# Are there sensitive neighbourhood effect periods during the life course on midlife health and wellbeing?

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#### **Abstract**

Since the turn of the century there has been an explosion in the number of epidemiological studies that have analysed neighbourhood effects on health and wellbeing. The vast majority of these studies are cross-sectional in nature and assume that a contemporaneous place of residence captures a meaningful neighbourhood effect. Over the same time frame, social epidemiology has focussed increasingly on life course effects. This paper aims to bring these two areas of study together and tests whether there a certain ages during the life course when neighbourhoods are more important for our health and wellbeing than others. We use two British birth cohort studies (1958 National Child Development Study and British Cohort Study 1970) each comprising approximately 6,000 sample members at midlife linked to historic census measures used to derived Townsend neighbourhood deprivation scores over the life course. We find little evidence to support our hypothesis that adolescence is a key period of neighbourhood effect, rather we find late-early-adulthood and middle age neighbourhood deprivation is more strongly related to mid-life health and wellbeing. We are not able to conclude whether these effects are causal and encourage further investigation of selection mechanisms into neighbourhoods and mediation throughout the life course using our newly created dataset.

# **Keywords**

Neighbourhood effects, neighbourhood deprivation, Townsend index, sensitive periods, cross-classified models, health and wellbeing,

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#### Introduction

There is a wealth of literature supporting the hypothesis that where you live affects your health and wellbeing (Galster, 2012; Pickett and Pearl, 2001; Schaefer-McDaniel et al., 2010). The 'neighbourhood effects' literature suggests that individuals are affected by their neighbourhood through social interaction, environmental features, spatial location and institutional resources (Galster, 2012). Deficits in these domains in a neighbourhood are often summarised using composite deprivation indices, such as the Townsend index (Buck, 2001; Stafford and Marmot, 2003).

The majority of neighbourhood effects literature in epidemiology is cross-sectional and does not take into consideration the possibility that earlier life neighbourhood can effect health and wellbeing later in life (Arcaya et al., 2016). This is one of a number of methodological challenges that has led to an impasse in progress in neighbourhood effects research (van Ham and Manley, 2012). Examples of empirical work where it is assumed individuals will be affected by their neighbourhood more (or less) at certain periods during the life course are rare (Kravitz-Wirtz, 2016a; Lekkas et al., 2017; Murray et al., 2012; Pearce, 2018). The potential of sensitive neighbourhood effect periods is an important hypothesis to test, not least because people move between neighbourhoods and neighbourhoods improve and decline, and therefore a single point in time measurement may misinterpret any neighbourhood effect (Murray et al., 2013).

A number of studies have theoretically posited that there are certain life periods when neighbourhood effects will be felt most strongly. These include childhood and adolescence (Anderson et al., 2014; Kravitz-Wirtz, 2016b; Wheaton and Clarke, 2004; Wodtke, 2013) and later age (Clarke et al., 2015; Marshall et al., 2014; Michael et al., 2014), because during these life periods, individuals are more dependent on local social networks and services in their neighbourhoods, and thereby more strongly affected by their neighbourhood through the mechanisms proposed by Galster (2012). During early to mid-adulthood it could be hypothesised that neighbourhood effects will be less important because people are not bound by their neighbourhood to the same extent and may commute and use services in places outside the neighbourhood more so than those younger and older.

The main hurdle in determining whether there are sensitive periods when neighbourhood effects are more important is the unavailability of longitudinal data that contain both neighbourhood exposures and individual health outcomes over multiple life periods (Lupton, 2003; Pearce, 2018). There are very few social surveys or other forms of data collection that have been resourced for long enough to enable researchers to track individuals from childhood to mid-to-later life in terms of their residential location. Those data that are available often have restrictions on linking neighbourhood variables. These restrictions include a lack of available neighbourhood data on measures in time periods before digitised census outputs and online small area statistics repositories were developed, and data security concerns that make it difficult to link individual survey records even when neighbourhood data are available.

There are pioneers who have responded to this impasse in neighbourhood effects research by overcoming data availability restrictions, albeit with their own limitations. Murray et al (2013) used a nationally representative sample of individuals from a 1946 British birth cohort, the National Survey of Health and Development, linked to census small area data at ages 4, 26 and 53. They tested sensitive periods using a cross-classified multilevel model that accounted for the movement of people between neighbourhoods between measurement points and enabled an estimate of the neighbourhood variability at each measurement point. Partitioning variance in individual health at older age and at the neighbourhood level, the latter at the different ages, indicated a combined compositional and contextual effect of neighbourhoods. By adding specific neighbourhood measures they were able to test whether certain aspects of the neighbourhood context explained the total neighbourhood variance in later life health. They found that at age 53 compared with age 26 and age 4, the total neighbourhood variance was stronger in three objective outcomes measuring physical capability (standing balance duration, chair rise speed and grip strength). A census measure of the percentage of employed persons with lower skilled occupations in local government districts was used to show fixed effects of area deprivation specifically. It partially explained the neighbourhood variance at each age and its specific effect was strongest at age 53.

Gustafsson et al (2017) applied the same analytical approach and came to the same conclusion using data from all 1981 school-leavers at age 16 in Luleå, Sweden. Data were collected at age 16 and in follow-up surveys at ages 21, 30 and 42. Their outcome was a summative score of functional somatic symptoms at age 42. Neighbourhood deprivation was measured using a composite index calculated for constant Small-Area Market Statistics areas containing 1,000 people, on average. There is less likely to be within neighbourhood variability in deprivation when using this level of spatial granularity, which allows a clearer test of neighbourhood effects, compared with Murray et al (2013), who used unfixed spatial boundaries containing considerably larger populations. Gustafsson et al (2017) find the neighbourhood variability in functional somatic symptoms stronger at age 42 and specific neighbourhood deprivation effect, as shown by a fixed effect, also stronger at age 42. The latter finding was not robust to individual confounding variables. They also partitioned variance in the interaction between neighbourhood at age 16 and neighbourhood at age 42 to determine a moderating effect of the neighbourhood variability in adolescence on the neighbourhood variability in midlife. They find a much greater variance in their outcome at this interaction level compared with the combined total variance at ages 16, 21, 30 and 42. This suggests that health variation by neighbourhood in midlife depends on neighbourhood of adolescence through direct and indirect pathways, a finding supported by their other work (Gustafsson and San Sebastian, 2014; Gustafsson et al., 2013). Murray et al (2019) confirmed indirect neighbourhood effects in a related analysis of early workforce exit showing how the neighbourhood of residence earlier in life determines later life neighbourhood residence, which, in turn, determines later life health. These findings and others support a notion that neighbourhood deprivation experienced in early

life and across the life course has a cumulative effect on later life health (Gustafsson et al., 2014; Johansson et al., 2015).

This paper aims to address some of the limitations of the Murray et al (2013) and Gustafsson et al (2017) papers. The prime limitations are a specific population (Gustafsson et al), temporally inconsistent neighbourhood boundaries (Murray et al) and lack of statistical control variables measured prior to measurement of neighbourhood effects (both). This papers uses nationally representative individual data linked to data on temporally constant neighbourhood boundaries (i.e. neighbourhood using the same boundaries at multiple time points). The latter is important because census boundaries, on which many neighbourhood studies are based can change substantially over time and therefore the sensitive period could reflect a potential modifiable area unit problem (Flowerdew et al., 2008). We also add to the existing literature by using data on two separate cohorts that enables us to explore whether sensitive periods are specific to one generation or can be indicative of a wider trend. We test multiple dimensions of health, including general (Dundas et al., 2014; Johnson et al., 2012; Kravitz-Wirtz, 2016a), physical (Clarke et al., 2014; Kravitz-Wirtz, 2016b; Murray et al., 2013; Ruel et al., 2010) and mental health (Clarke et al., 2015; Walsemann et al., 2017) to explore our wider concept of wellbeing. Each outcome used in this study has been shown in earlier literature to be affected by neighbourhood context. Our aim is not to test theories on why any specific aspect of health is related to neighbourhood deprivation across the life course, rather an explorative examination of whether there are sensitive periods when neighbourhoods are more affective given the established literature suggesting there is an effect on these specific outcomes. We use four distinctive outcomes to see whether our findings are specific (or not) to particular health outcomes. We aim to apportion the selection of individuals into neighbourhoods over time by controlling for confounding variables previously underexplored in the existing literature, for example, health and socioeconomic position prior to the first time neighbourhood context is measured. These were omitted in both the Gustafsson et al (2017) and the Murray et al (2013) papers.

