percentage of the neighbourhood population living in overcrowded accommodation, in rented accommodation, in households without a car, or who are unemployed, for each bespoke neighbourhood scale and separated by census year. Note that we do not report the 'extreme' values falling into the bottom and top 5th percentile of the respective distributions to increase readability.

Figure 4. Characteristics of bespoke neighbourhoods in 2001 and 2011 (Box-Whisker plots).



Notes: For readability, plots do not report the top / bottom 5th percentiles. For complete results, see Knies and Melo (2021) Tables A6 and A7.
Source: Bespoke neighbourhood characteristics for longitudinally harmonised OA01 characteristics. Based on 2001 and 2011 census for England and Wales. Sample restricted to areas that do not include any complex boundary changes. Bespoke areas for postcodes observed in Understanding Society, waves 1-6.

Overall, these plots show that there is not much variation in neighbourhood characteristics across the different neighbourhood scales: For each indicator, the medians are essentially the same at all scales. The interquartile range (i.e., the difference between the top and bottom 25th percentiles, indicated by the bottom and top edges of the box) is somewhat smaller at the larger scales (i.e., the boxes are less tall). Over time, neighbourhoods have seen increases in the percent of the population living in overcrowded housing, rented accommodation and households without a car, while there has been a decrease in neighbourhood levels of unemployment. While the neighbourhood characteristics in 2011 also do not show much variability across neighbourhood scales, the interquartile ranges are wider than in 2001, indicating greater heterogeneity in neighbourhood contexts as time goes on.

3.4 Conclusions and outlook

One of the reasons why we observe few differences in neighbourhood characteristics across scales may be due to design. The building blocks for creating bespoke neighbourhoods are nested within LAD and OAs are constructed so that aggregations of them to LSOAs and MSOAs result in the most similar neighbouring units to be grouped together. When joining two similarly sized groups with the same characteristics, we end up with a larger group that has the same average group characteristics as the two smaller groups. To alleviate these concerns we also created bespoke neighbourhoods without nesting nearest neighbours in LSOAs, MSOAs and LADs, respectively. The resulting bespoke neighbourhoods show the same patterns, i.e., there is little variation in neighbourhood characteristics across scales and an increase in spatial heterogeneity over time. We decided to stick to the nesting approach because the population homogeneity and similarity in status underpinning the nested structure can be expected to be one of the key characteristics underpinning local social interactions – friendships, social comparisons and completion rely on some similarity in status to be perceived either by the neighbours themselves or by outsiders. At the end of the day, without perceiving a particular areal unit as a social and physical unit, the residents would just be individuals, not neighbours.

By restricting possible neighbours to those from the same LAD we ignore the effect of any spatial processes that operate beyond these scales, the effects of which may loom particularly large for individuals living close to the boundary of their LAD. We may, for example, miss context effects that transpire through services that are delivered jointly by neighbouring LADs. While LADs represent clear administrative boundaries for some types of decision making, decisions or effects that pan out across their boundaries cannot be captured. Importantly, these arguments do not provide a clear indication as to what might be the more appropriate metropolitan or regional scale to use and any spatial aggregation has a potential to suffer from this type of misclassification error (for an empirical investigation of this issue see, for example, Flowerdew et al., 2008). A future project may apply a hybrid approach that maximised population homogeneity up to the scale of the longitudinally harmonised LSOAs, and minimises boundary effects beyond this scale. This may be achieved by picking the nearest OAs that is not already used in the own LSOA, then picking all OAs from that OAs LSOA, then picking the nearest OA that is not already included in the own or second nearest LSOA and so on until the respective population thresholds are reached.

4. Comparative Analyses of Neighbourhood Effects on Two Prominent Wellbeing Outcomes across Multiple Spatial Scales

4.1 Introduction

As discussed in Chapter 2, there have been promising developments in how the neighbourhood effects research addresses issues relating to the operationalisation of 'neighbourhood' and some of the identification challenges hindering conclusion about causal effects. The first challenge has been advanced by using 'bespoke' neighbourhoods that can better capture the environment surrounding each individual and the use, often in combination, of more soundly defined spatial units at very immediate scales. In Britain, new boundaries were delineated for the 2001 population census based on spatial proximity, natural boundaries as well as homogeneity of dwelling type and tenure so that aggregations to areas of around 600 households (~1,500 people, so-called Lower Super Output Areas, LSOAs) would refer to localities that local people conceive as neighbourhoods (see Chapter 3 for a more detailed description of census output areas). Much of the British neighbourhood research since 2001 has relied on neighbourhood characteristics at the LSOA level. It remains unclear, however, whether these units really are the most appropriate scales for measuring how neighbourhoods impact individual wellbeing. The limits of the face-to-face community, where we may expect social interaction effects to operate, for example, may need to be drawn more tightly since "150-250 people can maintain close, personal interaction", and "400 to 600 can maintain a more casual form of interaction" (Talen, 2019). By contrast, when examining local council policies, labour market competition or area reputation, neighbourhoods defined at broader spatial scales, using widely recognized administrative units, may be more relevant. Ultimately, there may not be a single operational definition of the neighbourhood and we need to acknowledge that there are instead "multiple scales of ecological influence", "ranging from the micro-level street blocks (…) to areas of political and organizational importance (…)" (Sampson, 2012) and that the relevant scale and the prevailing neighbourhood effect may be different for different outcomes.

Concerning the identification challenges relating to residential self-selection, empirical strategies to address them include restricting the sample to individuals for whom residential location is exogenous (e.g., young adults living with their parents in: O'Regan and Quigley, 1996; Dujardin et al., 2009), exploiting information from quasi-random housing assignment programs (e.g., Chetty et al., 2016), implementing fixed effects estimators (e.g., Knies, 2012), using propensity score matching (Brännström, 2004) or instrumental variables (e.g., number of children and their gender mix in the household in: Dujardin and Goffette-Nagot, 2010). A small number of studies have modelled residential mobility directly by combining the estimation of a discrete choice model of neighbourhood selection with the estimation of the neighbourhood effect model (Hedman et al., 2011; van Ham et al., 2018). Comparing results across estimation strategies suggests that studies that ignore individual self-selection into neighbourhoods tend to find sizeable neighbourhood ‘effects’, while those implementing some correction for selection bias or using experimental settings tend to find weaker evidence in support of neighbourhood effects.

In this chapter, we report the results from the empirical analyses developed using a rich individual panel data combined with external bespoke neighbourhood data (see Chapter 3) to investigate the extent to which the spatial scale at which we operationalise ‘neighbourhood’ affects our conclusions about the importance of neighbourhood deprivation for four wellbeing outcomes: life satisfaction, earnings, and the physical and mental components of self-reported health-related quality of life. We implemented alternative statistical methods to address issues of residential self-selection for each bespoke neighbourhood spatial scale to answer the research questions:

- Does living in a deprived area affect one’s subjective and objective wellbeing?
- Which spatial scale(s) are more relevant for the explanation of the relationship between neighbourhood deprivation and subjective and objective wellbeing?
- Does the nature of the relationship between neighbourhood deprivation and wellbeing differ across subjective and objective outcomes?

The analyses herein contribute to the existing literature with a novel focus on how the empirical research has defined neighbourhoods and how effects might vary, firstly, by neighbourhood scale and, secondly, by how rigorously econometric estimation challenges have been addressed.

