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There is long-standing evidence for the existence of geographical inequalities in health. Multiple conceptual frameworks have been proposed to explain why such patterns persist. The methodological design for these studies is often not appropriate for identifying causal effects of neighborhood context, however. It is possible that findings that show the importance of neighborhoods could be subject to confounding of individual-level factors, neighborhood sorting effects (i.e., health-selective migration), or both. We present an approach to investigating neighborhood-level factors that 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 as our measure of neighborhood 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 ten years following migration). Initially, we found some evidence that poorer neighborhoods were associated with an increased risk of poor health. Following controlling for an individual's health status prior to migration, the influence of neighborhood socioeconomic context was statistically nonsignificant. Our findings suggest that health-selective migration might help to explain the association between neighborhood-level factors and individual-level health. Our study design appears useful for both identifying causal effects of neighborhoods and accounting for health-selective migration. *Key Words: health, longitudinal, matching, migration, neighborhood.*

已有长期的证据, 证明健康存在着地理不均。至今已提出众多的概念架构, 用来解释此般模式为何仍持续存在。但这些研究的方法设计, 却经常不适用于指认邻里脉络的因果效应。显示出邻里重要性的研究发现, 有可能会受到混淆个人层级因素与邻里归类效应 (例如在健康上进行筛选的移民) 之影响, 抑或同时受到两者影响。我们提出对因果效益提供更强健的检视之探讨邻里层级因素的方法, 并应对混淆和归类的问题。我们运用英国家户面板调查 (1995 年至 2008 年) 的个人层级数据。我们根据个人的较低超级产出区域的中位数房价, 将个人分成五个群体, 作为我们对邻里社经脉络的评量。我们运用多变量倾向评分来配对个人, 以控制混淆因素, 并运用罗吉特迴归模型, 评估移民目的地和健康不佳的风险之间的关联性 (截至移民后的十年)。我们最初发现若干证据, 证明较穷困的邻里, 与增加的健康不佳风险相关。在控制移民前的个人健康状态之后, 邻里的社经脉络之影响在统计上并不显着。我们的发现主张, 在健康上进行筛选的移民或许有助于解释邻里层级因素和个人层级健康之间的关联性。我们的研究设计, 同时对于指认邻里的因果效应和考量在健康上进行筛选的移民皆有所助益。 *关键词: 健康, 纵向, 配对, 移民, 邻里。*

Hay evidencia de vieja data de la existencia de desigualdades geográficas en salud. Se han propuesto múltiples marcos conceptuales para tratar de explicar por qué persisten tales patrones. Sin embargo, el diseño metodológico de estos estudios con frecuencia no es apropiado para identificar los efectos causales del contexto vecinal. Es posible que los hallazgos que muestran la importancia de los vecindarios podrían estar sujetos a confusión de los factores de nivel individual, la clasificación vecinal de los efectos (*i.e.*, la migración selectiva por salud), o ambos. Presentamos un enfoque para investigar los factores de nivel vecinal que provee un examen más fuerte de los efectos causales, al tiempo que enfrenta problemas de confusión y clasificación. Utilizamos datos a nivel individual de la Encuesta del Panel Británico de Hogares (1995–2008). Los individuos se agruparon en quintiles basados en la media del precio de la vivienda del área de salida de capa más baja de un individuo, como nuestra medida del contexto

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socioeconómico vecinal. Los puntajes de propensión multivariada se usaron para emparejar los individuos con el fin de ejercer control de los factores de confusión, y se usaron modelos de regresión logística para calcular la asociación entre el destino de la migración y el riesgo de mala salud (hasta por los siguientes diez años de la migración). Inicialmente hallamos alguna evidencia de que los vecindarios más pobres estaban asociados con un incremento en el riesgo de mala salud. Siguiendo al control hecho sobre el estatus de la salud de un individuo antes de la migración, la influencia del contexto socioeconómico vecinal resultó ser estadísticamente no significativa. Nuestros descubrimientos sugieren que la migración selectiva por salud podría ayudar a explicar la asociación entre los factores a nivel de vecindario y la salud a nivel de individuo. El diseño de nuestro estudio parece útil para identificar los efectos causales de los vecindarios y para tomar en cuenta la migración selectiva por salud. *Palabras clave: salud, longitudinal, emparejamiento, migración, vecindario.*

