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Modelling residential mobility behaviour using a commercial data set: An analysis of mover/stayer characteristics across the life-course

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Abstract

Residential mobility is a key mechanism in the evolution of local population size and structure and is of importance to policy makers tasked to provide resources and services. However, while the broad spatial and compositional characteristics of (aggregate) migration flows are fairly well understood, a greater understanding of the more personal (individual-level) characteristics of movers and non-movers, for instance their neighbourhood satisfaction, household income and/or plans for a future moves, is essential if we are to fully understand the processes and patterns behind residential mobility and immobility. This paper exploits a bespoke commercial data set, Acxiom's Research Opinion Poll (ROP), for the analysis of individual residential mobility behaviour across the life-course. In doing so, it uncovers some interesting associational patterns specifically related to some of the characteristics of movers *vis-à-vis* stayers that have, until very recently, been seriously understudied due to the lack of suitable data. However, since the analysis draws on a commercial data set hitherto unused for population analysis, the first part of the paper is concerned with investigating whether there is a practical need for sampling weights, designed to account for the unequal probabilities of selection in a sample for which the user has no prior information on the sampling design/strategy employed. The comparison of like-for-like weighted and unweighted binary logistic regression models suggests a good deal of stability and reliability across the data, but particularly for the model estimates derived from the pooled (combining 2005, 2006, 2007) ROP data, where the effect size and directional relationships are in close agreement.

The substantive analytical focus in the second part of the paper capitalises on the confidence demonstrated in utilising pooled data, and the associated practical advantages gained with increased sample size and an inherently flexible data source, to explore how the complex and interlinked micro-level characteristics of movers and non-movers vary according to an individual's life-course stage. One important conclusion from this analysis relates to the relative unimportance of what are traditionally thought of as labour market characteristics. In contrast, however, characteristics associated with the housing market are found to be of great substantive relevance.

The paper suggests such findings are likely to occur as a result of measuring movers as a single homogenous group, irrespective of the distance travelled between origin and destination residence. Moreover, a focus on the more some of the less commonly observed behaviours/characteristics of (non)movers uncovers results worthy of attention. Future plans to move are found to be negatively associated with mobility, especially for those in their early adulthood, something which, at first sight, appears to contradict the cumulative inertia hypothesis. Furthermore, across the life-course, greater neighbourhood satisfaction is found to be consistently and rather strongly associated with those who have recently moved as opposed to those who remained *in situ*. Yet interestingly, all things being equal, a positive additional effect is associated with homeowners with a negative additional effect for renters regardless of type. The paper concludes by suggesting that reliable approximations for directional associations can be drawn from the ROP without the need for sampling weights; and calls for the analysis presented here to be extended, both technically and analytically, through the use of a multilevel statistical framework.

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1 Introduction

This paper focusses on modelling the behaviour of those who change their usual address and become movers over an observation period *vis-à-vis* those who remain in the same location during that period. When movement takes place over a relatively short distance and typically does not involve a change of job, it is termed residential mobility; whereas a longer-distance movement, often involving change of job as well as change of usual residence, is frequently distinguished as being an internal migration, especially when it crosses an administrative boundary (Cadwallader, 1992). The microdata that is the focus of the modelling reported here comes from a commercial organisation, Acxiom Ltd., and the initial aim of the paper is to outline and apply a technique, namely *survey raking*, that allows us to investigate potential distortions in model-based estimates, due to survey nonresponse bias, by accounting for the unequal probabilities of selection in a sample for which the user has little detailed information about the sampling design/strategy employed (Lumley, 2010).

In order to investigate the sensitivity of model-based estimates to survey nonresponse bias we have chosen a strategy of calibrating eight paired like-for-like binomial logistic regression models, four weighted and four unweighted, in order to compare the relative difference of the estimated odds ratios as well as the (dis)similarities in the magnitude and direction of associations both between and across all eight model pairings. The results demonstrate improved confidence in our unweighted estimates, particularly when the Acxiom data are pooled. The paper then proceeds to a more in-depth analysis, providing evidence of how patterns of demographic, socio-economic and lifestyle/behavioural characteristics of movers/stayers vary according to stage in the life-course, an overwhelmingly important phenomenon itself as is evidenced by the initial (un)weighted binomial logistic regressions. Before the model findings are presented in Sections 4 and 5, a short overview is provided on factors motivating mobility from the research literature (Section 2.1), micro modelling is distinguished from macro modelling (Section 2.2) and the data and methods used in the analyses are introduced (Section 3).

2 Background

2.1 Motivations for residential mobility and immobility

Residential mobility is something that will affect almost all of us at some point in our lifetime. Of the three demographic processes (i.e. fertility, mortality and migration), household migration within the country usually has the largest impact on local area population size and composition (Bogue, 1969; Nam *et al*., 1990; Rees *et al.*, 2009; Poston and Bouvier, 2010). Moreover, beyond the simple change in numbers, residential mobility has the ability to transform the demographic character and structure of populations, in some cases affecting real change to the social, cultural, physical and economic characteristics of an area. With this in mind, it is clear that the measurement and analysis of movers and non-movers, and their respective behaviours and characteristics, is a hugely important task. After all, as Rees *et al*. (2009: 1) suggest, such details are *"at the heart of decisions around policy development, resource allocation and service delivery, both nationally and locally"*. Indeed, research exploring the decision-making processes and experiences of movers stretches right back to seminal works by Thomas (1938) and Rossi (1955). While the theoretical and empirical analyses presented in these early pioneering works have been tested, rethought and developed, time and time again, the fundamental study of mobility and immobility, in equal measure, remains essential to the sub-disciplines of demography and population geography (Courgeau and Lelievre, 2006; Cooke, 2011).

Residential mobility and immobility are complex and multifaceted phenomena. Yet, broadly speaking, we can think of the mobility event, the change of address, as being largely driven by certain push and pull factors whose effects are further conditioned by the seemingly selective nature of the individual's socio-demographic, socio-economic, and behavioural/lifestyle characteristics. Push factors can include determinants such as: loss/change of job; changes in family or household structure (requiring more/less space); or low availability of social and life partners (Clark and Dieleman, 1996; Poston and Bouvier, 2010; Hedman *et al.*, 2011). Pull factors, on the other hand, can include, for example: raised opportunities for employment, education, or income; the lure of a more satisfying lifestyle and associated consumption possibilities; or the desire to live in an area with others who have common life experiences and group-specific services, such as ethnicity, social group or sexual orientation (Bowes *et al*., 1997; Champion *et al.*, 1998; Poston and Bouvier, 2010; Morrison and Clark, 2011). Of course these push and pull factors have been used, at least in part, to explain many of the clear and persistent patterns of residential mobility at various scales in the United Kingdom (UK), including the process of the urban-rural shift/counterurbanisation (Rees, 1989; Stillwell *et al.*, 1992; Champion, 2005a; Dennett and Stillwell, 2008), gentrification and increased city centre living (Boddy, 2007), and increasingly large student flows into university towns and cities around the UK (Champion, 2005b; Smith, 2009). Yet, while the broad spatial and compositional characteristics of migration flows are fairly well understood, a greater understanding of the more personal characteristics of movers and non-movers, from socio-demographic to income and lifestyle variables, is essential if we are to fully understand the processes and patterns behind residential mobility and immobility.

The micro-level dimensions commonly associated with greater mobility propensities include demographic variables such as: age, which acts as a rather consistent proxy for certain life-course transitions that are known to increase/decrease the likelihood of making a residential move (Rogers and Castro, 1981; Bates and Bracken, 1987; Warnes, 1992; Champion *et al.,* 1998; Champion, 2005b; Stillwell, 2008; Dennett and Stillwell, 2010); gender[1], with its strong ties to family formation, social mobility and labour market behaviours (Fielding, 1998; Atkins and Fotheringham, 2002; Fielding, 2011; 2012); and ethnicity, which itself has its own cultural and racial dimensions (Stillwell and Duke-Williams, 2005; Large and Ghosh, 2006; Finney and Simpson, 2008; Simpson and Finney, 2009; Stillwell and Hussain, 2010). There are also social variables such as: tenure, where for example, private renters tend to be more mobile than other tenure types for a number of interrelated reasons (Rossi and Shlay, 1982; Boyle, 1993; Champion *et al*., 1998; van Ham and Feijten, 2008); and socio-economic class, with greater immobility associated with the more traditional blue collar classes and greater mobility with the professional classes (Fielding 2007; 2012). Detailed reviews of the traditional socio-demographic dimensions associated with selective residential mobility can be found in Champion *et al*. (1998), Bailey and Livingston (2005) and Fielding (2012). Reviews and analysis of the more subjective/personal characteristics of movers and non-movers, for instance neighbourhood satisfaction, household income and plans for future moves, are, it appears, less commonplace. However, recent studies have started to explore these potentially rich areas of research (Rabe and Taylor, 2010; Coulter *et al.,* 2011, 2012; Findlay and Nowok, 2012).

2.2 Micro-level approaches to the modelling of residential mobility and immobility

The modelling of migration is often divided according to dichotomous approaches: micro-level and the macro-level (Stillwell and Congdon, 1991). The latter approach, which is not the focus here, is largely concerned with analysing aggregate population stocks and migrant flows with a broad interest in identifying the significance of explanatory variables including unemployment rates, environmental conditions, housing and labour markets, origin/destination population size or quantifying the frictional effect of distance (Wilson, 1967; 1970; Stillwell, 1978; Fotheringham, 1983; 1991; Fotheringham *et al.*, 2001; Flowerdew, 2010). Micro-level approaches, in contrast, are largely concerned with analysing individual person or household level factors, behaviours and characteristics, which in the case of the research presented here, are associated with the decision/ability to move as opposed to remaining in place. That said, we know from our own personal experiences, as well as a good deal of theoretical and empirical study (Massey, 1995;

[1] The term sex is used in this paper when discussing population statistics so as to be consistent with ONS terminology. However, from an analytical perspective we use gender to refer to the social and cultural dimensions of being male/female.

Courgeau and Lelievre, 2006; Bailey and Livingston, 2008; van Ham and Clark, 2009; Morrison, 2011; Champion, 2011; Fielding, 2012), that residential mobility and immobility are inextricably linked to complex structural processes that interact across various aggregate scales from the neighbourhood through to the broader region, nation, and beyond. Consequently, it is important for analyses, even at the micro level, to carefully consider the role that social and spatial context plays in shaping and interacting with an individual's likelihood to stay or move. Further considerations related to the importance of correctly modelling individual and aggregate behaviour patterns, as well as their interactions, are offered in the conclusion of this paper.

3 Data and Methods

3.1 Acxiom's Research Opinion Poll: Potential, limitations and corrections

The analyses presented in due course make use of commercial data derived from Acxiom's six-monthly Research Opinion Poll (ROP), a source of data hitherto unused for the analysis of residential mobility. The ROP is a large lifestyle survey carried out across Great Britain (GB) which is, essentially, a voluntary paper-based (although increasingly distributed via the internet) survey that is delivered through direct mail twice a year, in September and January, in order to capture detailed micro-level characteristics of the respondents. During the mid-2000s, the survey contained a series of questions relevant to the study of residential mobility in GB. Indeed, through the inclusion of current and previous addresses (at full postcode) as well as the timing of the previous move and an indication for the planning of a future move, the ROP is a source of data that have considerable potential for research examining the individual demographic, socioeconomic and lifestyle characteristics of those who have moved address in the past, those who planned to move in the future and those who had remained *in situ* (Table 1). Beyond this, the ROP's very large relative sample size allows one to analyse/model movers and stayers and determine geographical patterns of residential mobility at relatively detailed spatial scales including the district level and below.

