Using internal migration to estimate the causal effect of neighbourhood socioeconomic context on health: A longitudinal analysis (England, 1995-2008)

Abstract

There is longstanding evidence for the existence of geographical inequalities in health. Multiple conceptual frameworks have been proposed to explain why such patterns persist. However, the methodological design for these studies are often not appropriate for identifying causal effects of neighbourhood context. It is possible that findings which show the importance of neighbourhoods may be subject to confounding of individual level factors and/or neighbourhood sorting effects (i.e. health selective migration). We present an approach to investigating neighbourhood-level factors which provides a stronger examination for causal effects, as well as addressing issues of confounding and sorting. We use individual-level data from the British Household Panel Survey (1995-2008). Individuals were grouped into quintiles based on the median house price of an individual's Lower Super Output Area (LSOA) as our measure of neighbourhood socioeconomic context. Multivariate propensity scores were used to match individuals to control for confounding factors, and logistic regression models were used to estimate the association between destination of migration and risk of poor health (up to 10 years following migration). Initially, we found some evidence that poorer neighbourhoods were associated with an increased risk of poor health. Following controlling for an individual's health status prior to migration, the influence of neighbourhood socioeconomic context was statistically non-significant. Our findings suggest that health selective migration may help to explain the association between neighbourhood-level factors and individual-level health. Our study design appears useful for both identifying causal effects of neighbourhoods and accounting for health selective migration.

Keywords

Migration; neighbourhood; health; matching; longitudinal.

Introduction

The existence of health inequalities between poor and affluent neighbourhoods is well documented. For example, there is an estimated gap of 9 and 7 years in life expectancy at birth for males and females, respectively, between neighbourhoods in the most versus least deprived deciles in England (ONS 2016). Early debates focused on whether explanations for these patterns were due to compositional (i.e. individual-level) or contextual (i.e. area-level) factors. The growth of multi-level modelling helped researchers attempt to separate out these two factors, consistently finding support for contextual explanations suggesting that the social environment mattered (Riva et al. 2007; Mitchell 2001). Multiple processes and mechanisms have been proposed to explain the role of neighbourhood socioeconomic context for health including: living in stressful environments (Kaplan et al. 2013; Nieuwenhuis et al. 2015), a lack of social capital and/or cohesion (Pearce & Davey Smith 2003; Uphoff et al. 2013), and greater accessibility to unhealthy foods (Smith et al. 2016).

There are three main explanations for the existence of health inequalities across neighbourhoods:

(1) *Neighbourhoods influence health*. A vast amount of evidence, which appears consistent across outcomes, methods and contexts, would support this explanation (Pickett & Pearl 2001; Riva et al. 2007; Schüle & Bolte 2015; Oakes et al. 2015; Arcaya et al. 2016a).

(2) *Neighbourhood effects reflect individual-level confounders*. Where neighbourhood effects are detected, they may merely represent unknown, unmeasured social characteristics of individuals that are merely correlated with measures of neighbourhood socioeconomic context. This is commonly referred to as the

‘compositional’ explanation for neighbourhood effects. If the design of the study does not fully account for such confounding factors, results which suggest the importance of neighbourhood socioeconomic context may be misleading (Westfall & Yarkoni 2016). To analyse neighbourhood effects, researchers may have been relying on only observational data that may not capture or poorly measure the true construct of interest. A large proportion of the evidence base also draws upon cross-sectional data, which cannot be used to identify causal effects since such data only present relationships at a single point in time (i.e. they cannot separate out cause and effect for which you need temporal data). These issues have led to calls for greater focus on longitudinal life course studies to tease out the complex contextual effects of neighbourhoods on health (Morris et al. 2016; Oakes et al. 2015).

(3) *Individuals with poor health become sorted into deprived neighbourhoods*. Migration patterns are important for understanding the population structure of an area because the characteristics of migrants are different to non-migrants. Life events (e.g. childbirth, marriage, divorce), demographic (e.g. age, income, occupation, marital status), geographical (e.g. service, employment or family location) and cultural factors (e.g. neighbourhood satisfaction, moving up the ‘housing ladder’) each influence the propensity for individuals to migrate (Morris et al. 2016). Migration will therefore affect the population structure of both the origin and destination of movement patterns (Norman et al. 2005). If migrants differ from non-migrants in terms of their demographic characteristics and these characteristics are also associated to health outcomes, then migratory patterns will indirectly introduce bias into understanding the impact of neighbourhoods. For example, the most mobile population groups are the young and since they tend to also be healthy, high

in-migration of such individuals will make an area seem healthier than it actually is. Previous research suggests that migratory patterns may exaggerate the relationship between neighbourhood socioeconomic context and health (Brimblecombe et al. 1999; Brimblecombe et al. 2000; Norman & Boyle 2014; although see Geronimus et al. 2014). The systematic sorting of individuals with poor health into poorer neighbourhoods is termed 'health selective migration.' (Brimblecombe et al. 1999; Green et al. 2015; Arcaya et al. 2016b).

