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Modelling multilevel variations in distance moved between origins and destinations in England and Wales

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Abstract

Using individual records from a large and geographically detailed national research opinion survey, this paper employs a multilevel cross-classified statistical framework to demonstrate the relative importance of simultaneous individual and place-based (neighbourhood and city region) variations, at both the origin and the destination, in the distance moved by residential migrants in England and Wales. The results confirm strong micro-level variations in the distance moved according to key variables such as household income, educational attainment and housing tenure whilst simultaneously revealing the importance of substantial origin and destination place-based macro-geographic variations. Indeed, a typical migrant is found to be pulled over significantly longer distances towards rural/coastal (amenity-rich) destination environments and, at the same time, pushed over significantly longer distances from (increasingly) metropolitan origins. The paper is valuable in revealing the importance of simultaneously modelling origin and destination macro-geographical contexts net of individual and neighbourhood composition and for demonstrating the significance of differential place-based attractiveness as a key source of variation in the distance moved between origins and destinations in England and Wales. Substantively, the findings reveal the continued strength of counterurbanisation as a process that persists in drawing people, over long distances, from metropolitan cores and towards the amenity-rich environments of England and Wales' coast and countryside.

Keywords

Residential mobility; origin and destination context; distance moved; cross-classified multilevel model; place-based preferences

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Introduction

Implicit in the definition of residential mobility is the physical relocation from one place of usual residence to another where the origin and destination may be in close proximity or separated by a long distance. The theoretical literature relating to variations in the distance over which residential movement takes place emphasises the importance and complexity of influences that operate simultaneously at the origin and the destination, as well as the roles of distance and/or intervening opportunities or obstacles operating between them (Lee, 1966). Explanatory factors are likely to relate to variables impacting at various levels from the circumstances of the individual migrant and their household to the characteristics of the local neighbourhood in which the migrant's household is located, right through to the region, nation and indeed beyond, perhaps even to the global level. Individual migration behaviour in the UK in the second half of the 2000s has surely been influenced by the impact of global recession on housing and labour markets.

However, in practice, much empirical work on residential mobility falls short in terms of recognising these realistic complexities by focussing exclusively on one level and therefore failing to account for potentially important influences operating at other levels that are omitted (Cadwallader, 1989). Moreover, on the rare occasions where realistic multilevel structures/influences have been analysed (Boyle and Shen, 1997), a failure to simultaneously accommodate influences operating at both the origin *and* the destination is apparent. With the aim of rectifying this partiality, the intention of this paper is to develop an empirically informed modelling approach that captures effects at different levels which impact on the distance over which individuals travel to change residence. The paper proceeds in the following manner. First, the existing theoretical and empirical literature is reviewed with a key focus placed on drawing out the major processes, patterns and characteristics that operate at the micro- (individual/household), meso- (neighbourhood context) and macro-geographical (structural region) levels. Following this, the data and measures used for the analysis are described in detail before an analytical framework and modelling strategy is outlined that has

been designed with the purpose of accommodating the necessary levels of complexity for exploring multilevel variations in distance moved. The results of the multilevel analysis are then presented and discussed before the summary and conclusions are given.

Conceptualising multilevel variations in distance moved between origins and destinations

One of the most important contributions to an all-embracing multilevel origin to destination theory of population movement was given in Everett Lee's (1966) seminal paper "*A theory of migration*". Central to the paper are four strands that are thought essential for informing the decision to migrate and the process of migration, these are, factors associated with the *area of origin*, *area of destination*, *intervening obstacles*, and *personal factors* (Lee, 1966: 49). Functioning together, these factors are assumed to inform the subjective evaluation of a balance between the degree of satisfaction with the current residence and the desire, need and ability for residency elsewhere (Clark and Dieleman, 1996; Clark and Ledwith, 2006).

The patterns, processes and characteristics of residential mobility are therefore thought to be driven by certain 'push' and 'pull' dynamics that are conditioned (encouraged or discouraged) by different factors operating at different levels at both the origin and the destination (Rossi, 1955; Massey, 1990; Fielding, 2012). For example, the decision to change residence can be influenced by 'pulls' to a new residence, driven for instance by the potential for new or improved employment and/or lifestyle possibilities, as well as 'pushes' associated with current residence such as a sudden change in household composition (e.g. birth, death or cohabitation) or a gradual shift in lifestyle and consumption preferences. Yet whilst Lee (1966) provides a considerably more general theory of mobility in its broadest sense, it can be thought to hold great relevance and potential for the more specific examination of variations in distances moved.

Intervening distance and selective micro-level dynamics

The influence of intervening obstacles and selective micro behaviours and characteristics are well rehearsed in the literature (Rossi, 1955; Champion *et al.*, 1998; Fielding, 2012). However, given our focus here, it is important to (re)emphasise the importance of distance as a key obstacle. Indeed, intervening distance, when operating in parallel with other selective dimensions, makes residential movements over long distances largely the preserve of a relative social-economic elite. The increasing distance of move is thought to be linked to increasing restrictions and costs including: the relinquishing ties to locality-specific social networks and amenities (Brown, 2002); likely changes in employment and/or the workplace (Owen, 1992); financial costs and implications associated with searches and moves themselves (Flowerdew, 1976); and requirements for information on opportunities available in places further afield (Flowerdew, 1982). Thus, if a long-distance move is the desired outcome, these costs and restrictions can be understood to intervene in the process by filtering those individuals/households with sufficient resources and motivation to ultimately satisfy the desire to migrate to destinations further afield.

Arguments for the strong selective nature of the micro-level dynamics behind variations in distance moved are supported by empirical studies that have demonstrated how particular individual/household characteristics are associated with short-distance moves while others are more closely aligned with moves over longer distances. For example, the average distance moved is often found to increase in a linear manner with levels of educational attainment and household income (Fielding, 2012). Individuals with higher educational attainment and associated occupations are known to search over far wider labour markets and have greater spatial flexibility associated with, and driven by, career progression (van Ham *et al.*, 2001). This compares to those in the more routine and manual occupations, who are generally more spatially tied to certain locales and local labour markets (Fielding, 2012). Furthermore, those with greater educational and occupational attainment typically have access to greater financial resources, thus easing the mitigation of the increased costs

associated with longer-distance moves. However, somewhat separated from the underlying influence of the labour market, two important subgroups stand out. Whilst motivated by very different factors, both students and retirees form two distinctive migration streams commonly associated with moves over long distances and between particular types of origin and destination, be they university towns for students or amenity-rich environments for retirees (Champion *et al.*, 1998; Smith, 2009).

Beyond the labour market, differences in housing tenure have also been noted as important in determining variations in distances moved. Most notably in the UK context, attention has been paid to the restrictive nature of social housing provision where, through stringent local access rules, tenants of social housing find themselves particularly restricted in making moves between local authority districts and thus over longer distances (Hughes and McCormick, 2000). Similarly, though enacted through somewhat more subtle means, strong variations in distance have been observed when comparing different ethnic groups. Indeed, whether motivated by positive factors (e.g. maintaining familial ties or access to cultural amenities) or negative factors (e.g. reacting to discrimination or restricted opportunities), non-white ethnic groups tend to be more spatially concentrated in specific geographic locations, particularly in London but also in certain other large urban centres, than is the case for the more spatially dispersed majority white group (Simpson and Finney, 2009; Stillwell, 2010). Such variations in concentration and distribution can be expected to promote the variations in distance commonly observed for different ethnic groups. Whilst the examples given here are far from an exhaustive list of the selective micro characteristics thought to have influence on variations in the distance moved, they are useful in outlining what we understand as important intervening obstacles and selective dimensions operating at the micro level.