Whilst the size of the ROP is advantageous, with the raw sample containing approximately 350k responses a year for the period of study (2005-07), the survey data certainly does not come free of problems. Excluding the responding household's current postcode address, which is cleaned and prepared using the latest Postal Address File (PAF), the ROP data are delivered in raw format (Thompson *et al.*, 2010). As such, concerns surrounding missing values and/or 'impossible' values are left for the end user to decide upon. In this research, for reasons of practicality, and given the benefit the very large raw sample size, list-wise deletion (synonymous with complete case analysis) is employed following what was a significant period of data preparation and cleaning. A detailed description of the major issues associated with the initial data preparation and cleaning of the ROP's key migration related variables (previous address and duration at address) is provided by Thomas *et al*. (2012). Employing a theoretically and statistically sound multiple imputation method for item (question) nonresponse was considered, however, a number of theoretical (combining multiply imputed datasets with sampling weights for unequal probabilities of selection) and practical (sheer size of the raw samples and the magnitude of 'missingness' within them) obstacles prevented their use in this analysis. More simple single imputation methods were avoided due to their potential for introducing further bias into the sample (Bethlehem *et al.*, 2011) and their tendency to underestimate the uncertainty of the imputed/introduced data, leading to, in the worst case scenario, a type I error (Little, 2008). Given the scale of missing values and/or 'impossible' values in the raw ROP data, the cleaned complete case samples for the January 2005-07 ROPs, while still comparatively large, are reduced to approximately a third of the size of the raw ROPs (Table 6).

Table 1. Variables obtained from the Acxiom ROP for the years containing previous address data

Key survey variables	January 2005	September 2005	January 2006	January 2007	September 2007
Current address (postcode)	✓	✓	✓	✓	✓
Sex	✓	✓	✓	✓	✓
Age	✓	✓	✓	✓	✓
Ethnic group	✓	×	✓	✓	×
Marital status	✓	✓	✓	✓	✓
Occupation	✓	✓	✓	✓	✓
Education	✓	✓	✓	✓	✓
House price	×	×	×	✓	✓
Income	✓	✓	✓	✓	✓
Home type	✓	✓	✓	✓	✓
Home ownership	✓	✓	✓	✓	✓
Household size	✓	✓	✓	×	✓
Number of cars	✓	✓	✓	✓	✓
Time of move	✓	✓	✓	✓	✓
Previous address (postcode)	✓	✓	✓	✓	✓
Like neighbourhood	✓	✓	✓	✓	✓
Neighbourhood improved	×	×	✓	✓	✓
Future move	✓	✓	✓	✓	✓

Perhaps unsurprisingly given its form as a voluntary postal survey, the ROP sample contains inherent individual- and area-level biases on a number of important characteristics including: age, sex, ethnic group, migrant status, income group and geography (even at the regional level) (Thompson *et al.*, 2010; Thomas *et al.*, 2012). Such biases can be expected to be driven, to a large extent, by survey nonresponse and errors in the sampling frame. Unfortunately, due to commercial sensitivity, we are not privy to the number of survey forms that were distributed by Acxiom, thus not allowing calculation of basic response rates; nor is it possible to obtain information on the addresses of those who failed to provide a response. If such data were available it would not only have been possible to evaluate response rates but, through the use of auxiliary small area population statistics and/or geodemographics, it may have been possible to develop a reasonably detailed picture of the sorts of people who did not respond to the survey and further explore the response propensities. In the absence of such information a simple strategy of descriptive bivariate benchmarking against official statistics was employed, the results of which are discussed in Thomas *et al.* (2012). While the general directional relationships appeared quite reassuring, both in terms of district level migration patterns and various micro-level mover/stayer characteristics, the benchmarking exercise did reveal sample selection biases according to both individual and area characteristics. In extreme cases, such findings lead to a situation where any reported results are open to critiques of being simple artefacts of the sampling; and therefore not generalizable to the wider population.

Taking these concerns into account, and using auxiliary population data (Appendix A), it is possible to adjust key ROP sample distributions (e.g. age, sex, geography, (non-)mover status) so as to match those of the GB population. Sample raking, also known as raking ratio estimation (Kalton, 1983) or iterative proportional fitting (IPF) (Deming and Stephan, 1940; Deming, 1943), is a technique that repeatedly adjusts sampling weights in an attempt to rebalance the survey response counts to known population totals. The weights can be used to derive more reliable estimates of aggregate population parameters, including measures of migration and potentially intra/inter-district population flows[2], as well as offering a degree of protection against potential distortions in model-based estimators by accounting for the unequal probabilities of selection known to be in the ROP sample. The raking procedure is explained in the next section.

3.2 The survey raking procedure

Ideally we would like to construct a complete multi-way cross-tabulation of relevant variables, wherein we create a multi-dimensional table with known population counts for each cell value before rebalancing the survey values to the population counts. This technique, known as post-stratification, is multiplicative and therefore if we wanted to reweight our survey by post-stratifying according to say age (15 categories), sex (2 categories), region (10 categories) and ethnic group (5 categories) we would need a multi-dimensional population table with 1,500 known population cells ($15_{\mathrm{age}} * 2_{\mathrm{sex}} * 10_{\mathrm{reg}} * 5_{\mathrm{eth}} = 1{,}500$). Such a level detail could be problematic if not impossible, given the

[2] The potential for exploring estimated intra/inter-district migration flows by individual socio-economic and lifestyle characteristics is currently being explored by the authors.

lack of available/sufficient population data and the likelihood that some demographic and geographical sub-groups (i.e. combinations of variable categories) do not exist in the sample.

Raking, on the other hand, can be thought of as broadly similar to fitting a loglinear model for the probability of being observed in a particular cell of the complete multi-way cross-tabulation of variable categories given the probabilities for the known marginal distributions (Little and Wu, 1991). Therefore, using the example above, we would only require a marginal adjustment table with 32 marginal counts ($15_{\text{age}}+2_{\text{sex}}+10_{\text{reg}}+5_{\text{eth}} = 32$); however, the limitations associated with the available demographic sub-groups in the sample still need to be considered. Raking is practically very useful as it allows us to use marginal counts from different data sources; for instance, one could use the mid-year population estimates (MYE) to derive accurate GB population estimates of age, sex and geographical region for those aged 18 and over, and use the Annual Population Survey (APS) to derive timely 12 month residential mover counts, also for the GB population aged 18 plus. That said, marginal adjustments will be most effective when they are good predictors of both survey non-response and particularly of the proposed model outcome, in this case whether an individual moves or remains in place (Little and Vartivarian, 2005; Little, 2008). The marginal population counts derived from different sources used in this analysis can be found in Appendix A.

As mentioned above, access to detailed documentation of the ROP sampling strategy is not available, however, from what we do know, the ROP does not appear to follow a particularly complex design. Rather it is an attempt at generating a very large, while still broadly accurate, sample with postcode identifiers and as such we must, and in fact can only, assume that the ROP is equally weighted (i.e. each individual within the sample carries the same weight). Therefore, in the case of the unweighted ROP data, the individual weights w_i, where $i = 1, \dots, n$, are equal to 1, thus $w_i = 1$ for each i. These initial survey weights will then be modified, using the raking/IPF algorithm, to reflect the unequal probabilities of selection in the ROP sample when compared to the known marginal population totals. The resulting vector of weights can then be used within our analyses, be they descriptive or model based in nature, with the purpose of providing a degree of protection, through the incorporation of known population data, against potential unequal response related distortions.

Drawing on previous examples (Deming and Stephan, 1940; Bishop *et al.*, 1975; Simpson and Tranmer, 2005; and Battaglia *et al.*, 2009), the raking algorithm can now be defined. With the requirement to rake on a number of ROP variables, we can imagine a multidimensional table where the sum of the initial w_i in cell θ is defined as w_θ with a set of levels $q = 1, \dots, s$ varying for each of the known population control totals T, with $T_{\theta q}$ corresponding to cell θ. The algorithm proceeds iteratively, modifying the initial weights w_θ and thus producing new multidimensional totals m_θ that are superscripted with the number of the step. The first step of the first iteration uses the initial sample cell totals and fits these to the initial marginal levels (marginal subtotals) in order to derive our first modified estimates:

$$m_\theta^{(1)} = w_\theta^{(0)} \frac{T_\theta}{w_{\theta 1}^{(0)}} \tag{1}$$

This process is repeated for all of the q levels where the first cycle (r) of the required s steps is completed:

$$m_\theta^{(s)} = m_\theta^{(s-1)} \frac{T_{\theta s}}{m_{\theta s-1}^{(s-1)}} \tag{2}$$

In general, at the tth step, where $t - q$ is a multiple of s, the modified estimate is defined as:

$$m_\theta^{(t)} = m_\theta^{(t-1)} \frac{T_{\theta q}}{m_{\theta q}^{(t-1)}} \tag{3}$$

Iteration occurs until the rth cycle, where $t = rs$, and where the estimate $m_\theta^{(rs)}$ satisfies a predetermined convergence criterion δ^r, for example 0.1 or 0.001, at which point a further complete r cycle fails to modify any cell by more than this pre-specified criterion (Bishop *et al.*, 1975: 85), thus:

$$|m_\theta^{(rs)} - m_\theta^{(rs-s)}| < \delta^r \tag{4}$$

With the desired level of accuracy achieved, the final modified sampling weights are obtained, ready for use within the analyses.

3.3 A worked example of the raking procedure

To aid understanding of the process, a simple two-dimensional example of the procedure, using real data, can now be worked. The two variables used in the example are gross annual household income and household tenure. The marginal population totals for gross annual household income are weighted estimates derived from the 2006-2007 Survey of English Housing with the marginal totals for household tenure coming from the 2006 General Household Survey, the totals were adjusted so that, when summed, they agreed with the ONS Mid-2005 Population Estimates for individuals aged 18+ in Great Britain ($N =$ 45,775,200). The sample data used are from the complete case pooled ROP ($n =$ 348,953) (combining all cases from the January 2005, 2006, and 2007 ROPs) where each individual is equally weighted (i.e. each individual has a weight equal to 1, $w_i = 1$ for each i). In the initial two-dimensional table (Table 2) the row totals refer to the marginal population control totals for income while the column totals refer to the marginal population control totals for tenure. Each cell value (θ) is the sum of the sampled individuals (i), where $w_i = 1$, whose characteristics match the corresponding margins.

Table 2. Two-dimensional example of raking (IPF) procedure: Initial values

	Tenure →	**Own home**	**Council rent**	**Housing association rent**	**Private rent**
Income ↓		*32,972,701*	*4,829,504*	*3,342,199*	*4,630,796*
Up to £9,999	*3,432,360*	29,912	21,103	9,685	10,714
£10,000-£19,999	*9,111,355*	59,701	15,183	7,946	11,584
£20,000-£29,999	*8,420,083*	55,734	5,771	3,456	7,538
£30,000-£39,999	*8,813,724*	42,506	2,049	1,319	4,421
£40,000-£49,999	*6,891,122*	25,719	685	373	2,281
£50,000 plus	*9,106,556*	28,740	257	184	2,092

N.B. Italicised control totals indicate population control totals (or agreement with population control totals).

The first step (s) of the first cycle (r) is described in Equation 1 and involves fitting the initial cell totals (w_θ) to the corresponding marginal (row) population income totals (T_θ) (Table 3).