Our paper presents one approach to tackle the second and third explanations to evaluate the contribution of the first explanation.

Our approach is influenced by the Moving to Opportunity (MTO) experiment. MTO was funded by the US federal government between 1994 and 1998 to provide rental subsidies to individuals in poor areas on the condition individuals moved to a less deprived area (versus a control group of no subsidy, and a second intervention group with no restriction on location for using the subsidy to migrate to). The experiment was set up as a randomised control study, allowing for the program to be evaluated independent of confounding factors. Individuals who migrated to less deprived areas were associated with improved physical and mental health (albeit not for all health outcomes), although adolescent males were found to have poorer mental health following migration (Leventhal & Brooks-Gunn 2003; Kling et al. 2007; Ludwig et al. 2011). The MTO study provides some of the strongest evidence of the causal effects of neighbourhood socioeconomic context (Sampson 2012; Oakes et al. 2015), and has also been used to show the role of health sorting into neighbourhoods (Arcaya et al. 2016b). The MTO demonstrates the usefulness of testing for neighbourhood effects through experimental designs involving migration (i.e. individuals changing their neighbourhood context). However, running randomized experiments to test different aspects of neighbourhood features in varying contexts would be time consuming, unfeasible, expensive and potentially unethical (McCaffrey et al. 2004; Stuart 2010). Analysing observational data to estimate the causal effect of neighbourhood socioeconomic context on health avoids these issues and also allows the use of data that are more generalizable to the wider population.

We propose using a matching methods framework to examine migration as a quasi-experiment (Green et al. 2015). Because migrating individuals move from one neighbourhood socioeconomic context to another, accounting for differences in characteristics between migrants allows us to isolate the impact of neighbourhood socioeconomic context on health through accounting for any selection bias (Stuart 2010; McCaffrey et al. 2004; Johnson et al. 2008). Ignoring the issue of selection bias violates the assumptions of many regression based methods and is an issue often ignored in the neighbourhood effects literature (Ho et al. 2007; van Ham & Manley 2012; Oakes et al. 2015).

The aim of our study is to explore the association between neighbourhood socioeconomic context (as measured using house price data) and poor health among individuals migrating internally between different neighbourhood socioeconomic contexts using a matching methods framework of analysis.

Methodology

Data

Data were taken from the British Household Panel Survey (BHPS). The BHPS is a large (mean annual sample size 14,272) annual panel survey which ran between 1991 and 2008 before being incorporated into the survey 'Understanding Society'. We selected the BHPS because it contains both information on health and migration. The survey is also representative of Great Britain (and the UK from 2001). Special licence access was granted by the Economic and Social Data Service which provided data on the geographical location of individuals for each wave.

Our outcome variable was self-reported health status. Individuals were asked to rate their health using a Likert scale ('excellent', 'good', 'fair', 'poor', 'very poor'). We created a dichotomous variable indicating an individual's qualitative sense of whether they were in 'poor health,' which we coded as 1 when individuals reported that their health was "fair," "poor", or "very poor", and 0 when it was "good" or "excellent". The approach is based on common practice in previous research (Jylha 2009). Previous research has demonstrated that self-rated health is a useful predictor of actual health (Idler & Benyamini 1997; Jylha 2009) and it has been useful in previous neighbourhood effects research (Pickett & Pearl 2001; Riva et al. 2007).

Choice of covariates were limited to variables present at each wave, but were selected to account for characteristics strongly associated with health and which may account for differences in individuals' migration patterns. We included the following variables; age, sex, ethnicity (defined as 'Ethnic Minority' or not), highest level of education (categorised as 'No qualifications', 'Below degree level' and 'Degree, equivalent or higher'), and whether an individual smoked or not. Age, sex and ethnicity are non-modifiable personal characteristics which are associated to health status (Jylha 2009). Age displays a positive association with ill health, with older adults being more likely to report poor health. It is also strongly associated with migration (Morris et al. 2016). Females have greater likelihood of rating their health as poor. Ethnic minorities have also been associated with poorer health (Darlington-Pollock et al. 2016; Geronimus et al. 2014). Education reflects an individual's own socioeconomic status since higher education allows access to higher paid occupations (Green et al. 2014; Malmstrom et al. 1999). Finally, smoking displays one of the strongest behavioural associations to poor health (Shaw et al. 2000; Lawlor et al. 2003) and has been previously shown to contribute to selective migration patterns (Pearce & Dorling 2010). These variables have all been previously identified as important controls for understanding the association between neighbourhood socioeconomic context and poor self-rated health (Malmstrom et al. 1999).