Based on existing theory and evidence, we hypothesise that adolescence will be an important period when neighbourhoods are likely to affect midlife life health and wellbeing. We expect based on existing evidence that most, if not all, of this affect will be absorbed by the contemporaneous neighbourhood deprivation experienced in midlife because of its mediating effect. We do not expect neighbourhood effects during early adulthood will be important on midlife health and wellbeing because there is no theoretical or empirical evidence to support such an effect.

#### **Methods**

#### **Data**

The paper uses neighbourhood data from the 1971-2011 Censuses linked to two British birth cohort studies, the 1958 National Child Development Study (NCDS) and the 1970 British Cohort Study (BCS70) (Centre for Longitudinal Studies, 2013, 2012).

NCDS and BCS70 comprised all births, more than 17,000, in a single week in the respective baseline years (i.e. 1958 and 1970). Respondents who had immigrated to Britain were added to each sample between birth and age 16. We use the complete study sample comprising 18,558 in NCDS and 19,022 in BCS70. Data were taken from birth and follow-ups at ages 11 (1969), 16 (1974), 23 (1981), 33 (1991), 42 (2000) and 55 (2013) in NCDS and in BCS70 at ages 16 (1986), 26 (1996), 34 (2004), and 42 (2012). Data were collected through face-to-face interviews with respondents, and their parents when respondents were children. It is not currently possible to link census data before age 16 in NCDS and age 10 in BCS70 because address information is not geocoded for these study sweeps. Nonetheless, we do use information on individual circumstances of study members from birth. Supplementary table A1 lists the variables used, the age at which they were taken and the percentage missing from birth.

#### Measures

#### **Outcomes**

We use four outcome measures each in NCDS and BCS70 covering broad aspects of physical and mental health: self-reported general health, disability, body-mass index (BMI) and mental wellbeing. Each measure is taken at age 55 in NCDS and age 42 in BCS70. This ensures we test the longest possible period of neighbourhood effects in each study from childhood onwards. Sensitivity analysis is conducted using self-rated health, disability and BMI at age 42 in both cohorts to more accurately compare between NCDS and BCS70 at the same age. There was not a comparable mental health measurement at age 42 in NCDS. Findings are broadly the same and not reported here. General health is measured using a 5-point self-rated scale dichotomised into those that report fair or poor health compared with those that report excellent, very good or good health. Disability is measured using the 2011 Census limiting long-term illness definition which asks whether a respondent has any physical or mental health conditions or illnesses lasting or expected to last 12 months or more and whether it reduces their ability to carry out day-to-day activities. BMI (height / weight<sup>2</sup>) is calculated using self-reported measurements. Mental health is measured in NCDS using the revised CASP-6, an index specifically developed for older age samples (Wiggins et al., 2017, 2004). It measures quality of life on four domains of control, autonomy, self-realisation and pleasure using a summative index, with values ranging from 0 to 18. CASP-6 is not available in BCS70 at age 42. Mental wellbeing was measured in BCS70 using the Warwick-Edinburgh Mental Well-being scale (WEMWBS). WEMWBS was developed to enable the monitoring of mental wellbeing in the general population. It is a 14-item scale with five response categories, summed to provide a single score ranging from 14-70. WEMWBS is not available in NCDS at age 55.

#### Main exposure

All neighbourhood boundaries are set at 2011 Census middle layer super output areas (MSOAs). An output geography from the census, the 8,480 MSOAs in Britain

had a mean of 7,248 residents in 2011. This rose from 5,981 in 1971, 6,280 in 1981, 6,194 in 1991 and, 6,771 in 2001 using the apportionate methods described below. They do not attempt to recognise community boundaries per se, although they are constrained to physical borders such as roads, railways and waterways. MSOAs are an aggregation from the smaller building-brick geographical units, Output Areas that are designed to have internal homogeneity of housing tenure. MSOAs are also a spatial scale on which a range of data are available, most notably, census outputs. We fixed the neighbourhood to be constant over time by allocating NCDS and BCS70 respondents into 2011 MSOA boundaries at ages 16, 23, 33, 42 and 55 in NCDS and ages 16, 26, 34, and 42 in BCS70. The spatial linkage of all NCDS and BCS70 respondent's addresses to 2011 MSOAs was completed by the Centre for Longitudinal Studies (2017) by matching postcode centroids at the available ages to 2011 MSOAs using ArcGIS.

# Neighbourhood deprivation (ND)

We linked NCDS and BCS70 individuals to Townsend deprivation index scores at the MSOA level at each census, 1971-2011. The Townsend index is derived by taking the mean of summed standardised scores of four deprivation indicators available in each census: no car access, non-home ownership, unemployment and household overcrowding (Buck, 2001; Stafford and Marmot, 2003). Its use of car access as an indicator potentially patterns deprivation geographically rather than socioeconomically, however the index is strongly correlated at MSOA level with the income and employment domains of the widely used contemporary Index of Multiple Deprivation, which do not include such indicators.

Since census geographies change over time, the data for these variables are apportioned from the boundary systems used for each previous census to the 2011 Census MSOA definitions (Norman and Darlington-Pollock, 2017; Norman, 2016). This method may result in misclassification of neighbourhoods if there has been large-scale housing demolition and no reconstruction during the study period because the 2011 areal extent will reflect a spatial boundary that contains a much larger population and perhaps multiple meaningful neighbourhoods.

The composite deprivation index provides a relative measure of neighbourhood deprivation at each census and enables comparison over time. We used linear interpolation to impute the Townsend neighbourhood deprivation score at year of interview in NCDS and BCS70.

# **Confounding variables**

Selection into neighbourhoods by age 16 and beyond could produce an artefact effect if neighbourhood context is a mediator on the selection criterion-midlife health pathway. For example, children from low social class families may be more likely to perform worse at school, and in turn, find less well paid employment in adulthood and, in turn, go on to live in more deprived neighbourhoods. By not controlling for determinants of neighbourhood deprivation, which also predicts

health later in life (e.g. childhood social class), one could indirectly or artificially amplify the neighbourhood effect.

Therefore, childhood confounders taken into account are social class, family poverty, poor health, birth weight and gender. These are chosen on the basis of social causation and health selection theories and due to fact that they are all related to neighbourhood deprivation at midlife in our data. Social causation suggests that socioeconomic hardship leads to worse health, whereas health selection suggests those in poor health drift towards, or cannot escape, poverty (Mossakowski, 2014). All are measured at age 11 in NCDS and age 10 in BCS70 using data collected from mothers, except birth weight that was taken from medical records soon after birth. Childhood social class was measured by the father's occupation split into four categories using the General Register Office socio-economic group: (i) professional, (ii) non-manual skilled, (iii) manual skilled and (iv) semi skilled, unskilled or unclassified (Sacker and Cable, 2010). Receipt of free school meals is used to provide a measure of family poverty (yes/no) in childhood. During the 1960s and 1970s, free school meals were provided to children whose families received family income supplement, supplementary benefit, or whose income was below a minimum value on a national scale of income (Bynner and Joshi, 2002). A report of absence from school due to ill health for more than one month during an academic year is used to indicate childhood poor health (yes/no). Low birth weight was classified as up to 2.5kg (Mensah and Hobcraft, 2008). We also adjust for social class at each adult age when ND exposure is measured, using the same General Register Office categories as described above, to take account of the selection into neighbourhoods across the life course. There is sufficient variation within neighbourhood at each age by social class to disentangle selection effects.