Table 3. Two-dimensional example of raking (IPF) procedure: Fitting to marginal population income totals (cycle 1, step 1)

	Tenure →	**Own home**	**Council rent**	**Housing association rent**	**Private rent**
Income ↓		35,589,051.62	3,746,095.84	2,006,873.27	4,433,179.27
Up to £9,999	*3,432,360.00*	1,437,655.81	1,014,270.21	465,488.65	514,945.32
£10,000-£19,999	*9,111,355.00*	5,761,401.96	1,465,224.47	766,823.00	1,117,905.57
£20,000-£29,999	*8,420,083.00*	6,472,984.54	670,247.85	401,382.18	875,468.43
£30,000-£39,999	*8,813,724.00*	7,448,775.27	359,067.91	231,142.30	774,738.52
£40,000-£49,999	*6,891,122.00*	6,099,276.16	162,448.16	88,457.17	540,940.51
£50,000 plus	*9,106,556.00*	8,368,957.87	74,837.24	53,579.97	609,180.93

At the end of the first step, the counts in each cell will sum to the known control totals for income but will not sum to the column totals control totals for tenure. It follows therefore that the second and step of the first cycle is to fit the now modified cell totals (m_θ) to the corresponding marginal population totals for tenure (Table 4).

Table 4. Two-dimensional example of raking (IPF) procedure: Fitting to marginal population income totals (cycle 1, step 2)

Income ↓	Tenure →	Own home	Council rent	Housing association rent	Private rent
		32,972,701.00	*4,829,504.00*	*3,342,199.00*	*4,630,796.00*
Up to £9,999	3,952,686.56	1,331,965.68	1,307,607.24	775,213.73	537,899.91
£10,000-£19,999	9,671,617.92	5,337,849.02	1,888,981.95	1,277,048.78	1,167,738.17
£20,000-£29,999	8,444,155.67	5,997,119.17	864,090.19	668,452.34	914,493.97
£30,000-£39,999	8,558,300.71	6,901,174.06	462,913.92	384,938.89	809,273.84
£40,000-£49,999	6,572,682.32	5,650,884.19	209,429.78	147,314.47	565,053.88
£50,000 plus	8,575,756.82	7,753,708.88	96,480.91	89,230.80	636,336.23

With the second step completed, the cell values have been modified so as to match the tenure margins. However, as is clear in Table 4, they now no longer match with the population margins for income (Table 2). As is described in Equation 3, we continue this process, raking on each dimension, until we reach the rth cycle and the estimate ($m_{\theta}^{(rs)}$) satisfies the convergence criterion (δ^{r}), in this example 0.001. After 14 cycles, the desired level of accuracy was achieved with the results shown in Table 5.

For this worked example, we can obtain the final modified sampling weights for each sampled individual through a simple calculation: dividing the cell total w_{θ} (the sum of the sampled individuals (i), where the original sampling weights are specified as equal, $w_i = 1$, whose characteristics match of the given cell θ) (Table 2), by the final modified cell total $m_{\theta}^{(rs)}$ (Table 5).

Table 5. Two-dimensional example of raking (IPF) procedure: Convergence criterion satisfied (cycle 14, step 2)

Income ↓	Tenure →	Own home	Council rent	Housing association rent	Private rent
		32,972,701.000	*4,829,504.000*	*3,342,199.000*	*4,630,796.000*
Up to £9,999	*3,432,360.000*	1,104,293.728	1,176,796.269	691,839.824	459,430.180
£10,000-£19,999	*9,111,355.000*	4,880,074.750	1,874,650.842	1,256,782.743	1,099,846.666
£20,000-£29,999	*8,420,083.000*	5,873,861.845	918,697.467	704,764.512	922,759.176
£30,000-£39,999	*8,813,724.000*	7,030,366.743	511,902.949	422,123.293	849,331.014
£40,000-£49,999	*6,891,122.000*	5,883,273.340	236,686.480	165,097.524	606,064.657
£50,000 plus	*9,106,556.000*	8,200,830.594	110,769.994	101,591.104	693,364.308

We are effectively dividing the now modified cell frequency between its members in the sample. In this example, a homeowner with a gross annual household income of £30,000-£39,000 has a sampling weight approximately equal to 165.397 (7,030,366,743 ÷ 42,506 = 165.397), and therefore is estimated to represent 165.397 individuals in the 18+ GB population[3].

3.4 Binary logistic regression for survey data

Binary logistic regression models are used in the first instance as they allow for us to correctly model associations when the dependent variable follows a binomial distribution with possible values 0 or 1. Given that we are interested in exploring the individual characteristics of movers versus non-movers, our dependent variable is a 0-1 indicator (0 = non-mover, 1 = mover). The binary logistic regression model ($Y = 0{,}1$) with multiple predictor variables $x_1, x_2, \dots, x_k$ can be written as:

$$logit[\pi(\boldsymbol{x})] = \ln\left(\frac{\pi(\boldsymbol{x})}{1-\pi(\boldsymbol{x})}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k \qquad (5)$$

where $\pi(\boldsymbol{x})$ is the conditional probability of y occurring ($Y = 1$ (in this case, mover)) given the vector of observed predictor variables, $\boldsymbol{x}$. In the models presented here, β_0 represents the constant term, which contains all of the reference categories associated with each predictor variable. $\beta_1, \dots, \beta_k$ are the logistic regression coefficients, where β_k gives the change in the log odds of $Y = 1$ for a given category k within a predictor variable when compared to the odds that $Y = 1$ for the reference category within the said variable. Once the model is fitted, $\pi(\boldsymbol{x})$ can be recovered from the log scale through the antilogit function:

$$\hat{\pi}(\boldsymbol{x}) = \frac{\exp(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \cdots + \hat{\beta}_k x_k)}{1 + \exp(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \cdots + \hat{\beta}_k x_k)} \qquad (6)$$

By exponentiating the estimated parameters, $\widehat{\boldsymbol{\beta}}$, a more meaningful interpretation is provided where, for the variables modelled here, $\exp(\hat{\beta})$ (the odds ratio) represents the change in the estimated ratio of the odds of $Y = 1$ for a given category within a predictor variable, when compared to the odds that $Y = 1$ for the reference category. For a simple random sample, the binary logistic regression coefficients and standard errors are estimated using maximum likelihood based on the binomial distribution (Agresti, 2002). The likelihood function for logistic regression with a binomial dependent variable can be written as:

$$L(\boldsymbol{\beta}|x) = \prod_{i=1}^{N} \pi(x_i)^{y_i}\,[1 - \pi(x_i)]^{1-y_i} \qquad (7)$$

where:

[3] If necessary, the probability of selection for each sampled individual can be calculated as the reciprocal of the sampling weight (e.g. $1/165.397 = 0.006046$).

$$\pi(x_i) = \frac{\exp(x_i\boldsymbol{\beta})}{[1 + \exp(x_i\boldsymbol{\beta})]} \tag{8}$$

However, when sampling weights are included, the use of maximum likelihood estimation is no longer possible due to the fact that the probabilities of selection for the sample observations are no longer equal (Heeringa *et al*., 2010). Consequently, an alternative method of pseudo-maximum likelihood estimation (Binder, 1981; 1983) can be used which allows for complex sample characteristics to be modelled correctly by making use of the sampling weights (w_i) of the observed sample values (y_i) and the estimated $\hat{\pi}(x_i)$ values (Heeringa *et al*., 2010). Therefore, the weighted pseudo-likelihood function for logistic regression with a binomial dependent variable is defined as:

$$PL(\boldsymbol{B}|X) = \prod_{i=1}^{n} \{\pi(x_i)^{y_i} \cdot [1 - \pi(x_i)]^{1-y_i}\}^{w_i} \tag{9}$$

where:

$$\pi(x_i) = \frac{\exp(x_i\boldsymbol{B})}{[1 + \exp(x_i\boldsymbol{B})]} \tag{10}$$

In line with Heeringa *et al*. (2010) the parameters $\boldsymbol{\beta}$ are changed to $\boldsymbol{B}$ and now represent finite population parameters, which are the weighted function of the observed sample values (y_i) and the estimated $\hat{\pi}(x_i)$ values. To be clear, the unweighted models shown here use maximum likelihood estimation with the weighted models drawing on the pseudo-maximum likelihood approach to estimation.

When comparing the weighted models to the unweighted models, careful consideration must be given to the balance between the reduced precision in the weighted model (inflated standard errors) which is strongly related to highly variable weights, and the protection the weights can offer against distortions in the model-based estimators due to the fact that the unequal probabilities of selection, and some of the potential distortions, are known as a function of the design variables (DuMouchel and Duncan, 1983; Pfeffermann, 2007; Snijders and Bosker, 2012). Broadly speaking, "*if the sampling weights are **ignorable**, in the sense that the estimate is valid with or without the weights, the weighted estimates will be less precise*" (Lumley, 2010: 105 [original emboldening]). In such a case we can be relatively confident that the associational patterns that we derive are reasonably robust.

4 Modelling Analysis

4.1 Model specification

While five separate ROP datasets are available in total, the results presented here are based on the January 2005, January 2006 and January 2007 surveys due to the consistency of their questions and the variable detail for demographic, socio-economic, lifestyle, mobility and address information (Table 1). Replicate microdata models have been calibrated for different ROP samples (January 2005 (n = 125,945), January 2006 (n = 50,686), and January 2007 (n = 172,322) as well as on the pooled data (n = 348,953) in order to explore data consistency. There are a number of apparent advantages to the increased sample size associated with the pooling of the ROP data, including: the potential for greater precision in our estimates; an increase in the migrant subsample; and the reduced risk of *sparsity*, wherein we have very small numbers within modelled (sub)groups[4]. That said, given the small (two-year) temporal variation in the sample, it is necessary to incorporate dummy variables (indicating which sample the respondent is member of) within the models so as to control for any unwanted influence associated with this variation.

Table 6 provides a breakdown of the numbers of movers and non-movers in each data set as well as the percentage that moved. The numbers presented in Table 6 refer to the *cleaned* data, which contain records that provided usable answers to all the variables obtained for use in the analyses here.

Table 6. Tabulation of residential mobility status for the selected ROP data sets

Residential mobility status	January 2005	January 2006	January 2007	Pooled
Non-mover	121,551	49,711	168,337	339,599
Mover	4,394	975	3,985	9,354
% movers	3.49	1.96	2.37	2.68
N	125,945	50,686	172,322	348,953

The modelled binary response is non-mover (0) and mover (1); where movers are specified as individuals who have changed address in the 12 months prior to survey completion, providing full address details of their previous residence[5], with non-movers making up the remainder of the cases. The predictor variables used in the models presented below include a number of the key demographic and socio-economic characteristics that previous studies have shown to be important in explaining residential mobility and immobility. However, beyond this, a desire to explore some of the more subjective/personal and seemingly understudied characteristics of movers and non-movers, for instance their geodemographic area characteristics, neighbourhood satisfaction,

[4]Sparsity is potentially important for future research too as there are plans to extend these models through the use of multilevel modelling, including cross-classified structures. There are potential concerns with the implementation of the cross-classified design associated with the precision of model estimates if the areal units in the cross-classification contain very small numbers of sampled individuals (Fielding and Goldstein, 2006). By pooling the data, the risks reduce.

[5] While not used in this analysis, previous address data is used to define *movers* so that the definition matches that to be used in future analyses exploring variations in distance (postcode to postcode) moved.

household income and plans for a future move, offer a certain value-added dimension to this analysis and are thus included in the models. The rationale behind the choice of the reference category used for each explanatory variable varies; for ordinal categorical variables, the median value was used; while for nominal variables, the modal value in the sample and, occasionally, the most typical in the population was used.

Following recommendations by Hosmer and Lemeshow (2000), for reasons of parsimony and model fit, only those predictors that had a bivariate association with the dependent variable at the $p < 0.25$ significance level were selected for inclusion in the multivariate analysis. The January 2005, January 2007 and Pooled weighted models presented below use sampling weights that have been adjusted according to marginal population totals for age, sex, Government Office Region (GOR), and mover/non-mover status. Due to the relatively small sample size in the January 2006 ROP (especially for the mover sub-group, Table 6), the sampling weights designed for the January 2006 weighted model are limited to the use of population totals for age, sex and mover/non-mover status only. The inclusion of geography, even at the regional level, is not possible due to the nonexistence of sampled individuals in certain cells of the required multi-dimensional adjustment table[6]. Theoretically we can rake on as many variables as we have population data for; however, the size of the sample limits us to a select few in practice. See Appendix A for details on the sources of the population data and a full breakdown of the population counts for each marginal population total.