The role of multilevel context and place based attractiveness

Of course whilst micro-level influences are of great importance, ignoring context, including factors that operate at the origin and the destination, leaves the analyst open to accusations of atomistic

error/fallacy as well as a failure to accommodate substantively important realistic complexity (Lee, 1966; Massey, 1990; Courgeau and Baccaini, 1998). Indeed, aggregate level empirical research does suggest that simultaneous origin *and* destination residential contexts influence our ability and desire to move shorter or longer distances. With that said, it is important to first outline what we mean by contexts, and second, what our *a priori* expectations about the role of specific elements of the contexts are.

Kearns and Parkinson (2001) define three broad spatial levels as central to what they would understand as a relevant milieu; running from what is termed the *home area* of familiarity and community, through to the *locality*, a wider area associated with everyday residential activities, and finally up to the *urban district or region* which is theorised to be the landscape of social and economic opportunities, operationalized through employment connections, leisure interests and social networks (Kearns and Parkinson, 2001: 2104). A general understanding of social and spatial context in this way, as a multilevel phenomenon, is certainly very useful when attempting to conceptualise how an areal push-pull theory operates in practice.

Indeed, intertwined in the subjective assessment of one's residential satisfaction, the neighbourhood context (reflecting the home area and locality) has been identified as a *potentially* important predictor of mobility outcomes (Boehm and Ihlanfeldt, 1986). Whilst in practice the evidence is rather mixed (Clark and Ledwith, 2006; Rabe and Taylor, 2010), the characteristics of neighbourhoods are thought to play some role in conditioning the desire to move, the ability to move, and the decision of where to move to. For instance, levels of deprivation, ethnic heterogeneity and population stability have been noted as important drivers of neighbourhood desirability given their perceived role in influencing levels of social cohesion, crime, the physical environment and positive/negative social externalities (Galster and Killen, 1995; van Ham and Clark, 2009).

In this way, the profile of the neighbourhood can be expected to both push, particularly if it exacerbates the degree of residential dissatisfaction, or pull individuals/households, in the case where it offers enhanced opportunities to correct for residential dissatisfaction. Of course, individuals/households who have access to sufficient resources can act on such forces and do tend to move to neighbourhoods that reflect what are generally considered to be desirable living conditions (Clark and Dieleman, 1996). However, as with individual/household characteristics, the neighbourhood is also thought to act as a selective mechanism where, particularly for the most deprived neighbourhoods, those without sufficient resources are restricted in their opportunities to act on mobility desires and particularly to move over sufficient distances in order to reach the more desirable neighbourhoods (Galster and Killen, 1995), neighbourhoods, in the UK context, that are often spatially segregated (Dorling and Rees, 2003).

Beyond the neighbourhood, important factors are thought to operate at the broader regional (macro) level, for instance regional economic robustness and differential lifestyle opportunities are said to influence the attractiveness of different locations, and are thus used to explain many of the clear and persistent patterns of residential mobility at the macro-level. For instance, the long-standing pivotal role of London in the national migration system is well documented (Fielding, 1992; Champion, 2008). Whilst the capital tends to attract young and usually well-educated adults from across the country, largely for employment but also lifestyle reasons, it is by far the largest net loser of residential movements to elsewhere in the UK. Whilst London has continued to grow over the last decade or so, much of this observed growth has been driven by a combination of strong natural increase and significant net immigration from outside the UK (Champion, 2008). However, London is not alone in losing considerable numbers of people to other parts of the UK. Indeed, over recent decades the dominant characteristic of within-UK residential movement has been that of urban-rural shift and counterurbanisation (Champion, 2005a), a phenomenon that has been recognised by many to be driven by amenity migration, place-based preferences, an improvement in the ease of commuting, a growing proportion of pleasure-seeking retirees, and a widespread normative

attachment to the supposed 'rural idyll'. As Champion *et al.* (1998: 96) suggest, "[m]ythical or otherwise, the 'rural idyll' [...] would seem to be providing the cognitive framework within which many people are, consciously or subconsciously, making their decisions to join the urban exodus". Of course, whilst they are much smaller in their scale, there are important counterstreams, for instance, the persistent movement of young people away from smaller towns and rural areas towards the cities (Stockdale, 2004) and, as mentioned above, increasingly large student flows into university towns and cities (Champion, 2005b; Smith, 2009).

In summary, then, the key theoretical and empirical work suggests that factors operating simultaneously at the origin and the destination, from the micro-scale through to the macro-scale, combine to produce multilevel variations in distances moved between origins and destinations. With this in mind, the data and measures used in the present study are now considered, before a suitable modelling framework appropriate for dealing with such complexities is defined.

Data and measures

The data used in this analysis are drawn from the Acxiom Ltd. Research Opinion Poll (ROP), a voluntary and principally paper-based postal lifestyle survey of individual household respondents aged 18 and over in Great Britain (GB). By employing a number of address sources to ensure a geographically even and reasonably representative demographic response for GB (Rees *et al.*, 2009), the ROP generates a large and geographically extensive sample of geo-referenced individuals covering key demographic, socio-economic and behavioural/lifestyle characteristics. A comprehensive description and validation of the ROP as a source of data for population migration analysis can be found in Thomas *et al.* (2012; 2014). Indeed, whilst migrants are underrepresented in the ROP, descriptive benchmarking of the aggregate-level migrant flows against the 2001 Census produced reassuringly comparable results with Pearson correlation coefficients exceeding 0.7 (Thomas *et al.*, 2012). In addition to this, micro-level multivariate regression based approaches, comparing associational relationships of various characteristics on movement propensities in

weighted and unweighted ROP models as well as like-for-like comparisons with models using the 2001 Census Individual Licensed Sample of Anonymised Records (I-SAR, 3 % sample, $n = 1.75$ million), are particularly encouraging in demonstrating the relative robustness of model-based results derived from the ROP for migration analysis (Thomas *et al.*, 2014). The analysis presented here makes use of a subset derived from three tranches of ROP data for mainland England and Wales, covering the period January 2005 to January 2007, resulting in an analytical sample size of 26,688 individual residential migrants³. We define a migrant as an individual who has moved to his/her current postcode address (destination) within the three years prior to survey completion and who has additionally provided a full postcode address for their previous residence (origin).

The benefit of having detailed postcode identifiers is twofold: firstly we can define origin and destination areas in far greater detail than is allowed for in alternative sources such as the Census I-SAR (where only Government Office Region geography is provided at the origin); and second, we are able to measure continuous distance directly from origin postcode grid reference to destination postcode grid reference. By limiting the migration interval to three years, we reduce the potential for distortions associated with time-varying characteristics while allowing for the generation of a large sub-sample with good geographic coverage, the latter being of particular importance given our focus on spatial distribution and context. However, it should be noted that certain peoples' characteristics may well change more rapidly than others over the three year period, for instance young people when compared to the more settled older population, and therefore measurement error pertaining to micro-level non-stationarity is likely to be greater for the former. Similarly, it is unfortunate that the cross-sectional nature of the data means it is not possible to explore relationships between the individual/household at the beginning *and* end of the move. Finally, due to a degree of sparsity in the sample for certain Scottish regions, the analysis focusses on England and Wales only.

³ This migrant subsample represents 7.65% of the full GB (England, Wales & Scotland) analytical sample ($n = 348,953$) used in the previous model based benchmarking exercises in Thomas *et al.* (2014).

In terms of the micro-level characteristics used in the analysis, we refer to previous research and include covariates that are commonly observed and/or theorised to be important predictors of variation in distance moved. Measured at the time of survey completion only (i.e. the destination), these are: age, sex, ethnicity, marital status, household income, household tenure, occupational class and educational attainment. We also include variables to adjust for potential confounding effects associated with the small temporal variations in our analytical sample, these being the differences in duration at the current address and the year of survey completion. Finally, it should be noted that the household could be considered as a level in its own right (Massey, 1990). Unfortunately, however, the ROP only refers to a single household representative, and thus we have exactly the same number of individuals as there are households in the sample, leading to a situation where it is impossible to separate the residual variance between individuals and households. Therefore, in the analysis presented here, we incorporate the household characteristics into the micro-level, as ‘fixed-part’ covariates⁴.