# Statistical analysis

We use cross-classified multilevel models to determine whether there are sensitive periods when neighbourhood effects are more important for mid-life health: at age 16, 23, 33, 42 and 55 in NCDS (years 1974 to 2013) and age 16, 26, 34 and 42 (years 1986 to 2012) in BCS70. A cross-classified model allows for data structures where the lower level may belong to more than one higher level unit. For example, individuals at age 16 will each belong to a set of neighbourhoods, but by age 23 in NCDS, for example, that nested structure will be broken for individuals who have moved. A cross-classified model allows an individual (level 1) to belong to one neighbourhood at age 16 (level 2) and another or the same neighbourhood at age 23 (level 3), and so on.

Model 1 (null model) fitted partitioned variance in each outcome at each age and tests for the combined compositional context effect across the geocoded NCDS and BCS70 study sweeps. This model will not determine the element of neighbourhood that is important (i.e. the balance between compositional or contextual effects) and therefore should not be considered as evidence for specific neighbourhood effects (e.g. due to neighbourhood deprivation). Linear models were fitted for BMI and mental health, and logistic models for poor general health and disability. The linear

model for BMI in the BCS70 cohort is specified using classification notation (Leckie, 2013) as follows:

$$y_i = \beta_0 + u_{NH16(i)}^{(1)} + u_{NH26(i)}^{(2)} + u_{NH34(i)}^{(3)} + u_{NH42(i)}^{(4)}$$

where  $y_i$  is the observed BMI for respondent i (i = 1, ... ,3993),  $\beta_0$  is the mean BMI across neighbourhoods at all ages, and  $u_{NH16-42(i)}^{(1-4)}$  are the random effects for neighbourhood at ages 16, 26, 34 and 42. The total neighbourhood variance is the sum of the random effects  $\{u_{NH16(i)}^{(1)} + u_{NH26(i)}^{(2)} + u_{NH34(i)}^{(3)} + u_{NH42(i)}^{(4)}\}$ .

Model 2 adds fixed effects separately for ND at each age to determine the bivariate associations between ND and each outcome. The linear model for BMI in the BCS70 cohort including ND at age 16 is specified as follows:

$$y_i = \beta_0 + \beta_1 ND16_i + u_{NH16(i)}^{(1)} + u_{NH26(i)}^{(2)} + u_{NH34(i)}^{(3)} + u_{NH42(i)}^{(4)}$$

Model 3a adds fixed effects for ND at each prior age to determine the potential attenuating affect of ND at early points during the life course. The linear model for the BCS70 cohort including ND at ages 16, 26, 34 and 42 is specified as follows:

$$y_{i} = \beta_{0} + \beta_{1}ND16_{i} + \beta_{2}ND26_{i} + \beta_{3}ND34_{i} + \beta_{4}ND42_{i} + u_{NH16(i)}^{(1)} + u_{NH26(i)}^{(2)} + u_{NH34(i)}^{(3)} + u_{NH42(i)}^{(4)}$$

Model 3b adds individual confounders to Model 2 to test whether selection has a stronger attenuating effect compared with prior neighbourhood deprivation. The linear model for the BCS70 cohort including ND at age 42, social class at ages, 10, 26, 34 and 42, child poverty at age 10, child health at age 10, birth weight and birth gender is specified as follows:

$$y_{i} = \beta_{0} + \beta_{1}ND42_{i} + \beta_{2}CLASS10_{i} + \beta_{3}CLASS26_{i} + \beta_{4}CLASS34_{i} + \beta_{5}CLASS42_{i} + \beta_{6}POVERTY10_{i} + \beta_{7}HEALTH10_{i} + \beta_{8}BIRTHWEIGHT_{i} + \beta_{9}GENDER_{i} + u_{NH16(i)}^{(1)} + u_{NH26(i)}^{(2)} + u_{NH34(i)}^{(3)} + u_{NH42(i)}^{(4)}$$

where social class is a categorical term as described in the section above.

Model 4 includes neighbourhood deprivation and confounding variables at each prior age (i.e model 3a + model 3b) and is compared with models 2, 3a and 3b to determine whether there sensitive periods when ND is more important. A set of models were fitted to show how ND attenuated the ND association at age 16 to specifically test whether adolescence is a sensitive period. The models were fitted by Markov chain Monte Carlo estimation using the *runmlwin* command in Stata for 5,000 iterations after a burn in of 500 (Leckie and Charlton, 2011). Starting values (priors) of the variance and fixed effect estimates were derived from two level multilevel models where individuals were nested in neighbourhoods at midlife in NCDS and BCS70 fitted using an IGLS estimation routine.

Multiple imputation by chained equations was used to replace missing values for the variables added to Model 3b and Model 4 (i.e. confounding variables). The sample size was reduced between 57-59% when fitting model 3b compared with model 3a due to missingness in the covariates. The region of residence at age 11 in NCDS and age 10 in BCS70 is used as an auxiliary variable in the imputation model based on evidence showing it strongly predicts missingness in the childhood NCDS and BCS70 follow-ups (Ploubidis and Mostafa, 2016). Twenty-five imputed datasets were created. Missing values in the outcome variables and missing values of MSOAs or Townsend scores were not imputed. The former accounted for a ~1% of respondents when limiting the sample to those with a valid MSOA level at the ages when neighbourhood deprivation is taken, except for BMI in both NCDS and BCS70 and mental health in BCS70 when the missingness was as high as 12% on the outcome. Missing MSOA values, largely missing because the respondents were not present at a sweep rather than missing their address information, accounted for the majority of missing data. MSOAs were not imputed because of the complication that would be required to preserve the spatial nature of the data and ensure the imputation does not artificially inflate the level of residential mobility and therefore crossclassification between neighbourhoods over time. Restricting the sample to respondents who were present at ages when neighbourhood deprivation was measured meant excluding respondents who were more likely to live in more deprived neighbourhoods at each age and, if they were living in a more deprived neighbourhood, were more likely to have worse health and wellbeing compared with a respondent living in a less deprived neighbourhood.

The inclusion of an interaction between the random effect at 16 and midlife in NCDS and BCS70 meant the vast majority of respondents were in one group which would limit the reliability of its variance estimate and therefore is not reported here. A fixed effect interaction between neighbourhood deprivation at age 16 and midlife in NCDS and BCS70 was not significant in any model and therefore is not presented here. There was also no evidence of effect modification of gender on the exposure-outcome relationship.

# **Results**

To illustrate the distribution of respondents across different levels of area deprivation at different ages, Figure 1 shows boxplots of the Townsend ND score percentile at ages 16, 23, 33, 42 and 55 in NCDS and ages 16, 26, 34 and 42 in BCS70. The horizontal line represents the mid-point of the distribution among all MSOAs in Britain, with higher scores representing greater deprivation than the national average. In the NCDS sample, the average ND Townsend scores of cohort members were slightly above (worse) than the national average at age 16, worsened by age 23, but then through ages 33, 42 and 55 declined (improved); so that by the time of the age 55 data collection, cohort members were living in an MSOA below the 40th percentile on the ND national distribution. The BCS respondents showed a similar pattern to the NCDS respondents, but the majority of sample members were living in

neighbourhoods less deprived than the national average ND at all selected ages. The variance in ND, shown by the interquartile range, narrowed as NCDS sample members aged, whereas it remained fairly constant in BCS70 respondents.