In terms of evaluating model goodness-of-fit (GOF), a number of statistics are provided at the bottom of Tables 7-10. The deviance statistics measure how much unexplained information there is after a model is fitted and are approximate to the residual sum of squares in a standard multiple regression (Field *et al.*, 2012). A smaller deviance statistic suggests fewer unexplained observations within the model. The improvement (X^2), is the difference between the null deviance (constant only model) and the residual deviance (fitted model), both of which follow a Chi-square distribution making it possible to calculate the significance of this value. The effect of adding/removing variables on the model fit can also be analysed in this manner by checking the improvement in Model 2 (full suite of variables) when compared to Model 1 (reduced variables). Finally, the Akaike information criterion (AIC), allows us to check the improvement in the model fit while effectively penalising the model that contains more explanatory variables (Agresti, 2007; Field *et al.*, 2012). Without penalising, the simple addition of a further variable would increase the model fit while failing to account for the additional complexity the added variable brings.

[6] There are 484 cells in the multi-dimensional adjustment table for age (11), sex (2), geography (11), and mover/non-mover status (2) and only 44 cells in the adjustment table used for the January 2006 ROP sample.

4.2 Regression Modelling Results

As stated in the introduction, this paper is focussed, at least from a substantive point of view, on exploring the variations in the associational patterns of demographic, socio-economic and behavioural/lifestyle characteristics for movers when compared to non-movers. However, in order to improve confidence in the results drawn from such analyses, a major focus on their reliability, in the face of what are known sample biases, is required. With this in mind, the paper is also concerned with comparing estimates derived from like-for-like weighted and unweighted binary logistic regression models. Accordingly, the results presented here are in two sub-sections, the first of which offers a very brief analytical discussion of the core model findings but is primarily focussed on the important task of assessing the reliability of our estimates through a comparison of weighted and unweighted model results. The second section builds on what is observed in the first, and therefore attempts to take the analytical focus of the models a stage further by exploring how the intricate, and interlinked, micro-level behaviours and characteristics of movers and non-movers vary according to their stage in the life-course.

4.3 Comparing unweighted and weighted main effects model results

The results of the unweighted and weighted main effects models for each ROP sample can be seen in Tables 7-10 and Figures 1-4. For each tabular comparison (Tables 7-10), the relative difference in the odds ratios (in percentage terms) are provided in order for us to assess the extent to which the weighted and unweighted models diverge. It should be noted that the estimated odds ratio for the constant has no real substantive analytical value; however, for comparative purposes, in terms of measuring the relative difference, it is included in Tables 7-10. The plotting of the results in Figures 1-4 greatly helps in assessing not only the (dis)similarities in the directional patterns, but also in comparing the size of effects and therefore the relative substantive importance, above and beyond the simple statistical significance, that certain characteristics may have over others in terms of their associated relationship with residential (im)mobility in GB. To be clear, an estimated coefficient ($\hat{\beta}$) that falls to the right of the dashed line (marking zero – i.e. no difference) suggests that individuals with this characteristic are, *ceteris paribus*, more likely to have moved than those with the reference characteristic of a given categorical predictor. Estimated coefficients that fall to the left of the line, therefore, suggest a move is less likely than it is for the reference.

Table 7. January 2005 ROP: Main effects comparison and relative difference

Predictor	January 2005 unweighted			January 2005 weighted			Relative difference
	B	SE	Odds	B	SE	Odds	(%)
Constant	-4.495	0.103	0.011	-3.885	0.125	0.021	-83.903
Age (ref: 45-49)							
18-19	2.435	0.178	11.418	2.370	0.190	10.700	6.287
20-24	2.094	0.081	8.120	2.096	0.102	8.136	-0.197
25-29	1.601	0.075	4.958	1.616	0.085	5.033	-1.503
30-34	1.181	0.073	3.257	1.188	0.081	3.281	-0.747
35-39	0.704	0.074	2.022	0.706	0.081	2.025	-0.138
40-44	0.293	0.077	1.340	0.305	0.083	1.357	-1.227
50-54	-0.161	0.086	0.851	-0.183	0.091	0.833	2.117
55-59	-0.228	0.086	0.796	-0.271	0.091	0.762	4.273
60-64	-0.409	0.097	0.664	-0.384	0.103	0.681	-2.481
65-69	-0.410	0.106	0.664	-0.340	0.113	0.712	-7.224
70-74	-0.421	0.117	0.656	-0.393	0.125	0.675	-2.831
75-79	-0.693	0.144	0.500	-0.683	0.151	0.505	-0.952
80+	-0.903	0.178	0.405	-0.826	0.186	0.438	-8.024
Gender (ref: Female)							
Male	-0.157	0.036	0.854	-0.135	0.047	0.874	-2.264
Ethnic group (ref: white)							
Asian	0.249	0.113	1.283	0.062	0.134	1.063	17.118
Black	0.560	0.131	1.751	0.334	0.164	1.396	20.263
Other	-0.077	0.112	0.926	-0.162	0.150	0.851	8.112
Marital status (ref: single)							
Married	0.010	0.050	1.010	0.157	0.058	1.170	-15.911
Living with partner	0.450	0.051	1.568	0.558	0.059	1.748	-11.478
Divorced/separated	0.543	0.057	1.721	0.562	0.064	1.755	-1.956
Widowed	0.240	0.099	1.271	0.170	0.110	1.185	6.780
Occupation (ref: Higher managerial administrative and professional occupations)							
Not economically active	0.003	0.035	1.003	0.031	0.041	1.032	-2.846
Routine and manual occupations	0.061	0.040	1.063	0.118	0.047	1.126	-5.888
Intermediate occupations	0.024	0.039	1.024	-0.066	0.047	0.936	8.592
Annual gross household income (ref: £20,000-£29,999)							
Up to £9,999	0.115	0.058	1.122	-0.004	0.067	0.996	11.217
£10,000-£19,999	0.064	0.047	1.066	0.004	0.055	1.004	5.835
£30,000-£39,999	-0.089	0.053	0.915	0.052	0.062	1.054	-15.156
£40,000-£49,999	0.109	0.047	1.115	0.024	0.056	1.025	8.073
£50,000 plus	0.022	0.039	1.022	0.069	0.047	1.072	-4.820
Highest qualification (ref: 5 or more GCSEs)							
No formal qualifications	0.152	0.034	1.165	0.179	0.040	1.196	-2.719
2+ 'A' levels	0.144	0.035	1.154	0.143	0.042	1.153	0.088
First degree and higher	-0.099	0.039	0.906	-0.131	0.047	0.877	3.174
Tenure (ref: Own home)							
Council rent	0.039	0.057	1.173	0.168	0.067	1.183	-0.846

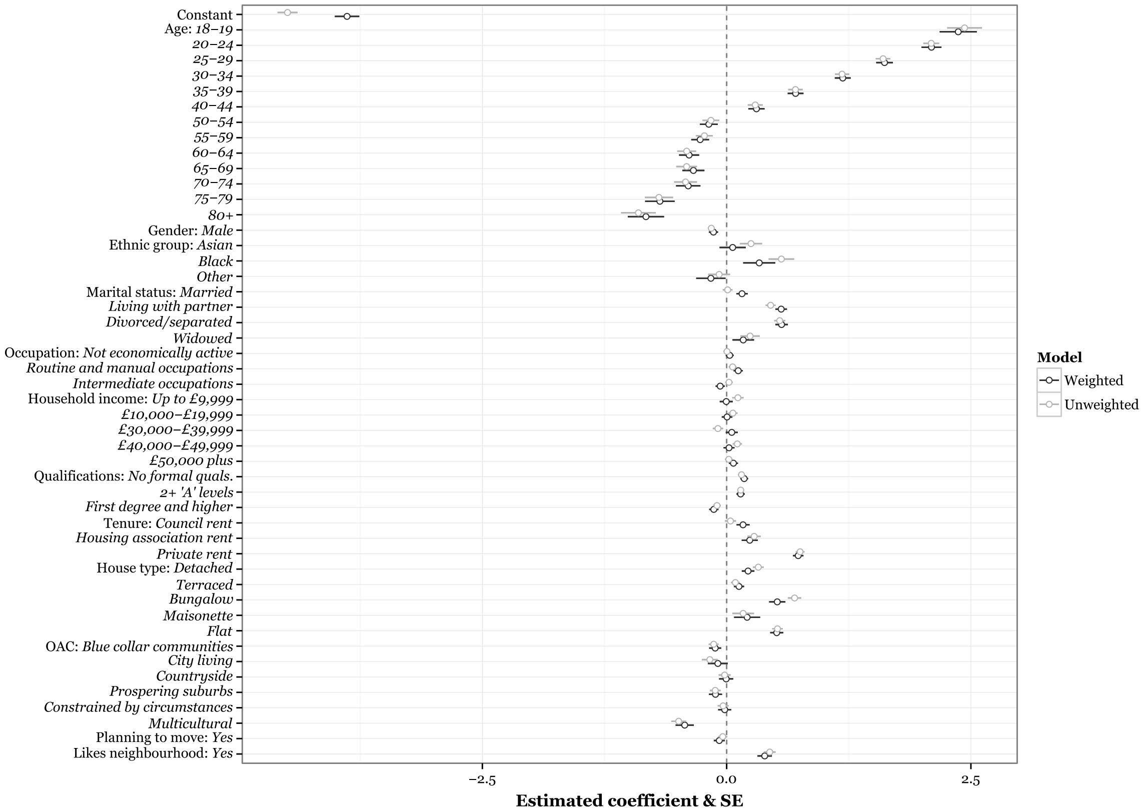
Housing association rent	0.281	0.068	1.324	0.236	0.082	1.266	4.363
Private rent	0.752	0.045	2.122	0.732	0.054	2.080	1.978
Type of home (ref: Semi-detached)							
Detached	0.324	0.055	1.383	0.219	0.065	1.245	9.962
Terraced	0.089	0.044	1.094	0.126	0.053	1.134	-3.725
Bungalow	0.695	0.069	2.004	0.518	0.083	1.678	16.261
Maisonette	0.169	0.111	1.185	0.209	0.133	1.233	-4.077
Flat	0.520	0.054	1.682	0.512	0.067	1.669	0.728
OAC Super-group level (ref: Typical traits)							
Blue collar communities	-0.133	0.051	0.875	-0.117	0.061	0.889	-1.613
City living	-0.172	0.082	0.842	-0.090	0.102	0.914	-8.562
Countryside	-0.021	0.061	0.980	-0.005	0.072	0.995	-1.579
Prospering Suburbs	-0.117	0.055	0.890	-0.115	0.067	0.892	-0.222
Constrained by circumstances	-0.036	0.056	0.965	-0.020	0.067	0.980	-1.577
Multicultural	-0.491	0.076	0.612	-0.429	0.094	0.651	-6.359
Plan to move in next 12 months (ref: No)							
Yes	-0.040	0.047	0.961	-0.075	0.056	0.927	3.503
Like your neighbourhood (ref: No)							
Yes	0.441	0.060	1.555	0.389	0.074	1.476	5.067

Null deviance	38122 on 125944 *df*
Residual deviance	33639 on 124896 *df*
Improvement (X^2)	4482.644, *df* = 48
AIC	33737

*N.B. n = 125,945. 95% confidence intervals can be calculated as: coefficient (B) minus 1.96 * SE (lower boundary) and coefficient (B) plus 1.96 * SE (upper boundary) where SE is the standard error. Underlined estimates are significant at the 95 per cent level. Relative differences in the odds ratios ≥20 per cent are underlined. The GOF summary measures relate to the unweighted model, such statistics are currently not incorporated in the R 'survey' (Lumley, 2012) package software for complex sample survey data analysis.*

The modelled results for the January 2005 ROP (Table 7 and Figure 1) are reassuring with the similarity in the direction and magnitude of the weighted and unweighted estimates immediately apparent. Moreover, beyond the simple similarities, the coefficients of both models suggest relationships commonly cited in the literature (Section 2.1). Indeed, it appears that age (stage in life-course) is, as we would expect, a very significant influence on the propensity to move, with the younger age groups having higher propensities to move than those in the older age categories. Other findings that suggest a substantively important relationship with mover/non-mover status can be found for marital status, with the likelihood of moving being far greater for those living with a partner and those that are divorced/separated than those that are single; and tenure, with renters having a far greater likelihood of moving than home owners. The Output Area Classification (OAC) functional geographies suggest varying propensities to move, however, in substantive terms, those living in multicultural neighbourhoods tend to be characterised by greater immobility than those living in areas that reflect more typical traits. Finally, it appears that greater neighbourhood satisfaction is associated with recent movers.