Lower Super Output Areas (LSOAs) were chosen as the geographical scale for the analysis. LSOAs are administrative zones created to disseminate data, and were designed to have similar population sizes (approximately 1600) and be socially homogenous (Martin 2002). These factors make them useful for assessing the contribution of neighbourhood on health. We used 2001 LSOAs boundaries and kept their geographical boundaries fixed to their 2001 boundaries throughout the period of the BHPS so that our geographical scale remained constant to allow for fairer comparisons between years of our measure of neighbourhood socioeconomic context.

House price data from the land registry (1995-2008) was used as our measure of neighbourhood socioeconomic context. While using house price data to measure neighbourhood socioeconomic context is somewhat reductionist, few other data sources were available annually at small geographical zones for the period of the BHPS. House prices are a useful measure for socioeconomic context since house prices reflect both income and wealth within a neighbourhood, as well as a qualitative sense of neighbourhood desirability. Neighbourhood house price metrics have been demonstrated to be associated with self-rated health within cities (Moudon et al. 2012; Jiao et al. 2016). Less work has been undertaken to explore their usefulness at the national level. Median house price at each year was calculated for LSOAs (through linking postcodes of house prices to LSOA boundaries) and we then grouped LSOAs into quintiles within each year to allow us to make relative comparisons between years.

We restricted our analysis to data collected between 1995 and 2008 because this was the time period during which neighbourhood level data were available. Data for all years were converted from 'long' to 'wide' format. We set the first wave where an individual recorded that they had migrated since the previous wave as the baseline and followed individuals over time (i.e. baseline was coded as time point 0, with each subsequent year following migration a one unit increase). For individuals that moved multiple times in the survey, we took only their first migration and did not consider subsequent years of data following additional migrations (i.e. if an individual moved every two years during the survey then they only contribute two person years following their first migration in our analysis). 9225 individuals who were matched to geographical data migrated at any point in the BHPS (31.7%).

Statistical Analysis

The fundamental barrier to making causal inferences about human behaviour is that no true counterfactual can be observed (McCaffrey et al. 2013; Ho et al. 2007). In this case, we only observe individuals' actual neighbourhood moves and health, not what would have happened to their health if they migrated to a different neighbourhood socioeconomic context. Matching methods address the lack of a counterfactual observation by comparing individuals who are similar in their underlying propensity to move to various contexts, but are different in terms of their neighbourhood socioeconomic context (Stuart 2010; Green et al. 2015).

We matched individuals using a multinomial propensity score (Imbens 2000; Imai & van Dyk 2004; McCaffrey et al. 2013). Propensity score methods operate by fitting regression models predicting the selection process (in our case quintile of median house price for the neighbourhood individuals migrated to) across a series of covariates. The model can then be used to predict the probability (recorded as a weight) that an individual would migrate to a particular quintile of house price based on its observed covariates (Rosenbaum & Rubin 1983; McCaffrey et al. 2004). These weights can then be applied in subsequent analyses to balance observations and minimise their differences so that the main difference between observations is the factor of interest (in our case the quintile of median house price of the neighbourhood an individual migrated to). The result of any subsequent analysis is independent of the covariates used for matching individuals (Stuart 2010; Ho et al. 2007).

We use the approach set out in McCaffrey et al. (2014) who used generalised boosted models (GBMs) to fit the multinomial propensity score. GBM is an iterative machine learning approach which uses multiple regression trees to assess the similarities between categories in terms of their covariates. Dissimilarity between covariates was measured using the mean Kolmogorov-Smirnov statistic. We also use the average treatment effect (ATE) as our estimand which in the context of our study corresponds to the differences in mean values of covariates between each quintile of house price (Rosenbaum & Rubin 1983; Imai & van Dyk 2004; Ho et al. 2007).

We matched individuals on the median house price quintile of the neighbourhood they migrated to, predicted by age, sex, ethnicity, education, whether an individual smoked or not, and the quintile of median house price of the neighbourhood they migrated from. We also separately matched individuals on whether they reported that their health was poor at the time point prior to migration (including the other covariates) to reduce the impact of health selective migration. We present the two matching models separately to assess the impact of health selective migration. Matching was undertaken on characteristics of individuals in the year prior migration (i.e. 'pre-exposure' to the new neighbourhood type) which is necessary for defining a causal model (Imbens 2000; Stuart 2010).