Table 1 presents descriptive differences in midlife health for those living in the 10% most and least deprived neighbourhoods at the selected ages. 13.3% of NCDS respondents and 8.4% of BCS70 respondents who resided in the least deprived neighbourhoods at age 16 were in poor general health compared with 22.1% and 15.0% in the most deprived neighbourhoods among NCDS and BCS70 respondents, respectively. The differences in poor general health, disability and mental health widened by neighbourhood deprivation as respondents aged in NCDS. The mid-life poor general health gap by ND widened from 8.8 (i.e. 22.1% minus 13.3%) to 17.2 (i.e 30.5% minus 13.3%) percentage points from age 16 to 55 among NCDS respondents. The inequality gap in midlife health by neighbourhood at each age remained fairly constant in BCS70. For example, inequalities in disability at midlife in BCS70 by neighbourhood deprivation across the life course did not change, with people living in the most deprived neighbourhoods consistently 4-5 percentage points more likely to be disabled across the selected ages.

Figure 2 shows the variance estimates from the cross-classified null model (model 1) for each health outcome, partitioned by the neighbourhood a respondent was living in at the selected ages in NCDS and BCS70. The dots are point estimates and the horizontal lines are 95% credible intervals. For both cohorts, credible intervals overlapped at almost every age for most health outcomes. This suggests there is very little evidence across the outcome variables for a sensitive period effect when the total neighbourhood variability is stronger or weaker. The total variance partitioned at the neighbourhood level across the life course was between 4-29% in the outcomes in model 1. The relative variance at the neighbourhood level was greatest for general health in both NCDS and BCS70 and least for BMI in both samples.

Tables 2a-2b present fixed effect regression estimates of Townsend ND score at every age on each of the health outcomes in NCDS and BCS70, respectively, from models 2-4. The results from model 2 demonstrate a bivariate relationship between general health, disability, BMI and mental health by ND at each selected age in the expected direction (i.e. higher ND, poorer health). For example, a one standard deviation increase in the ND score at age 16 was associated with a 0.15 increase in BMI at age 55 in NCDS and a 0.13 increase in BMI at age 42 in BCS70. The bivariate ND association was typically stronger at the older ages for each outcome in both NCDS and BCS70.

When adding prior ND in model 3a and prior confounding variables in model 3b the attenuation was strongest at ages 23 and 42 in NCDS and age 26 in BCS70. The ND association was robust to prior ND at age 33 (and to some extent at age 55) in NCDS and age 34 (and to some extent at age 42) in BCS70, suggesting a potential ND effect in the respondents' early thirties. Selection into neighbourhoods by childhood health, poverty and social class and adult social class had a greater attenuating affect

at age 33 and age 34 in NCDS and BCS70, respectively. In general, the attenuating affect of prior ND was stronger than the affect of selection by prior confounding variables.

Model 4 shows the combination of models 3a and 3b including both prior ND and prior confounding variables. The associations at the ages 33 and 55 in NCDS and ages 34 and 42 in BCS70 was robust to the same adjustment, albeit attenuated, in most models. For example, when controlling for prior ND and prior confounding variables, a one standard deviation increase in neighbourhood deprivation at age 55 in NCDS and age 42 in BCS70 was associated with a decline in midlife mental wellbeing by 0.13 and 0.17 in NCDS and BCS70, respectively.

Table 3 shows the estimates of ND at age 16 on health and wellbeing outcomes when adding ND at later ages in a series of steps. The association was attenuated, often fully, at age 16 in most outcomes in both samples. For example, ND at age 16 was not associated with general health, disability or mental health in NCDS and disability in BCS70, when controlling for ND in cohort members' early thirties. The pattern was slightly different for BMI in both cohorts and SRH in BCS70. ND at age 16 remained a predictor of BMI (and general and mental health in BCS70) after adjustment for ND at older ages. Tables 2a-2b show that these estimates were strongly confounded by characteristics we consider to select people into neighbourhoods by age 16.

# **Conclusion**

This paper has tested whether there are sensitive periods of neighbourhood effects over the life course on midlife health and wellbeing using two British birth cohort studies: 1958 National Child Development Study and 1970 British Cohort Study. We find little evidence to support the notion that certain points during the life course are more important than others in terms of total neighbourhood variability due to contextual and compositional effects combined in the outcomes we study. This is shown by a constant variance in poor general health, disability, BMI and mental health at the neighbourhood level at selected ages from age 16 to 55 (NCDS) or 16 to 42 (BCS70) using a cross-classified model in both cohorts. In support of Murray et al's (2013) and Gustafsson et al's (2017) findings, specific neighbourhood deprivation (ND) at contemporaneous age (age 55 in NCDS and age 42 in BCS70), as measured using the Townsend index, was found to be most strongly associated with health and wellbeing at midlife. In support of the existing literature and our hypothesis, ND at adolescence did not significantly predict midlife health and wellbeing once taking ND at later points during the life course and confounding variables that may explain selection into neighbourhoods throughout the life course. In contrast to previous literature, we find a ND at late early-adulthood (age 33 in NCDS and age 34 in BCS70) is associated with health and wellbeing, independent of prior ND and individual confounding variables.

These findings are against a backdrop of both cohorts' sample members living in relatively less deprived neighbourhoods compared to the national average. NCDS sample members became more likely to live in less deprived neighbourhoods as they age. On the face of it, this suggests that ND has a stronger effect at later ages. It could be the case that ND is more important once most people settle in a locality after a period of residential instability during early adulthood when they move out of the parental home and finish education, whereas other aspects of the neighbourhood are more important in childhood. We estimate (analysis not shown here) fewer than 1 in 4 NCDS and BCS70 respondents were living in the same neighbourhood at age 42 that they were living in during their 20s. Moreover, the correlation between neighbourhood deprivation for respondents in both cohorts was stronger after age 30 than before this age. There is, however little theoretical support to suggest that independently ND would be more important when an individual is in their thirties or when they reach middle age compared with earlier ages because the former are not periods during the life course when one would expect individuals to interact most with their neighbourhood. Further investigation could explore whether this is related to new parenthood or purchase of first house, both potential life stages when people interact more with their neighbourhood.

It is perhaps more likely that ND at older ages are mediators of the ND effect at younger ages. Our statistical models support this notion, given the attenuation of ND associations at younger ages when adjusting for ND at older ages. We do not believe our findings suggest that ND at points earlier in the life course is less important, rather it is important to consider the neighbourhood deprivation at early points in the life course to avoid a misestimation of the total neighbourhood effect. It could be the case that the ND experienced is cumulative and mediated through prior neighbourhood of residence. This could be explored with more explicit analysis on the cumulative affect of neighbourhoods on health and wellbeing across the life course.

Alternative explanations for our findings could be a drift towards more deprived neighbourhoods among the unhealthy and towards less deprived neighbourhoods among the healthy, or that neighbourhoods where the unhealthy respondents live became more deprived and the neighbourhoods where the healthy respondents live became less deprived. Both imply a form of selection rather than a neighbourhood effect. We find tentative evidence for the former because the number of people living in the 10% least deprived neighbourhoods at later ages increases in size in both samples, suggesting net in-migration to these areas. These residential mobilities, with respect to ND and of health inequalities in mid-life being greatest, are consistent with Norman and Boyle (2014). Our statistical models also support an element of selection because the ND association is attenuated when we control for individual characteristics that may explain neighbourhood selection.