Defining neighbourhoods and regions

It was decided that a specially designed measure of small area profiles, the 2001 Output Area Classification (OAC) (Vickers and Rees, 2007), provided the best option for operationalising neighbourhood context. The OAC is a hierarchical geodemographic classification of small areas into groups based on the similarity of the demographic, socio-economic and housing profile of their residents; all of which are factors raised in the literature as being potentially important factors for influencing neighbourhood attractiveness and more general residential satisfaction. Defined at the 2001 Census Output Area level of geography, where there are 175,434 OAs in England and Wales, each comprising on average a population of 297 individuals and 124 households (Martin, 2002), OACs provide a census based measure of the immediate neighbourhood profile for both origins and the destinations. Drawn from the OAC’s three-level hierarchy (7, 21 and 52 clusters respectively), we

⁴ A definition of the ‘fixed’ and ‘random’ parts of the fully specified cross-classified model is given following Equation 1.

use the second level which contains 21 geodemographic groups ranging, for instance, from OAs defined as '*Terraced Blue Collar and Public Housing*' to those categorised as '*Accessible Countryside*', '*Senior Communities*', and '*Prospering Younger Families*'.

To represent the macro-regional level, we use a system of 'city regions' which are functional aggregations of local authority districts designed to provide a manageable set of regions based on metropolitan cores and their 'tributary' hinterland areas ('Metro Rest', 'Near', 'Coast and Country' areas). Through the employment of city regions at the macro-level, we are able to get a direct measure of the spatial distribution of migrants' origins and destinations, and more specifically, we are able to explore this in relation to important macro processes linked to population density (the urban hierarchy) and the spatial economic system, for which the geography of city regions was designed to represent in work comparing internal migration in the UK and Australia (Stillwell *et al.*, 2000). The 33 macro-geographical regions are based on the major metropolitan centres of England and Wales (Birmingham, Bristol, Cardiff, Leeds, Liverpool, London, Manchester, Newcastle and Sheffield).

Multilevel framework for modelling and analysis

Multilevel models (MLM) provide a flexible methodology that allow for efficient simultaneous estimation and partitioning of variability across different levels, classifications and/or groups (Paterson and Goldstein, 1991). From a MLM where there is a *strictly hierarchical* structure among units, for instance where migrants (level-1 units) are nested within origin *or* destination neighbourhoods (level-2 units), which are themselves nested within city regions (level-3 units), it is possible to generate estimates of the relative contribution of each level to the total variation in distance migrated, while at the same time being able to explore and control for individual and contextual heterogeneity and (spatial) autocorrelation (Goldstein, 2011). However, despite these advantages, when analysing origin-destination distance, a *strictly hierarchical MLM* can only be used to account for influences operating at either the origin *or* the destination.

In a *cross-classified MLM* (Fielding and Goldstein, 2006; Goldstein, 2011), the methodology is extended so as to account for a more complex structure, i.e. where we have an individual situated simultaneously nested within an area of origin hierarchy and an area of destination hierarchy. From a substantive point of view, the cross-classified structure allows us to observe not only the micro-level drivers of variation in distance moved, but also the remaining meso/macro contextual variations, having controlled for the micro-level composition.

If there are remaining contextual effects at the origin and the destination, we should expect to observe a degree of spatial heterogeneity wherein certain areas, driven by the degree of attraction, send/receive (push/pull) migrants over longer/shorter distances than others. From a statistical modelling perspective, if both origin *and* destination factors are found to contribute to variations in the outcome, the modelling of only one such context/classification, the origin *or* the destination, would fail to account for possible confounding effects associated with an underspecified model (Fielding and Goldstein, 2006). For example, if we only include the destination context in our model, we run the risk of overstating its importance as a source of variation at the expense of the origin; that is, we fail to disentangle variation between different destination contexts from that which may be more accurately estimated as variation between different origin contexts.

Therefore, drawing on the classification notation of Browne *et al.* (2001), the cross-classified model that forms the basis of the analysis presented here (Model 4) can be specified as follows:

$$\begin{aligned}
y_i &= (X\beta)_i + u_{orig\ region(i)}^{(5)} + u_{orig\ neighbourhood(i)}^{(4)} + u_{dest\ region(i)}^{(3)} + u_{dest\ neighbourhood(i)}^{(2)} + e_i, \\
orig\ region(i) &\in (1, \dots, J_5), \quad orig\ neighbourhood(i) \in (1, \dots, J_4), \\
dest\ region(i) &\in (1, \dots, J_3), \quad dest\ neighbourhood(i) \in (1, \dots, J_2), \\
u_{orig\ region(i)}^{(5)} &\sim N(0, \sigma_{u(5)}^2), \quad u_{orig\ neighbourhood(i)}^{(4)} \sim N(0, \sigma_{u(4)}^2), \quad u_{dest\ region(i)}^{(3)} \sim N(0, \sigma_{u(3)}^2), \\
u_{dest\ neighbourhood(i)}^{(2)} &\sim N(0, \sigma_{u(2)}^2), \quad e_i \sim N(0, \sigma_{e_i}^2), \quad i = 1, \dots, N,
\end{aligned} \tag{1}$$

where y_i is the natural logarithm of origin to destination distance in kilometres (km) for the i th migrant of N migrants in total, itself a function of $(X\beta)_i$ which represents the fixed part of the model, a vector of X explanatory variables whose parameters, β , are referred to as ‘fixed

parameters' and, for this analysis, are all measured at the migrant level. Within this vector, the first element, the constant (β_0), takes a value of one for each migrant (i) and, when all other explanatory variables are held at their base (i.e. 0), provides the estimated mean logged distance migrated from origin to destination across all origin and destination neighbourhood types and regions. The random part of the model reflects the remaining residual variation where $u_{orig\ region}^{(5)}(i)$ is the additional effect of migrant i 's region at origin (level 3), $u_{orig\ neighbourhood}^{(4)}(i)$ is the additional effect of migrant i 's neighbourhood at origin (level 2), $u_{dest\ region}^{(3)}(i)$ is the additional effect of migrant i 's region at destination (level 3), $u_{dest\ neighbourhood}^{(2)}(i)$ is the additional effect of migrant i 's neighbourhood at destination (level 2) and e_i represents the remaining migrant level residual error. All parameters in the random part of the model are assumed to follow a normal distribution with a mean of zero and a constant variance and, additionally, are assumed to be independent across cross-classifications as well as independent of the explanatory variables included in the fixed part. Due to the complex structure of the cross-classified model and the relatively small number of city region units, Bayesian Markov chain Monte Carlo (MCMC) estimation is used, providing more efficient and robust estimation to the maximum likelihood based alternatives (Browne, 2012). All models are estimated using the MLwiN software (Rasbash *et al.*, 2013). Initial parameter starting values are based on maximum likelihood methods with model convergence assessed following the good-practice recommendations of Draper (2006) and Jones and Subramanian (2013). For assessing and comparing the fit of our models, we use the Deviance Information Criterion (DIC) (Spiegelhalter *et al.*, 2002). The DIC is a 'badness-of-fit' measure that penalises for model complexity; and when comparing models, those with a smaller value of DIC are preferred.