4.2 Overview of existing evidence for the selected wellbeing outcomes

In the empirical analysis we set out to explore the key research questions by examining at which scale of the neighbourhood the effect of neighbourhood socio-economic disadvantage transpires. The most direct approach to test empirically ‘which scale matters’ is to conduct parallel analyses of a particular outcome using neighbourhood indicators measured at different scales. Our review of the neighbourhood effects literature (see Chapter 2) indicated that two wellbeing outcomes for which this may be the case are earnings and life satisfaction. We additionally focus on two further subjective wellbeing outcomes which are prominently used in the subjective wellbeing research: the mental and physical functioning components of health-related quality of life.

We focus on an overall summary measure of neighbourhood socio-economic disadvantage because this is the most commonly used ‘catch-all’ indicator used to investigate neighbourhood effects (Knies et al., 2020b; Jivraj et al., 2019). The downside of such an indicator is that it makes it more difficult to identify and distinguish between specific alternative causal mechanisms underlying potential neighbourhood effects. Jivraj et al. (2019) summarised the longitudinal research examining neighbourhood effects on various wellbeing outcomes and concluded that studies using poverty rates to determine the socioeconomic position of the neighbourhoods provided the most convincing strategy because they more clearly specified the mechanisms leading to poorer health, for example. Nevertheless, differences in how poverty is defined and measured (e.g., income levels, types of goods and services accessible, etc.) may also hide a multitude of causal mechanisms. For Britain, we do not have any measure of neighbourhood poverty at small scales which we could aggregate flexibly to larger scales[14].

Tables 8-10 summarise the key features of papers that have examined the effect of neighbourhood socio-economic disadvantage on the four wellbeing outcomes of interest. We have discussed the studies focussing on earnings and life satisfaction in more detail in Knies et al. (2020a). In brief, the main takeaway message is that these studies are somewhat inconclusive as to which scales matter most. While the life satisfaction research has mainly focused on identifying effects on neighbourhood socio-economic status in very small to small neighbourhoods and found that there may be positive effects of having less affluent or lower social status neighbours (**Table 8**), the neighbourhood effects research on income has mainly focused on larger scales and found negative effects of neighbourhood socio-economic disadvantage (**Table 10**), albeit these effects tend to be not statistically significant when residential self-selection is accounted for (Kline and Moretti, 2014). A small number of studies focused on a range of neighbourhood scales as is the case of our study, but there is no overall consensus on the most relevant spatial, which may also be linked to differences in research design and deprivation indicators across studies.

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[14] Estimates of total household income (gross, net, before and after housing costs) are available at the MSOA level (Office for National Statistics, 2020). The bi-annual time series uses different boundaries across time and incomes are not adjusted to account for household size.

Table 8. Overview of research findings on the effect of neighbourhood socio-economic position on life satisfaction

Study	Neighbourhood scale	Neighbourhood indicator	Effect mechanism(s)	Residential selection addressed	Findings in a nutshell
Cheung and Lucas (2016)	US counties and county equivalents (~200 to 10m residents)	a) Median income b) Income inequality (GINI)	Social comparison (-)	No	Negative effect. People were more strongly influenced by the income of their neighbours when income inequality was high, possibly due to comparisons being more salient in such a context.
Clark et al. (2009)	Danish 'small neighbourhoods' (150-600 households)	Average income	Not specified (+/-)	Yes – individual fixed effects.	Individual satisfaction is positively associated with close neighbours' incomes.
Dittmann and Goebel (2010)	German blocks of houses (8-25 households)	Social status classification	Social comparison (-)	Yes – via individual fixed effects, but results not reported.	Cross-sectional associations in expected direction. Results claimed to be robust to absorbing individual fixed effects.
Deaton and Stone (2013)	US a) zip code area b) county c) congress area d) Metropolitan Statistical Area e) State	Average income	Social comparison (-) Neighbourhood quality (+)	No	Positive associations with happiness and life satisfaction. Effect size decreasing in neighbourhood scale. Negative effect at the largest scale.
Kingdon and Knight (2007)	South Africa a) enumeration cluster (~2,900 residents) b) district (~125,000 residents) c) province (~4.46m residents)	Average income	a) social protection mutual insurance (+) b) social comparison (-) c) Ditto.	No	Positive associations at the smallest scale, negative association at scales b) and c) in multivariate models.
Knies (2007)	Germany a) postcode areas (~9,000 residents)	Average household income	Relative deprivation (-)	No – only one wave of small-scale	Effects similar at all scales but associations stronger at the smallest geographical scale.

	b) Market cell (~200 households) c) Street section (~25 household)			neighbourhood data available	
Knies et al. (2008)	German postcode areas (~9,000 residents)	Average household income	Relative deprivation (-)	Yes – fixed effects and neighbourhood fixed effects estimators	Effects in expected direction but not robust to absorbing individual and neighbourhood fixed effects
Knies (2012)	German Street section (~25 households)	Average household income	West Germany: Social comparison (-) East Germany: Tunnel effect (+)	Yes – fixed effects and neighbourhood fixed effects estimators	Effects in West and East Germany in opposite directions. Only the negative effects in West Germany are statistically significant. Robust to absorbing individual and neighbourhood fixed effects.
Luttmer (2005)	US Census Public Use Micro Areas (~150,000 residents)	Average earnings of local population in same occupation	Conspicuous consumption (-)	Yes – individual fixed effects and neighbourhood fixed effects.	Negative effects are statistically significant and robust to absorbing individual fixed effects. Not robust to absorbing neighbourhood fixed effects.
Mouratidis (2020)	Oslo city neighbourhoods (~1,000-10,000 residents)	a) Neighbourhood deprivation index b) Distance to amenities c) Neighbourhood satisfaction	Not specified (+/-)	No	Negative correlation between deprivation and life satisfaction when unadjusted. No statistically significant associations with any of the neighbourhood context variables in the multivariate models.
Shields et al. (2009)	Australian census enumeration areas (~250 households)	Proportion: a) Immigrants b) single parents c) Unemployed d) Homeowners e) professional workers f) older-age population	Not specified (+/-)	No – one wave of panel data only.	Negative associations with indicators a) and b). No statistically significant association with indicators c)-f). Analysis Includes neighbourhood ids to control for unobserved differences at this level.

Table 9. Overview of research findings on the effect of neighbourhood socio-economic position on health-related quality of life

Study	Neighbourhood scale	Neighbourhood indicator	Effect mechanism(s)	Residential selection addressed	Findings in a nutshell
Drukker and van Os (2003)	Maastricht city neighbourhoods (300 and 8,500 residents)	Socio-economic deprivation	Catch-all	No	Negative association between deprivation and Mental health (SF-36). No association with Vitality.
Rocha et al. (2017)	Portuguese census tract (~ residents)	European Deprivation Index	Catch-all	No	Significant negative effect on PCS when comparing least and most deprived neighbourhoods. No effect on MCS.
Voigtländer et al. (2010)	German Street section (~25 households)	Average Purchasing Power	Catch-all	No	Negative association with Physical health (SF36). Mental health not examined.
Williams et al. (2020)	Britain, Lower Super Output Areas (~1,000 residents)	Index of Multiple Deprivation	Catch-all	No	Negative association between deprivation and MCS but not with PCS.

