

RESEARCH ARTICLE

How far is a long distance? An assessment of the issue of scale in the relationship between limiting long-term illness and long-distance migration in England and Wales

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Abstract

Research consistently shows that those in poor health are less likely to migrate over long distances, but analyses rarely consider what constitutes a long distance in this context. Additionally, the migration literature often fails to account for place of residence effects on migration behaviour. This paper addresses these issues through analysis of the distance of residential moves by working age adults in the year preceding the 2011 Census. Multilevel logistic regression models predict the odds of having moved long-distance relative to short distance, for different definitions of long distance: ≥ 10 km, ≥ 20 km and ≥ 50 km. We test whether those reporting a limiting long-term illness (LLTI) are less likely to move long distance in all models, controlling for local authority at the time of the 2011 Census. We find no evidence for health selection in long-distance migration in the 10 and 20 km models, but uncover a significant effect in the 50 km model. By age, the odds of having moved long distance do not vary for middle-working age adults (25–54) by LLTI, whereas those with an LLTI in the pre-retirement age group (55–64) are less likely to move long distance in all models. We uncover clusters of local authorities where those with an LLTI are more likely to have moved long distance in the 10 and 20 km models, but in the 50 km model, only two of these areas remain significantly positive. We conclude that health selection in distances moved occurs above a cut-off somewhere between 20 and 50 km.

KEYWORDS

census microdata, health-selective migration, internal migration, limiting long-term illness, multilevel modelling

1 | INTRODUCTION

A large body of research is dedicated to establishing whether variations in health behaviours and outcomes are the result of “places” affecting health or a reflection of varying population characteristics across areas (Kearns & Moon, 2002; Smyth, 2008). The role of internal migration is often overlooked as a driver of these spatial variations in health (Norman, Boyle, & Rees, 2005). In the United Kingdom (UK), healthy people tend to move to less deprived areas, whereas those in poor health tend to move to more deprived areas; these migration patterns widen regional health inequalities as

some areas of the UK have a positive net migration for unhealthy migrants, whereas others have a negative net migration (Boyle, Norman, & Popham, 2009; Brimblecombe, Dorling, & Shaw, 1999; Norman & Boyle, 2014). The size of this effect is small, as the majority of migrants move between areas with similar mortality patterns (Green, Subramanian, Vickers, & Dorling, 2015), but migration patterns do have a significant effect on geographies of health. This phenomenon is not particular to the UK, as similar patterns have been found for rates of smoking in New Zealand (Pearce & Dorling, 2010) and poor self-rated health in the Netherlands (Dijkstra, Kibele, Verweij, Van Der Lucht, & Janssen, 2015).

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Migration leads to a change in an individual's environment; thus, migration is selective for characteristics which are related to adaptability (Lu, 2008). In this framework, distance is as an intervening obstacle for migrants (Thomas, Stillwell, & Gould, 2015); increasing distances are associated with loss of social networks (Brown, 2002) and greater financial costs due to searches and moves (Flowerdew, 1976). Thus, there are characteristics which are not only selective for the propensity to move but also selective of the distances moved among migrants. Long distance migrants are younger, have higher levels of education attainment (Thomas et al., 2015), and are more likely to be in the higher social classes (Boyle & Shen, 1997) than the general population, for example. Migration over long distances is relatively uncommon; an estimated 9.3% of the population living in England and Wales at 2001 moved to an address 50 km or further away by 2011, compared to 27.5% moving less than 10 km (Champion & Shuttleworth, 2015). The literature suggests that these long distance moves are driven primarily by employment, housing, amenities, and education (Champion, Fotheringham, Rees, Boyle, & Stillwell, 1998).

The healthy migrant hypothesis posits that good health is one of the characteristics that relate to adaptability (Fennelly, 2007). Individuals in good health are more able to move over long distances, as they are free of constraints on physical mobility and reliance on long-term healthcare. Conversely, the onset of poor health can lead to long distance migration. Individuals may move back to their area of origin due to place-based ties and the family being seen as factors aiding recovery from ailments, a phenomenon known as the "salmon bias" (Abraído-Lanza, Dohrenwend, Ng-Mak, & Turner, 1999). Analysis of the British Household Panel Survey shows that individuals who died during the survey period tended to have recently moved back to their area of birth (Brimblecombe et al., 1999). Evidence for the salmon bias is mixed, as no evidence of such flows is found when moves between England and Scotland are considered (Wallace & Kulu, 2014). The lack of accessible rural healthcare in the UK (Jordan, Roderick, Martin, & Barnett, 2004) may also drive long distance migration for those in poor health. Administrative records from New York and Western Australia show that the onset of mental disorder leads to rural residents moving towards urban areas surrounding hospitals (Breslow, Klinger, & Erickson, 1998; Moorin, Holman, Garfield, & Brameld, 2006); a similar effect may exist for physical health conditions.

The healthy migrant hypothesis for long distance migration has largely been supported by research based in the UK since the 1980s. Long distance migrants are healthier than those who do not migrate (Boyle, Norman, & Rees, 2002; Strachan, Leon, & Dodgeon, 1995) and are healthier than those who migrate over short distances (Boyle, Gatrell, & Duke-Williams, 2001; Fox, Goldblatt, & Adelstein, 1982). In addition, the association between health and long distance migration varies by age: sickness rates decrease with increasing distances moved for those aged 21–44, but converge for short and long distance migrants at ages 45+ (Bentham, 1988). Outside of the UK, however, several measures of poor health are found to be associated with long distance migration. For example, mental health disorders (except schizophrenia) in the United States (McCarthy, Valenstein, & Blow, 2007), chronic diseases in the United States (Findley, 1988), and health specialist usage in Australia (Larson, Bell, & Young, 2004) are associated with long distance moves. It is plausible that there is an opposing "unhealthy

migrant effect": the onset of health conditions which require long-term health care leads to moves from rural to urban areas, where there is a greater degree of health service provision. Evidence from outside of the UK supports this explanation (Breslow et al., 1998; Moorin et al., 2006), whereas this idea has not been tested explicitly within the UK. In this paper, we aim to assess the healthy migrant theory for distances moved. First, we draw on the literature to determine how a long distance move may be measured within the UK context.