There are a number of limitations to our current study. We aimed to test sensitive periods across the life course, however, we only have data up to age 55 in NCDS and age 42 in BCS70. Our hypothesis suggested that neighbourhood effects may become stronger as people become less spatially mobile in later age and perhaps more

dependent on their neighbourhood. This hypothesis could be tested in future providing older age sweeps of the NCDS and BCS70 are conducted. A common limitation using cohort data is attrition bias. The study sample declined 37% in NCDS and 43% in BCS70 from birth to the most recent sweep used here, when excluding missing due to death, emigration or not being part of the original birth cohort (i.e. immigrants added between birth and age 16). There is evidence reported elsewhere that this attrition is socially selective (Ploubidis and Mostafa, 2016). However, attrition bias is unlikely to result in an overestimation in neighbourhood effects because one could assume that those who attrite, who are more likely to be living in the most deprived neighbourhoods, would have even worse health and wellbeing compared with their neighbours who remain in the study. Attempts to provide advice on dealing with longitudinal attrition in these specific datasets is ongoing (ibid). A related limitation is that we were not able to fully adjust for selection into neighbourhoods over the life course. We attempt to control for social selection using social class at every age we measured ND, however, we did not have measures of health and wellbeing to adequately deal with health selection across the age period analysed. Moreover, our measure of social class is unlikely to be the only factor explaining social selection into neighbourhoods across the life course.

Notwithstanding these limitations, this study adds to the current literature by testing a hypothesis that neighbourhood effects are more important at certain ages during the life course using two nationally representative cohort studies born 12 years apart and both linked to meaningfully defined neighbourhood measures and using a range of health and wellbeing outcomes. The findings lend themselves to support for more detailed investigation of the process through which neighbourhood throughout the life course leads to poorer health and wellbeing and whether selection into the most deprived neighbourhoods or mediation is the main explanation for lack of support for a sensitive period in adolescence.

#### References

- Anderson, S., Leventhal, T., Dupere, V., 2014. Exposure to Neighborhood Affluence and Poverty in Childhood and Adolescence and Academic Achievement and Behavior. Appl. Dev. Sci. 18, 123–138. https://doi.org/10.1080/10888691.2014.924355
- Arcaya, M.C., Tucker-Seeley, R.D., Kim, R., Schnake-Mahl, A., So, M., Subramanian, S. V, 2016. Research on neighborhood effects on health in the United States: A systematic review of study characteristics. Soc. Sci. Med. 168, 16–29. https://doi.org/https://doi.org/10.1016/j.socscimed.2016.08.047
- Buck, N., 2001. Identifying Neighbourhood Effects on Social Exclusion. Urban Stud. 38, 2251–2275. https://doi.org/10.1080/00420980120087153
- Bynner, J., Joshi, H., 2002. Equality and Opportunity in Education: Evidence from the 1958 and 1970 birth cohort studies. Oxford Rev. Educ. 28, 405–425. https://doi.org/10.1080/0305498022000013599
- Centre for Longitudinal Studies, 2017. Census.
- Centre for Longitudinal Studies, 2013. National Child Development Study (1958-2013). https://doi.org/SN: 5560, http://dx.doi.org/10.5255/UKDA-SN-5560-3
- Centre for Longitudinal Studies, 2012. 1970 British Cohort Study (1958-2012). https://doi.org/SN: 5641, http://dx.doi.org/10.5255/UKDA-SN-5641-2
- Clarke, P., Morenoff, J., Debbink, M., Golberstein, E., Elliott, M.R., Lantz, P.M., 2014.

  Cumulative exposure to neighborhood context: consequences for health transitions over the adult life course. Res. Aging 36, 115–42.

  https://doi.org/10.1177/0164027512470702
- Clarke, P.J., Weuve, J., Barnes, L., Evans, D.A., de Leon, C.F.M., 2015. Cognitive decline and the neighborhood environment. Ann. Epidemiol. 25, 849–854. https://doi.org/10.1016/j.annepidem.2015.07.001
- Dundas, R., Leyland, A.H., Macintyre, S., 2014. Early-life school, neighborhood, and family influences on adult health: a multilevel cross-classified analysis of the Aberdeen children of the 1950s study. Am. J. Epidemiol. 180, 197–207. https://doi.org/10.1093/aje/kwu110
- Flowerdew, R., Manley, D.J., Sabel, C.E., 2008. Neighbourhood effects on health: does it matter where you draw the boundaries? Soc. Sci. Med. 66, 1241–55. https://doi.org/10.1016/j.socscimed.2007.11.042
- Galster, G., 2012. The Mechanism(s) of Neighbourhood Effects: Theory, Evidence,

- and Policy Implications, in: van Ham, M., Manley, D., Bailey, N., Simpson, L., Maclennan, D. (Eds.), Neighbourhood Effects Research: New Perspectives SE 2. Springer Netherlands, pp. 23–56. https://doi.org/10.1007/978-94-007-2309-2\_2
- Gustafsson, P.E., Bozorgmehr, K., Hammarström, A., San, M., 2017. What role does adolescent neighborhood play for adult health? A cross- classi fi ed multilevel analysis of life course models in Northern Sweden. Health Place 46, 137–144. https://doi.org/10.1016/j.healthplace.2017.04.013
- Gustafsson, P.E., Hammarström, A., San Sebastian, M., 2014. Cumulative contextual and individual disadvantages over the life course and adult functional somatic symptoms in Sweden. Eur. J. Public Health 1981, 1–6. https://doi.org/10.1093/eurpub/cku213
- Gustafsson, P.E., San Sebastian, M., 2014. When does hardship matter for health?

  Neighborhood and individual disadvantages and functional somatic symptoms from adolescence to mid-life in the Northern Swedish Cohort. PLoS One 9. https://doi.org/10.1371/journal.pone.0099558
- Gustafsson, P.E., San Sebastian, M., Janlert, U., Theorell, T., Westerlund, H., Hammarström, A., 2013. Residential selection across the life course: adolescent contextual and individual determinants of neighborhood disadvantage in midadulthood. PLoS One 8, e80241. https://doi.org/10.1371/journal.pone.0080241
- Johansson, K., San Sebastian, M., Hammarström, A., Gustafsson, P.E., 2015.
   Neighbourhood disadvantage and individual adversities in adolescence and total alcohol consumption up to mid-life-Results from the Northern Swedish Cohort. Health Place 33, 187–194.
   https://doi.org/10.1016/j.healthplace.2015.03.005
- Johnson, R.C., Schoeni, R.F., Rogowski, J.A., 2012. Social Science & Medicine Health disparities in mid-to-late life: The role of earlier life family and neighborhood socioeconomic conditions q. Soc. Sci. Med. 74, 625–636. https://doi.org/10.1016/j.socscimed.2011.10.021
- Kravitz-Wirtz, N., 2016a. Cumulative Effects of Growing Up in Separate and Unequal Neighborhoods on Racial Disparities in Self-rated Health in Early Adulthood. J. Health Soc. Behav. 57, 453–470. https://doi.org/10.1177/0022146516671568
- Kravitz-Wirtz, N., 2016b. Temporal Effects of Child and Adolescent Exposure to
   Neighborhood Disadvantage on Black/White Disparities in Young Adult Obesity.
   J. Adolesc. Heal. 58, 551–557. https://doi.org/10.1016/j.jadohealth.2016.01.004
- Leckie, G., 2013. Module 12: Cross-Classified Multilevel Models, in: Steele, F.,