Table 10. Overview of research findings on the effect of neighbourhood socio-economic position on earnings

Study	**Neighbourhood scale**	**Neighbourhood indicator**	**Effect mechanism(s)**	**Residential selection addressed**	**Findings in a nutshell**
Andersson and Musterd (2010)	Sweden a) Block level (~40-60 households) b) Small Area for Market Statistics, SAMS (~400-600 residents) c) Municipality level	Socio-economic disadvantage	Catch-all	No	Negative effects most pronounced at the SAMS scale). No effect at municipality level. In areas targeted by local regeneration policies, block level most important.
Bolster et al. (2007)	Britain; bespoke neighbourhoods ranging from 500 to 10,000 people	neighbourhood disadvantage	Catch-all	Yes – individual fixed effects	No effects and no variation across scales. Small positive effect for property owners and couples; most marked at bespoke 500.
Galster et al. (2008)	Swedish Small Area for Market Statistics, SAMS (~400-600 residents)	proportion of low-income males	Catch-all	Yes – individual and neighbourhood fixed effects.	Negative effect that was robust to absorbing time-invariant unobserved individual characteristics and to restricting the analysis to non-movers.
Galster et al. (2015)	Swedish Small Area for Market Statistics, SAMS (~400-600 residents)	proportion low-income	Catch-all	Yes – individual fixed effects	Non-linear negative effect that increases sharply when the proportion of low-income neighbours exceeds 40 percent.
Mellander et al. (2017)	Sweden a) Block level (~40-60 households) b) Small Area for Market Statistics, SAMS (~400-600 residents) c) Municipality level d) Local labour market scale	proportion higher-skilled	Catch-all	No	Positive sizeable effect at the block and SAMS scales; small negative effect at the municipality and local labour market scales.
Propper et al. (2007)	Britain; Bespoke neighbourhoods with at least 500 people	neighbourhood disadvantage	Catch-all	Yes – restriction to sample of less selected social renters	Negative effect on future income

Our literature review protocol (see Chapter 2) had not returned any studies focussing on neighbourhood effects on health-related quality of life such as the SF-12 or SF-36, but a more flexible search returned a small number of such studies, see **Table 9**. The research tends to find a significant relation between local area deprivation and health-related quality of life, but the nature of the effect can differ both between and within studies depending on whether the focus is on the mental or physical functioning components. These studies tend to measure socio-economic deprivation using small spatial units and, overall, they do not seem to address potential endogeneity bias due to non-random residential self-selection. Furthermore, some studies only consider one of the two components of health-related quality of life. Williams et al. (2020) study both components and find a negative association between neighbourhood deprivation and the mental health summary score, and no association with physical health. Residential selection is not considered in these studies.

4.3 Data

We use individual longitudinal data from the first six waves of Understanding Society (University of Essex et al., 2018), linked to the longitudinally harmonised census data at multiple bespoke scales, described in Chapter 3. The panel study, also known as the UK household longitudinal study (UKHLS), started in 2009 with a nationally representative, stratified, clustered sample of around 30,000 households in the UK and was enhanced further in the second and sixth waves when the around 8,000 households-strong continuing sample of the British Household Panel Survey (BHPS) and a new immigrant and ethnic minority boost (IEMB), respectively, were added. The annual face-to-face survey collects information about various aspects of people’s life, including education, employment, income and health. All members of the household aged 16 and above are eligible for interview. Overall, 76,151 individuals provided a full interview in the first six rounds of annual interviews, offering 292,322 person-year observations.

The UKHLS includes a great deal of indicators of subjective and objective wellbeing. For the purpose of our study, we focused on measures that are included in each wave of the study and which are measured in continuous form. More specifically, we focused on three subjective and one objective wellbeing outcome.

4.3.1 Subjective wellbeing outcomes

Our first measure of subjective wellbeing is life satisfaction. Life satisfaction is based on the respondent's reflective appraisal of how well life is going and has been going (Argyle, 2001). In particular, the measure is the response to the question "How satisfied are you with life overall?" with responses ranging from 1 "completely dissatisfied" to 7 "completely satisfied". The nature of the relationship between life satisfaction and neighbourhood deprivation is not a priori definite. To the extent that better off neighbourhoods provide better services and better amenities, one could expect a positive effect on individual life satisfaction. However, peer pressure and treadmill effects – the desire to keep up with the Joneses and their ever increasing consumption habits at increased prices - may actually reduce one's perceived life satisfaction.

Our second and third indicator of subjective wellbeing measure health-related quality of life. More specifically, we use the mental and physical component summary scores derived from the Short Form–12 Health Survey (SF-12), a self-reported assessment of health relating to the eight dimensions of physical functioning (PF), role limitations due to physical (RP) and emotional health problems (RE), freedom from bodily pain (BP), general health perception (GH), vitality (VT), social functioning (SF), and mental health (MH). The self-assessments can be used to compute a physical component summary and a mental component summary of health-related quality of life following the scoring algorithm outlined in the SF-12 manual (Ware et al., 1996). Both scores use data from all eight dimensions but VT, SF, RE and MH have a large weight in the mental component and a low weight in the physical component summary. Conversely, PF, RP, BP, and GH have a large weight in the physical summary score and a low weight in the mental summary score. The summaries are routinely provided with the Understanding Society data.[15] Scores can range from 0 to 100; the lower the summary score, the lower the health-related quality of life on the respective dimension.

4.3.2 Objective wellbeing outcomes

In the interest of comparing neighbourhood effects across multiple outcomes applying the same methods, we decided to focus on continuous measures and this resulted in focussing on only one indicator of objective wellbeing: the hourly wage. It is derived from the ratio between usual gross monthly salaries (including any overtime compensation, bonuses, commission, tips, and

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[15] The respective variable stem names are sf12mcs_dv and sf12pcs_dv. The constituent variables are scsf1 scsf2a scsf2b scsf3a scsf3b scsf4a scsf4b scsf5 scsf6a scsf6b scsf6c scsf7. PDFs of the questionnaires are available online, see www.understandingsociety.ac.uk and provide the exact question wording and response options.

tax refund before any deduction) and hours normally worked and overtime for individuals in paid employment (excluding self-employment). We removed observations whose hourly wages fell short of the age- and year- specific national minimum wage (which ranged from £3.30 to £7.20 in the period studied), or whose wages were 25 per cent higher than the 99th percentile. All incomes are adjusted for inflation using the Consumer Price Index (100=2015 prices).[16]

4.3.3 Key independent variable: Neighbourhood deprivation at multiple scales

Our key measure of neighbourhood deprivation is the Townsend Deprivation Score. This is a popular indicator of neighbourhood socio-economic disadvantage and allows us to relate our findings to those obtained by Buck (2001)'s foundational work on neighbourhood effects for Great Britain using the BHPS. The deprivation score summarises four census indicators at bespoke neighbourhood scales (as described in Chapter 3), namely: the proportion of economically active residents who are unemployed; the proportion of residential households who do not own a car or van; the proportion of households not in owner-occupied accommodation; and the proportion in overcrowded households. Since the distribution of the first and fourth indicator is highly skewed they are log transformed, and every component is standardised and summed up. To provide a more realistic depiction of the local context of a given neighbourhood, we standardised the scores using the local authority mean and standard deviation in deprivation. Higher scores indicate greater relative deprivation and a score of zero represents the average level of deprivation in the local authority area. Summary statistics for the Townsend Deprivation Index are provided in **Table 11**.

4.3.4 Other control variables

To account for the role of other relevant factors impacting on one's wellbeing, we include basic socio-economic and demographic controls, namely: age, gender, ethnicity, whether the respondent was born in the UK, marital status, presence of children in the household, highest educational qualification, social class, and the current main economic activity status. In the life satisfaction and health-related quality of life models only, we additionally include net equivalent household income. Descriptive statistics are provided in **Table 12**.