In terms of the modelling strategy, we specify three initial 'null' (constant only) models with random intercepts, Model 1 with neighbourhood (level 2) and regional (level 3) contexts defined at the origin; Model 2 with neighbourhood (level 2) and regional (level 3) contexts defined at the

destination; and finally, Model 3 where the individual (level 1) is nested within the two simultaneous hierarchies, an origin (level 2 and level 3) and destination (level 2 and 3) cross-classification. The ‘null’ variance components model allows the partitioning of the total variability in logged distance across the different levels/classifications. For instance, before accounting for the compositional differences between areas, we can use null models to inspect whether there is indeed any evidence for variation in distance attributable to differences between city regions and/or differences between geodemographic neighbourhood types within city regions. This can be done for the origin and destination separately and also as a cross-classification of the two, where, in the latter case, we are able to explore the relative contribution of the multilevel contexts at the origin net of the relative contribution of multilevel contexts at the destination, and *vice versa*. Following this, we account for the compositional differences between areas by introducing the individual/household level covariates into the fixed part of the cross-classified model. Whilst the influence of micro-level covariates on variations in origin to destination distance is of interest in itself, having controls for the compositional effects is additionally beneficial in that we are better able to identify which areas send/receive (attract/repulse) migrants over longer or shorter distances.

Model results

Variance components models

Table 1 shows the results of the three null models for migrants nested within their origin hierarchy (Model 1), migrants nested within their destination hierarchy (Model 2) and migrants nested within a unified cross-classification of their origin and destination (Model 3). For the strictly hierarchical models, the majority of variation is found between individuals, as we would expect; however, there is some evidence of non-individual variation. Indeed, the within-city region-between-neighbourhood variation (i.e. level 2) is estimated to account for around 4%⁵ of the total variation in distance migrated in both Model 1 and Model 2, with the observed between-city region differences (i.e. level

⁵ The origin value (Model 1), for example, is calculated as: $\sigma_{u(4)}^2 / (\sigma_{u(5)}^2 + \sigma_{u(4)}^2 + \sigma_e^2)$. Using Model 1 estimates the level-2 variation is: $0.151 / (0.069 + 0.151 + 3.468) = 0.041$.

3) accounting for around 2% of the total variation in Models 1 and 2. However, as has been argued above, the casting of the model as a strict hierarchy has serious statistical and substantive analytical limitations, both of which can be expected to have serious implications for the reliability of the modelled results and subsequent substantive interpretations.

Table 1. Variance components models for migrant origin to destination distance moved (log km)

	Model 1		Model 2		Model 3	
	Null origin		Null destination		Null cross-classified	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Fixed Part						
Constant	1.254	0.052	1.339	0.055	1.233	0.208
Random Part						
$\sigma_{u(5)}^2$ Origin city region variance	0.069	0.023			0.728	0.205
$\sigma_{u(4)}^2$ Origin neighbourhood variance	0.151	0.018			0.129	0.017
$\sigma_{u(3)}^2$ Destination city region variance			0.081	0.028	0.672	0.187
$\sigma_{u(2)}^2$ Destination neighbourhood variance			0.155	0.019	0.067	0.011
σ_e^2 Individual migrant variance	3.468	0.031	3.498	0.031	3.187	0.028
DIC	109228.061		109459.595		107187.676	
<i>d.o.f</i>	302.608		305.670		520.564	
Nos. Units: Origin city region	33				33	
Nos. Units: Origin neighbourhood	621				621	
Nos. Units: Destination city region			33		33	
Nos. Units: Destination neighbourhood			621		621	
Nos. Units: Individual migrant	26,688		26,688		26,688	

When the model is specified as a cross-classification of origins and destinations the model fit is considerably improved (the DIC in Model 3 is more than 2,000 units smaller than in Models 1 and 2), while the change in the way in which total variation is partitioned between the different classifications is equally substantial. The between-individual differences remaining as the primary source of total variation (67%), the total macro-geographical variation, that is, the total macro origin and destination contexts combined, is now estimated to account for a substantial 29% of the total variation in distance migrated⁶ (15% at origin and 14% at destination).

Before any exploration of potential patterning to the observed macro-level variation is made, it is important consider the micro-level predictors and, in doing so, allow for the socio-demographic composition to be taken into account. Indeed, without allowing for the composition, it is hard to argue that the quite substantial variations found at the macro-level are the result of place-based

⁶ Calculated as: $(\sigma_{u(5)}^2 + \sigma_{u(4)}^2) / (\sigma_{u(5)}^2 + \sigma_{u(4)}^2 + \sigma_{u(3)}^2 + \sigma_{u(2)}^2 + \sigma_e^2)$ and including Model 4 estimates is: $(0.728+0.672)/(0.728+0.129+0.672+0.067+3.187) = 0.293$

differences, as opposed to a mere reflection of simple variations in composition of origin and destination neighbourhoods and city regions.

Introducing predictors to the cross-classified model

The introduction of the micro-level covariates into the fixed part of the cross-classified model (Model 4, Table 2) is reflected by a further substantial reduction in the DIC. The estimated grand mean distance moved, that is the distance of the typical migrant across all neighbourhoods and all regions, is predicted to be 3.34 km (once anti-logged), corresponding closely with previous estimates using census data and commercial estate agency records (Boyle and Shen, 1997; Hamptons International Ltd., 2013). Turning to the random part of Model 4, the inclusion of the micro-level covariates has reduced the unexplained variation at the migrant level by approximately 3.4%⁷ while at the same time, through controlling for areal unit composition, the already very marginal variations between neighbourhood type (4% in Model 3) have reduced by 42.6% (origin) and 44.8% (destination). Yet even after controlling for micro-level factors and neighbourhood type, at both the origin and the destination, considerable differences between the city regions remain evident (28% of the remaining residual variation lies at the combined macro-level). Whilst the city region geography is designed to reflect critical geographical components including the wider spatial economic system and urban hierarchy in England and Wales (Stillwell et al., 2000), potentially important additional macro-geographical variables, including measures of median house price and job density, were included in preliminary models (not shown here) in an attempt to explain some of the remaining macro-level variation. Perhaps unsurprisingly, given the small number of city region units (and thus degrees of freedom), their inclusion was found to be neither statistically nor substantively important.

The results from the fixed part of the model (Table 2 and Figure 1) confirm that residential movements over longer distances are largely the preserve of a subgroup of individuals who possess

⁷ Calculated as: $(3.187 - 3.080) / 3.187$ (using level-1 variances from Models 3 and 4).

characteristics indicative of relative social-economic advantage. For instance, of the various individual/household factors that were taken into account, many of the largest differentials in distance can be found to relate to specific variations in migrants' educational attainment, occupation, annual household income and housing tenure. Beyond this, however, certain additional socio-demographic differences can be seen to play some role in predicting variations in origin to destination distance; though, aside from one or two examples, their influence is less pronounced when compared to the socio-economic factors. Nevertheless, for a more extensive and better revealing insight of the micro-level dynamics, it is helpful to provide a detailed breakdown of some of the key individual/household covariates shown in Table 2 and Figure 1, the latter of which has had its axes scaled to allow comparison of the relative size of the effects associated with each fixed part covariate⁸. In terms of ethnicity, there is very little difference in average distance moved for the Black and Other ethnic groups and the reference group, the White majority. However, there does appear to be a substantively rather interesting pattern for the Asian ethnic group (Indian, Pakistani and Bangladeshi), wherein the average distance migrated for this group is considerably shorter than that of the other groups. This pattern has been observed in Finney and Simpson's (2008) analyses of census data.

The effects of differing marital status, which for lack of any better alternative is used here as a rather crude proxy for relational dependency and cohabitation, does not suggest any particularly striking influence over variations in distance moved. However, those recorded as currently divorced/separated are estimated to have moved marginally shorter distances, on average, than those in the married reference category. Whilst we have no measure of whether individual migrants have dependent children, or whether the measured migration follows the dissolution of a relationship, previous research by Feijten and van Ham (2007) suggests that the separated are likely

⁸ The results presented in Figure 2 are derived using the simulation-based procedures of the MLwiN customised predictions facility (Rasbash *et al.*, 2012).

to stay relatively 'local' so as to maintain their location-specific capital and social networks, and, perhaps most importantly, the relationship with any dependent children they may have.