1.1 | The issue of scale—How long is long distance?

The association between good health and long distance migration is established in several UK studies (Bentham, 1988; Boyle et al., 2001, 2002; Fox et al., 1982; Strachan et al., 1995). It is common in the internal migration literature for the Euclidean distance moved between residences to be calculated, and those who migrate over distances greater than a certain value (cut-off) are then considered to be long distance migrants. Alternatively, moves between administrative areas may be referred to as long distance moves, whereas moves within such areas are referred to as short distance moves. There is disagreement in the literature over which cut-off is considered to be indicative of long distance migration (Table 1).

In Table 1, all of the studies within the UK find evidence for the healthy migrant effect regardless of the way in which poor health is measured, whereas studies from outside the UK find evidence for an "unhealthy migrant effect." The issue of scale is problematic for the understanding of the health and migration relationship, as it is unclear at which distances health selection occurs. For example, two studies authored by Boyle et al. (2001, 2002) find that long distance migrants are healthier than short distance migrants, using the 50 and 10 km cut-offs, respectively. The 2001 study uses microdata from the Scottish Census, whereas the 2002 study uses microdata from the England and Wales Census, so it is not apparent whether the association persists at and above the 10 km cut-off in England and Wales, nor at and above the 50 km cut-off in Scotland. Recent work on internal migration in the UK which does not include health in their analysis has also defined long distance migration using 5 mile (8 km) (Cho & Whitehead, 2013) and 20 km cut-offs (Sapiro, 2016). These definitions have not been explored in the health literature. Several studies define moves across administrative regions as long distance; this is also problematic as individuals living near boundaries can move relatively short distances to cross such boundaries and be considered a long distance migrant. There is a distinct lack of justification for the use of cut-off points and little evidence of reflection on the implications this may have for findings. Of the aforementioned studies, only Sapiro (2016, p.16) justifies the usage of a cut-off, stating that "only one person in eight commut[es] further than [20km]." We conclude that as there is little theoretical justification in defining long distance migration using one cut-off over another, in this paper, we will test whether there is evidence for the healthy migrant effect using the 10, 20, and 50 km cut-offs previously used to define long distance migration in the UK context.

In addition to inconsistent definitions of long distance, research on migration and health in the UK often fails to account for multilevel structures in migration behaviour (Thomas et al., 2015). Individual (micro) behaviours are shaped by the environments in which

TABLE 1 Definitions of long distance in selected studies investigating the association between health and long distance migration

Study	Country	Measure of health	Distance cut-off	Sample	Finding
(Boyle et al., 2001)	England and Wales	LLTI	50 km	1991 England and Wales Census microdata	Long distance migrants are less likely to report an LLTI (OR .86) than short distance and nonmovers.
(Strachan et al., 1995)	England and Wales	Stroke	Regional	1991 ONS LS for England and Wales	Migrants into greater London have lower rates of stroke-related mortality than nonmovers.
(Boyle et al., 2002)	Scotland	LLTI	10 km	1991 Scotland Census microdata	Long distance migrants have lower rates of LLTI than short distance migrants.
(Bentham, 1988)	UK	Self-report permanent and temporary "sickness"	Within district versus between district versus between region	1981 Census	Between district and region migrants have lower rates of permanent sickness than within district migrants. Between region migrants have lower rates of temporary sickness than between and within district migrants.
(Larson et al., 2004)	Australia	Numerous self-reported measures	Within postcode mover versus stayer, between postcodes mover versus stayer	Australian Longitudinal Study on Women's Health 1996 & 1998 (NB study included data on women aged 45–50 in 1996)	Those who expect their health to deteriorate and experience several symptoms are more likely to move over short distances, those with several visits to health specialists are more likely to move long distance. Chronic diseases and smoking are associated with short and long distance moves.
(McCarthy et al., 2007)	United States	Disability, substance abuse, schizophrenia, bipolar disorder, depression	Linear distance	U.S. Veterans' Association data	Disability, substance abuse, bipolar disorder and depression are associated with moves over longer distances, whilst schizophrenia is associated with moves over shorter distances.
(Findley, 1988)	United States	Onset of chronic disease	500 miles	National Health Interview Survey 1979 & 1980	Those who are diagnosed with a chronic disease are more likely to move long distance, this effect is strengthened for those who had a pre-existing condition

individuals operate (macro), and controlling for these macro influences is necessary when inferences are made on the behaviours of individuals (Goldstein, 2011). Recent advances in methodology show regional variation in distances moved by destinations, with movers to coastal and rural areas in the north of England tending to move further than average, whereas movers to metropolitan cores tend to move shorter distances (Thomas et al., 2015). This regional variation in distances moved has not been linked to health. We expect the population in poor health to be reliant on healthcare provision and, therefore, less likely to move over long distances into rural areas relative to the population in good health, as healthcare provision is less accessible in rural areas of the UK. This has implications for previous studies that show that poor health is associated with short distance migration; selection may play a role, as those in poor health are concentrated in urban and deprived areas (Dorling, 2013) where short distance moves are more common (Champion, 2005; Kearns & Parkes, 2003), thus exaggerating the role of health in determining short distance moves.

There are three aims of our study, drawn from the above review of the literature. In models accounting for the areas individuals live in at the time of the 2011 Census, we test whether there is an association between health and long distance migration using different definitions of long distance found in the literature. Second, we test whether the association between health and long distance migration varies by age. Third, we assess whether there is spatial variation in the likelihood of long distance migration by health status.