Figure 1. January 2005 ROP weighted and unweighted model estimates



In terms of the stability between the model estimates, there are only three cases (the constant and Black ethnic group) where the relative difference in the estimated coefficient odds ratio has exceeded the 20 per cent level. However, for both the constant and Black ethnic groups, the directional patterns (+/-) remain in agreement. The models do present contradictory estimates, where one model suggests a positive/negative associational pattern in contrast to the other. These additional contradictory estimates are the household income groups "up to £9,999" and "£30,000-£39,999", yet in both cases, the contradictory estimates are statistically non-significant in the weighted model with the size of the standard errors suggesting that both estimates could easily have pointed to the same directional association suggested by the unweighted model.

Table 8. January 2006 ROP: Main effects comparison and relative difference

Predictor	January 2006 unweighted			January 2006 weighted			Relative difference
	B	SE	Odds	B	SE	Odds	(%)
Constant	-5.329	0.221	0.005	-3.672	0.257	0.025	-424.384
Age (ref: 45-49)							
18-19	1.523	0.316	4.585	1.428	0.338	4.169	9.062
20-24	1.480	0.167	4.394	1.362	0.219	3.905	11.129
25-29	1.245	0.149	3.474	1.101	0.179	3.008	13.403
30-34	1.023	0.137	2.782	0.926	0.156	2.524	9.280
35-39	0.600	0.132	1.822	0.560	0.144	1.751	3.909
40-44	-0.012	0.144	0.988	-0.042	0.151	0.958	2.982
50-54	-0.506	0.173	0.603	-0.476	0.181	0.621	-3.066
55-59	-0.329	0.165	0.720	-0.335	0.173	0.715	0.616
60-64	-0.382	0.183	0.682	-0.384	0.191	0.681	0.199
65-69	-0.629	0.222	0.533	-0.666	0.228	0.514	3.674
70-74	-0.469	0.225	0.626	-0.473	0.235	0.623	0.418
75-79	-0.954	0.295	0.385	-0.886	0.306	0.412	-7.090
80+	-0.541	0.279	0.582	-0.474	0.298	0.623	-6.944
Gender (ref: Female)							
Male	-0.161	0.075	0.851	-0.269	0.091	0.764	10.194
Ethnic group (ref: white)							
Asian	0.248	0.218	1.281	0.085	0.278	1.089	14.982
Black	-0.042	0.350	0.959	-0.156	0.400	0.855	10.788
Other	0.530	0.227	1.698	0.226	0.287	1.253	26.185
Marital status (ref: single)							
Married	0.151	0.110	1.163	0.125	0.127	1.133	2.593
Living with partner	0.795	0.112	2.214	0.846	0.131	2.331	-5.302
Divorced/separated	0.413	0.126	1.511	0.165	0.138	1.180	21.945
Widowed	0.358	0.195	1.430	0.041	0.211	1.042	27.152
Occupation (ref: Higher managerial administrative and professional occupations)							
Not economically active	0.050	0.071	1.051	0.069	0.084	1.072	-1.984
Routine and manual occupations	0.177	0.083	1.194	0.204	0.096	1.226	-2.697
Intermediate occupations	-0.107	0.078	0.898	-0.129	0.094	0.879	2.160
Annual gross household income (ref: £20,000-£29,999)							
Up to £9,999	0.049	0.107	1.050	-0.081	0.122	0.923	12.116
£10,000-£19,999	0.006	0.088	1.006	-0.119	0.099	0.888	11.771
£30,000-£39,999	-0.132	0.099	0.876	-0.032	0.113	0.969	-10.565
£40,000-£49,999	-0.115	0.089	0.892	-0.240	0.104	0.787	11.802
£50,000 plus	0.007	0.079	1.007	-0.004	0.092	0.996	1.058
Highest qualification (ref: 5 or more GCSEs)							
No formal qualifications	0.275	0.066	1.317	0.381	0.077	1.464	-11.162
2+ 'A' levels	0.216	0.073	1.241	0.270	0.087	1.310	-5.515
First degree and higher	-0.104	0.083	0.901	-0.055	0.101	0.947	-5.037
Tenure (ref: Own home)							
Council rent	0.025	0.130	1.026	-0.074	0.154	0.928	9.506

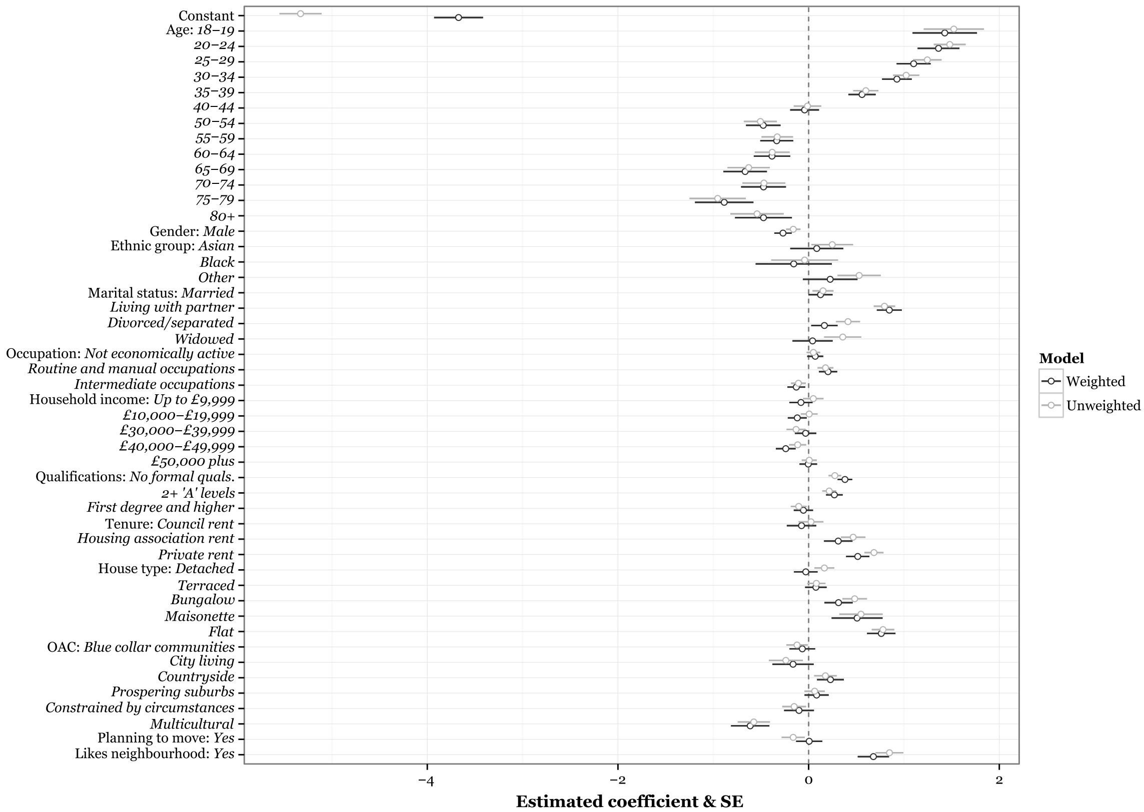
Housing association rent	0.467	0.129	1.596	0.311	0.150	1.364	14.514
Private rent	0.685	0.100	1.983	0.515	0.122	1.674	15.604
Type of home (ref: Semi-detached)							
Detached	0.165	0.105	1.179	-0.030	0.124	0.971	17.670
Terraced	0.081	0.095	1.085	0.076	0.113	1.079	0.530
Bungalow	0.483	0.129	1.621	0.313	0.149	1.368	15.580
Maisonette	0.549	0.227	1.732	0.508	0.267	1.662	4.035
Flat	0.780	0.118	2.182	0.762	0.149	2.142	1.846
OAC Super-group level (ref: Typical traits)							
Blue collar communities	-0.122	0.112	0.886	-0.066	0.134	0.936	-5.707
City living	-0.239	0.178	0.788	-0.164	0.216	0.849	-7.817
Countryside	0.176	0.118	1.193	0.229	0.141	1.257	-5.397
Prospering Suburbs	0.063	0.107	1.065	0.084	0.127	1.087	-2.088
Constrained by circumstances	-0.152	0.125	0.859	-0.101	0.157	0.904	-5.278
Multicultural	-0.575	0.169	0.563	-0.613	0.201	0.542	3.737
Plan to move in next 12 months (ref: No)							
Yes	-0.162	0.121	0.851	0.006	0.138	1.006	-18.293
Like your neighbourhood (ref: No)							
Yes	0.848	0.146	2.335	0.679	0.164	1.972	15.518

Null deviance	9635.5 on 50685 *df*
Residual deviance	8752.7 on 50637 *df*
Improvement (X^2)	882.834, *df* = 48
AIC	8850.7

*N.B. n = 50,686. 95% confidence intervals can be calculated as: coefficient (B) minus 1.96 * SE (lower boundary) and coefficient (B) plus 1.96 * SE (upper boundary) where SE is the standard error. Underlined estimates are significant at the 95 per cent level. Relative differences in the odds ratios ≥20 per cent are underlined. The GOF summary measures relate to the unweighted model, such statistics are currently not incorporated in the R 'survey' (Lumley, 2012) package software for complex sample survey data analysis.*

The model results for the 2006 ROP (Table 8 and Figure 2) suggest that the comparability between the weighted and unweighted models is somewhat less impressive. However, this is not unexpected given the substantial (approx. 60 per cent) reduction in the sample size relative to the 2005 ROP. The general directional associations and patterns depicted in Figure 2 suggest that the substantive findings again appear to be fairly well reflected in both. As with the 2005 results, there is strong evidence of the important role that age (stage in life-course) plays on the likelihood of moving or staying, with the younger age groups being generally more likely to move than those in more elderly age groups. Again, as with the 2005 results, the likelihood of moving is found to be far greater for those living with a partner than those who are single. Additionally, those living in flats as well as those who rent privately or from a housing association, are on average, significantly more likely to have moved in the 12 months prior to the survey than those who live in semi-detached accommodation and those who own their property. As before, we also associate greater neighbourhood satisfaction with those who move residence as opposed to those who do not.