[16] See https://www.ons.gov.uk/economy/inflationandpriceindices. We used the monthly CPI and the version dated 13th November 2019.

Models additionally take into account conditions at higher spatial scales that may influence individual wellbeing and may be confounded with neighborhood deprivation: whether the respondent lives in England or Wales, the national and local authority-level unemployment rate, and an area classification used on the National Travel Survey that unlike the ONS' rural-urban classification, provides greater granularity regarding the different types of urban areas in England and Wales.

Table 11. Summary statistics of Townsend Deprivation Score at bespoke neighbourhood scales

Neighbourhood scale	Townsend Deprivation Score	**Mean**	**CV**	**Min**	**Max**
Output Area	- raw	-0.2	-15.94	-6.78	9.95
	- LAD standardised	-0.1	-10.30	-4.3	5.07
Population threshold 500	- raw	-0.26	-12.84	-7.72	9.69
	- LAD standardised	-0.12	-8.34	-4.91	4.59
Population threshold 1k	- raw	-0.3	-11.47	-7.17	10.49
	- LAD standardised	-0.14	-7.23	-3.97	4.39
Population threshold 2k	- raw	-0.31	-11.33	-8.18	10.55
	- LAD standardised	-0.15	-6.64	-4.43	3.91
Population threshold 3k	- raw	-0.31	-11.21	-7.14	10.42
	- LAD standardised	-0.16	-6.34	-3.96	3.98
Population threshold 4k	- raw	-0.31	-11.20	-7.22	10.58
	- LAD standardised	-0.17	-6.14	-4.08	3.67
Population threshold 5k	- raw	-0.33	-10.84	-7.12	10.74
	- LAD standardised	-0.18	-5.83	-3.69	3.89
Population threshold 6k	- raw	-0.34	-10.54	-7.03	10.74
	- LAD standardised	-0.19	-5.54	-3.5	3.83
Population threshold 7k	- raw	-0.34	-10.44	-7.14	10.28
	- LAD standardised	-0.19	-5.35	-3.66	3.72
Population threshold 8k	- raw	-0.33	-10.78	-7.37	10.23
	- LAD standardised	-0.2	-5.30	-3.75	3.91
Population threshold 9k	- raw	-0.32	-11.10	-7.24	10.33
	- LAD standardised	-0.19	-5.26	-3.82	3.65
Population threshold 10k	- raw	-0.31	-11.48	-7.19	10.39
	- LAD standardised	-0.19	-5.27	-3.54	3.44

Notes: Computation of the Townsend Score relies on standardization of the four input variables. We use the mean and standard deviation of the national distribution of the respective characteristics at the scale of each bespoke neighborhood to standardize, and additionally, we standardize the Townsend Score by the LAD level of relative deprivation.

Source: Understanding Society (2019), Waves 1-6, linked with UK Census 2001 and 2011 for England and Wales.

Table 12. Descriptive statistics of analysis sample

	Mean	SD	Average change	Min	Max
a) Subjective wellbeing sample					
Life satisfaction	5.14	1.48	-0.025	1	7
SF-12 Physical Component Summary (PCS)	50.29	10.74	-0.201	4.56	76.29
SF-12 Mental Component Summary (MCS)	49.58	9.77	-0.193	0.00	78.08
Social class of first job:					
Management & Professional	0.18	0.39	0.000	0	1
Intermediate	0.27	0.44	0.000	0	1
Routine	0.50	0.50	0.000	0	1
Still At School/Never Went To School/Never Paid Job	0.05	0.22	0.000	0	1
Parental social class (respondent aged 14):					
Management & Professional	0.31	0.46	0.000	0	1
Intermediate	0.25	0.43	0.000	0	1
Routine / Not Working	0.43	0.50	0.000	0	1
Parent Deceased/Unknown	0.01	0.09	0.000	0	1
Samples for robustness tests:					
Social Housing	0.17	0.38	-0.004	0	1
Private Renting	0.10	0.30	-0.000	0	1
Number of Observations	127,728				
b) Objective wellbeing sample					
Hourly wage (log)	13.57	7.57	0.730	3.25	66.82
Social class of first job:					
Management & Professional	0.21	0.41	0.000	0	1
Intermediate	0.29	0.45	0.000	0	1
Routine	0.49	0.50	0.000	0	1
Still At School/Never Went To School/Never Paid Job	0.01	0.10	0.000	0	1
Parental social class (respondent aged 14):					
Management & Professional	0.36	0.48	0.000	0	1
Intermediate	0.25	0.43	0.000	0	1
Routine / Not Working	0.38	0.49	0.000	0	1
Parent Deceased/Unknown	0.00	0.07	0.000	0	1
Samples for robustness tests:					
Social Housing	0.11	0.32	-0.003	0	1
Private Renting	0.11	0.31	-0.003	0	1
Number of Observations	64,196				

Source: Understanding Society (2019), Waves 1-6, linked with UK Census 2001 and 2011 for England and Wales.

4.4 Empirical strategy

We employ regression models to estimate the effect of neighbourhood deprivation on the aforementioned wellbeing outcomes for each bespoke neighbourhood scale. We adopted a four-stage approach, whereby we successively add a set of control variables to the model specification and adapt the statistical estimator as appropriate. To set the scene, we estimate regression models which account for individual heterogeneity in wellbeing with respect to basic demographic and socio-economic characteristics, but do not attempt to address the major identification challenges discussed earlier in the report. In the second through fourth stages, we apply methods that help address the identification issues to get an unbiased and consistent estimate of the effect of neighbourhood deprivation on individual wellbeing. The remainder of this section describes these stages.

We start by adopting a standard model that assumes that exogenous individual and neighbourhood characteristics have a direct impact on the level of wellbeing:

$$Y_{it} = \alpha + \beta' X_{it} + \gamma' N_{j(i)t} + \varepsilon_{it} \qquad (1)$$

where i denotes individuals, j neighbourhoods, and t time. Individual wellbeing (Y_{it}) is a function of individual characteristics (X_{it}) and neighbourhood characteristics (N_{jt}) that have been shown to influence wellbeing, and the error ($\varepsilon_{\mathrm{it}}$). This model is implemented using the pooled ordinary least squares (OLS) estimator. As we are working with panel data, all standard errors are adjusted for clustering on individuals and for heteroscedasticity.

In the first stage, we include a standard set of individual demographic and socio-economic characteristics, and area characteristics that may otherwise confound the association between neighbourhood deprivation and wellbeing. For instance, ethnicity has been found to be a robust predictor of life satisfaction and earnings (Brynin and Güveli, 2012), and macro trends in labour markets affect both wellbeing outcomes and as well as area levels of deprivation.

Next, we gauge the importance of neighbourhood selection on a set of observable characteristics relating to family background. As parents play a major role in helping their children to set up homes of their own, we include measures of parental socio-economic status (i.e., the higher of the mother's or father's social class when the respondent was aged 14) and of the own socio-economic status when entering the labour market (i.e., the social class of the first job after leaving full-time education). The conjecture is that these factors, dubbed here as 'initial conditions', will impact the initial neighbourhood choice and that the effects of previous choices will linger on to impact on the current level of wellbeing (Hedman et al., 2015; Sharkey and Elwert, 2011). Nevertheless, there may be other unobserved individual characteristics (e.g., residential preferences) and neighbourhood conditions correlated with area deprivation, leading to inconsistent estimates of the effect of neighbourhood deprivation on wellbeing. Furthermore, in the case of individual earnings, there may be simultaneity bias because individuals and households with lower earnings generally cannot afford to live in the most sought-after neighbourhoods and hence may have to live in more deprived areas.