Matching requires observations to be complete for each variable (McCaffrey et al. 2013). All cases with missing data were dropped from the regression analyses. Table 1 reports sample size in terms of year following migration. Sample size decreased by the number of years following migration partially due to attrition and individuals entering the panel at differing years. As we matched on covariates prior to migration, this also constrained our sample size. The degree of missing data reported in Table 1 should be regarded as a limitation of our study and may have introduced bias into our estimates.

Logistic regression was then used to examine how our predictor variable, the quintile of median house price of the neighbourhood an individual migrated to (i.e. socioeconomic context), is associated with our outcome variable (an individual's risk of poor health). We fit a separate logistic regression model for each time point separately because a single longitudinal model was a poor fit of the data. As such, our results examine whether health status at any year within a ten year period can be explained by the neighbourhood socioeconomic context an individual migrated to. The models were weighted using the weights created in the matching process. Since the matching process accounts for each of our covariates, there is no need to further control for their effects in our models (Ho et al. 2007), and sensitivity analyses showed that including them did not alter our findings. We also stratified our regression models by of median house price quintile of the origin neighbourhood, after removing this variable from the matching model, to explore whether our results varied between particular combinations of neighbourhood socioeconomic context for origin and destination.

All analyses were performed using statistical software R.

Results

Table 2 describes the characteristics of our analytical sample. Key differences between migrants and the entire BHPS sample included that migrants were younger and more likely to smoke. In terms of education, a smaller proportion of individuals with no qualifications migrated, and a larger proportion of individuals with secondary level of education did move. There was little difference by sex, ethnicity, the percentage with poor health and quintile of median house price in a neighbourhood. These differences are in line with past research into the characteristics of migrants (Morris et al. 2016).

Table 3 presents the number of individuals who were identified as having migrated at baseline by the quintile of neighbourhood median house price of the neighbourhood they originated from and the quintile they migrated to. The largest flow of migrants for each quintile was to a neighbourhood of the same quintile. The transfer within the same quintile was largest for quintile 5 (the areas with the lowest median house prices) with 57% of migrations at baseline remaining in the same quintile. The percentage of same quintile moves was also high (43%) for the most affluent areas (quintile 1). The next most common type of flow was to a quintile on either side of the origin quintile. This is most notable in quintile 3 (i.e. the areas in the middle of the distribution for median house price), where 46% of migrations were to either quintile 2 or 4. There were few individuals who migrated between the extremes (i.e. from quintile 1 to 5 or vice versa).

Table 4a presents the results from the first model matching on all covariates other than health status prior to migration. Overall, there are few significant associations found across each model. There was some evidence of the negative impact of neighbourhood socioeconomic context on health. In the first wave of data collected after an individual migrated (equivalent to 0 years following migration, since migration was recorded as being in-between waves), individuals who had moved to areas with the lowest median house prices (i.e. were in quintile 5) were 31% more likely to be in poor health (Odds Ratio (OR) = 1.310, 95% Confidence Intervals (CIs) = 1.062-1.614) than compared to those who moved to areas with the highest median house prices (quintile 1). Three years following migration, individuals who had migrated to the poorest areas (quintile 5) at baseline were 29.7% more likely to report that their health was poor (OR = 1.297, 95% CIs = 1.074-1.610) compared to those who migrated to the most affluent areas (quintile 1). In between 0 and 3 years following migration, positive associations for quintile 5 were also detected but these associations were not significant (1 year following migration: OR = 1.200, 95% CIs = 0.959-1.509), 2 years following migration: OR = 1.160, 95% CIs = 0.917-1.470). We also found that individuals who migrated to the middle quintile of areas (quintile 3) at baseline were 31.5% more likely to report poor health (OR = 1.315, 95% CIs = 1.074-1.610) than compared to individuals migrating to the most affluent areas (quintile 1). No other associations were statistically significant.

Table 4b shows results from the same analysis presented in Table 4a but with individuals additionally matched based on their health status prior to migration. We included the variable to test whether the associations found in Table 4a were consistent following accounting for potential health selective migration. Associations between low neighbourhood socioeconomic status and subsequent poor health were statistically non-significant after we added baseline health status to our matching model. The association for individuals who migrated to the middle quintile of areas (quintile three) compared to the most affluent areas to health three years following migration has not only remained statistically significant but its effect size has increased to 1.54 (albeit the confidence intervals (1.083-2.191) overlap the previous estimate).

We also stratified our analyses by the quintile of median house price for the neighbourhood of origin to explore whether the effects varied by combination of origin and destination neighbourhood socioeconomic context. The results were mainly insignificant with wide confidence intervals. This was in part due to small sample sizes between each combination of neighbourhood contexts, which was compounded by the decreasing sample size over time (see Table 3). Given their high uncertainty we chose not to report them.