2 | METHODS

2.1 | Data

This analysis uses data on internal migrants living within England and Wales in 2011, drawn from the 2011 Census Individual Secure Sample (CISS). The UK census is a mandatory decennial questionnaire for UK residents (Office for National Statistics, 2011a), and we use data from the England and Wales version of the census. Ten percent of individuals within each Output Area are randomly selected for inclusion in the CISS by the Office for National Statistics (ONS) to ensure that the sample represents the usually resident population of England and Wales (Office for National Statistics, 2011b). The lowest available level of geography in the CISS is Local Authorities (LAs); there are 348 LAs in England and Wales each containing an average of 120,000 individuals. Due to small LA sizes, we combine the Isles of Scilly with Cornwall and exclude those living in the City of London. We use LAs as an analytical level to reflect regional variations in pull factors (employment rates, access to healthcare, tenure composition), which are known to be determinants of long distance moves (Boyle & Shen, 1997; Breslow et al., 1998; Thomas et al., 2015). The LA an individual lived within 1 year before the Census (origin) and the LA they live within at the time of the Census (destination) are provided in the CISS. Although there is evidence of variation in distances moved both at the origin and destination (Thomas et al., 2015), the measure of health used in this analysis only captures health at the time of the Census (when individuals lived within their

destination LA), not 1 year prior (when individuals lived within their origin LA). If we were to include origins as an analytical level, an unknown quantity of individuals with an limiting long-term illness (LLTI) would not have reported an LLTI 1 year prior when they lived within origin LAs and vice versa. As a result, we only include destination LAs in our analytical models.

Census Individual Secure Sample microdata may only be accessed at the ONS Virtual Microdata Laboratory. Access is granted for approved research projects conditional on disclosure control training. Due to the risk of disclosure from sensitive individual level microdata, all analytical outputs are vetted by the ONS before release.

2.2 | Inclusion criteria

We limit our study to working age adults (aged 16–64) at the time of the census in line with previous studies on internal migration using census microdata (Bailey & Livingston, 2005; Wilding, Martin, & Moon, 2016), as recent research shows that the drivers of migration among the very young and very old differ from the working age population (Thomas, Stillwell, & Gould, 2016). Migration is measured using the question “one year ago, what was your usual address” (Office for National Statistics, 2011a); respondents may answer “the address on the front of this questionnaire” (non-movers), write in a different address within the UK (movers), or write in the country where they lived 1 year ago (recent immigrants). We exclude non-movers and those who lived outside of England and Wales 12 months prior to the Census, as distances are calculated by the ONS only for those who moved within England and Wales. Students who move from a term-time address to another address are also excluded, as distances are not calculated for this group by the ONS. Those who report living rent free are also excluded from our sample; this is likely a very heterogeneous group who experience very different drivers of migration than those in other living arrangements. Excluding participants with missing data for family status (902), whether they are part of a wholly moving household (257) or report living rent free (5,821), our final sample contains 442,340 working-age adult internal migrants.

2.3 | Outcome

The outcome measures in this analysis derive from a variable containing the straight line distance (in kilometres) between an individual's address at the time of the 2011 Census and their address 12 months prior. The Euclidean (straight line) distance between the two residences is calculated from household to household by the ONS (Office for National Statistics, 2014) and provided as a continuous measure. To explore the issue of scale, we use three definitions of long distance migration, where moves are considered long distance if an individual moved: (a) 10 km or further; (b) 20 km or further; and (c) 50 km or further; herein referred to as the 10 km model, 20 km model and 50 km model, respectively. These outcomes allow us to test whether there is an association between health and long distance migration across these definitions of long distance, drawn from the literature (see Table 1).

2.4 | Exposure variable

There are two measures of health captured by the Census, a measure of self-rated health (“how is your health in general”) and a measure of

LLTI. The exposure variable used in this analysis is LLTI. LLTI is measured by the following question: “Are your day-to-day activities limited because of a health problem or disability which has lasted, or is expected to last, at least 12 months? Include problems related to old age” (recoded as 0 = *no* and 1 = *yes, limited a little* or *yes, limited a lot*) in line with other studies exploring the relationship between health and migration (e.g. Norman et al., 2005). We expect those with an LLTI to be less likely to move long distance (Bentham, 1988; Boyle et al., 2001; Fox et al., 1982). We find no significant differences if self-rated health is used instead of LLTI in fully adjusted models. We proceed with LLTI as our exposure variable, as LLTI has been used in previous studies based on Census microdata (Boyle et al., 2002; Boyle, Norman, & Rees, 2004; Norman et al., 2005; Norman & Boyle, 2014).

Self-reported measures of health are often used as proxies for morbidity in social science research (Curtis, Setia, & Quesnel-Vallee, 2009). Although LLTI is a subjective valuation of health, those reporting an LLTI have higher rates of mortality, hospitalisation, and serious conditions than those who do not report an LLTI (Manor, 2001; Payne & Saul, 2000) and are more likely to access health services in the future (Jordan, 2003). Comparisons of different dimensions of health show that LLTI is closely aligned with physical limitations and less associated with mental and social wellbeing (Cohen, Forbes, & Garraway, 1995), whereas area rates of LLTI correlate with the number of cases of chronic heart disease and hypertension (Martin & Wright, 2009). It is important to note that LLTI is measured at the time of the Census and migration in the year preceding the Census, so it is not possible to ascertain whether there is a difference in pre and post move health status.

2.5 | Covariates

We include 12 covariates in our analysis, to control for factors confounding the association between distance moved and LLTI, shown in Table 2.

2.6 | Modelling strategy

All models are estimated using multilevel logistic regression with individuals nested within LA at destination, as we expect the average distance moved to vary by destination (Thomas et al., 2015). We allow the effect of LLTI to vary randomly across destination LAs, to test whether those with an LLTI are less likely to have moved long distance in all LAs.