The existence of health inequalities between poor and affluent neighborhoods is well documented. For example, there is an estimated gap of nine and seven years in life expectancy at birth for males and females, respectively, between neighborhoods in the most versus least deprived deciles in England (Office for National Statistics 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 multilevel modeling helped researchers attempt to separate out these two factors, consistently finding support for contextual explanations suggesting that the social environment mattered (Mitchell 2001; Riva, Gauvin, and Barnett 2007). Multiple processes and mechanisms have been proposed to explain the role of neighborhood socioeconomic context for health, including living in stressful environments (Kaplan et al. 2013; Nieuwenhuis, Hooimeijer, and Meeus 2015), a lack of social capital or cohesion (N. Pearce and 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 neighborhoods:

1. *Neighborhoods influence health*. A vast amount of evidence, which appears consistent across outcomes, methods, and contexts, would support this explanation (Pickett and Pearl 2001; Riva, Gauvin, and Barnett 2007; Oakes et al. 2015; Schüle and Bolte 2015; Arcaya, Tucker-Seeley, et al. 2016).
2. *Neighborhood effects reflect individual-level confounders*. Where neighborhood effects are detected, they might merely represent unknown, unmeasured social characteristics of individuals that are merely correlated with measures of neighborhood socioeconomic context. This is commonly referred to as the compositional explanation for neighborhood effects. If the design of the study does not fully account for such confounding factors, results that suggest the importance of neighborhood socioeconomic context might be misleading (Westfall and Yarkoni 2016). To analyze neighborhood effects, researchers might have been relying on only observational data that might not capture or poorly measure the true construct of interest. A large proportion of the evidence base also draws on cross-sectional data, which cannot be used to identify causal effects because 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 neighborhoods on health (Oakes et al. 2015; Morris, Manley, and Sabel 2016).
3. *Individuals with poor health become sorted into deprived neighborhoods*. Migration patterns are important for understanding the population structure of an area because the characteristics of migrants are different from those of nonmigrants. 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., neighborhood satisfaction, moving up the "housing ladder") each influence the propensity for individuals to migrate (Morris, Manley, and Sabel 2016). Migration will therefore affect the population structure of both the origin and destination of movement patterns (Norman, Boyle, and Rees 2005). If migrants differ from nonmigrants 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 neighborhoods. For example, the most mobile population groups are the young, and because they tend to also be healthy, high inmigration of such individuals will make an area seem healthier than it actually is. Previous research suggests that migratory patterns might exaggerate the relationship between neighborhood socioeconomic context and health (Brimblecombe, Dorling, and Shaw 1999, 2000; Norman and Boyle 2014; although see Geronimus, Bound, and Ro 2014). The systematic sorting of individuals with poor health into poorer neighborhoods is termed *health-selective migration* (Brimblecombe, Dorling, and Shaw 1999; Green et al. 2015; Arcaya, Graif, et al. 2016).

Our article 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 U.S. 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 (vs. 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 randomized 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 and Brooks-Gunn 2003; Kling, Liebman, and Katz 2007; Ludwig et al. 2011). The MTO study provides some of the strongest evidence of the causal effects of neighborhood socioeconomic context (Sampson 2012; Oakes et al. 2015) and has also been used to show the role of health sorting into neighborhoods (Arcaya, Graif, et al. 2016). The MTO demonstrates the usefulness of testing for neighborhood effects through experimental designs involving migration (i.e., individuals changing their neighborhood context). Running randomized experiments to test different aspects of neighborhood features in varying contexts would be time consuming, unfeasible, expensive, and potentially unethical, however (Stuart 2010; McCaffrey, Ridgeway, and Morral 2014). Analyzing observational data to estimate the causal effect of neighborhood 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 neighborhood socioeconomic context to another, accounting for differences in characteristics between migrants allows us to isolate the impact of neighborhood socioeconomic context on health through accounting for any selection bias (Johnson, Oakes, and Anderton 2008; Stuart 2010; McCaffrey, Ridgeway, and Morral 2014). Ignoring the issue of selection bias violates the assumptions of many regression-based methods and is an issue often ignored in the neighborhood effects literature (Ho et al. 2007; van Ham and Manley 2012; Oakes et al. 2015).