Discussion

Our study presents an approach to exploring the role of neighbourhood socioeconomic context on health. We find little evidence for any association between quintile of median neighbourhood house price and health at least up to 10 years following migration following the inclusion of an individual's health status prior to migration. While we do detect a single sole association even after accounting for health selective migration, and the direction of the association is in the expected direction, we posit that the association may be spurious. The strengths of our study lie in its study design and use of fine scale longitudinal data.

The lack of evidence of neighbourhood socioeconomic contextual effects following controlling for health status prior to migration suggests that health selective migration is an important phenomena that may help to explain findings from previous studies that have examined the role of neighbourhood effects. It indicates that geographical inequalities may be explained by the sorting of unhealthy and healthy individuals into poorer and affluent areas respectively. Our results support the analyses of Norman et al. (2005) and Norman and Boyle (2014) who showed that the process of health selected migration exaggerated the relationship between neighbourhood socioeconomic context and health. We build on their work through using a single year time points compared to ten-year periods, demonstrating that process occurs in the short term to support their longer term findings. Brimblecombe and colleagues also claimed that selective migration over the life course accounted for all geographical inequalities in mortality in Britain at a spatial scale larger than ours (Brimblecombe et al. 1999), although they subsequently found that the process was influenced by early life (social) conditions (Brimblecombe et al. 2000). Similar observations of the importance of health selective migration have also been made in Canada, New

Zealand and the US (Smith et al. 2016; Pearce & Dorling 2010; Darlington-Pollock et al. 2016; Arcaya et al. 2016a; although see Geronimus et al. 2014).

There are several mechanisms that help explain the sorting process of individuals of poor health migrating to deprived neighbourhoods. Housing costs (i.e. house prices, rental prices, or the stock of affordable housing options in less deprived areas) have been shown to be an important factor in understanding the sorting process (Baker et al. 2016) and was the mechanism targeted in the MTO study to tackle socioeconomic inequalities (Sampson 2012). Individuals of low socioeconomic status will be limited in the neighbourhoods they can afford to live in as result hence becoming sorted into deprived neighbourhoods. With individuals of low socioeconomic status also more likely to have poorer health (Malmstrom et al. 1999; Geronimus et al. 2014), health selective migration reflects the process of sorting by socioeconomic status rather than health. It is also plausible that as individuals become ill, they experience a loss of income if they cannot work and may begin to drift to areas with lower house prices. Boyle et al. (2002) also demonstrate that individuals who migrate to social housing (which are typically located in deprived neighbourhoods) are more likely to be of poor health, partly because disabled people received priority for social housing.

The sorting process is also influenced by migration patterns taking place in the opposite direction. One of the dominant migratory process is of younger (and hence healthier) migrants moving to less deprived areas (Norman et al. 2005). If younger and healthier migrants are moving to more affluent areas, then it may sift the population structure of deprived areas towards unhealthier populations. The interacting process of poorer individuals drifting to poorer neighbourhoods, combined with younger and healthier populations migrating to less deprived neighbourhoods, will exaggerate the relationship between health and neighbourhood socioeconomic context (Norman & Boyle 2014). It may also contribute to mechanisms such as house prices (and affordability), where less deprived areas become more desirable and house prices increase (and vice versa) (Baker et al. 2016). The poor are not also just drifting to the poorest areas, but are also most likely to migrate within the same quintile (see Table 3) suggesting that they are less upwardly mobile.

The decision for migration may also help to explain patterns. Difficult life events (e.g. divorce, unemployment, housing eviction) have been shown to influence an individual's propensity to migrate and may offer some explanation for selective migration effects given their independent association to mental health (Tunstall et al. 2015). Migration types that are associated with negative reasons are more stressful (Morris et al. 2016), and stress has an established biological pathway to impacting health. Reason for migration helps to explain why short distance moves are more strongly associated to poorer health outcomes than longer moves, because even though longer moves are more disruptive they are more likely to be due to positive reasons (e.g. new jobs) (Boyle et al. 2002).

So does this put the knife in the neighbourhood effects literature? Not exactly. What we call for is greater consideration of study design when analysing similar research questions with observational data. Multi-level modelling revolutionised the field of health geography for understanding the role of neighbourhood context on health (Mitchell 2001). These approaches are still important and have led to a great deal of discovery (Riva et al. 2007; Pickett & Pearl 2001; van Ham & Manley 2012; Arcaya et al. 2016a; Oakes et al. 2015; Schüle & Bolte 2015). However, we need to be thinking through how best to identify causal effects if we are to progress our understanding. Identifying causal mechanisms is necessary to be able to design effective policies. Our study therefore forms part of a small but growing literature trying to understand new methodological applications for teasing out causal effects within health geography (van Ham et al. 2012).