We model the log odds of having moved long distance ($p = 1|X$) relative to the odds of having moved short distance ($p = 0|X$) for migrant i living in LA j as follows (van Ham, Mulder, & Hooimeijer, 2001):

$$\log(\text{odds})_{ij} = \beta_0 + \beta_n X_n + LLTI_i + \mu_{0j} + \mu_{1j} + e_i \quad (1)$$

where β_0 is a fixed constant, $\beta_n X_n$ is the matrix of fixed covariates defined in Table 2, $LLTI_i$ is the fixed coefficient for individuals with an LLTI, μ_{0j} is the random intercept associated with LA j , μ_{1j} is the random slope for individuals with an LLTI in LA j , an additional effect for the population with an LLTI, and e_i an error term for individual i . We use the random effects approach, such that μ_{0j} and μ_{1j} have a mean of 0 and a standard deviation equal to $\sigma_{\mu_{0j}}^2$ and $\sigma_{\mu_{1j}}^2$, respectively. Utilising random intercepts U_{0j} and slopes U_{1j} , we investigate whether health differences in the log-odds of having moved long distance vary across LAs and definitions of long distance. The average log-odds of having

TABLE 2 Covariates included in the analysis and their relationship to distances moved

Variables	Groupings	Which group(s) are more likely to move long distance
Age	0 = 16–24, 1 = 25–34, 2 = 35–44, 3 = 45–54, and 4 = 55–64	Those aged 30 and over (Boyle & Shen, 1997; Thomas et al., 2015)
Sex	0 = male and 1 = female	Men (Boyle & Shen, 1997; Thomas et al., 2015)
Ethnicity	0 = White, 1 = Indian, Pakistani or Bangladeshi, 2 = Chinese or other Asian, 3 = African, Caribbean or Black, 4 = Other or Mixed	One study finds that all minority ethnic groups move shorter distances (Finney & Simpson, 2008) whilst others report that only the Asian group to move shorter distances than other ethnic groups (Cho & Whitehead, 2013; Thomas et al., 2015).
Marital status	0 = single, 1 = married or civil partners, 2 = divorced, separated or widowed	One study finds that the divorced and separated move shorter distances, with no difference between single and married (Thomas et al., 2015) whilst another finds that the divorced and separated move longer distances (Cho & Whitehead, 2013).
Family status	0 = no family or household, 1 = in a couple or married family, 2 = in a lone parent family	Those living without children (Boyle & Shen, 1997)
Country of birth	0 = UK born 1 = born outside of the UK	Non-UK born (Finney & Simpson, 2008)
Educational qualifications	0 = none, 1 = GCSE or apprenticeship, 2 = A level, 3 = Degree or higher	Higher educated (Boyle & Shen, 1997; van Ham et al., 2001; Fielding, 2012; Thomas et al., 2015)
Tenure	0 = private renter, 1 = LA or housing association renter, 2 = owner	Those in LA housing to move shorter distances (Cho & Whitehead, 2013; Thomas et al., 2015) and private renters to move further (Boyle & Shen, 1997; Cho & Whitehead, 2013)
Car access	0 = none, 1 = one car, 2 = two or more cars	Those with access to a car, as a proxy for wealth (Boyle & Shen, 1997)
Employment status	0 = employed, 1 = unemployed, 2 = economically inactive	Economically inactive moves further than the employed, whilst the unemployed moves the furthest (Boyle & Shen, 1997; Thomas et al., 2015).
Wholly moving households	0 = partially moving household 1 = wholly moving household	Partial movers (Cho & Whitehead, 2013)
Interactions	Age and gender interactions	Younger women to be more likely to move long distance (Finney, 2011)
	Age and LLTI interactions	Young adults without an LLTI to be more likely to move long distance (Bentham, 1988)

moved long distance for an individual without an LLTI is given by the parameter β_0 , the average log-odds of having moved long distance for an individual without an LLTI in LA j is given by the parameters $\beta_0 + U_{0j}$, and the average log-odds of having moved long distance for an individual with an LLTI in LA j is given by the parameters $\beta_0 + LLTI_j + U_{0j} + U_{1j}$.

The odds are then converted into a percentage using the following transformation:

$$\%moved\ long\ distance_{ij} = \frac{\exp(\log(odds_{ij}))}{(1 + \exp(\log(odds_{ij}))) * 100} \quad (2)$$

We estimate models using the `xtnlogit` command in Stata 12.1 (Statacorp, 2013). Fixed effect coefficients are estimated in a similar manner to standard logistic regression, whereas random effect coefficients and log-likelihood values are estimated using Laplacian approximation (adaptive quadrature), the distribution of which is assumed to be Gaussian (Statacorp, 2015).

We include interaction terms between age and LLTI to test whether the relationship between health and long distance migration differs across age groups. In order to calculate confidence intervals for the log odds for each age group by LLTI, we use the `lincom` command in STATA. As the 16–24 age group are used as a reference

category, the log odds for an individual without an LLTI are given by the parameter β_0 and for those with an LLTI by the parameters $\beta_0 + LLTI_j$. Thus, the difference in log odds for the 16–24 age group shows the overall effect of LLTI on long distance migration. For all other age groups, the log odds for an individual without an LLTI are given by the parameters $\beta_0 + AGE_i$ and for those with an LLTI by the parameters $\beta_0 + LLTI_j + AGE_i + LLTI * AGE_i$.

3 | RESULTS

In this section, we examine the relationship between health status and long distance migration. In our sample, 404,004 movers (91.3%) do not report an LLTI, whereas the remaining 38,336 (8.7%) report an LLTI. Individuals without an LLTI have a higher mean and median for distances moved, as well as greater variation as indicated by the standard deviation. These differences in continuous distance moved are statistically significant at the 99% level (Table 3). Turning to the distance cut-offs, the percentages suggest increasing health selectivity over greater distances, as the ratio of probabilities shifts further from one.