Table 2. Multilevel cross-classified model estimates for origin to destination distance moved (log km)

	Model 4 Full cross-classified			
	Estimate	S.E.	CI(2.5%)	CI(97.5%)
Fixed Part				
Constant	1.208	0.198	0.817	1.599
Age (centred at 40)	0.011	0.001	0.008	0.014
Gender (1 = Male)	0.057	0.024	0.010	0.104
<i>Ethnic group (ref = White)</i>				
Asian	-0.380	0.076	-0.530	-0.231
Other	-0.024	0.074	-0.169	0.122
Black	-0.059	0.091	-0.236	0.120
<i>Marital status (ref = Married)</i>				
Single	0.037	0.035	-0.031	0.106
Living with partner	0.025	0.031	-0.036	0.085
Divorced/separated	-0.111	0.037	-0.184	-0.038
Widowed	-0.093	0.066	-0.222	0.036
<i>Highest qualification</i>				
Linear polynomial	0.349	0.028	0.294	0.404
Quadratic polynomial	0.068	0.024	0.020	0.115
Annual household income (linear polynomial)	0.255	0.056	0.145	0.365
<i>Occupation group (ref = Intermediate)</i>				
Retired	0.528	0.052	0.428	0.629
Student	0.498	0.063	0.373	0.622
Homemaker	0.177	0.042	0.094	0.259
Unemployed	0.209	0.061	0.089	0.328
Routine & manual	-0.017	0.042	-0.099	0.066
Higher managerial administrative & professional	0.091	0.031	0.030	0.152
<i>Housing tenure (ref = Home owner)</i>				
Rent private	0.052	0.032	-0.012	0.116
Rent council	-0.525	0.041	-0.605	-0.445
Rent housing association	-0.347	0.047	-0.440	-0.254
<i>Duration at destination (ref = <1 year)</i>				
<2 years	-0.038	0.027	-0.090	0.014
<3 years	-0.033	0.027	-0.085	0.019
<i>Data set (ref = January 2005)</i>				
January 2006	-0.130	0.034	-0.197	-0.062
January 2007	-0.108	0.025	-0.157	-0.060
<i>Housing tenure * Age</i>				
Rent private, Age(40)	-0.021	0.002	-0.025	-0.017
Rent council, Age(40)	-0.019	0.002	-0.024	-0.015
Rent housing association, Age(40)	-0.013	0.003	-0.018	-0.007
Random Part				
$\sigma_{u(5)}^2$ Origin city region variance	0.657	0.183	0.387	1.093
$\sigma_{u(4)}^2$ Origin neighbourhood variance	0.074	0.012	0.052	0.099
$\sigma_{u(3)}^2$ Destination city region variance	0.605	0.168	0.357	1.010
$\sigma_{u(2)}^2$ Destination neighbourhood variance	0.037	0.008	0.023	0.054
σ_e^2 Individual migrant variance	3.080	0.027	3.027	3.134
DIC	106201.116			
d.o.f	444.019			

N.B. CI, Bayesian credible interval.

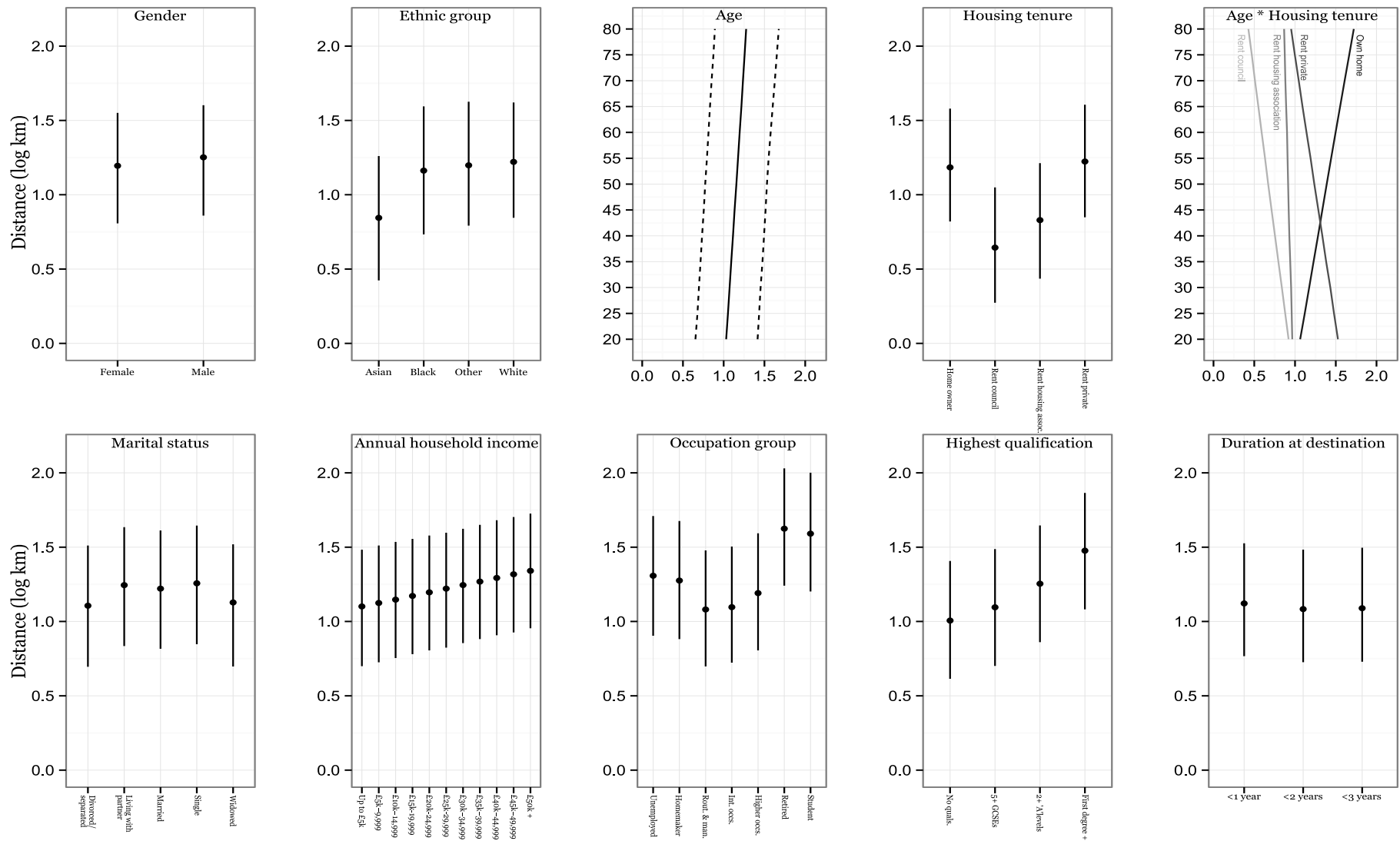


Figure 1. Model 4 fixed part predictions and 95% credible intervals

With respect to the migrant's age, there is a rather complex relationship which is inextricably linked to housing tenure. Figure 1 shows that the main effect for age, free of any interaction effects, has a positive linear relationship with the distance moved. The main effect for housing tenure are also shown, where council and housing association renters are observed to move particularly shorter distances than private renters and homeowners. However, when age is interacted with housing tenure type, the nature and direction of the relationships are found to vary greatly. Contrary to the relationship shown by the simple main effects, *ceteris paribus* a single unit increase in age is actually found to be negatively associated with distance moved for those migrants who are recorded as being renters at the destination. It is likely that this relates to a broader socio-economic dimension. Where renting during early adulthood is generally the norm, a combination of insecurity of tenure and a strong normative preference for homeownership in GB, may well suggest that those still renting in older age more accurately reflect a position of greater relative deprivation (Mulder, 2013). Somewhat interlinked with this, the tenure type associated with the longest distance moves varies according to age. Whilst private renters are found, on average, to move longer distances in the younger age groups, the propensity for longer-distance moves reduces year-on-year until, at approximately 40-45 years of age, homeowners take over as the group most likely to migrate over longer distances. Again, whilst those in the older age groups are more likely to be free from occupational and familial (dependent-child) constraints, homeowners in the older age groups are also likely to be relatively more (asset-) affluent, at least when compared to other tenure groups. Consequently, if a long-distance move is the desired outcome, perhaps for reasons linked to retirement and the pursuit of residential milieu that better reflect their lifestyle and consumption desires, a combination of such factors could be expected to make this group particularly able when attempting to overcome the intervening obstacles commonly associated with longer-distance migrations.