An advantage of the panel nature of our data set is that it allows us to separate out individual unobserved factors that are time-invariant from those that are not. Eq. 1 may be extended to

$$\mathrm{Y_{it}} = \alpha + \beta'\mathrm{X_{it}} + \gamma'\mathrm{N_{j(i)t}} + \omega_\mathrm{i} + \mu_\mathrm{it} \qquad (2)$$

where ω_i captures individual-specific time-invariant features. In the economics literature, the fixed effects approach is typically operationalised using the within panel estimator, but the correlated random effects estimator shares the advantages of the fixed effects approach, as shown by Mundlak (1978) is more efficient than the fixed effects estimator and allows us to examine the effects of time-invariant characteristics (Bell et al., 2019).[17] Thus, we implement the models using the random effects estimator and apply the Mundlak correction:

$$\mathrm{Y_{it}} = \alpha + \beta'\mathrm{X_{it}} + \delta'\overline{\mathrm{X}}_\mathrm{i} + \gamma'\mathrm{N_{j(i)t}} + \vartheta'\overline{\mathrm{N}}_\mathrm{j(i)} + \omega_\mathrm{i} + \mu_\mathrm{it} \qquad (3)$$

All models are estimated using the “xtreg” command in Stata 15. Next, just as individual fixed effects allow us to take into account spatial sorting on time-invariant unobserved features, there may be unobserved aspects of neighbourhoods that not only make them (un)attractive places to live but which may also be correlated with neighbourhood deprivation. To account for neighbourhood-specific features, we add the component ρ_j to Eq.2 and estimate the following two-way fixed effects model:

$$\mathrm{Y_{it}} = \alpha + \beta'\mathrm{X_{it}} + \gamma'\mathrm{N_{j(i)t}} + \omega_\mathrm{i} + \rho_\mathrm{j} + \mu_\mathrm{it} \qquad (4)$$

We implement this this model and deal with the large number of individuals and neighbourhoods in our data efficiently by using the “reghdfe” package in Stata (Correia, 2017). The approach does not allow us to report the results for time-invariant characteristics but helps to shed light on how much the effect of neighbourhood deprivation may be biased due to correlated unobserved neighbourhood characteristics.

[17] A number of neighbourhood studies have adopted this approach (e.g., Hedman et al., 2015; Knies, 2013).

4.4.3 Robustness tests

To test the sensitivity of our results to omitted sources of selection bias unaccounted for in our models, we apply a set of sample restrictions and repeat the same model specifications and statistical estimators. We contrast the estimation results for individuals living in social housing against those living in private rented accommodation. We argue, as others have done before us (Propper et al., 2007; Weinhardt, 2014), that residential location is essentially exogenous for social renters in England and Wales: due to the shortage of social housing social renters have very limited choice in selecting neighbourhoods or moving from the initial residential allocation. In contrast, for private renters, the residential choice is likely to be endogenous as they can and do move around more freely and across a greater range of different neighbourhoods. We will consider social renters as 'less selected' and private renters as 'more selected', and would expect the associated biases to be attenuated in these samples. Moreover, since social housing allocation is random, we would not expect any differences between the pooled OLS and the fixed effects estimates in this sample (as unobserved individual factors should not play a role).[18]

4.5 Findings

Given the many tables of results – i.e., one for each bespoke neighbourhood, wellbeing outcome, model specification and estimator - we summarise the results visually in **Figure 5**, focussing on the coefficients of the main variable of interest: neighbourhood deprivation. The first panel refers to life satisfaction, the second and third panels refer to the mental and physical component summaries of health-related quality of life, respectively, while the fourth panel refers to hourly wages. Each panel summarises the results obtained from the pooled OLS (blue line), the pooled OLS with the set of controls for individual's initial conditions (red line), the estimations accounting for individual-level unobserved heterogeneity (green line) and those accounting for both individual and neighbourhood-level sources of unobserved heterogeneity (orange line).

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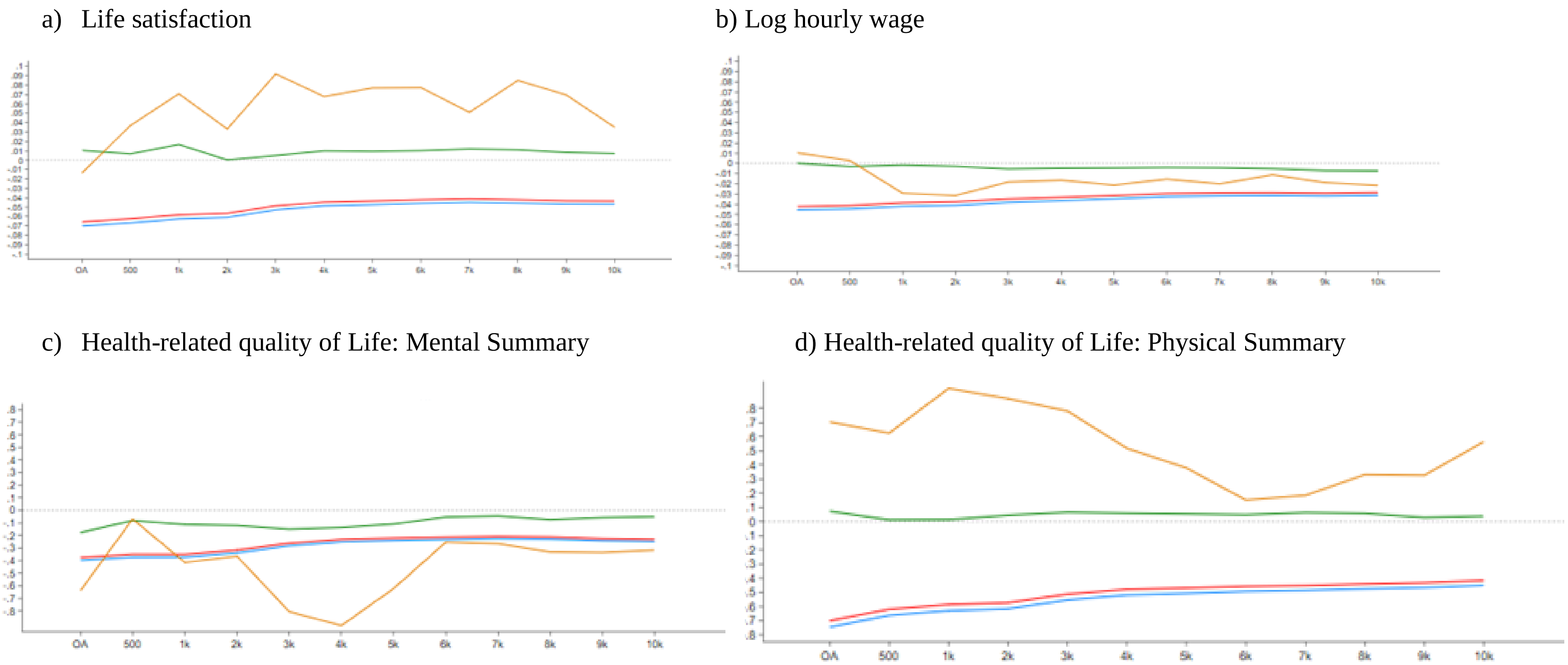
[18] Residential selection may also be captured by respondents' satisfaction with the neighbourhood as revealed by their stated preference to stay or move. The claim of no residential selection is more convincing in the 'social housing' case than in the 'prefer to move' case, but the results overall hold for both restrictions.