Our approach builds on a larger and more established literature across social epidemiology applying propensity score matching to understand (and control for) selection bias (Oakes et al. 2015; Mansson et al. 2007; Walsh et al. 2012). We add to these previous approaches through using a multinomial approach rather than dichotomising neighbourhood socioeconomic context into a binary measure which may oversimplify its role. Our results also support similar epidemiological evidence demonstrating how useful matching is to reduce the effects of selection bias which can otherwise exaggerate the importance of socioeconomic context (Johnson et al. 2008).

It is plausible that the drive to identify neighbourhood effects is an elusive question to be chasing. Both our approach and other similar techniques such as multi-level modelling seek to control for the role of individual-level factors to separate out neighbourhood effects. But can we really separate out these two factors? They are often not mutually exclusive; social and spatial process typically operate together (Mitchell 2001). For example, while we account for educational attainment in the matching process, we also ignore the fact that geography plays an important role in determining the educational opportunities afforded to individuals (Rees et al. 2007). There are also wider issues of what constitutes neighbourhoods (Kwan 2012), the scales that they operate at (Flowerdew et al. 2008) and how they relate to varying outcomes over time (Musterd et al. 2012). Identifying the contribution of neighbourhoods and geography to understanding health is difficult at best.

Even if neighbourhoods and geography did not matter, this does not rule out their usefulness particularly within a policy setting (van Ham & Manley 2012). Individuals reside in neighbourhoods, and it is these neighbourhoods that display distinct geographical patterns. Neighbourhoods are our 'lens' through which we view the world. It will always be useful to consider neighbourhoods particularly when targeting policies. Indeed it can often be easier to implement some interventions aimed at improving individual health through targeting specific areas than compared to targeting individuals (Dummer 2008). However, we do not live in a social vacuum independent from our local surroundings and so it is unlikely that geography does not imprint on our lives to some degree.

There are several limitations to our study. Our measure of health status is self-reported and therefore may be subject to bias. Replicating our study using objective measures will be important for future research. It will also be important to expand on the number of outcomes measured, particularly as the role of selective migration has been shown to differ between general and mental health outcomes (Tunstall et al. 2014). Our study uses data on migrants to focus on the role of neighbourhood and reduce other confounding factors, however the approach may be less generalizable to the wider population (e.g. see Table 2). Missing data was also an issue and particularly attrition as it has been previously shown that individuals who migrate have increased probability of exiting panel surveys like the BHPS (Uhrig 2008). While we account for health status prior to migration, there was some moderate correlation between health status at baseline and at each time point. Future research should build on our approach to address these issues and understand how it may bias our estimates of neighbourhood socioeconomic context or health selective migration.

We only consider the impacts on health up to 10 years following migration. It may be that 10 years is too short to detect the influence of neighbourhood socioeconomic context. Many chronic health conditions develop over longer periods and so our analyses may be inadequate to detect such processes. Neighbourhood stressors are unlikely to have a sudden impact on health, rather their adverse effects are more likely to accumulate over longer time periods with most theories assuming medium- to long-term exposures before health effects materialise (Geronimus et al. 2014; van Ham & Manley 2012; Musterd et al. 2012). Understanding the timings, durations and thresholds for how different neighbourhood characteristics impact on health throughout the entire life course is required to evaluate their relative contributions. Residential mobility will be important in these life course analyses given that individuals migrate between multiple different neighbourhood contexts (Norman et al. 2005; Morris et al. 2016). While we do not find any evidence for neighbourhood effects in particular combinations of migrations between differing socioeconomic contexts, we feel that exploring this feature with larger data sets would be an important opportunity for future research.

Using only house price data as a proxy measure to examine neighbourhood socioeconomic context is reductionist. While neighbourhood house price is a valid measure since house prices reflect the wealth and income of residents, as well as neighbourhood desirability, it only represents one aspect of neighbourhood socioeconomic context. As such, it avoids the inherent complexities of how neighbourhood effects (and migration) may influence health by ignoring other mechanisms such as access to unhealthy foods (Smith et al. 2016) or level of social capital (Pearce & Davey Smith 2003; Uphoff et al. 2013). The decision was born out data availability issues since there are few other annual neighbourhood data sources. We also ignore how individual-level factors may mediate or moderate neighbourhood effects. For example, adolescents with 'resilient personalities' can buffer negative neighbourhood effects through building capacity to cope with neighbourhood stressors (Nieuwenhuis et al. 2015). The simplicity of our approach for measuring neighbourhood socioeconomic context requires improving to develop our analytical approach in future research (van Ham & Manley 2012), and it may be that our approach requires combining with methods such as Structural Equation Modelling to be able to tackle such complexities of neighbourhood socioeconomic context.