Income and qualifications

Estimates associated with the migrant's annual household income and educational attainment (highest qualification) present the directional relationships found in many previous studies. Both variables are measured using orthogonal polynomials, a parameter coding system that allows for the maintenance and measurement of order within a categorical variable that is itself measured on an ordinal scale (Rasbash *et al.*, 2012). Making use of this parameterisation, we observe that greater levels of household income are positively, and linearly, associated with greater distance. Moreover, greater levels of educational attainment are also found to be positively associated with greater distance. Thus in common with the previous findings outlined above, individuals with access to higher household income and a better education (particularly degree level and above) are more likely to have migrated over longer distances than those in the lower income brackets and those with poorer educational attainment.

With that said, the greatest effects are found amongst the different occupational groups. For those in paid employment, there is little difference in the mean distance travelled, although for what small differences do appear, the trend of increasing distance being linked to higher occupational groups is visible (Figure 1). Moreover, there is some evidence of increased distance being associated with those who are currently unemployed and those who describe themselves as homemakers (i.e. tied-movers). However, the single largest estimated effects are found for the retired and student groups. As mentioned above, both groups have been observed to form well-known and distinctive migration streams which often entail residential moves over longer distances.

Random effects for a fully specified cross-classified model

Each random part classification is found to have a statistically significant contribution to the residual variation in origin to destination distance (Table 2). However, from a substantive point of view, the remaining within-city region-between-neighbourhood variation is found to be quite minor. Instead,

the place-based differentials of noticeable size and interest are found to operate at the macro-geographical level, where 28% of the remaining variation is located. Having controlled for the compositional influences at the micro- (individual/household) and meso- (neighbourhood type) levels, there appears clear evidence of systemic spatial heterogeneity in place based attractiveness, wherein certain macro-geographical areas send/receive (attract/repulse) migrants over significantly longer or shorter distances than would otherwise be expected.

The conditional 95% coverage interval for the origin macro regions⁹ suggests that city regions which lie at the 97.5th percentile of the distribution send the typical migrant a distance of 16.40km whereas for an origin region in the bottom 2.5th percentile of the ‘sending’ distribution, that same migrant is estimated to move just 0.68km. Similarly, for the ‘receiving’ city region (destination) distribution, the typical migrant whose destination is in the top 2.5% percentile, is estimated to move 15.37km; whilst those whose destination is in the bottom 2.5% percentile move 0.73km. Yet whilst such statistics are useful in demonstrating the existence of considerable macro-level spatial heterogeneity, they are of little help when attempting to draw out any underlying patterns to the variation. Consequently, where the dashed lines represent the estimated grand mean distance, i.e. the average distance moved across all residential migrants, all neighbourhood types and all regions, Figure 2 plots the modelled origin and destination city region residuals (differentials) against one another and in doing so uncovers the types of macro-geographic regions that lie at the extremes. Indeed, drawing on Figure 2, a clear systemic pattern to the heterogeneity emerges, one that closely reflects a process of urban-rural shift and counterurbanisation observed in previous aggregate-level studies of the UK (Champion, 2005a). As a general trend it is apparent that the major metropolitan cores (particularly London core), and to a certain extent their surrounding satellite towns and cities (i.e. Metropolitan Rest), send migrants over longer distances and attract migrants over shorter distances than the national average. Conversely, for the macro regions described as ‘Coast and Country’ migrants are pulled over longer distances and sent over considerably shorter distances.

⁹ Calculated as: $(-1.96\sigma_{u(5)}, +1.96\sigma_{u(5)}) = (-1.96\sqrt{0.657}, +1.96\sqrt{0.657}) = (-1.59, +1.59)$

Therefore, having controlled for individual and neighbourhood composition within the city regions, we observe a persistent pattern of strong urban repulsion, with urban cores pushing migrants over considerably longer distances, and an equally strong rural/coastal attraction, where such areas are seen to pull migrants over significantly longer distances, when compared to the national average.

Whilst longstanding neo-classical economic theories would suggest a pull towards the major metropolitan cores, for employment/labour market reasons (Sjaastad, 1962), a growing volume of evidence presents place-based attractiveness to be increasingly driven by desires for improved lifestyle and consumption opportunities, and therefore towards the more rural/coastal amenity-rich destinations (Champion, 2005a; Stockdale, 2010; Morrison and Clark, 2011). Indeed, beyond the significant contribution associated with the major economic restructuring of the 1970s, itself an important driver of (uneven) decentralisation of employment opportunities away from the old metropolitan cores and towards new nodes of economic growth (for instance, the M4 and M11 motorway corridors) (Fielding, 2012), an improvement in the ease of travel and communications has enabled an increasing disconnect between one's place of work and place of residence to emerge.