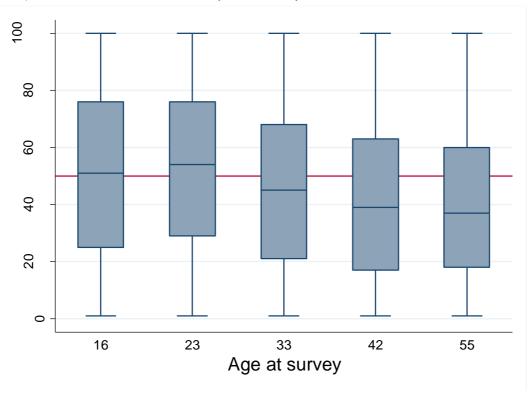
- Browne, W., Clarke, P., Leckie, G., Goldstein, H., Jones, K., Windmeijer, F., Charlton, C. (Eds.), LEMMA (Learning Environment for Multilevel Methods and Applications). Centre for Multilevel Modelling, Bristol, pp. 1–60.
- Leckie, G., Charlton, C., 2011. runmlwin: Stata module for fitting multilevel models in the MLwiN software package. Centre for Multilevel Modelling, University of Bristol.
- Lekkas, P., Paquet, C., Howard, N.J., Daniel, M., 2017. Illuminating the lifecourse of place in the longitudinal study of neighbourhoods and health. Soc. Sci. Med. 177, 239–247. https://doi.org/10.1016/j.socscimed.2016.09.025
- Lupton, R., 2003. CASE Paper 'Neighbourhood Effects': Can we measure them and does it matter? LSE STICERD Res. Pap. No. CASE073.
- Marshall, A., Jivraj, S., Nazroo, J., Tampubolon, G., Vanhoutte, B., 2014. Does the level of wealth inequality within an area influence the prevalence of depression amongst older people? Health Place 27, 194–204. https://doi.org/http://dx.doi.org/10.1016/j.healthplace.2014.02.012
- Mensah, F.K., Hobcraft, J., 2008. Childhood deprivation, health and development: associations with adult health in the 1958 and 1970 British prospective birth cohort studies. J. Epidemiol. Community Health 62, 599 LP 606.
- Michael, Y.L., Nagel, C.L., Gold, R., Hillier, T.A., 2014. Does change in the neighborhood environment prevent obesity in older women? Soc. Sci. Med. 102, 129–137. https://doi.org/10.1016/j.socscimed.2013.11.047
- Mossakowski, K.N., 2014. Social Causation and Social Selection. Wiley Blackwell Encycl. Heal. Illness, Behav. Soc., Major Reference Works. https://doi.org/doi:10.1002/9781118410868.wbehibs262
- Murray, E.T., Ben-Shlomo, Y., Tilling, K., Southall, H., Aucott, P., Kuh, D., Hardy, R., 2013. Area Deprivation Across the Life Course and Physical Capability in Midlife: Findings From the 1946 British Birth Cohort. Am. J. Epidemiol. 178, 441–450. https://doi.org/10.1093/aje/kwt003
- Murray, E.T., Southall, H., Aucott, P., Tilling, K., Kuh, D., Hardy, R., Ben-Shlomo, Y., 2012. Challenges in examining area effects across the life course on physical capability in mid-life: findings from the 1946 British Birth Cohort. Health Place 18, 366–74. https://doi.org/10.1016/j.healthplace.2011.11.007
- Murray, E.T., Zaninotto, P., Fleischmann, M., Stafford, M., Carr, E., Shelton, N., Stansfeld, S., Kuh, D., Head, J., 2019. Linking local labour market conditions across the life course to retirement age: Pathways of health, employment

- status, occupational class and educational achievement, using 60 years of the 1946 British Birth Cohort. Soc. Sci. Med 226, 113-122.Norman, P., 2016. The Changing Geography of Deprivation in Britain: 1971 to 2011 and Beyond, in: Population Change in the United Kingdom. Rowman & Littlefield, London, pp. 193–214.
- Norman, P., Boyle, P., 2014. Are health inequalities between differently deprived areas evident at different ages? A longitudinal study of census records in England and Wales, 1991–2001. Health Place 26, 88–93. https://doi.org/https://doi.org/10.1016/j.healthplace.2013.12.010
- Norman, P., Darlington-Pollock, F., 2017. The Changing Geography of Deprivation in Great Britain: Exploiting Small Area Census Data, 1971 to 2011, in: Stillwell, J. (Ed.), The Routledge Handbook of Census Resources, Methods and Applications: Unlocking the UK 2011 Census. International Population Studies. Routledge, pp. 404–420.
- Pearce, J.R., 2018. Complexity and Uncertainty in Geography of Health Research: Incorporating Life-Course Perspectives. Ann. Am. Assoc. Geogr. 1–8. https://doi.org/10.1080/24694452.2017.1416280
- Pickett, K.E., Pearl, M., 2001. Multilevel analyses of neighbourhood socioeconomic context and health outcomes: a critical review. J. Epidemiol. Community Health 55, 111 LP 122.
- Ploubidis, G.B., Mostafa, T., 2016. Centre for Longitudinal Studies Missing Data Strategy, in: Longitudinal Methodology Series IX. Centre for Longitudinal Studies, London.
- Ruel, E., Reither, E.N., Robert, S.A., Lantz, P.M., 2010. Health & Place Neighborhood effects on BMI trends: Examining BMI trajectories for Black and White women. Health Place 16, 191–198. https://doi.org/10.1016/j.healthplace.2009.09.009
- Sacker, A., Cable, N., 2010. Transitions to adulthood and psychological distress in young adults born 12 years apart: constraints on and resources for development. Psychol. Med. 40, 301–313. https://doi.org/DOI: 10.1017/S0033291709006072
- Schaefer-McDaniel, N., O'Brien Caughy, M., O'Campo, P., Gearey, W., 2010. Examining methodological details of neighbourhood observations and the relationship to health: A literature review. Soc. Sci. Med. 70, 277–292. https://doi.org/https://doi.org/10.1016/j.socscimed.2009.10.018
- Stafford, M., Marmot, M., 2003. Neighbourhood deprivation and health: does it affect us all equally? Int. J. Epidemiol. 32, 357–366.

- van Ham, M., Manley, D., 2012. Neighbourhood effects research at a crossroads. Ten challenges for future research. Environ. Plan. A 44, 2787–2793.
- Walsemann, K.M., Child, S., Heck, K., Margerison-Zilko, C., Braveman, P., Marchi, K., Cubbin, C., 2017. Are the poverty histories of neighbourhoods associated with psychosocial well-being among a representative sample of California mothers? An observational study. J. Epidemiol. Community Health 71, 558 LP 564.
- Wheaton, B., Clarke, P., 2004. Early Adulthood SPACE MEETS TIME: INTEGRATING TEMPORAL AND last decade, Am. Sociol. Rev. 68, 680–706.
- Wiggins, R.D., Brown, M., Ploubidis, G.B., 2017. General health is measured using a 5-point self-rated scale dichotomised into those that report fair or poor health compared with those that report excellent, very good or good health. Disability is measured using the 2011 Census limiting long-term illnes, CLS working paper 2017/2. London.
- Wiggins, R.D., Higgs, P.F.D., Hyde, M., Blane, D.B., 2004. Quality of life in the third age: key predictors of the CASP-19 measure. Ageing Soc. 24, 693–708. https://doi.org/10.1017/S0144686X04002284
- Wodtke, G.T., 2013. Duration and Timing of Exposure to Neighborhood Poverty and the Risk of Adolescent Parenthood. Demography 50, 1765–1788. https://doi.org/10.1007/s13524-013-0219-z

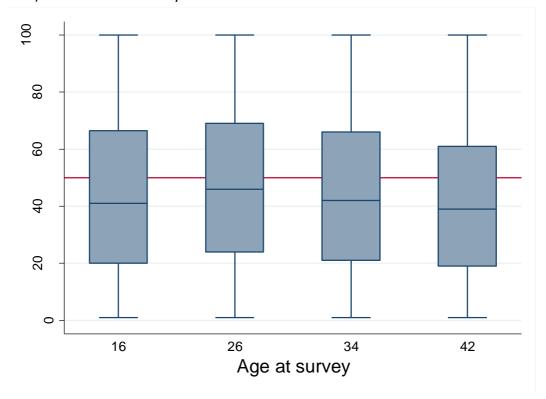
Figure 1. Study respondents Townsend neighbourhood deprivation percentile at selected ages during the life course

a) 1958 National Child Development Study



Sample size: 5,839

b) British Cohort Study 1970



Sample size: 4,572

Table 1. Descriptive differences in midlife health outcomes (age 55 in NCDS and age 42 in BCS70) by neighbourhood deprivation at selected ages during the life course