Figure 2. January 2006 ROP weighted and unweighted model estimates



When thinking about the stability in the estimated odds ratios, and while accepting that the comparability between the estimates is less impressive than the January 2005 ROP, none of the observed contradictions should be considered particularly problematic. For the 2006 analysis, there are four cases where the relative difference in the estimated coefficient odds ratio exceeds the ±20 per cent point (the constant, Other ethnic group, divorced/separated and widowed) but again the relative differences do not result in a disagreement with the direction (+/-) of the associations. There are contradictions in the models' estimates, however, in all cases (detached housing; council rent; income up to £9,999, £10,000-£19,999, £50,000 plus; and planning to move), the substantive effects are very small and statistically non-significant in both models.

Table 9. January 2007 ROP: Main effects comparison and relative difference

Predictor	January 2007 unweighted			January 2007 weighted			Relative difference
	B	SE	Odds	B	SE	Odds	(%)
Constant	-5.061	0.109	0.006	-3.686	0.124	0.025	-295.792
Age (ref: 45-49)							
18-19	1.254	0.168	3.505	1.304	0.181	3.685	-5.148
20-24	1.448	0.085	4.255	1.491	0.106	4.441	-4.358
25-29	1.204	0.075	3.333	1.251	0.086	3.494	-4.842
30-34	0.829	0.074	2.291	0.850	0.083	2.339	-2.130
35-39	0.583	0.073	1.792	0.609	0.080	1.838	-2.595
40-44	0.207	0.076	1.230	0.234	0.083	1.263	-2.731
50-54	-0.040	0.084	0.961	-0.051	0.090	0.951	1.040
55-59	-0.093	0.086	0.911	-0.097	0.092	0.907	0.457
60-64	-0.045	0.090	0.956	-0.043	0.096	0.958	-0.238
65-69	-0.150	0.107	0.861	-0.133	0.113	0.875	-1.696
70-74	-0.246	0.125	0.782	-0.255	0.132	0.775	0.949
75-79	-0.521	0.153	0.594	-0.478	0.166	0.620	-4.415
80+	-0.853	0.189	0.426	-0.789	0.199	0.455	-6.686
Gender (ref: Female)							
Male	0.011	0.035	1.012	0.017	0.042	1.017	-0.530
Ethnic group (ref: white)							
Asian	-0.235	0.116	0.791	-0.326	0.131	0.722	8.667
Black	-0.484	0.167	0.616	-0.506	0.198	0.603	2.166
Other	-0.230	0.139	0.794	-0.353	0.152	0.702	11.586
Marital status (ref: single)							
Married	0.058	0.054	1.060	0.129	0.061	1.138	-7.361
Living with partner	0.545	0.054	1.724	0.606	0.060	1.833	-6.325
Divorced/separated	0.443	0.064	1.557	0.454	0.071	1.575	-1.173
Widowed	0.348	0.101	1.417	0.363	0.110	1.437	-1.436
Occupation (ref: Higher managerial administrative and professional occupations)							
Not economically active	0.170	0.034	1.185	0.187	0.037	1.206	-1.711
Routine and manual occupations	0.019	0.036	1.019	0.026	0.039	1.026	-0.670
Intermediate occupations	0.031	0.038	1.031	0.067	0.040	1.069	-3.681
Annual gross household income (ref: £20,000-£29,999)							
Up to £9,999	0.068	0.050	1.070	0.000	0.054	1.000	6.607
£10,000-£19,999	0.042	0.041	1.043	0.014	0.045	1.014	2.767
£30,000-£39,999	-0.045	0.049	0.956	-0.021	0.054	0.980	-2.507
£40,000-£49,999	0.070	0.045	1.073	0.053	0.050	1.054	1.741
£50,000 plus	0.071	0.039	1.074	0.079	0.043	1.082	-0.755
Highest qualification (ref: 5 or more GCSEs)							
No formal qualifications	0.149	0.033	1.160	0.181	0.036	1.198	-3.242
2+ 'A' levels	0.074	0.036	1.076	0.065	0.039	1.068	0.819
First degree and higher	-0.129	0.041	0.879	-0.194	0.045	0.823	6.309
Tenure (ref: Own home)							
Council rent	-0.281	0.069	0.755	-0.291	0.077	0.748	1.033

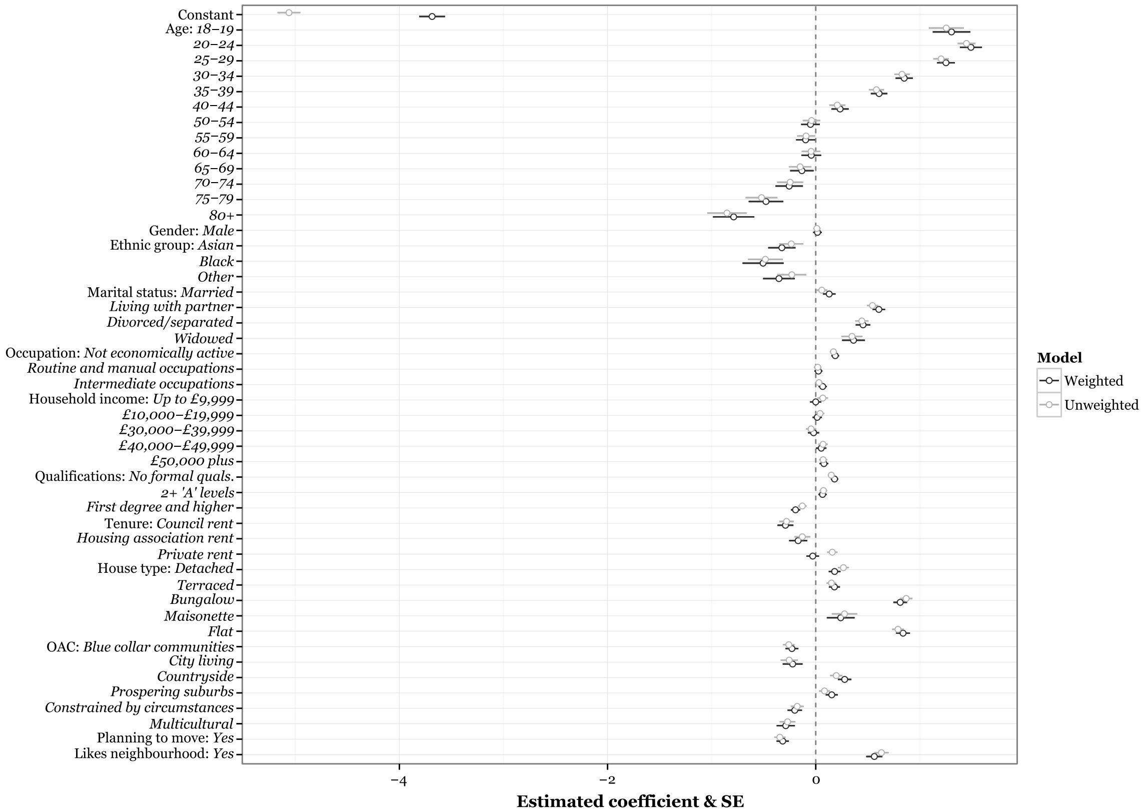
Housing association rent	-0.129	0.077	0.879	-0.169	0.087	0.844	3.878
Private rent	0.159	0.050	1.172	-0.029	0.061	0.972	17.112
Type of home (ref: Semi-detached)							
Detached	0.266	0.053	1.305	0.181	0.057	1.199	8.144
Terraced	0.151	0.047	1.163	0.179	0.053	1.197	-2.849
Bungalow	0.869	0.060	2.386	0.812	0.066	2.251	5.628
Maisonette	0.276	0.122	1.318	0.240	0.134	1.271	3.535
Flat	0.790	0.057	2.204	0.839	0.066	2.313	-4.975
OAC Super-group level (ref: Typical traits)							
Blue collar communities	-0.259	0.056	0.772	-0.229	0.062	0.796	-3.058
City living	-0.255	0.083	0.775	-0.222	0.096	0.801	-3.340
Countryside	0.197	0.059	1.218	0.278	0.065	1.320	-8.381
Prospering Suburbs	0.084	0.052	1.087	0.154	0.058	1.166	-7.251
Constrained by circumstances	-0.178	0.062	0.837	-0.201	0.070	0.818	2.344
Multicultural	-0.271	0.076	0.762	-0.288	0.088	0.750	1.634
Plan to move in next 12 months (ref: No)							
Yes	-0.345	0.054	0.708	-0.317	0.059	0.728	-2.807
Like your neighbourhood (ref: No)							
Yes	0.631	0.069	1.880	0.563	0.078	1.756	6.593

Null deviance	37899 on 172321 *df*
Residual deviance	35770 on 172273 *df*
Improvement (X^2)	2129.008, *df* = 48
AIC	35868

*N.B. n = 172,322. 95% confidence intervals can be calculated as: coefficient (B) minus 1.96 * SE (lower boundary) and coefficient (B) plus 1.96 * SE (upper boundary) where SE is the standard error. Underlined estimates are significant at the 95 per cent level. Relative differences in the odds ratios ≥20 per cent are underlined. The GOF summary measures relate to the unweighted model, such statistics are currently not incorporated in the R 'survey' (Lumley, 2012) package software for complex sample survey data analysis.*

The results for the weighted and unweighted models using January 2007 ROP data (Table 9 and Figure 3) are more consistent than both of the previous data sets. The substantive patterns seen in the 2005 and 2006 ROPs reappear, with the greatest likelihood of mobility found for the youngest age groups and the greatest immobility in the eldest age groups. The importance of the type of accommodation is reemphasised with those living in flats or bungalows characterised by greater mobility rates, on average, than those who live in semi-detached accommodation. Marital status is also found to have a statistically significant and reasonably large effect on propensities to move with those living with their partner being particularly more likely to move than those who are single. Greater immobility is observed for those in Asian, Black and Other ethnic groups, when compared to those from White ethnic backgrounds. Again, as with the 2005 ROP findings, individuals living in multicultural neighbourhoods tend to be characterised by greater immobility than those living in areas characterised by more typical traits, with those living in blue collar communities and areas constrained by circumstances also characterised by particularly greater immobility. Greater satisfaction with their neighbourhood and a lower likelihood of planning for a future move are also significantly associated with movers when compared to stayers.

Figure 3. January 2007 ROP weighted and unweighted model estimates



In terms of consistency in the model estimates, only the constant has a relative difference in the estimated coefficient odds ratio that exceeds the ±20 per cent mark. Moreover, the only example of a contradictory estimate is for private rent; however, the effects are very small in both models and the standard error in the weighted model crosses zero.