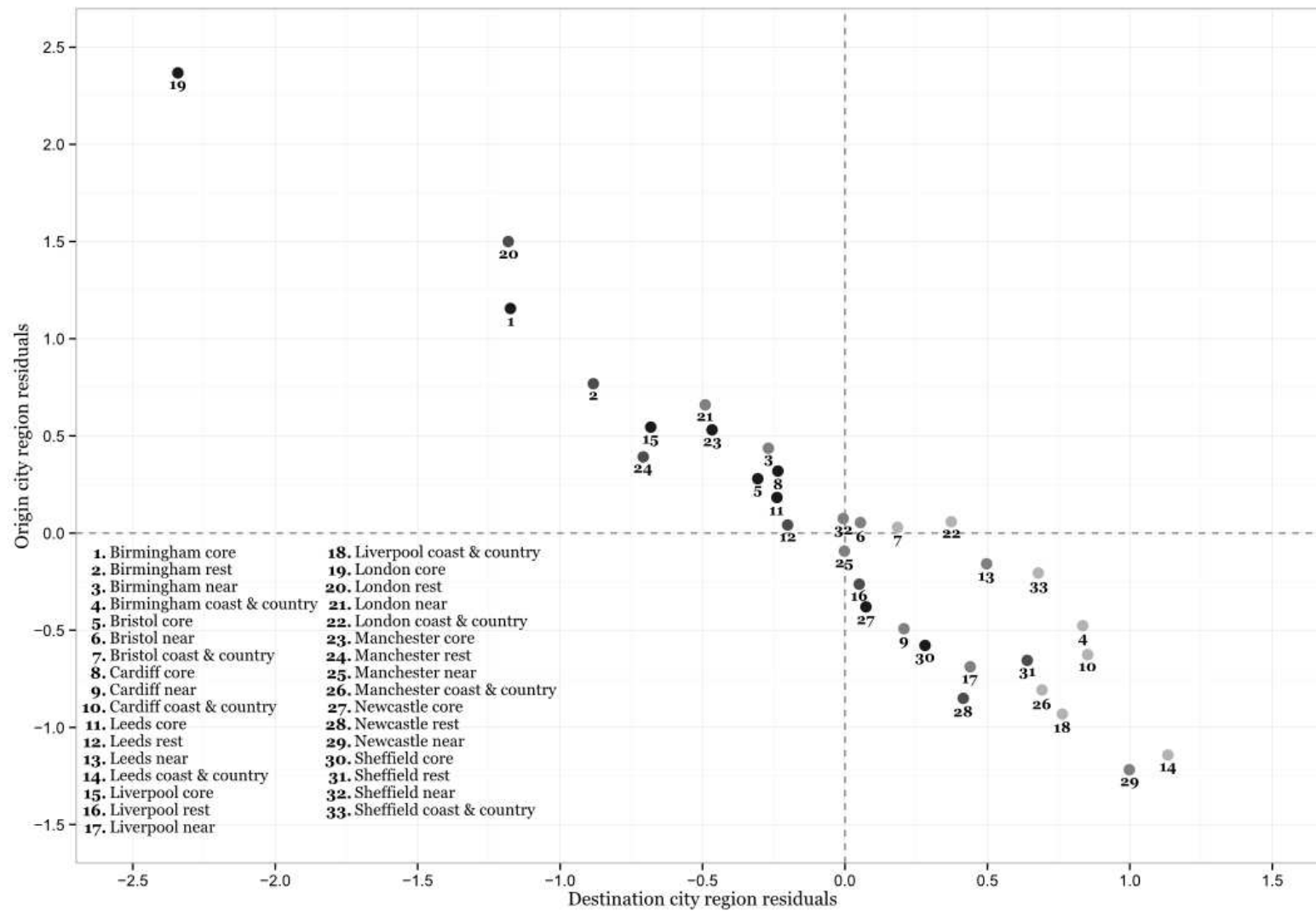


Figure 2. Model 4 origin and destination city region residuals (log scale). *N.B* grayscale used to differentiate the urban-hierarchy.

Empirical work has shown recent (working-age) in-migrants to the surrounding peri-urban and rural regions to be, on average, more likely to commute over significantly longer distances and durations (Boyle *et al.*, 2001; Axisa *et al.*, 2011). Moreover, in a comparative analysis of commute data from the 1991 and 2001 Censuses, Nielsen and Hovgesen (2007) suggest a strong growth in longer-distance commuting to have occurred, a growth which, they argue, is explained by a combination of the deconcentration of populations and jobs as well as a general socio-cultural preference for rural living. Of course, as has been alluded to above, place-based attraction and repulsion, and the ability to act on these things, are different for different people. For example, in contrast to the dominant theme of counterurbanisation, students and young professionals are known to form a significant counterstream *towards* the larger urban centres, and particularly London. However, when focussing on the residential mobility system as a whole, as we have done here, it would appear fair to agree with Morrison and Clark (2011) in suggesting that, whilst continued employment is of paramount importance for the majority of working-age migrants, in countries where employment opportunities are relatively abundant both spatially and in absolute terms, “*migration to enhance employment gives way to movement to enhance other goals*” (p.1949). Thus, under such circumstances, it is perhaps unsurprising to observe the trend for long distance moves towards amenity-rich rural and coastal destination environments.

Conclusion

This paper enhances previous studies by analysing variations in the distance over which migrants move in a manner that better reflects the realistic multilevel complexity associated with such a phenomenon. Whilst major theoretical contributions to explaining residential movement have emphasised the importance of processes and characteristics that operate simultaneously across different levels, at both the origin and the destination, existing research has struggled to confirm this empirically. However, drawing on a series of multilevel statistical models, it is our contention that the analysis presented in this paper goes some way to addressing this shortfall.

The findings suggest that the simultaneous inclusion of micro-level influences *and* wider origin and destination contextual settings are necessary for a more statistically robust and substantively complete understanding of variations in origin-destination distance, and particularly the additional role of place-based attractiveness. As expected, residential moves over longer distances are found to be strongly associated with individuals/households who have access to greater resources, both social and economic. Thus, relatively speaking, those moving the longest distances tend to be those who are highly educated, have access to greater annual household income, are older homeowners and, free from the spatial constraints of employment, are retired. It follows therefore that, *ceteris paribus*, migrants typically moving the shortest distances tend to be low paid, have very basic educational attainment, are members of an Asian ethnic minority group, and rent from a local authority or housing association.

Whilst the micro-level determinants are of clear substantive and empirical relevance, significant spatial heterogeneity, particularly at the macro-geographic level, is also observed. When cast as a multilevel cross-classified origin and destination model, a clear pattern of urban-rural shift emerges, wherein, on average, a typical residential migrant is pulled over significantly longer distances towards rural/coastal (amenity-rich) city region destinations and, at the same time, is pushed significantly longer distances if the origin city region type happens to be a metropolitan core (or metropolitan rest). Thus, by incorporating measures for neighbourhood type and macro-geographical context at the area of origin and destination, we are better able to get a handle on the relative importance of additional place-based attractiveness, net of their socio-demographic composition, for observed variations in the distance over which people move.

Given the strong spatial pattern of urban repulsion and rural/coastal attraction, our findings would appear to add further weight behind the argument that residential movement is increasingly a means through which people attempt to satisfy their leisure, lifestyle and consumption desires, a situation which has driven a quite significant redistribution of the population over long distances and

towards the amenity-rich environments of England and Wales' coast and countryside (Fotheringham *et al.*, 2000; Morrison and Clark, 2011).

In terms of future research, it would be particularly interesting to perform the same analysis but for specific policy relevant population subgroups. As mentioned, we can expect additional variations in distance relating to place-based attractiveness to be different for young and highly educated adults when compared to the general pattern of counterurbanisation described here, and in other aggregate based empirical analyses of the population as a whole. Yet a lack of suitable data, in terms of size and geographic/variable coverage and detail, currently precludes such a focussed multilevel approach in the UK.

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References:

- Axisa, J., Scott, D.M. & Newbold, K.B. (2011). Factors influencing commute distance: A case study of Toronto's commuter shed, *Journal of Transport Geography*, 24, 123-129.
- Boehm, T P. & Ihlanfeldt, K.R. (1986). Residential mobility and neighborhood quality, *Journal of Regional Science*, 26, 411–424.
- Boyle, P.J. & Shen, J. (1997). Public Housing and Migration: a Multi-Level Modelling Approach, *International Journal of Population Geography*, 3, 227-242.
- Boyle, P.J., Cassidy, S., Duke-Williams, O. Rees, P., Stokes, G. & Turner, A. (2001). *Commuting patterns in rural areas*. London: Countryside Agency.

- Brown, D. (2002). Migration and community: social networks in a multilevel world, *Rural Sociology*, 67(1), 1-23.
- Browne, W.J. (2012). *MCMC estimation in MLwiN, v2.26*. Centre for Multilevel Modelling, University of Bristol. Online at:
<http://www.bristol.ac.uk/cmm/software/mlwin/download/manuals.html>.
- Browne, W.J., Goldstein, H. & Rasbash, J. (2001). Multiple membership multiple classification (MMMC) models, *Statistical Modelling*, 1, 103-124.
- Cadwallader, M. (1989). A conceptual framework for analysing migration behaviour in the developed world, *Progress in Human Geography*, 13(4), 101-113.
- Champion, T. (2005a). The counterurbanization cascade in England and Wales since 1991: The evidence of a new migration dataset, *BELGEO*, 1-2, 85-101.
- Champion, T. (2005b). Population movement within the UK, in Chappell, R. (ed.), *Focus on people and migration*. Basingstoke: Palgrave Macmillan, pp. 92-114.
- Champion, T. (2008). Population change in England since 1981: Is an 'urban renaissance' really underway?, *Géocarrefour*, 83(2), 77-86.
- Champion, T., Fotheringham, A., Rees, P., Boyle, P., & Stillwell, J. (1998). *The determinants of migration flows in England: A review of existing data and evidence*, Report for the Department of the Environment, Transport and the Regions, University of Newcastle upon Tyne.
- Clark, W.A.V. & Dieleman, F.M. (1996). *Households and Housing: Choice and Outcomes in the Housing Market*. New Brunswick: Rutgers University Press.
- Clark, W.A.V. & Ledwith, V. (2006). Mobility, housing stress, and neighborhood contexts: Evidence from Los Angeles, *Environment and Planning A*, 38(6), 1077-1093.