a) 1958 National Child Development Study

Outcome	Deprivation decile	Statistic	Age 16	Age 23	Age 33	Age 42	Age 55
	Least deprived	N	646	461	704	861	851
		Percent	13.3%	14.5%	13.2%	13.7%	13.3%
Poor-rated general	Most deprived	N	587	482	286	220	167
health		Percent	22.1%	19.9%	27.6%	30.0%	30.5%
	Least deprived	N	645	460	702	861	850
		Percent	17.7%	16.7%	15.1%	15.6%	15.8%
	Most deprived	N	584	481	285	219	167
Disability	wost deprived	Percent	20.0%	18.7%	27.7%	26.9%	26.9%
	Least deprived	N	604	426	659	801	792
		Mean	26.7	26.7	26.5	26.7	26.5
		SD	4.8	4.5	4.3	4.5	4.5
		N	529	445	259	198	143
	Most deprived	Mean	28.1	27.7	27.8	27.6	28.1
BMI		SD	5.4	5.2	5.4	5.6	6.1
		N	638	456	699	855	846
	Least deprived	Mean	13.2	13.3	13.3	13.1	13.3
		SD	3.4	3.4	3.3	3.4	3.2
		N	575	471	276	214	158
	Most deprived	Mean	12.5	12.7	11.8	12.0	11.4
Mental health*		SD	3.6	3.6	3.9	3.9	4.2

b) British Cohort Study 1970

Outcome	Deprivation decile	Statistic	Age 16	Age 26	Age 34	Age 42
	Least deprived	N	596	475	591	651
		Percent	8.4%	9.9%	7.4%	8.9%
Poor-rated	Most deprived	N	254	303	242	204
general health		Percent	15.0%	16.2%	15.3%	16.7%
	Least deprived	N	593	472	591	650
		Percent	11.1%	11.9%	10.8%	11.8%
	Most deprived	N	254	302	242	204
Disability		Percent	18.9%	16.9%	17.8%	19.6%
	Least deprived	N	523	420	528	585
		Mean	26.0	25.9	25.9	25.8
		SD	4.9	4.9	4.6	4.8
	Most deprived	N	207	248	195	160
		Mean	27.6	27.0	26.3	26.5
BMI		SD	5.0	5.2	5.3	5.3
	Least deprived	N	538	420	526	577
		Mean	50.6	50.6	50.6	51.0
		SD	7.4	8.1	7.6	7.4
Mental health*	_ Most deprived	N	213	257	207	165

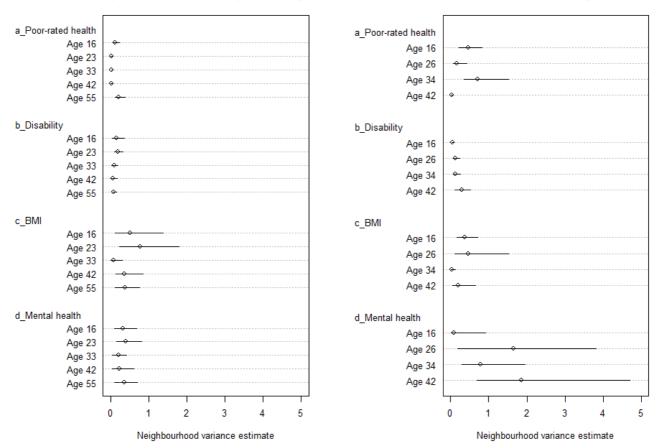
 Mean	48.8	48.9	50.0	49.4
SD	8.7	8.4	7.8	7.6

<sup>\*</sup> Higher score indicates better mental health

Figure 2. Null model neighbourhood variance estimates and 95% credible intervals in midlife health outcomes (age 55 in NCDS and age 42 in BCS70) at selected ages during the life course (National Child Development Study, British Cohort Study 1970)

# a) National Child Development Study

# b) British Cohort Study 1970



Sample sizes

NCDS: Poor-rated health- 5764; Disability- 5752; Body-mass index- 5317;

Mental health- 5693

BCS70: Poor-rated health-4558; Disability-4540; Body-mass index- - 3993;

Mental health-3983

Table 2a. 1958 National Child Development Study fixed effect regression estimates and 95% credible intervals for Townsend deprivation score on midlife health outcomes at selected ages during the life course

		Model 2	Model 3a	Model 3b	Model 4
		(ND separately)	(Prior ND only)	(Individual confounders	(full model [model 3a +
Outcome	Fixed effect			only)	model 3b])
	Age 16	0.049 (0.027, 0.071)	Identical to model 2	0.027 (0.001, 0.052)	Identical to model 3b
Poor-rated	Age 23	0.044 (0.020, 0.069)	0.024 (-0.005, 0.053)	0.023 (-0.002, 0.047)	-0.018 (-0.012, 0.047)
general	Age 33	0.104 (0.079, 0.129)	0.107 (0.075, 0.138)	0.074 (0.047, 0.102)	0.084 (0.052, 0.116)
health	Age 42	0.123 (0.093, 0.154)	0.067 (0.025, 0.112)	0.085 (0.051, 0.119)	0.048 (-0.000, 0.096)
	Age 55	0.128 (0.097, 0.159)	0.075 (0.034, 0.121)	0.086 (0.053, 0.118)	0.057 (0.011, 0.102)
	Age 16	0.027 (0.002, 0.052)	Identical to model 2	0.011 (-0.014, 0.037)	Identical to model 3b
	Age 23	0.034 (0.011, 0.058)	0.025 (-0.004, 0.052)	0.020 (-0.004, 0.043)	-0.023 (-0.006, 0.052)
	Age 33	0.079 (0.054, 0.103)	0.084 (0.056, 0.113)	0.063 (0.036, 0.089)	0.073 (0.042, 0.104)
	Age 42	0.092 (0.062, 0.122)	0.043 (0.002, 0.087)	0.067 (0.033, 0.100)	-0.027 (-0.020, 0.074)
Disability	Age 55	0.101 (0.069, 0.133)	0.068 (0.022, 0.111)	0.074 (0.043, 0.105)	0.059 (0.013, 0.104)
	Age 16	0.150 (0.103, 0.196)	Identical to model 2	0.085 (0.037, 0.133)	Identical to model 3b
	Age 23	0.095 (0.051, 0.140)	0.020 (-0.033, 0.075)	0.050 (0.006, 0.094)	-0.016 (-0.036, 0.069)
	Age 33	0.169 (0.118, 0.221)	0.132 (0.077, 0.190)	0.109 (0.058, 0.160)	0.097 (0.039, 0.155)
BMI	Age 42	0.153 (0.091, 0.215)	0.016 (-0.105, 0.074)	0.078 (0.015, 0.141)	-0.039 (-0.129, 0.050)
	Age 55	0.188 (0.127, 0.249)	0.151 (0.066, 0.236)	0.123 (0.062, 0.184)	0.127 (0.039, 0.214)
	Age 16	-0.043 (-0.075, -0.012)	Identical to model 2	-0.014 (-0.047, 0.020)	Identical to model 3b
	Age 23	-0.051 (-0.081, -0.022)	-0.039 (-0.075, -0.004)	-0.027 (-0.057, 0.004)	0.035 (-0.071, 0.000)
Mental	Age 33	-0.128 (-0.162, -0.094)	-0.129 (-0.168, -0.091)	-0.090 (-0.125, -0.056)	-0.102 (-0.142, -0.063)
health	Age 42	-0.140 (-0.182, -0.098)	-0.057 (-0.118, 0.004)	-0.090 (-0.133, -0.048)	-0.038 (-0.097, 0.022)
score*	Age 55	-0.177 (-0.218, -0.137)	-0.156 (-0.213, -0.099)	-0.125 (0.168, -0.086)	-0.129 (-0.186, -0.072)

<sup>\*</sup> Higher score indicates better mental health

Sample sizes: Poor-rated general health- 5764; Disability- 5752; Body-mass index- 5317; Mental health- 5693

Model 2 adjusts for neighbourhood disdvantage at each age in separate models. Models 3a simultaneously adjusts for prior ND only, Model 3b adjusts for prior confounding variables only (social class in adulthood, childhood social class, childhood health, childhood poverty, birthweight and gender), and Model 4 adjusts for prior ND and confounding variables.