Similarly, the simplicity in our measure of neighbourhood socioeconomic context is problematic through using a single administrative geographical zone (LSOAs) for identifying 'neighbourhoods'. While the geographical identifiers were the smallest scale made accessible for the data, it is unlikely that LSOAs reflect the *lived* contextual experiences of neighbourhoods since they were designed for data dissemination (Martin 2002). The spatial uncertainty in the contextual influence of neighbourhoods, and how this varies temporally, is termed the 'uncertain geographic context problem (UGCoP)' (Kwan 2012). The spatial delineation of the geographic boundaries may restrict our ability to make accurate inferences about neighbourhood effects. The complexity of the issue is compounded since residents of the same 'neighbourhood' may be subject to different contextual exposures (Kwan 2012; van Ham & Manley 2012). Contextual exposures may operate at varying scales or geographical extents. Future research will need to combine UGCoP issues, with the previous criticism of accounting for the complex nature of socioeconomic context, to accurate identify the role of neighbourhoods. Utilising residential mobility within our approach could be a useful means for assessing both UGCoP and the role of additional mechanisms which capture neighbourhood socioeconomic context.

In conclusion, we present findings from an alternative approach for estimating the causal role of neighbourhoods for understanding whether it influences an individual's health. Our findings suggest that social inequalities in health status may be explained by the health status prior to migration indicative of health selective migration. Given that the vast evidence that demonstrates the importance of neighbourhood socioeconomic context often does not account for selective migration it is possible that the evidence base is slightly misleading. While our study does not rule out the contribution of neighbourhood-level factors towards health, we hope that it can be a useful approach for exploring how geography influences health.

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Tables

Table 1: Sample size by number of years in relation to migration.

Year in relation to move	Total data	*N* in regression (model 1)	*N* in regression (model 2)
-1	7515		
0	9225	4914	4908
1	7807	4272	4267
2	6907	3833	3830
3	6080	3399	3396
4	5343	3034	3031
5	4649	2723	2721
6	3974	2399	2397
7	3325	2040	2038
8	2779	1683	1682
9	2205	1300	1300
10	1820	1008	1008

Table 2: Analytical sample characteristics of the BHPS and at baseline for migrants.

	Average throughout BHPS	Baseline characteristics of migrants	Missing data (%) at baseline (migrants)	Sample size of complete records (migrants)
Age (mean)	45.5	36.1	0.01	7514
Male (%)	46.0	46.0	0.31	7492
Ethnic Minority (%)	2.7	2.8	8.58	6870
Education (%)			1.98	7366
No qualifications	23.3	16.3		
Secondary Level	39.3	47.2		
Degree or higher	37.4	36.5		
Smoker (%)	26.5	31.8	0.65	7466
Poor health (%)	32.4	30.6	0.31	7492
House price quintile* (%)			7.54	6948
1 (highest)	15.7	15.6		
2	17.7	18.4		
3	20.5	20.2		
4	21.9	22.8		
5 (lowest)	24.1	22.9		

* Destination for movers

Table 3: Origin and destination of migrants by quintile of neighbourhood house price.

		Origin (quintile)				
		1	2	3	4	5
Destination (quintile)	1	339	221	146	73	32
	2	219	336	241	128	84
	3	126	219	311	274	146
	4	78	111	255	453	361
	5	21	53	108	253	814

Table 4: Results from a series of logistic regression models (undertaken separately by year since migration) predicting whether an individual's health status was poor by the neighbourhood socioeconomic context of the destination of their migration (quintile 1, which is the highest median house price quintile, is the reference category for each model).