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

Method

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 that ran between 1991 and 2008 before being incorporated into the survey "Understanding Society." We selected the BHPS because it contains information on both health and migration. The survey is also representative of Great Britain (and the UK from 2001). Special license 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 he or she was 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 and Benyamini 1997; Jylha 2009) and it has been useful in previous neighborhood effects research (Pickett and Pearl 2001; Riva, Gauvin, and Barnett 2007).

Choice of covariates was limited to variables present at each wave, but covariates were selected to account for characteristics strongly associated with health and that could 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 (categorized as no qualifications, below degree level, and degree, equivalent or higher), and whether an individual smoked or not. Age, sex, and ethnicity are nonmodifiable personal characteristics that are associated with 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, Manley, and Sabel 2016). Females have a greater likelihood of rating their health as poor. Ethnic minorities have also been associated with poorer health (Geronimus, Bound, and Ro 2014; Darlington-Pollock et al. 2016). Education reflects an individual's own socioeconomic status because higher education allows access to higher paid occupations (Malmstrom, Sundquist, and Johansson 1999; Green et al. 2014). Finally, smoking displays one of the strongest behavioral associations to poor health (Shaw, Mitchell, and Dorling 2000; Lawlor et al. 2003) and has been previously shown to contribute to selective migration patterns (J. R. Pearce and Dorling 2010). These variables have all been previously identified as important controls for understanding the association between neighborhood socioeconomic context and poor self-rated health (Malmstrom, Sundquist, and Johansson 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 1,600) and be socially homogenous (Martin 2002). These factors make them useful for assessing the contribution of neighborhood to health. We used 2001 LSOA 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 neighborhood socioeconomic context.

House price data from the land registry (1995–2008) were used as our measure of neighborhood socioeconomic context. Although using house price data to measure neighborhood 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 because house prices reflect both income and wealth within a neighborhood, as well as a qualitative sense of neighborhood desirability. Neighborhood 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 neighborhood-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 he or she 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 who 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, he or she only contributes two person years following his or her first migration in our analysis). A total of 9,225 individuals who were matched to geographical data migrated at any point in the BHPS (31.7 percent).

Statistical Analysis

The fundamental barrier to making causal inferences about human behavior is that no true counterfactual can be observed (Ho et al. 2007; McCaffrey et al. 2013). In this case, we only observe individuals' actual neighborhood moves and health, not what would have happened to their health if they migrated to a different neighborhood 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 neighborhood socioeconomic context (Stuart 2010; Green et al. 2015).

We matched individuals using a multinomial propensity score (Imbens 2000; Imai and 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 neighborhood 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 and Rubin 1983; McCaffrey, Ridgeway, and Morral 2014). These weights can then be applied in subsequent analyses to balance observations and minimize 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 neighborhood an individual migrated to). The result of any subsequent analysis is independent of the covariates used for matching individuals (Ho et al. 2007; Stuart 2010).

We use the approach set out in McCaffrey et al. (2014), who used generalized boosted models (GBMs) to fit the multinomial propensity score. GBM is an iterative machine learning approach that 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 and Rubin 1983; Imai and van Dyk 2004; Ho et al. 2007).