- Courgeau, D. & Bacchini, B. (1998). Multilevel analysis in the social sciences, *Population: An English Selection*, 10(1), 39-71.
- Dorling, D. & Rees, P. (2003). A nation still dividing: the British census and social polarisation 1971-2001, *Environment and Planning A*, 35(7), 1287-313.
- Draper, D. (2006). *Bayesian multilevel analysis and MCMC*. New York: Springer.
- Feijten, P. & van Ham, M. (2007). Residential mobility and migration of the divorced and separated, *Demographic Research*, 17(21), 623-654.
- Fielding, A.J. (1992). Migration and social mobility: South East England as an escalator region, *Regional Studies*, 26, 1-15.
- Fielding, A.J. (2012). *Migration in Britain: Paradoxes of the present, prospects for the future*. Cheltenham: Edward Elgar.
- Fielding, A. & Goldstein, H. (2006). Cross-classified and multiple membership structures in multilevel models: An introduction and review. *Research Report RR791*. Department for Education and Skills: London.
- Finney, N. & Simpson, L. (2008). Internal migration and ethnic groups: Evidence for Britain from the 2001 Census, *Population, Space and Place*, 14, 63-83.
- Flowerdew, R. (1976). Search strategies and stopping rules in residential mobility, *Transactions of the Institute of British Geographers*, 1, 47-57.
- Flowerdew, R. (1982). Institutional effects on internal migration, in Flowerdew, R. (ed.), *Institutions and Geographical Patterns*. New York: St Martin's Press. pp. 209-227.
- Fotheringham, A.S., Champion, T., Wymer, C. & Coombes, M. (2000). Measuring destination attractivity: A migration example, *International Journal of Population Geography*, 6, 391-421.

- Galster, G.C. & Killen, S.P. (1995). The Geography of Metropolitan Opportunity: A Reconnaissance and Conceptual Framework, *Housing Policy Debate*, 6(1), 7–43.
- Goldstein, H. (2011). *Multilevel Statistical Models (4th edition)*. Chichester: Wiley.
- Hamptons International Ltd. (2013). 32 Years Old and Living in London? Chances are You're About to Escape, but Only by 26 Miles, Press release Monday 2 December 2013. London: Hamptons International Ltd.
- Hughes, G. & McCormick, B. (2000). *Housing policy and labour market performance*. London: ODPM.
- Jones, K. & Subramanian, V.S. (2013). Developing multilevel models for analysing contextuality, heterogeneity and change (Volume 1). Centre for Multilevel Modelling, University of Bristol. Online at: <http://www.mendeley.com/profiles/kelvyn-jones/>.
- Kearns, A. & Parkinson, M. (2001). The significance of neighbourhood, *Urban Studies*, 38(12), 2103-2110.
- Lee, E.S. (1966). A Theory of Migration, *Demography*, 3(1), 47-57.
- Martin, D. (2002). Geography for the 2001 Census in England and Wales, *Population Trends*, 108, 7-15.
- Massey, D.S. (1990). Social structure, household strategies, and the cumulative causation of migration, *Population Index*, 56(1), 3-26.
- Morrison, P.S. & Clark, W.A.V. (2011). Internal migration and employment: macro flows and micro motives, *Environment and Planning A*, 43, 1948-1964.
- Mulder, C.H. (2013). Family dynamics and housing: Concepts issues and empirical findings, *Demographic Research*, 29, 355-378.

- Nielsen, T.A.S. & Hovgesen, H.H. (2008). Exploratory mapping of commuter flows in England and Wales, *Journal of Transport Geography*, 16, 90-99.
- Owen, D. (1992). Migration and employment, In Stillwell, J., Rees, P. & Boden, P. (eds.), *Migration processes & patterns (Volume 2): Population redistribution in the United Kingdom*. London: Belhaven Press. pp. 205-224.
- Paterson, L. & Goldstein, H. (1991). New statistical methods for analysing social structures: An introduction to multilevel models, *British Educational Research Journal*, 17(4), 387-393.
- Rabe, B. & Taylor, M. (2010). Residential mobility, quality of neighbourhood and life-course events, *Journal of the Royal Statistical Society, Series A*, 173, 531–555.
- Rasbash, J., Charlton, C., Jones, K. & Pillinger, R. (2012). Manual supplement to MLwiN Version 2.26. Centre for Multilevel Modelling, University of Bristol.
- Rasbash, J., Browne, W., Healy, M., Cameron, B. & Charlton, C. (2013). MLwiN Version 2.28. Centre for Multilevel Modelling, University of Bristol.
- Rees P, Stillwell J, Boden P & Dennett A. (2009). A review of migration statistics literature, in Rees, P, Stillwell J, Boden P & Dennett A (eds.), *Migration Statistics: The Way Ahead?*. London: UKSA.
- Rossi, P. (1955). *Why Families Move: A Study in the Social Psychology of Urban Residential Mobility*. Illinois: Free Press.
- Simpson, L. & Finney, N. (2009). Spatial patterns of internal migration: Evidence for ethnic groups in Britain, *Population, Space and Place*, 15, 37-56.
- Sjaastad, L.A. (1962). The costs and returns of human migration, *Journal of Political Economy*, 70(5), 80-93.
- Smith, D.P. (2009). 'Student geographies', *Environment & Planning A*, 41, 1795-1804.

- Spiegelhalter, D.J., Best, N.G., Carlin, B.R. & van der Linde, A. (2002). Bayesian measures of model complexity and fit, *Journal of the Royal statistical society: Series B*, 64, 583-616.
- Stillwell, J. (2010). Ethnic population concentration and net migration in London, *Environment and Planning A*, 42, 1439-1456.
- Stillwell, J., Bell, M., Blake, M., Duke-Williams, O. & Rees, P. (2000). Net migration and migration effectiveness: A comparison between Australia and the United Kingdom, 1976–96 Part 1: Total migration patterns, *Journal of Population Research*, 17(1), 17-38.
- Stockdale, A. (2004). Rural out-migration: community consequences and individual migrant experiences, *Sociologia Ruralis* 44, 149-176.
- Stockdale, A. (2010). The diverse geographies of rural gentrification in Scotland, *Journal of Rural Studies*, 26, 31-40.
- Thomas, M., Gould, M. & Stillwell, J. (2012). Exploring the potential of microdata from a large commercial survey for the analysis of demographic and lifestyle characteristics of internal migration in Great Britain, *Working Paper 12/03*, School of Geography, Leeds University, Leeds. Online at: <http://www.geog.leeds.ac.uk/fileadmin/documents/research/csap/12-03.pdf>.
- Thomas, M., Stillwell, J. & Gould, M. (2014). Exploring and validating a commercial lifestyle survey for its use in the analysis of population migration, *Applied Spatial Analysis and Policy*, 7(1), 71-95.
- van Ham, M., Mulder, C.H. & Hooimeijer, P. (2001). Spatial flexibility in job mobility: macro-level opportunities and micro-level restrictions, *Environment and Planning A*, 33, 921-940.
- Vickers, D. & Rees, P. (2007). Creating the UK National Statistics 2001 output area classification, *Journal of the Royal Statistical Society: Series A*, 170(2), 379-403.