Table 10. Pooled (January 2005-07) ROP: Main effects comparison and relative difference

Predictor	Pooled unweighted			Pooled weighted			Relative difference
	B	SE	Odds	B	SE	Odds	(%)
Constant	-4.455	0.071	0.012	-3.262	0.081	0.038	-229.592
Age (ref: 45-49)							
18-19	1.610	0.111	5.001	1.592	0.117	4.914	1.732
20-24	1.726	0.054	5.616	1.724	0.068	5.607	0.159
25-29	1.374	0.050	3.950	1.385	0.057	3.996	-1.150
30-34	1.009	0.049	2.742	1.013	0.054	2.754	-0.446
35-39	0.644	0.048	1.904	0.651	0.053	1.917	-0.683
40-44	0.220	0.051	1.246	0.228	0.055	1.256	-0.801
50-54	-0.156	0.056	0.856	-0.178	0.060	0.837	2.258
55-59	-0.205	0.057	0.815	-0.244	0.061	0.784	3.798
60-64	-0.268	0.061	0.765	-0.294	0.065	0.746	2.513
65-69	-0.372	0.069	0.689	-0.397	0.073	0.672	2.438
70-74	-0.433	0.078	0.649	-0.498	0.082	0.608	6.274
75-79	-0.732	0.097	0.481	-0.767	0.103	0.464	3.513
80+	-0.887	0.116	0.412	-0.891	0.122	0.410	0.445
Gender (ref: Female)							
Male	-0.089	0.023	0.915	-0.082	0.029	0.922	-0.700
Ethnic group (ref: white)							
Asian	-0.005	0.076	0.995	-0.149	0.087	0.862	13.406
Black	0.025	0.097	1.025	-0.107	0.113	0.898	12.351
Other	-0.082	0.081	0.922	-0.156	0.097	0.855	7.175
Marital status (ref: single)							
Married	0.066	0.034	1.069	0.148	0.039	1.159	-8.488
Living with partner	0.549	0.034	1.732	0.636	0.039	1.890	-9.128
Divorced/separated	0.492	0.040	1.635	0.495	0.044	1.640	-0.268
Widowed	0.319	0.066	1.376	0.291	0.071	1.337	2.827
Occupation (ref: Higher managerial administrative and professional occupations)							
Not economically active	0.139	0.022	1.149	0.165	0.024	1.180	-2.677
Routine and manual occupations	-0.015	0.024	0.986	-0.017	0.027	0.984	0.203
Intermediate occupations	-0.103	0.023	0.902	-0.121	0.026	0.886	1.779
Annual gross household income (ref: £20,000-£29,999)							
Up to £9,999	0.085	0.035	1.088	-0.002	0.038	0.998	8.334
£10,000-£19,999	0.051	0.029	1.052	0.007	0.032	1.007	4.324
£30,000-£39,999	-0.034	0.033	0.966	0.046	0.036	1.047	-8.360
£40,000-£49,999	0.043	0.030	1.044	-0.014	0.034	0.986	5.535
£50,000 plus	0.051	0.026	1.052	0.077	0.029	1.080	-2.648
Highest qualification (ref: 5 or more GCSEs)							
No formal qualifications	0.183	0.022	1.200	0.224	0.024	1.251	-4.203
2+ 'A' levels	0.134	0.023	1.143	0.137	0.026	1.147	-0.346
First degree and higher	-0.123	0.026	0.884	-0.170	0.030	0.844	4.536
Tenure (ref: Own home)							
Council rent	-0.016	0.041	0.984	-0.051	0.045	0.950	3.425

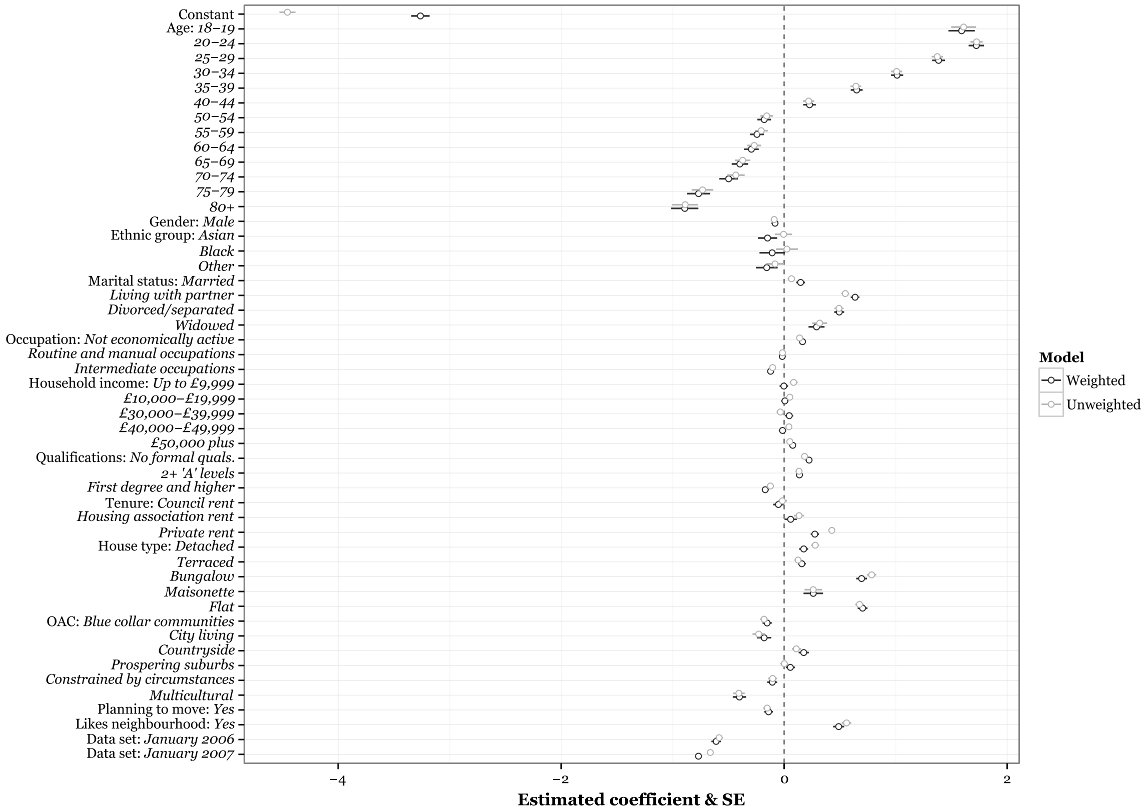
Housing association rent	0.134	0.047	1.144	0.058	0.054	1.060	7.311
Private rent	0.428	0.031	1.534	0.276	0.037	1.317	14.127
Type of home (ref: Semi-detached)							
Detached	0.279	0.036	1.321	0.176	0.040	1.192	9.759
Terraced	0.125	0.030	1.133	0.159	0.035	1.172	-3.467
Bungalow	0.785	0.042	2.193	0.695	0.048	2.003	8.674
Maisonette	0.261	0.077	1.299	0.262	0.087	1.299	-0.030
Flat	0.676	0.037	1.966	0.704	0.044	2.021	-2.813
OAC Super-group level (ref: Typical traits)							
Blue collar communities	-0.180	0.036	0.835	-0.153	0.040	0.858	-2.768
City living	-0.228	0.055	0.796	-0.179	0.065	0.836	-4.980
Countryside	0.109	0.040	1.115	0.176	0.045	1.192	-6.906
Prospering Suburbs	0.002	0.035	1.002	0.056	0.041	1.057	-5.482
Constrained by circumstances	-0.103	0.039	0.902	-0.106	0.044	0.900	0.305
Multicultural	-0.406	0.051	0.667	-0.401	0.059	0.670	-0.435
Plan to move in next 12 months (ref: No)							
Yes	-0.152	0.033	0.859	-0.139	0.037	0.870	-1.302
Like your neighbourhood (ref: No)							
Yes	0.560	0.043	1.750	0.489	0.049	1.631	6.791
Data set (ref: January 2005)							
January 2006	-0.583	0.036	0.558	-0.610	0.041	0.543	2.677
January 2007	-0.662	0.023	0.516	-0.768	0.027	0.464	10.061

Null deviance	86162 on 348952 *df*
Residual deviance	78866 on 348902 *df*
Improvement (X^2)	7295.825, *df* = 50
AIC	78968

*N.B. n = 348,953. 95% confidence intervals can be calculated as: coefficient (B) minus 1.96 * SE (lower boundary) and coefficient (B) plus 1.96 * SE (upper boundary) where SE is the standard error. Underlined estimates are significant at the 95 per cent level. Relative differences in the odds ratios ≥20 per cent are underlined. The GOF summary measures relate to the unweighted model, such statistics are currently not incorporated in the R 'survey' (Lumley, 2012) package software for complex sample survey data analysis.*

The comparisons between the weighted and unweighted models for the January 2005, 2006, and 2007 ROP samples suggest reasonable levels of reliability. We also observe impressive levels of comparability, in terms of the direction and magnitude of the associational patterns, across the different survey cross-section for: life-course, gender, marital status, tenure, type of home, occupational class, and neighbourhood satisfaction. Subsequently, a similar investigation of the pooled data (combining all cases from the January 2005, 2006, and 2007 ROPs) is performed in order to determine its reliability for further, and more sophisticated, analysis. That said, given the relatively small (two-year) temporal variation, the changes in residential mobility frequencies and overall sample sizes (Table 6), and the small but observable analytical variations between the ROP samples, it is deemed useful to incorporate dummy terms indicating for which sample respondents are member of. The inclusion of the dummy terms is designed to help to control for some of the unwanted influence associated with this inter-sample variation.

Figure 4. Pooled (January 2005-07) ROP weighted and unweighted model estimates



The results from the pooled models (Table 10 and Figure 4) suggest an impressive level of agreement with only the constant exceeding the ±20 per cent level of relative difference in the estimated coefficient odds ratio. Moreover, where there are directional relationship disagreements in the models (i.e. Black ethnic groups and up to £9,999, £30,000-£39,999, £40,000-£49,999 income groups), the effects are found to be substantively small and statistically non-significant (with the standard errors crossing the zero, in most cases) in at least one of the comparative models. In terms of the most influential characteristics, the prominence of age (stage in life-course) for the propensity to move/stay is striking, with the common patterns associated with marital status, home type, neighbourhood satisfaction, neighbourhood type, and plans for a future move also revealed. It is also clear that the inclusion of the (nuisance) dummy indicators for each of the ROP samples is justified given that they are both statistically significant and have relatively large effect sizes.

While the influence of nonresponse bias in the unweighted model results cannot be discounted, a reasonable degree of stability is observed both across and between the eight models. Furthermore, from an analytical point of view, the major associational patterns to do with the demographic, socio-economic and behavioural/lifestyle characteristics of movers/non-movers are repeated across each model. Taking this and the substantive nature of this research into account, it is proposed that the pooled ROP data form the basis of all further analysis. Indeed, given the observed stability between the unweighted and weighted model estimates for the pooled ROP data, it can now be argued, with greater confidence, that unweighted models drawing on raw data will provide us with reassuringly accurate substantive findings. With this in mind, and given the practical advantages of a significantly increased sample size and the inherent flexibility offered by the ROP, attention can now be focussed on a more detailed exploration of how the complex and interlinked micro-level behaviours and characteristics of movers and non-movers vary according to the stage in the life-course, an overwhelmingly important phenomenon itself as evidenced in the models above.

5 Exploring the micro-level behaviours and characteristics of movers and non-movers across the life-course

As has been observed in the models above, as well as in many previous analyses, age is a fundamental characteristic upon which the propensity to move, or remain *in situ*, is influenced. It has been mentioned already that age works as a rather consistent proxy for certain life-course transitions that are known to increase/decrease the likelihood of making a residential move. For instance, we can think of life-course transitions into adulthood associated with either a move from school to university or directly into employment, or into employment following higher education – all of which may necessitate a change of residence. The subsequent years for those aged in their early 30s to mid 40s, are commonly characterised by relatively sharp reductions in mobility and are generally considered the years of family formation and child rearing. The decline then reduces somewhat for the years 45-64, with more recent research associating the reduction with a transition from parenthood to 'empty nesting', prompting the desire, at least for some, to change residence in order to downsize (Wulff *et al*., 2010). Finally, for the transition into retirement and old age the picture is more mixed, with some small but noticeable recoveries in the mobility rate associated with the exit from the labour market, but with greater immobility as older age increases (Fielding, 2012). Finally, the mobility rate is observed to increase again, to some extent, for those in the eldest age groups, commonly associated with a need for closer proximity to family members and social/health services.