Figure 5. Plot of the effect of neighbourhood deprivation on life satisfaction, hourly wage and mental and physical components of health-related quality of life at different scales of neighbourhood.



Notes: For full results, see Knies and Melo (2021), Tables A2-A5.
Source: Understanding Society 2018, Waves 1–6, linked to longitudinally harmonised information from the Census 2001 and 2011 for England and Wales.

The results from the pooled OLS regressions produce statistically significant coefficients for the relation between neighbourhood deprivation and wellbeing for all the outcomes considered. In all cases, higher local area deprivation is associated with lower levels of wellbeing. The magnitude of the effect does not vary with spatial scale for life satisfaction and hourly wages. By contrast, there is considerable variation for both health-related quality of life measures, showing a reduction in size as the spatial scale enlarges, by a factor between 1.5 to nearly 2 when comparing output areas (OAs) with the larger size neighbourhoods, i.e., the relationship is stronger the smaller the definition of the neighbourhood boundary.

Once we include controls for individuals' initial conditions (i.e., family background), we observe very minor changes in the magnitude of the coefficients, which tend to become marginally smaller (in absolute value). Otherwise, the overall pattern of results is exactly the same as for the pooled OLS without controls for family background.

The following step consisted of controlling for individual-level unobserved heterogeneity. Absorbing unobserved individual effects attempts to address endogeneity bias due to residential sorting on individual unobserved time-invariant characteristics. It also allows us to disentangle the longitudinal (within) effect, which shows how individual wellbeing co-varies with changes in the level of deprivation experienced, from the cross-sectional (between) effect, which reports how wellbeing varies by level of neighbourhood deprivation.

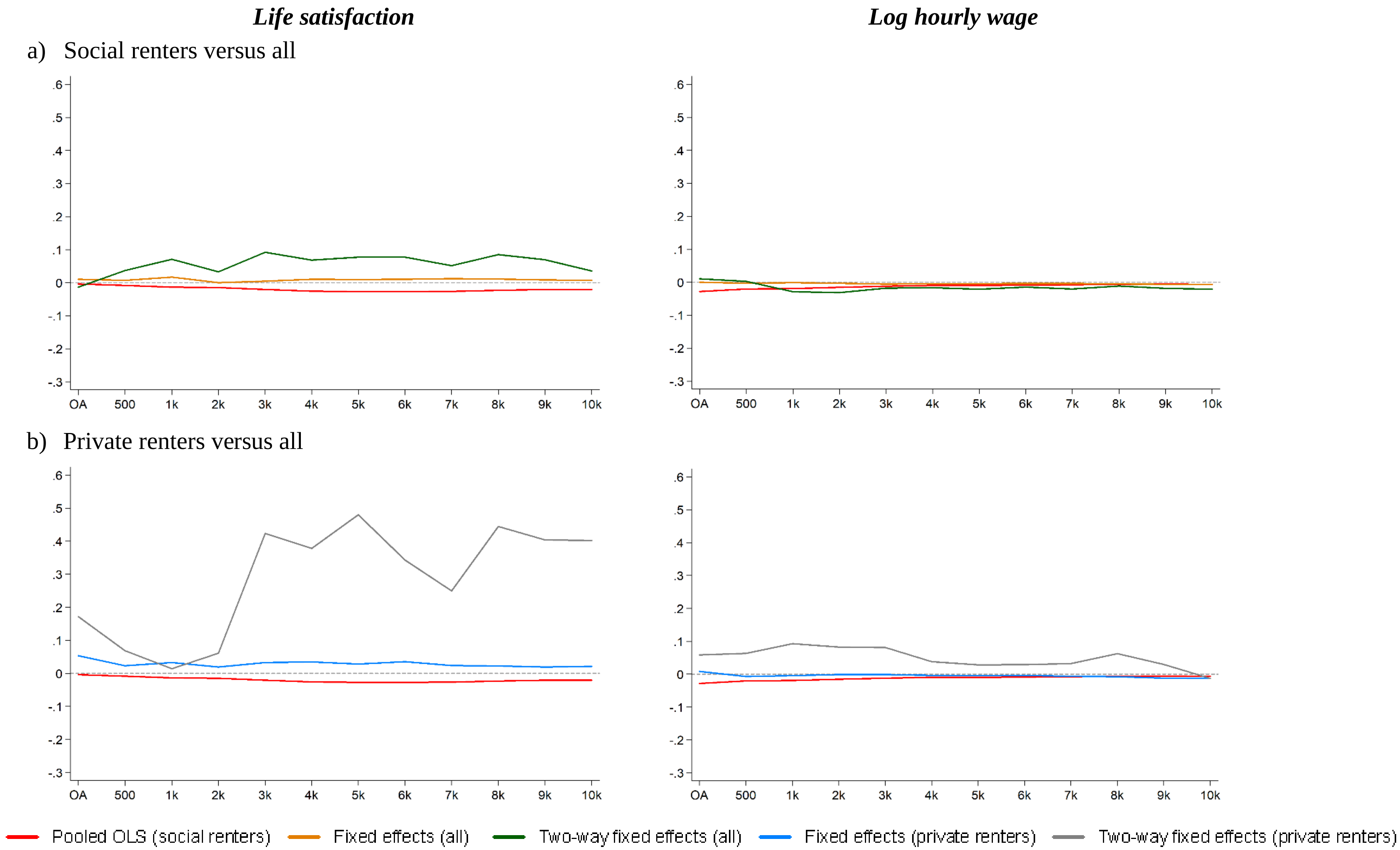
The results for life satisfaction, the physical component of health-related quality of life, and hourly wage are in line with those obtained from the pooled OLS: for the cross-sectional effects we observe negative and statistically significant associations between deprivation and wellbeing; however, the within estimates do not reach conventional levels of statistical significance and thus there is no empirical support for the conjecture that individuals may get more satisfied with their lives, improve their physical functioning-related quality of life or get higher pay as they experience a reduction in local area deprivation. As for the results concerning the mental functioning-related quality of life, both the between and within estimates fail to reach conventional levels of statistical significance, which suggests that individual unobserved heterogeneity was the main factor explaining the relationship between neighbourhood deprivation and this outcome.