We matched individuals on the median house price quintile of the neighborhood to which they migrated, predicted by age, sex, ethnicity, education, whether an individual smoked or not, and the quintile of median house price of the neighborhood from which they migrated. 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 to migration (i.e., "pre-exposure" to the new neighborhood 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 years 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 might 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 neighborhood to which an individual migrated (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 neighborhood socioeconomic context to which an individual migrated. The models were weighted using the weights created in the matching process. Because 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 median house price quintile of the origin neighborhood, after removing this variable from the matching model, to explore whether our results varied between particular combinations of neighborhood socioeconomic context for origin and destination.

All analyses were performed using the statistical software R (R Core Team 2016).

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	7,515		
0	9,225	4,914	4,908
1	7,807	4,272	4,267
2	6,907	3,833	3,830
3	6,080	3,399	3,396
4	5,343	3,034	3,031
5	4,649	2,723	2,721
6	3,974	2,399	2,397
7	3,325	2,040	2,038
8	2,779	1,683	1,682
9	2,205	1,300	1,300
10	1,820	1,008	1,008

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 a 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 neighborhood. These differences are in line with past research into the characteristics of migrants (Morris, Manley, and Sabel 2016).

Table 3 presents the number of individuals who were identified as having migrated at baseline by the quintile of neighborhood median house price of the neighborhood from which they originated and the quintile to which they migrated. The largest flow of migrants for each quintile was to a neighborhood 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 percent of migrations at baseline remaining in the same quintile. The percentage of same-quintile moves was also high (43 percent) 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 percent 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 3. Origin and destination of migrants by quintile of neighborhood 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 includes 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 neighborhood socioeconomic context on health. In the first wave of data collected after an individual migrated (equivalent to zero years following migration, as 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 percent more likely to be in poor health (odds ratio [OR] = 1.310, 95 percent confidence interval [CI], [1.062, 1.614]) than compared to those who moved to areas with the highest median house prices (Quintile 1). Three years

Table 2. Analytical sample characteristics of the British Household Panel Survey and at baseline for migrants

	Average throughout BHPS	Baseline characteristics of migrants	Missing data (%) at baseline (migrants)	Sample size of complete records (migrants)
Age (M)	45.5	36.1	0.01	7,514
Male (%)	46.0	46.0	0.31	7,492
Ethnic minority (%)	2.7	2.8	8.58	6,870
Education (%)			1.98	7,366
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	7,466
Poor health (%)	32.4	30.6	0.31	7,492
House price quintile[a] (%)			7.54	6,948
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		

[a]Destination for movers.

following migration, individuals who had migrated to the poorest areas (Quintile 5) at baseline were 29.7 percent more likely to report that their health was poor (OR = 1.297, 95 percent CI, [1.074, 1.610]) compared to those who migrated to the most affluent areas (Quintile 1). In between zero and three years following migration, positive associations for Quintile 5 were also detected, but these associations were not significant (one year following migration: OR = 1.200, 95 percent CI, [0.959, 1.509]; two years following migration: OR = 1.160, 95 percent CI, [0.917, 1.470]). We also found that individuals who migrated to the middle quintile of areas (Quintile 3) at baseline were 31.5 percent more likely to report poor health (OR = 1.315, 95 percent CI, [1.074, 1.610]) than individuals migrating to the most affluent areas (Quintile 1). No other associations were statistically significant.

Table 4 also shows results from the same analysis presented earlier 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 4 were consistent following accounting for potential health selective migration. Associations between low neighborhood socioeconomic status and subsequent poor health were statistically nonsignificant after we added baseline health status to our matching model. The association for individuals who migrated to the middle quintile of areas (Quintile 3) compared to the most affluent areas to health three years following migration not only remained statistically significant, but its effect size increased to 1.54 (albeit the CI, [1.083, 2.191], overlap the previous estimate).

We also stratified our analyses by the quintile of median house price for the neighborhood of origin to explore whether the effects varied by combination of origin and destination neighborhood socioeconomic context. The results were mainly insignificant with wide CIs. This was in part due to small sample sizes between each combination of neighborhood 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 neighborhood socioeconomic context on health. We found little evidence for any association between quintile of median neighborhood house price and health at least up to ten years following migration following the inclusion of an individual's health status prior to migration. Although we did 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 might be spurious. The strengths of our study lie in its study design and use of fine-scale longitudinal data.