Having established that LLTI is associated with lower odds of long distance migration, we consider whether there are variations in the

TABLE 3 Cross-tabulation of long distance migration and limiting long-term illness (LLTI)

	Overall	No LLTI (a)	LLTI (b)	Ratio (b/a)
Mean (km)	30.1	30.4	25.7	0.84
SD (km)	66.3	66.5	61.8	
Median (km)	4.1	4.1	3.7	0.90
T-test (b = a)		4.8, $p < .01$		
10 km + (%)	32.3	32.9	28.9	0.88
20 km + (%)	22.8	23.3	19.4	0.83
50 km + (%)	15.2	15.6	12.5	0.80
N	442,340	404,004	38,336	

Source: CISS (Office for National Statistics, 2011b), authors' own calculations.

relationship between health and definitions of long distance, after controlling for demographic characteristics. Table 4 shows the results of multilevel logistic regressions for the 10, 20, and 50 km models. All coefficients are shown as additive effects on the log odds of having moved long distance (see Equation 1). Coefficients greater than zero indicate that this characteristic is associated with greater odds of having moved long distance in each model, although the inverse is true of coefficients lower than zero. The estimates and confidence intervals for the standard deviation of the random intercept (μ_0) and slope (μ_1) are also shown.

Comparing coefficients across the three models, the direction of effects is consistent in the majority of cases and conforms to our expectations (Table 2); thus, many of the characteristics we control for are scale invariant. Figure 1 presents the estimates by health and age across the three models, transformed into percentages predicted to move long distance (Equation 2), and their associated 95% confidence intervals. Comparing the difference in probabilities by health for the 16–24 age group, LLTI is associated with a lower likelihood of having moved long distance only in the 50 km model, as the odds for those with and without an LLTI overlap in the 10 and 20 km models, despite a p value $< .01$ in the latter model. After taking the uncertainty in the estimate of the constant into account (Wolfe & Hanley, 2002), health selection occurs above a cut-off somewhere between 20 and 50 km, as the confidence intervals for those with and without an LLTI overlap in the 20 km model, but do not in the 50 km model. Looking at the differences for other age groups, the only significant difference is found in the 55–64 age group, where having an LLTI is associated with a lower likelihood of having moved long distance in all models. This suggests that the healthy migrant effect for long distance migration is specific to the youngest and oldest working age groups.

Comparing probabilities across age and model, for the population with and without an LLTI, we observe that the relationship between age and long distance migration is u-shaped. Adults in the youngest and oldest age groups (16–24 and 55–64) are more likely to move long distance relative to those in the 25–34, 35–44, and 45–54 age groups. For the population without an LLTI, the predicted percentages are significantly higher for the 16–24 and 55–64 age groups relative to all other age groups in the 10, 20, and 50 km models; except adults aged

45–54 are not significantly less likely to move long distance in the 10 km model. For the population with an LLTI, the u-shaped distribution is less pronounced; those aged 25–34 are less likely to move long distance than those aged 16–24 or 55–64 in the 50 km model, whereas all other age differences overlap. The variance partition coefficient (Browne, Subramanian, Jones, & Goldstein, 2005) shows that a relatively small proportion of the variance in long distance migration is explained at the destination LA level (6% in the 10 km model and 5% in the 20 and 50 km models), with the remainder explained at the individual level.

3.1 | Random intercepts and slopes

Having explored effects at the individual level, we turn to effects at the destination LA level. Figure 2a–c illustrates these transformed parameters. The percentage predicted to have moved long distance for each LA is represented on the y axis, and the ratio of predicted percentages for those with an LLTI relative to those without an LLTI is represented on the x axis. If the ratio is greater than one, this indicates that those with an LLTI are more likely to move long distance in this LA, whereas the inverse is true if the ratio is less than one. Reference lines illustrate the global mean for the percentage predicted to move long distance (30.8%, 20.3%, and 12.5%) in the 10, 20, and 50 km models, respectively.

In the 10 km model, we observe that the population with an LLTI are more likely to have moved long distance than those without an LLTI in destinations with higher than average rates of long distance migration (top-right quadrant). In the 20 km model, the same trend is found; however, the distribution of ratios shifts to the left, such that there are fewer areas where the population with an LLTI are more likely to have moved long distance. Finally, in the 50 km model, the distribution of ratios shifts further to the left; the population with an LLTI are more likely to have moved long distance only in two LAs (of a total of 346). Thus, there is no evidence of health selection in the 10 km model, but the effect is present in the 20 km model and strongest in the 50 km model.

To explore the spatial pattern of these residuals for destination areas, we plot the values for LAs using ArcMap 10.4.1 (ESRI, 2014). The ratio of predicted percentages from Figure 2 is shown for the 10, 20, and 50 km models in Figure 3a–c, respectively. Destinations where those with an LLTI are more likely to have moved long distance are hatched, whereas destinations where those without an LLTI are more likely to have moved long distance are shaded in grey. Areas with a random intercept (U_{0j}) within 1SD from the mean are unshaded, to investigate the relationship between health- and destination-specific probabilities in the more extreme ends of the distribution.

Figure 3a shows that there are a greater number of areas where those with an LLTI have higher odds to have moved long distance (55%) in the 10 km model, clustered in London, southern Wales, and eastern England. Areas with higher odds for those without an LLTI are clustered in the South of England, south east from London, and north from London. Figure 3b shows that there is a clearer spatial pattern in the 20 km model. Areas where those with an LLTI have higher odds are fewer in number (22%), and these are now clustered in London and south Wales, whereas areas with higher odds for those

TABLE 4 Multilevel logistic regressions predicting the log-odds of having moved long distance relative to short distance