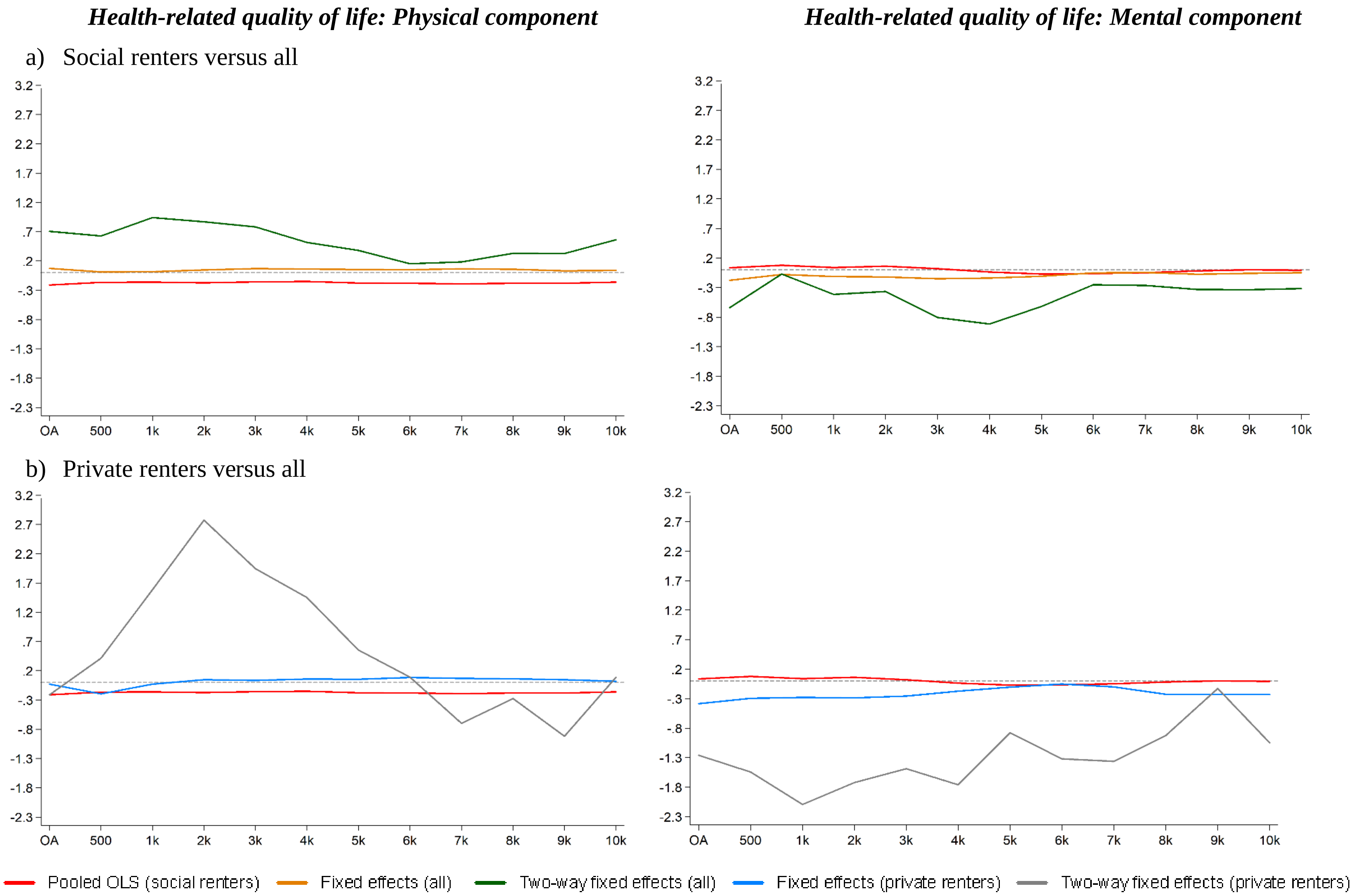
By additionally including neighbourhood fixed effects, we can account for time-invariant unobserved heterogeneity at both the neighbourhood and individual levels. Overall, adding this additional control further reduces the level of statistical significance (where it still persisted), but there are some exceptions. With regards to life satisfaction, there is no change as the results continue to be statistically insignificant. Concerning health-related quality of life, the results for the mental component suggest a negative but very weak association (only significant at the level of statistical significance of 10%) for bespoke neighbourhoods with a minimum population of 3k or 4k people. Effectively, these results seem to be in line with those obtained from the models controlling for individual-level unobserved heterogeneity. By contrast, there are a priori counterintuitive changes for the relation between local area deprivation and the physical component of health-related quality of life: we observe an increase in the levels of significance, but only for the smaller spatial scales up to 3k people and the highest values are obtained for neighbourhoods with a population threshold of 1k and 2k people. Furthermore, the nature of the relation is now that higher local area deprivation is associated with better self-reported physical health, in contrast to the previous models. It seems that neighbourhood level heterogeneity at these smaller scales may hide important information that is averaged out at wider spatial scales. However, what exactly drives this relationship cannot be answered from our models. These models can be more unstable because the neighbourhood effects are identified only from movers which refers to a much smaller sample of individuals. Furthermore, there may be differences in the demographic and socio-economic characteristics between the samples of mover and non-movers, which may also correlate to the results obtained for each sample. One of such differences related to demographics, in particular the fact that individuals tend to mover residence more frequently when they are younger and younger individuals tend to have better physical health than older ones. Finally, the results for hourly wages remain essentially the same as before since there is only a very weak association between deprivation and wages (only significant at the level of statistical significance of 10%) for the 1k and 2k neighbourhood thresholds.

4.5.1 Robustness tests

We conducted a number of robustness tests to assess the stability and validity of the results. **Figure 6** contrasts the coefficients for the four wellbeing outcomes from the pooled OLS estimates for the ‘less selected’ social renters with the coefficients obtained from estimations that account for individual and neighbourhood-level sources of unobserved heterogeneity in the full sample (top panel) and the ‘more selected’ sample of private renters (bottom panel). Results for life satisfaction and earnings are presented in the top left and top right panel, respectively, followed by results for the physical and mental component summaries of health-related quality of life in the bottom left and bottom right panels, respectively.

Figure 6. Plot of the effect of neighbourhood deprivation on four wellbeing outcomes at different scales of neighbourhood.




Health-related quality of life: Physical component
Health-related quality of life: Mental component
a) Social renters versus all
b) Private renters versus all
OA 500 1k 2k 3k 4k 5k 6k 7k 8k 9k 10k
Pooled OLS (social renters)
Fixed effects (all)
Two-way fixed effects (all)
Fixed effects (private renters)
Two-way fixed effects (private renters)

The top-right panel of **Figure 6** shows that the full-sample parameter estimates of the individual- and two-way fixed effects models compare relatively well with those obtained from the pooled OLS in the sample of social renters (except at the smallest spatial scale). This lends some support to correcting residential sorting on time-invariant individual- and neighbourhood-specific unobserved characteristics. While the panel shows apparent variation in the effect size across spatial scales, the effect of deprivation on earnings for social renters is statistically significant only at scales up to 2k people. Although the plot suggests differences in patterns across the two wellbeing outcomes, they are the same in statistical terms. The effect of deprivation on life satisfaction is not statistically significant in any of the three estimations (i.e., pooled OLS for social renters compared to individual- and two-way fixed effects for the full sample) and there is virtually no variation in the effect sizes across spatial scales.

The bottom panels compare the same estimations for the sample of private renters. For earnings, we observe that the parameter estimates from the social renters' pooled OLS and the private renters' individual fixed effects models are generally similar to each other (except at the smallest neighbourhood scale). This indicates that correcting for sorting on individual-specific unobserved characteristics using the correlated random effects estimator works well in removing residential selection bias. However, the parameter estimates for the private renters' two-way fixed effects model exhibit a very different pattern (although the coefficients are only marginally statistically significant at the scale of 1k people [p-value=0.053]). The difference suggests that other, time-variant, neighbourhood-specific characteristics confounded with area deprivation are not accounted for in the restricted sample. We observe a similar pattern for the parameter estimates from the life satisfaction models (albeit the coefficients are not statistically significant). With regards to the results for the mental and physical component summaries of health-related quality of life, the results overall show a similar pattern to those obtained in the baseline analysis with an overall lack of statistical significance for the pooled OLS estimates obtained from the sample of social renters (i.e., sample of 'less selected' individuals). The estimates obtained from the individual fixed effects estimators for the full and the private renters samples also fail to reach conventional statistical significance levels, suggesting that individual unobserved heterogeneity accounts for factors that impact wellbeing. However, further accounting for neighbourhood specific heterogeneity makes the estimates for the effect of neighbourhood deprivation on the physical component of health-related quality of life statistically significant for neighbourhood scale up to 3k, as was the case for the full sample. These models can be more unstable because the neighbourhood effects are identified only from movers, i.e., a much smaller sample. Movers and non-movers tend to differ in potentially important ways. For example, younger people do not only move more frequently, they also tend to have better physical health than older people. Private renters, too, are more likely to move than social renters, and they tend to be younger than social renters (in our sample the median age is 35 years-old vs. 43 years-old, respectively).