The lack of evidence of neighborhood socioeconomic contextual effects following controlling for health status prior to migration suggests that health-selective migration is an important phenomenon that might help to explain findings from previous studies that have examined the role of neighborhood effects. It indicates that geographical inequalities could be explained by the sorting of unhealthy and healthy individuals into poorer and affluent areas, respectively. Our results support the analyses of Norman, Boyle, and Rees (2005) and Norman and Boyle (2014), who showed that the process of health-selective migration exaggerated the relationship between neighborhood socioeconomic context and health. We build on their work through using single-year time points compared to ten-year periods, demonstrating that this 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, Dorling, and Shaw 1999), although they subsequently found that the process was influenced by early life (social) conditions (Brimblecombe, Dorling, and Shaw 2000). Similar observations of the importance of health-selective migration have also been made in Canada, New Zealand, and the United States (J. R. Pearce and Dorling 2010; Arcaya, Tucker-Seeley, et al. 2016; Darlington-Pollock et al. 2016; Smith et al. 2016; although see Geronimus, Bound, and Ro 2014).

There are several mechanisms that help explain the sorting process of individuals of poor health migrating to deprived neighborhoods. 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 neighborhoods they can afford to live in as result, hence becoming sorted into deprived neighborhoods. With individuals

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 neighborhood socioeconomic context of the destination of their migrations

Matching without health status					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 year since migration					1 year 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

(*Continued on next page*)

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 neighborhood socioeconomic context of the destination of their migrations *(Continued)*

Matching without health status					Matching including health status				
Model	Odds ratio	95% confidence intervals		*p* value	Model	Odds ratio	95% confidence intervals		*p* value
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

Note: Quintile 1, which is the highest median house price quintile, is the reference category for each model.

of low socioeconomic status also more likely to have poorer health (Malmstrom, Sundquist, and Johansson 1999; Geronimus, Bound, and Ro 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 might begin to drift to areas with lower house prices. Boyle, Norman, and Rees (2002) also demonstrated that individuals who migrate to social housing (which are typically located in deprived neighborhoods) 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 processes is of younger (and hence healthier) migrants moving to less deprived areas (Norman, Boyle, and Rees 2005). If younger and healthier migrants are moving to more affluent areas, then it might shift the population structure of deprived areas toward unhealthier populations. The interacting process of poorer individuals drifting to poorer neighborhoods, combined with younger and healthier populations migrating to less deprived neighborhoods, will exaggerate the relationship between health and neighborhood socioeconomic context (Norman and Boyle 2014). It might 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 might 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 might offer some explanation for selective migration effects given their independent association with mental health (Tunstall et al. 2015). Migration types that are associated with negative reasons are more stressful (Morris, Manley, and Sabel 2016), and stress has an established biological pathway to affecting 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, Norman, and Rees 2002).

So does this put the knife in the neighborhood effects literature? Not exactly. What we call for is greater consideration of study design when analyzing similar research questions with observational data. Multilevel modeling revolutionized the field of health geography for understanding the role of neighborhood context on health (Mitchell 2001). These approaches are still important and have led to a great deal of discovery (Pickett and Pearl 2001; Riva, Gauvin, and Barnett 2007; van Ham and Manley 2012; Oakes et al. 2015; Arcaya, Tucker-Seeley, et al. 2016; Schüle and Bolte 2015). We need to be thinking through how best to identify causal effects, however, 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 (Mansson et al. 2007; Walsh et al. 2012; Oakes et al. 2015). We add to these previous approaches through using a multinomial approach rather than dichotomizing neighborhood socioeconomic context into a binary measure that might oversimplify its role. Our results also support similar epidemiological evidence demonstrating how useful matching is to reduce the effects of selection bias that can otherwise exaggerate the importance of socioeconomic context (Johnson, Oakes, and Anderton 2008).