	10 km			20 km			50 km		
	Logit	LB	UB	Logit	LB	UB	Logit	LB	UB
Constant	-0.81**	-0.87	-0.75	-1.37**	-1.43	-1.31	-1.94**	-2.01	-1.88
Age (ref 16–24)									
25–34	-0.18**	-0.20	-0.15	-0.32**	-0.35	-0.30	-0.50**	-0.53	-0.46
35–44	-0.12**	-0.15	-0.09	-0.23**	-0.27	-0.20	-0.42**	-0.46	-0.37
45–54	-0.05*	-0.09	-0.01	-0.15**	-0.19	-0.10	-0.28**	-0.33	-0.23
55–64	0.22**	0.17	0.27	0.15**	0.10	0.20	0.11**	0.05	0.16
LLTI (ref none)	0.03	-0.03	0.09	-0.10**	-0.17	-0.04	-0.24**	-0.32	-0.16
LLTI and age interactions									
LLTI & 25–34	0.06	-0.02	0.14	0.16**	0.08	0.25	0.28**	0.17	0.38
LLTI & 35–44	0.03	-0.05	0.11	0.14**	0.05	0.23	0.30**	0.19	0.40
LLTI & 45–54	-0.05	-0.13	0.04	0.01	-0.09	0.10	0.10	-0.01	0.21
LLTI & 55–64	-0.23**	-0.32	-0.15	-0.14*	-0.23	-0.04	-0.01	-0.12	0.10
Sex (ref male)	-0.13**	-0.15	-0.10	-0.15**	-0.18	-0.13	-0.17**	-0.20	-0.14
Sex and age interactions									
Female & 25–34	0.10**	0.06	0.13	0.10**	0.06	0.13	0.09**	0.05	0.14
Female & 35–44	-0.01	-0.05	0.03	0.01	-0.03	0.06	0.06*	0.00	0.11
Female & 45–54	0.03	-0.01	0.08	0.07*	0.01	0.12	0.11**	0.05	0.17
Female & 55–64	0.11**	0.05	0.17	0.14**	0.08	0.21	0.20**	0.13	0.27
Ethnicity (ref white)									
Indian, Pakistani or Bangladeshi	0.13**	0.10	0.17	0.26**	0.23	0.30	0.30**	0.25	0.34
Chinese or other Asian	0.18**	0.14	0.22	0.19**	0.15	0.24	0.20**	0.15	0.25
African, Caribbean, or Black	0.21**	0.17	0.25	0.24**	0.19	0.28	0.25**	0.20	0.30
Other or mixed	0.20**	0.16	0.23	0.21**	0.17	0.25	0.21**	0.17	0.26
Marital status (ref single)									
Married or civil partners	0.06**	0.04	0.08	0.15**	0.12	0.17	0.22**	0.20	0.25
Separated or widowed	0.00	-0.02	0.03	-0.07**	-0.10	-0.04	-0.16**	-0.20	-0.13
Family status (ref none)									
In a couple or married family	-0.14**	-0.17	-0.11	-0.10**	-0.13	-0.07	-0.03	-0.06	0.01
In a lone parent family	0.13**	0.12	0.15	0.19**	0.17	0.21	0.21**	0.19	0.24
Nativity (ref UK born)	-0.24**	-0.26	-0.22	-0.26**	-0.28	-0.24	-0.27**	-0.30	-0.24
Education (ref none)									
GCSE or apprenticeship	0.14**	0.11	0.17	0.16**	0.13	0.19	0.18**	0.14	0.22
A level	0.30**	0.27	0.33	0.39**	0.35	0.42	0.47**	0.43	0.51
Degree	0.84**	0.82	0.87	1.01**	0.98	1.04	1.14**	1.10	1.18
Tenure (ref private renter)									
LA or charity renter	-0.31**	-0.33	-0.29	-0.42**	-0.45	-0.39	-0.51**	-0.55	-0.48
Owns	0.08**	0.07	0.10	0.07**	0.05	0.09	0.06**	0.03	0.08
Car access (ref none)									
One	0.12**	0.10	0.14	0.11**	0.09	0.13	0.08**	0.06	0.10
Two or more	0.16**	0.14	0.18	0.08**	0.06	0.10	0.02	0.00	0.05
Employment status (ref employed)									
Unemployed	0.42**	0.39	0.45	0.56**	0.53	0.60	0.67**	0.64	0.71
Economically inactive	0.32**	0.30	0.35	0.47**	0.44	0.50	0.55**	0.51	0.58
Student	0.05**	0.02	0.07	0.16**	0.13	0.18	0.18**	0.16	0.21
Whole household moved (ref nol)	-0.58**	-0.59	-0.56	-0.64**	-0.65	-0.62	-0.65**	-0.67	-0.63
Random effects									
σ_{u0j}^2	0.19	0.16	0.22	0.18	0.15	0.21	0.17	0.15	0.20
σ_{u1j}^2	0.03	0.02	0.04	0.01	0.00	0.03	0.02	0.00	0.03
Covariance $\sigma_{u0j}^2, \sigma_{u1j}^2$	0.05	0.03	0.06	0.04	0.03	0.05	0.03	0.01	0.05

(Continues)

TABLE 4 (Continued)

	10 km			20 km			50 km		
	Logit	LB	UB	Logit	LB	UB	Logit	LB	UB
VPC	0.06			0.05			0.05		
Log likelihood	-25,986			-220,140			-173,869		
N	442,340			442,340			442,340		

Source: CISS (Office for National Statistics, 2011b), authors' own calculations.

LB = 95% confidence interval lower bound; UB = 95% confidence interval upper bound; VPC = variance partition coefficient.

**= significant at the .99 level.

*= significant at the .95 level.

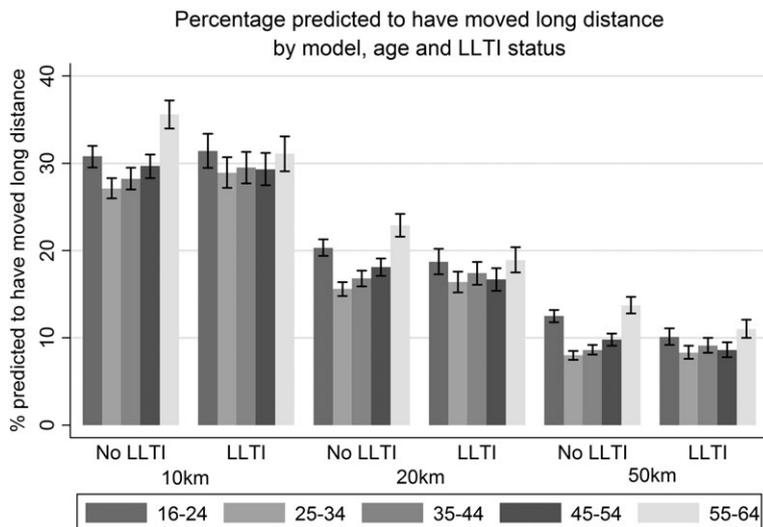


FIGURE 1 Percentage predicted to have moved long distance by model, age, and limiting long-term illness (LLTI) status