4.6 Conclusions

This work compared the effect of neighbourhood deprivation on three indicators of subjective wellbeing and one indicator of objective wellbeing, across different spatial scales using a rich longitudinal individual dataset combined with multiscale administrative data for England and Wales. The structure of the dataset allows to follow individuals and their respective residential neighbourhoods over time. Neighbourhoods are defined using varying spatial scales (see Chapter 3) to allow exploring for variation across multiple scales.

We implemented a range of estimators and sample restrictions, moving along the path of rigour in addressing residential selection bias (i.e., moving from the top to the bottom of methodologies listed in **Table 6**) inasmuch as was feasible given the data and time restrictions of the project. An obvious direction for future research would be to model residential selection directly and jointly with models of neighbourhood effects.

Overall, we conclude that the apparent negative associations between neighbourhood deprivation and wellbeing outcomes are largely due to non-random selection into neighbourhoods, and not a genuine causal effect. The only exception seems to be self-reported physical health, for which the effects of neighbourhood deprivation are statistically significant when we control for neighbourhood time-invariant unobserved heterogeneity (besides individual fixed effects) in both the baseline and robustness tests. The effect is only significant at smaller scales below the 3k people threshold.

There are avenues for research that we have not taken. Our research focused on the contemporaneous neighbourhood effects of a specific measure of neighbourhood disadvantage on four specific measures of individual wellbeing. Within the short timeframe of the project, it was not possible to consistently track respondents' residential location since birth and to measure characteristics such as the length (i.e., number of years) of exposure to neighbourhood deprivation. In principle this could be pursued in future research, albeit sample sizes (and statistical power, in particular for identification strategies that rely on movers) will be significantly smaller. Future work may also investigate the depth of exposure; we assumed the effect of neighbourhood deprivation is linear but there may be threshold effects. Another avenue for future research is to consider alternative measures of socio-economic disadvantage, i.e., beyond the limited set of neighbourhood characteristics summarised in the Townsend Deprivation Score. Considering alternative indicators both simultaneously and separately may also provide an opportunity to discriminate between alternative causal mechanisms, which may operate at multiple scales and thus may be cancelling each other out. Disentangling alternative causal mechanisms remains a major challenge in this literature due to the problem of observational equivalence, that is, the fact that alternative mechanisms can result in similar outcomes.

5. Project Conclusions and Next Steps

The project provides new insights into the richness of empirical approaches to studying neighbourhood effects on individual wellbeing as well as new evidence for England and Wales for a range of subjective and objective wellbeing outcomes.

Our review of the empirical literature (Chapter 2) highlights that this interdisciplinary field of study shares common research questions, data needs, and empirical identification challenges. The research questions are, however, still addressed mainly from each discipline's perspective using its specific methods. The lack of a multidisciplinary approach to the study of neighbourhood effects limits the ability to address some of the more cumbersome challenges. For example, we observe little progress in defining neighbourhoods and relevant contexts meaningfully when testing specific processes through which the local context may impact wellbeing. Although there is greater use of smaller-scale geographies and greater diversity of indicators for local disadvantage, the choice of spatial scale and associated causal pathway remains vague, at best, and is often ill-defined or not mentioned at all. There has been considerable progress in dealing with the main identification challenges, particularly within the more quantitative-oriented disciplines or disciplines where quasi-natural type experiments may be more viable. Nevertheless, a sizeable number of studies still fail to address residential selection bias while claiming to look at causal neighbourhood effects. This malpractice appears to be less common in health and economic studies compared to sociological and geographical studies.

Regarding the empirical research, the project has innovatively combined longitudinal data from the UK Household Longitudinal Study (UKHLS) with geo-coded administrative data that we have derived specifically for this project from the 2001 and 2011 census for England and Wales (see Chapter 3). As a contribution to the scientific community we will share, in due course, the code that will allow researchers to create the bespoke neighbourhood data on their own desktop, including for census variables other than the ones we used to construct the Townsend Deprivation Score. We undertook several empirical analyses of this rich longitudinal microdata, presented in Chapter 4, to address the key identification issues that hinder the estimation of genuine neighbourhood effects, particularly those relating to residential self-selection bias. We implemented both individual and neighbourhood fixed effects models, used information on individuals' family background, and implemented robustness tests based on sample restrictions (e.g., social renters vs. private renters) to explore further sources of exogenous variation. Our main conclusion is that the negative association between neighbourhood deprivation and subjective and objective wellbeing is largely due to non-random selection into neighbourhoods and not a genuine causal effect. The work shows that selection bias is predominantly due to unobserved time-invariant characteristics at the individual level rather than at the neighbourhood level. Unlike other studies, we do not find evidence for variation in the size of the association across neighbourhood scales. It remains to be seen if this finding also holds when the neighbourhood context is measured differently: be it by defining the thresholds differently or by swapping the Townsend Deprivation Score that did not appear to vary much across scales. Conceptually, too, the Townsend Score may not as adequately capture neighbourhood disadvantage in contemporary Britain as in the late 1970s.

Overall, the work undertaken in this project allows us to make some important recommendations for the academic community and policymakers. There has been a push towards researchers using ever smaller geographical context measures, with many studies suggesting that use of smaller geographical unit is per se better. Our empirical analysis suggests that this is not necessarily the case as there is no variation in the neighbourhood effect across scales; for some outcomes such as health-related quality of life the widely-available Townsend Deprivation Score at the LSOA scale may have worked just fine. Of course, we did not know this before doing the research using multiple bespoke scales, and we cannot generalise findings from one specific study to other contexts, outcomes and neighbourhood measures. Furthermore, it does not follow that researchers should simply continue to use neighbourhood indicators readily-available at large spatial scales. It remains germane to use theory and observation when choosing the spatial scale most amenable to measurement of specific processes or mechanisms relating to a given wellbeing outcome. Researchers should also try to include more robustness tests via sample restrictions or use of auxiliary data on the family background to put some bounds on how large the neighbourhood effect may be.

The main recommendation for policymakers is to be aware that many neighbourhood effects studies continue to claim to find causal effects when the analysis does not correct residential selection bias and is based on simple correlational analyses. A careful review of the evidence and its methodology is prudent. In the absence of a genuine causal neighbourhood effect, targeting resources specifically on the most deprived neighbourhoods may not necessarily be more efficient in improving residents' wellbeing outcomes than targeting individuals or households in need irrespective of where they live. Individual (or household targeting also removes arbitrary definitions of which community is the most deprived. Efficient individual targeting may be achieved, for example, through policies that increase long-term employment opportunities available to disadvantaged individuals, develop regional labour markets, or raise skills levels. This is not an appeal for policymakers to dismiss any neighbourhood-basis for policy intervention: Given the strong correlation between neighbourhood deprivation and concentration of disadvantaged groups, local targeting can still be efficient in reaching large numbers of individuals in need.

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