It is plausible that the drive to identify neighborhood effects is an elusive question to be chasing. Both our approach and other similar techniques such as multilevel modeling seek to control for the role of individual-level factors to separate out neighborhood effects. Can we really separate out these two factors? They are often not mutually exclusive; social and spatial processes typically operate together (Mitchell 2001). For example, although 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, Power, and Taylor 2007). There are also wider issues of what constitutes neighborhoods (Kwan 2012), the scales at which they operate (Flowerdew, Manley, and Sabel 2008), and how they relate to varying outcomes over time (Musterd, Galster, and Andersson 2012). Identifying the contribution of neighborhoods and geography to understanding health is difficult at best.

Even if neighborhoods and geography did not matter, this does not rule out their usefulness, particularly within a policy setting (van Ham and Manley 2012). Individuals reside in neighborhoods, and it is these neighborhoods that display distinct geographical patterns. Neighborhoods are the "lens" through which we view the world. It will always be useful to consider neighborhoods, 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). We do not live in a social vacuum independent from our local surroundings, however, 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 might 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 neighborhood and reduce other confounding factors; however, the approach might be less generalizable to the wider population (e.g., see Table 2). Missing data were 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). Although 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 might bias our estimates of neighborhood socioeconomic context or health selective migration.

We only consider the impacts on health up to ten years following migration. It could be that ten years is too short to detect the influence of neighborhood socioeconomic context. Many chronic health conditions develop over longer periods and so our analyses might be inadequate to detect such processes. Neighborhood 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 materialize (Musterd, Galster, and Andersson 2012; van Ham and Manley 2012; Geronimus, Bound, and Ro 2014). Understanding the timings, durations, and thresholds for how different neighborhood characteristics affect 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 neighborhood contexts (Norman, Boyle, and Rees 2005; Morris, Manley, and Sabel 2016). Although we do not find any evidence for neighborhood 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 neighborhood socioeconomic context is reductionist. Although neighborhood house price is a valid measure, as house prices reflect the wealth and income of residents, as well as neighborhood desirability, it only represents one aspect of neighborhood socioeconomic context. As such, it avoids the inherent complexities of how neighborhood effects (and migration) might influence health by ignoring other mechanisms such as access to unhealthy foods (Smith et al. 2016) or level of social capital (N. Pearce and Davey Smith 2003; Uphoff et al. 2013). The decision was borne out by data availability issues because there are few other annual neighborhood data sources. We also ignore how individual-level factors might mediate or moderate neighborhood effects. For example, adolescents with resilient personalities can buffer negative neighborhood effects through building capacity to cope with neighborhood stressors (Nieuwenhuis, Hooimeijer, and Meeus 2015). The simplicity of our approach for measuring neighborhood socioeconomic context requires improving to develop our analytical approach in future research (van Ham and Manley 2012), and it might be that our approach requires combining with methods such as structural equation modeling to be able to tackle such complexities of neighborhood socioeconomic context.

Similarly, the simplicity in our measure of neighborhood socioeconomic context is problematic through using a single administrative geographical zone (LSOAs) for identifying neighborhoods. Although the geographical identifiers were the smallest scale made accessible for the data, it is unlikely that LSOAs reflect the lived contextual experiences of neighborhoods because they were designed for data dissemination (Martin 2002). The spatial uncertainty in the contextual influence of neighborhoods, and how this varies temporally, is termed the *uncertain geographic context problem* (UGCoP; Kwan 2012). The spatial delineation of the geographic boundaries might restrict our ability to make accurate inferences about neighborhood effects. The complexity of the issue is compounded because residents of the same neighborhood might be subject to different contextual exposures (Kwan 2012; van Ham and Manley 2012). Contextual exposures could 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 accurately identify the role of neighborhoods. Using residential mobility within our approach could be a useful means for assessing both UGCoP and the role of additional mechanisms that capture neighborhood socioeconomic context.

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

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