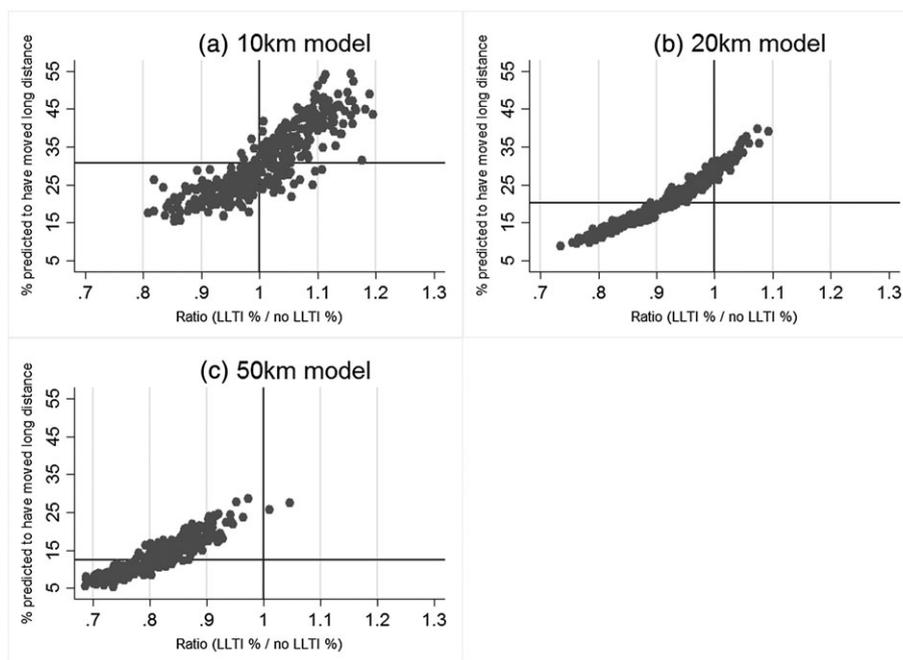


FIGURE 2 Ratio of health differences in long distance migration by local authority (LA) and model

without an LLTI are spread across the South, North, and East of England. Figure 3c shows that in the 50 km model, there are only

two areas (2%) where those with an LLTI have higher odds, Powys and Methyr Tydfil in south Wales.

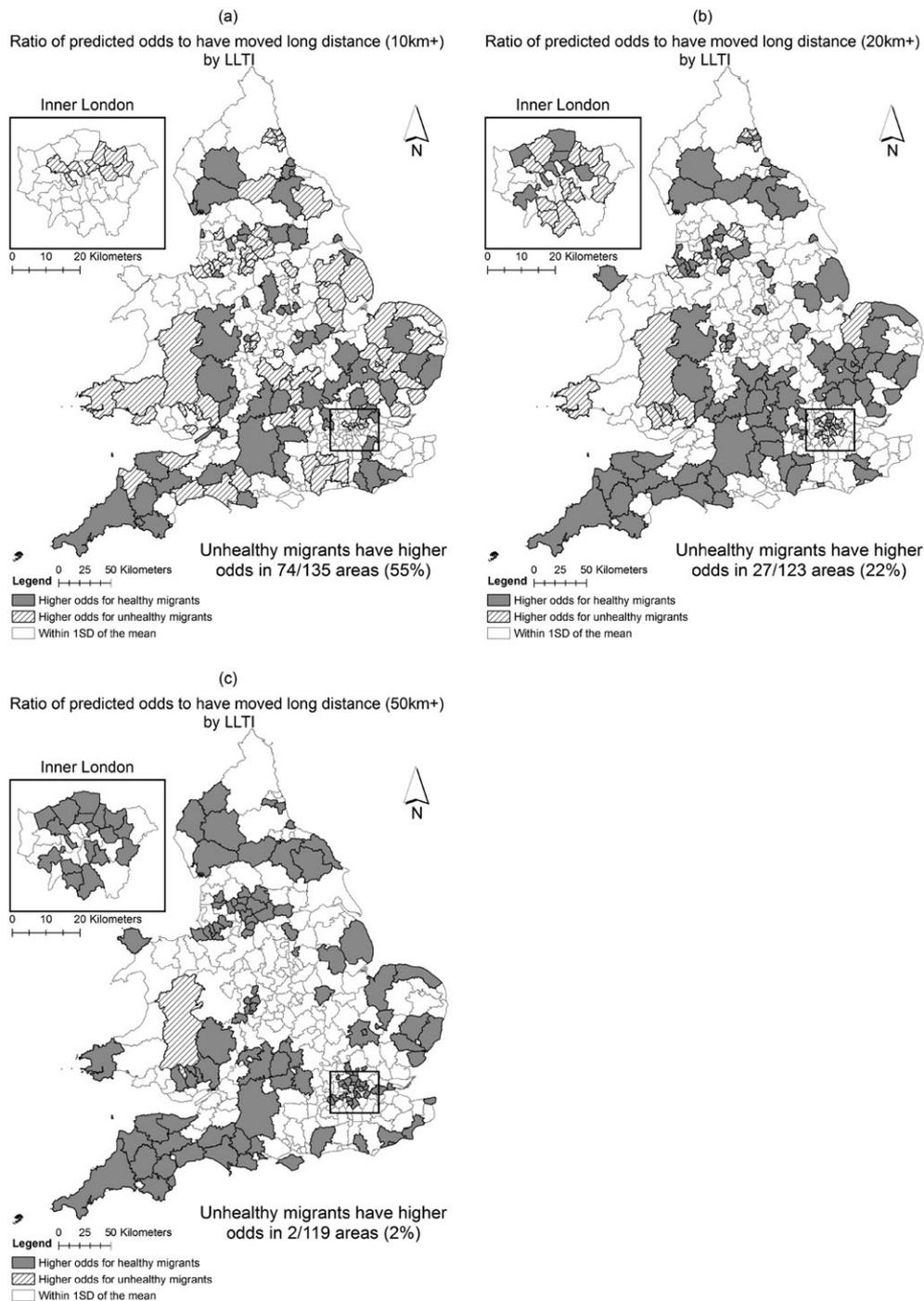


FIGURE 3 Ratio of predicted odds to have moved long distance by model and limiting long-term illness (LLTI)