(a) Matching without health status					**(b) Matching including health status**				
Model	**Odds Ratio**	**95% Confidence Intervals**		***p*-value**	**Model**	**Odds Ratio**	**95% Confidence Intervals**		***p*-value**
0 years since migration					*0 years since migration*				
Quintile 2	1.091	0.897	1.325	0.383	Quintile 2	1.154	0.821	1.622	0.408
Quintile 3	1.135	0.943	1.367	0.182	Quintile 3	1.186	0.859	1.638	0.300
Quintile 4	1.072	0.893	1.287	0.458	Quintile 4	1.086	0.788	1.497	0.613
Quintile 5	1.310	1.062	1.614	0.012	Quintile 5	1.253	0.883	1.776	0.206
1 years since migration					*1 years since migration*				
Quintile 2	0.995	0.808	1.226	0.961	Quintile 2	0.970	0.677	1.389	0.867
Quintile 3	1.001	0.822	1.220	0.989	Quintile 3	0.954	0.680	1.340	0.787
Quintile 4	1.012	0.832	1.230	0.907	Quintile 4	0.981	0.699	1.377	0.913
Quintile 5	1.200	0.959	1.501	0.111	Quintile 5	1.088	0.754	1.571	0.651
2 years since migration					*2 years since migration*				
Quintile 2	0.886	0.716	1.097	0.268	Quintile 2	0.807	0.558	1.167	0.254
Quintile 3	1.062	0.868	1.298	0.560	Quintile 3	1.054	0.747	1.488	0.765
Quintile 4	0.928	0.760	1.134	0.466	Quintile 4	0.867	0.612	1.228	0.422
Quintile 5	1.161	0.917	1.470	0.214	Quintile 5	1.083	0.744	1.576	0.678
3 years since migration					*3 years since migration*				
Quintile 2	1.044	0.841	1.296	0.697	Quintile 2	1.089	0.745	1.591	0.660
Quintile 3	1.315	1.074	1.610	0.008	Quintile 3	1.540	1.083	2.191	0.016
Quintile 4	1.166	0.951	1.429	0.140	Quintile 4	1.293	0.903	1.852	0.160
Quintile 5	1.297	1.023	1.645	0.032	Quintile 5	1.335	0.905	1.971	0.146
4 years since migration					*4 years since migration*				
Quintile 2	1.134	0.892	1.441	0.305	Quintile 2	1.265	0.826	1.939	0.280
Quintile 3	1.111	0.886	1.393	0.362	Quintile 3	1.154	0.771	1.728	0.487
Quintile 4	1.127	0.898	1.414	0.301	Quintile 4	1.201	0.800	1.802	0.376
Quintile 5	1.189	0.924	1.530	0.178	Quintile 5	1.159	0.756	1.776	0.498
5 years since migration					*5 years since migration*				
Quintile 2	1.039	0.809	1.334	0.765	Quintile 2	1.130	0.730	1.748	0.583
Quintile 3	1.024	0.806	1.301	0.845	Quintile 3	1.052	0.692	1.598	0.813
Quintile 4	1.021	0.806	1.294	0.864	Quintile 4	1.063	0.699	1.616	0.774
Quintile 5	1.095	0.843	1.422	0.499	Quintile 5	1.060	0.686	1.638	0.792
6 years since migration					*6 years since migration*				
Quintile 2	1.075	0.830	1.392	0.583	Quintile 2	1.162	0.740	1.825	0.515
Quintile 3	1.057	0.827	1.350	0.660	Quintile 3	1.079	0.703	1.657	0.727
Quintile 4	1.146	0.898	1.462	0.275	Quintile 4	1.265	0.822	1.946	0.285
Quintile 5	1.250	0.944	1.656	0.119	Quintile 5	1.373	0.863	2.185	0.181

7 years since migration					*7 years since migration*			
Quintile 2	1.074	0.810	1.423	0.621	Quintile 2	1.156	0.708	1.885	0.562
Quintile 3	1.041	0.797	1.361	0.768	Quintile 3	1.026	0.643	1.638	0.914
Quintile 4	1.084	0.827	1.420	0.560	Quintile 4	1.141	0.711	1.832	0.584
Quintile 5	1.090	0.797	1.491	0.590	Quintile 5	1.028	0.614	1.718	0.917
8 years since migration					*8 years since migration*				
Quintile 2	0.865	0.633	1.181	0.361	Quintile 2	0.795	0.459	1.375	0.412
Quintile 3	1.153	0.861	1.544	0.339	Quintile 3	1.217	0.737	2.009	0.443
Quintile 4	0.989	0.737	1.328	0.942	Quintile 4	0.917	0.552	1.525	0.739
Quintile 5	1.180	0.841	1.657	0.338	Quintile 5	1.213	0.692	2.127	0.500
9 years since migration					*9 years since migration*				
Quintile 2	0.771	0.547	1.088	0.139	Quintile 2	0.666	0.364	1.218	0.187
Quintile 3	1.177	0.853	1.624	0.322	Quintile 3	1.254	0.725	2.169	0.418
Quintile 4	1.010	0.728	1.403	0.950	Quintile 4	0.998	0.568	1.754	0.994
Quintile 5	1.012	0.678	1.510	0.955	Quintile 5	0.910	0.480	1.724	0.773
10 years since migration					*10 years since migration*				
Quintile 2	0.795	0.555	1.140	0.213	Quintile 2	0.748	0.399	1.401	0.364
Quintile 3	1.168	0.829	1.645	0.375	Quintile 3	1.304	0.732	2.324	0.368
Quintile 4	1.033	0.732	1.457	0.855	Quintile 4	1.038	0.579	1.862	0.900
Quintile 5	0.899	0.603	1.338	0.599	Quintile 5	0.827	0.433	1.580	0.565