Table 2b. British Cohort Study 1970 fixed effect regression estimates for Townsend deprivation score on midlife health outcomes at selected ages during the life course

		Model 2	Model 3a	Model 3b	Model 4
		(ND separately)	(Prior ND only)	(Individual	(full model)
Outcome	Fixed effect			confounders only)	
	Age 16	0.075 (0.044, 0.107)	Identical to model 2	0.042 (0.007, 0.078)	Identical to model 3b
	Age 26	0.070 (0.035, 0.107)	0.03 (-0.012, 0.072)	0.040 (0.001, 0.080)	-0.029 (-0.017, 0.076)
Poor-rated	Age 34	0.104 (0.062, 0.145)	0.075 (0.03, 0.119)	0.078 (0.035, 0.122)	0.076 (0.025, 0.128)
general health	Age 42	0.097 (0.056, 0.139)	0.042 (-0.016, 0.099)	0.063 (0.022, 0.105)	0.019 (-0.038, 0.077)
	Age 16	0.049 (0.018, 0.081)	Identical to model 2	0.020 (-0.010, 0.051)	Identical to model 3b
	Age 26	0.042 (0.010, 0.076)	0.018 (-0.019, 0.055)	0.020 (-0.014, 0.054)	-0.014 (-0.025, 0.053)
	Age 34	0.082 (0.043, 0.120)	0.076 (0.031, 0.119)	0.061 (0.025, 0.097)	0.068 (0.026, 0.109)
Disability	Age 42	0.082 (0.050, 0.119)	0.054 (0.001, 0.107)	0.062 (0.027, 0.097)	0.043 (-0.006, 0.091)
	Age 16	0.130 (0.076, 0.183)	Identical to model 2	0.056 (-0.003, 0.115)	Identical to model 3b
	Age 26	0.094 (0.032, 0.154)	0.022 (-0.053, 0.095)	0.034 (-0.029, 0.097)	0.014 (-0.059, 0.087)
BMI	Age 34	0.090 (0.022, 0.158)	0.031 (-0.049, 0.111)	0.030 (-0.038, 0.097)	0.012 (-0.065, 0.089)
	Age 42	0.122 (0.056, 0.188)	0.097 (0.004, 0.185)	0.059 (-0.007, 0.126)	0.067 (-0.022, 0.156)
	Age 16	-0.193 (-0.278, -0.106)	Identical to model 2	-0.106 (-0.201, -0.010)	Identical to model 3b
	Age 26	-0.150 (-0.247, -0.051)	-0.047 (-0.165, 0.068)	-0.068 (-0.169, 0.034)	0.035 (-0.150, 0.080)
	Age 34	-0.183 (-0.288, -0.079)	-0.112 (-0.238, 0.012)	-0.113 (-0.222, -0.005)	-0.097 (-0.220, 0.026)
Mental health*	Age 42	-0.250 (-0.354, -0.146)	-0.212 (-0.354, -0.071)	-0.168 (-0.276, -0.061)	-0.165 (-0.312, -0.018)

<sup>\*</sup> Higher score indicates better mental health

Sample sizes: Poor-rated general health-4558; Disability-4540; Body-mass index- - 3993; Mental health-3983

Model 2 adjusts for ND at each age in separate models. Models 3a simultaneously adjusts for prior ND only, Model 3b adjusts for prior confounding variables only (social class in adulthood, childhood social class, childhood health, childhood poverty, birthweight and gender), and Model 4 adjusts for prior ND and confounding variables.

Table 3. NCDS/BCS70 fixed effect regression estimates for Townsend deprivation score at age 16 on midlife health outcomes

		Age 16 ND only	Age 16 + 23/26 ND	Age 16 + 23/26 + 33/34	Age 16 + 23/26 + 33/34	Age 16 + 23 + 33 + 42
Sample	Outcome			ND	+ 42 ND	+ 55 ND
NCDS	Poor-rated health	0.049 (0.027, 0.071)	0.038 (0.007, 0.068)	0.019 (-0.014, 0.054)	0.017 (-0.013, 0.046)	0.018 (-0.013, 0.048)
NCDS	Disability	0.027 (0.002, 0.052)	0.013 (-0.016, 0.043)	-0.002 (-0.031, 0.029)	-0.004 (-0.032, 0.024)	-0.005 (-0.036, 0.024)
NCDS	BMI	0.146 (0.096, 0.198)	0.143 (0.083, 0.205)	0.117 (0.055, 0.18)	0.116 (0.054, 0.178)	0.116 (0.054, 0.178)
NCDS	Mental health*	-0.043 (-0.075, -0.012)	-0.019 (-0.056, 0.019)	0.002 (-0.035, 0.04)	0.005 (-0.034, 0.043)	0.006 (-0.031, 0.043)
BCS70	Poor-rated health	0.075 (0.044, 0.107)	0.061 (0.024, 0.098)	0.051 (0.014, 0.09)	0.053 (0.012, 0.097)	n/a
BCS70	Disability	0.049 (0.018, 0.081)	0.038 (0.005, 0.072)	0.034 (-0.005, 0.072)	0.028 (-0.012, 0.067)	n/a
BCS70	BMI	0.130 (0.076, 0.183)	0.120 (0.055, 0.185)	0.117 (0.049, 0.111)	0.113 (0.046, 0.178)	n/a
BCS70	Mental health*	-0.193 (-0.278, -0.106)	-0.171 (-0.275, -0.069)	-0.159 (-0.261, -0.057)	-0.15 (-0.254, -0.047)	n/a

<sup>\*</sup> Higher score indicates better mental health

Sample sizes

NCDS: Poor-rated general health- 5764; Disability- 5752; Body-mass index- 5317; Mental health- 5693

BCS70: Poor-rated general health -4558; Disability-4540; Body-mass index- - 3993; Mental health-3983

Supplementary table 1 – Missing data from birth

		1 – Missing data from birth	1	0/ malasina francis latin li
Sample	Variable		Age	% missing from birth
NCDS		Poor-rated health	55	51.3%
NCDS		Disability	55	51.4%
NCDS		BMI	55	58.4%
NCDS	Outcomes	Mental health	55	52.0%
NCDS			16	33.7%
NCDS			23	33.3%
NCDS			33	39.0%
NCDS			42	38.7%
NCDS	Exposure	ND	55	51.7%
NCDS			11	26.8%
NCDS			23	46.5%
NCDS			33	43.0%
NCDS			42	48.3%
NCDS		Social class	55	61.8%
NCDS		Childhood poverty	11	24.8%
NCDS		Childhood health	11	25.6%
NCDS		Birth weight	0	6.2%
NCDS	Covariates	Birth gender	0	0.0%
NCDS		Respondents		18,558
BCS70		Poor-rated health	42	48.5%
BCS70		Disability	42	48.7%
BCS70		BMI	42	59.6%
BCS70	Outcomes	Mental health	42	57.6%
BCS70			16	39.7%
BCS70			26	55.5%
BCS70			34	49.4%
BCS70	Exposure	ND	42	48.4%
BCS70	'		10	35.7%
BCS70			26	64.3%
BCS70			34	58.0%
BCS70		Social class	42	56.5%
BCS70		Childhood poverty	10	28.5%
BCS70		Childhood health	10	37.5%
BCS70		Birth weight	0	9.6%
BCS70	Covariates	Birth gender	0	0.1%
BCS70		Respondents		19,022
200,0			1	10,022

Includes missing due to death, emigration and not being issued due to entering the sample after birth (this account for 17% and 21% of missings in BCS70 and NCDS, respectively).