4 | DISCUSSION

The work here must be placed in context of its shortfalls. Our measure of health (LLTI) is a self-reported measure, whereas the healthy migrant theory is mainly drawn from research on mortality (Abraído-Lanza et al., 1999), which finds that individuals who move have lower future mortality rates than those who do not move. It is plausible that conditions that are conducive to mortality in working age adults are barriers to long distance migration, whereas our measure does not have the specificity to identify the forms of poor health which drive long distance moves. The focus on working age adults is in contrast

with the fact that rates of LLTI are much higher at post-retirement ages, and the relationships between health and long distance migration may differ in this older age group. Additional cut-off points are found in the wider migration literature but are beyond the scope of the present paper. The issue of scale in the health and long distance migration relationship may be unique to the data source used here, or to England and Wales, thus, further work is needed from other countries to assess the robustness of the association.

Our first aim in this analysis is to test whether there is an association between health and long distance migration across a range of definitions of "long distance." Adjusting for mediators and taking into

account the uncertainty present in our estimates, we find evidence of health selection on the propensity to have moved long distance only when the definition of 50 km or more is used. This finding contradicts research from Scotland (Boyle et al., 2002) and Great Britain (Bentham, 1988), which find evidence of health selection at the 10 km and interdistrict cut-offs, respectively, but confirms research on England and Wales using 1991 data (Boyle et al., 2001). We conclude that for migration within England and Wales, the healthy migrant effect occurs above a cut-off somewhere between the 20 and 50 km cut-offs.

There are several plausible explanations for the lack of healthy migrant effect at the 10 and 20 km cut-offs. First, covariates in our model, which are not present in previous research (nativity and whether the individual moved as part of a wholly moving household), may explain the heterogeneity in distances moved of those in good and poor health. Second, the healthy migrant effect may not be present at the 10 and 20 km cut-offs specifically in England and Wales, with studies showing contrary results being drawn from Great Britain and Scotland data. Third, the inclusion of multilevel modelling may also influence the direction of the relationship, as the error of the health effect is partitioned into the individual and destination LA levels, and the variance explained by individual health may be too small at the 10 and 20 km cut-offs to remain significant. Finally, this is an analysis of individuals and their migration behaviour, although the characteristics of one's family also influence migration behaviour. For instance, if an individual's partner is unwell, then they may be particularly reluctant to move over long distances, despite being coded as "healthy" in our design. It is not possible to control for this in the CISS as not all household relationships are preserved, although an analysis of "unhealthy households" and their migration behaviour could be conducted using the household counterpart of the dataset.

Our second aim is to test whether the association between health and long distance migration varies by age across definitions of long distance. Our findings contradict past research showing that poor health is associated with moves over shorter distances in all working age groups (Bentham, 1988), as we find evidence for the healthy migrant effect only in the youngest (16–24) and oldest (55–64) working age groups. We identify a scale dimension to the health and long distance migration relationship, LLTI is associated with reduced odds of having moved long distance for the 16–24 age group at the 50 km cut-off, although this difference is not significant at the 10 and 20 km cut-offs. There is one effect that is consistent across all models; among the oldest age group (55–64), those without an LLTI are more likely to move long distance. We conclude that the healthy migrant effect is scale-invariant at preretirement ages (55–64), observable only over great distances for the youngest age group (16–24), and is not present for adults of mid-working age (25–54). This reinforces recent calls for age differences in the health and migration relationship to be accounted for (Norman & Boyle, 2014).

Our third aim is to assess whether there is spatial variation in long distance migration by health status. We identify that those with an LLTI who moved to London, south Wales, and eastern England are more likely to have moved long distance, relative to those without an LLTI in the 10 km model. Over greater distances, however, long distance migration becomes increasingly health selective, and for the

furthest moves, those with an LLTI are more likely to move long distance to only two LAs in southern Wales. These findings show that those with and without an LLTI are attracted to different areas over distances less than 20 km, but those with an LLTI are not more likely to have moved further than 20 km to most areas relative to those without an LLTI. We conclude that, the healthy migrant effect is apparent in destination LAs for residential moves of 20 km or further, and the effect is even stronger when only moves of 50 km or further are considered to be long distance.

In terms of policy, we find health differences in the spatial pattern of long distance migration. We find that the youngest (16–24) and oldest (55–64) working age adults with an LLTI are less likely to move over very long distances (50 km+), and health services can adequately plan long-term provision for those with an LLTI in these age groups with the knowledge that when these populations change residence, these moves are likely to be of distances less than 50 km. The population without an LLTI appear to be drawn over long distances to rural areas of England and to Inner London: This reflects wider trends of counter-urbanisation in the UK (Stockdale, 2015) and the migration of healthy young people to London (Norman & Boyle, 2014). The relative lack of very long distance migration into rural areas by the population with an LLTI may be the result of poor rural healthcare provision failing to "pull" this population towards these areas, although this factor is considered less important for the population in good health. Given that the incumbent Government is pushing for the devolution of healthcare planning and provision to LA with the 2016 Cities and Devolution Act (Sandford, 2016), rural LAs will need to account for the needs of incoming long distance migrants, whom may require health services in future as they age.

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DISCLAIMER

This work contains statistical data from ONS, which is Crown Copyright. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets that may not exactly reproduce National Statistics aggregates.

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