Yet while we have a reasonably detailed understanding of these major demographic influences, there is surprisingly little understanding of how certain other characteristics, for instance neighbourhood satisfaction, household income and/or plans for a future moves, vary as we move along the major life-course trajectory. Therefore, four binomial logistic regression models (Table 11) have been specified and estimated with the purpose of exploring the variations in the associational patterns of demographic, socio-economic and behavioural/lifestyle characteristics of movers when compared to non-movers for four major life-course stages: 18-29, the transition into adulthood with the associated high levels of mobility (Figure 5); 30-44, traditionally the stage of family formation and reductions in mobility (Figure 6); 45-64, a stage of reduced decline in mobility (Figure 7); and finally 65+, the transition into retirement and old age and relatively low propensities to move (Figure 8). The rationale behind initially using four separate models, instead of a single all-embracing model, is related to the modelling of interaction effects. By separating the models by stage in the life-course we can more easily and efficiently model interactions that may be specific to a single stage in the life-course, while avoiding the need to model others that do not help in explaining variations in mobility behaviour for that stage. The use of an all-embracing model removes this ability and would therefore require a greater number of model interaction terms, further increasing the risk of *sparsity*. That said, any significant interactions found in the models presented here can be used to inform the parsimonious specification of, potentially all-embracing, complex multilevel models.

As with the models presented above, only those predictors that have a bivariate association with the dependent variable at the $p < 0.25$ significance level are selected for inclusion in the multivariate analysis. Moreover, grouped parameter Wald tests are employed in order to test the contribution of *sets* of parameters, while holding others fixed, in the fitted multivariate model (e.g. testing the contribution of all of the dummy terms associated with a categorical predictor variable together) (Heeringa *et al*., 2010). Broadly speaking, non-significance in the Wald test suggests that the parameters associated with the variable, or the interaction between variables, are not significantly different form zero. In the context of this analysis, this can suggest that the variable, or interaction, may not be an important predictor of migrant status, given the other variables included in the model.

Table 11. Pooled (January 2005-07) ROP: Binomial logistic regression of mobility across the broad stages of life-course

Predictor	**Model 1: Ages 18-29**			**Model 2: Ages 30-44**			**Model 3: Ages 45-64**			**Model 4: Ages 65+**		
	B	**SE**	**Odds**	**B**	**SE**	**Odds**	**B**	**SE**	**Odds**	**B**	**SE**	**Odds**
Constant	-2.806	0.185		-4.161	0.151		-5.081	0.179	0.006	-5.763	0.349	
Age												
Model 1 (ref: 18-19)												
20-24	-0.087	0.203	0.917									
25-29	-0.262	0.126	0.770									
Model 2 (ref: 30-34)												
35-39				-0.725	0.040	0.484						
40-44				0.001	0.037	1.001						
Model 3 (ref: 45-49)												
50-54							-0.198	0.046	0.820			
55-59							0.029	0.042	1.029			
60-64							-0.031	0.042	0.970			
Model 4 (ref: 65-69)												
70-74										-0.461	0.086	0.631
75-79										-0.089	0.079	0.915
80+										0.086	0.076	1.090
Gender (ref: Female)												
Male	-0.258	0.082	0.772	-0.001	0.038	0.999	-0.185	0.044	0.831	-0.189	0.073	0.827
Ethnic group (ref: White)												
Asian	-0.342	0.135	0.710	0.181	0.108	1.199	0.227	0.187	1.255	0.118	0.419	1.125
Black	-0.298	0.191	0.743	0.123	0.139	1.131	0.390	0.200	1.477	0.290	0.596	1.337
Other	-0.246	0.142	0.782	0.123	0.121	1.130	0.008	0.176	1.008	-1.993	1.001	0.136
Marital status (ref: Single)												
Married	0.141	0.072	1.151	-0.139	0.054	0.870	-0.063	0.077	0.939	0.255	0.160	1.291
Living with partner	0.493	0.057	1.637	0.326	0.059	1.385	0.399	0.097	1.490	0.933	0.238	2.542
Divorced/separated	-0.046	0.165	0.955	0.405	0.062	1.500	0.395	0.077	1.484	0.301	0.178	1.351

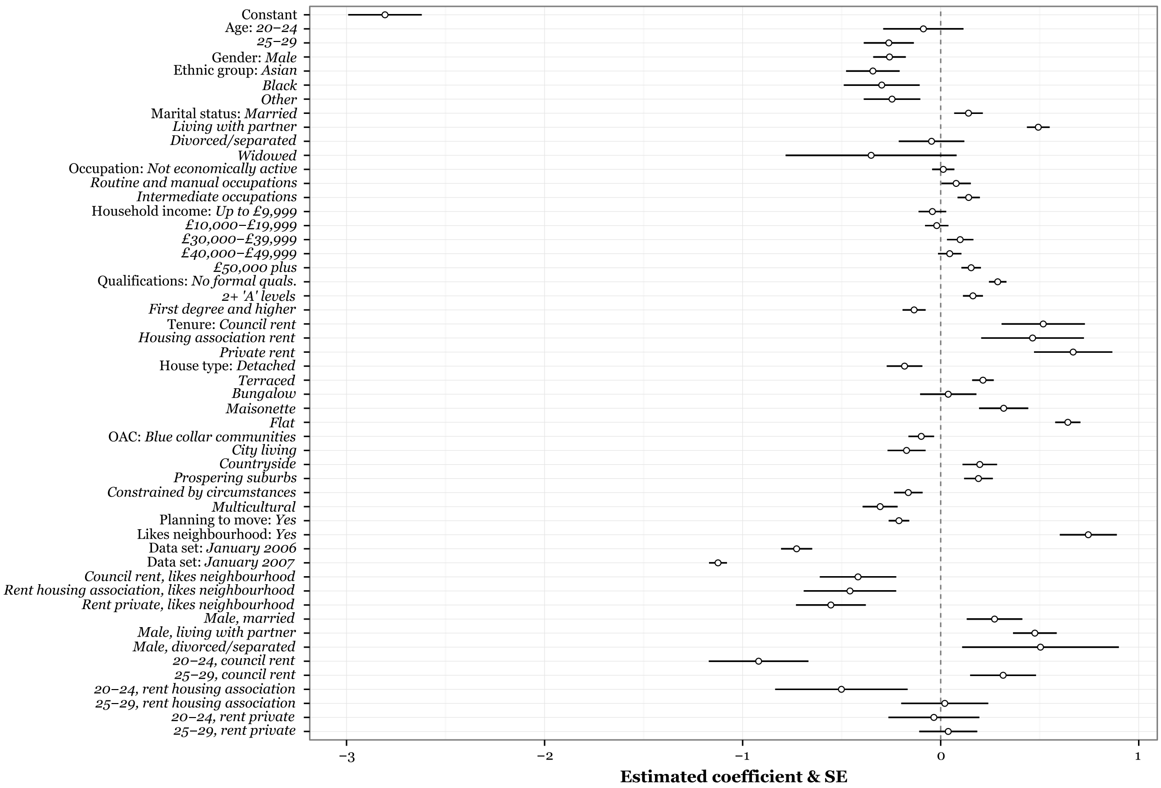
Widowed	-0.351	0.432	0.704	-0.918	0.359	0.399	0.249	0.114	1.282	0.496	0.165	1.643
Occupation (ref: Higher managerial administrative and professional occupations)												
Not economically active	0.013	0.056	1.013	0.041	0.049	1.042	0.023	0.058	1.023	-0.268	0.191	0.765
Routine and manual occupations	0.078	0.074	1.081	-0.005	0.058	0.995	0.132	0.064	1.141	-0.141	0.217	0.868
Intermediate occupations	0.141	0.056	1.152	0.110	0.045	1.117	0.095	0.060	1.100	-0.164	0.262	0.849
Annual gross household income (ref: £20,000-£29,999)												
Up to £9,999	-0.042	0.069	0.959	0.227	0.057	1.255	0.049	0.069	1.050	0.164	0.179	1.179
£10,000-£19,999	-0.020	0.059	0.980	0.141	0.044	1.151	0.001	0.057	1.001	0.169	0.154	1.184
£30,000-£39,999	0.098	0.067	1.103	-0.129	0.054	0.879	-0.018	0.063	0.982	-0.320	0.162	0.726
£40,000-£49,999	0.046	0.059	1.047	0.088	0.049	1.092	-0.023	0.058	0.977	0.227	0.148	1.254
£50,000 plus	0.154	0.049	1.166	0.043	0.042	1.044	-0.038	0.051	0.963	0.004	0.117	1.004
Highest qualification (ref: 5 or more GCSEs)												
No formal qualifications	0.288	0.044	1.334	0.165	0.035	1.179	0.119	0.043	1.126	0.072	0.081	1.074
2+ 'A' levels	0.163	0.050	1.177	0.143	0.042	1.154	0.149	0.046	1.161	0.060	0.085	1.062
First degree and higher	-0.134	0.058	0.874	-0.149	0.048	0.862	-0.093	0.050	0.911	-0.203	0.088	0.816
Tenure (ref: Own home)												
Council rent	0.518	0.210	1.678	0.425	0.197	1.530	-0.161	0.282	0.852	0.298	0.132	1.347
Housing association rent	0.464	0.259	1.590	0.479	0.230	1.614	0.553	0.282	1.738	0.617	0.141	1.853
Private rent	0.669	0.198	1.952	1.266	0.188	3.545	1.362	0.223	3.902	0.900	0.115	2.460
Type of home (ref: Semi-detached)												
Detached	-0.182	0.090	0.833	0.437	0.053	1.549	0.278	0.068	1.320	0.772	0.141	2.164
Terraced	0.213	0.054	1.238	-0.033	0.048	0.967	0.163	0.064	1.177	0.198	0.159	1.219
Bungalow	0.038	0.142	1.039	0.434	0.090	1.544	0.995	0.069	2.705	1.484	0.122	4.409
Maisonette	0.318	0.124	1.374	-0.010	0.136	0.990	0.324	0.162	1.382	0.755	0.327	2.127
Flat	0.642	0.063	1.900	0.301	0.067	1.351	0.708	0.077	2.030	1.595	0.143	4.927
OAC Super-group level (ref: Typical traits)												
Blue collar communities	-0.098	0.065	0.907	-0.159	0.057	0.853	-0.276	0.075	0.759	-0.308	0.142	0.735
City living	-0.172	0.096	0.842	-0.346	0.103	0.707	-0.135	0.110	0.874	-0.121	0.158	0.886
Countryside	0.197	0.087	1.218	0.055	0.066	1.056	0.103	0.073	1.108	0.064	0.119	1.066
Prospering suburbs	0.191	0.072	1.210	0.016	0.056	1.016	-0.046	0.069	0.955	-0.268	0.118	0.765

Constrained by circumstances	-0.163	0.072	0.849	-0.043	0.065	0.958	-0.066	0.077	0.936	-0.330	0.133	0.719
Multicultural	-0.306	0.088	0.737	-0.315	0.082	0.730	-0.483	0.109	0.617	-0.737	0.220	0.478
Plan to move in next 12 months (ref: No)												
Yes	-0.211	0.052	0.810	-0.109	0.055	0.896	0.043	0.081	1.044	-0.130	0.207	0.878
Like your neighbourhood (ref: No)												
Yes	0.745	0.144	2.107	1.019	0.136	2.769	0.792	0.152	2.208	0.745	0.220	2.106
Data set (ref: January 2005)												
January 2006	-0.727	0.078	0.483	-0.516	0.057	0.597	-0.451	0.071	0.637	0.580	0.117	0.560
January 2007	-1.124	0.045	0.325	-0.708	0.038	0.493	-0.228	0.045	0.796	-0.139	0.163	0.871
Tenure x Like your neighbourhood												
Council rent, likes neighbourhood	-0.417	0.193	0.659	-0.502	0.205	0.605	0.265	0.288	1.303			
Rent housing association, likes neighbourhood	-0.458	0.233	0.633	-0.427	0.241	0.652	-0.304	0.294	0.738			
Rent private, likes neighbourhood	-0.554	0.176	0.574	-0.656	0.192	0.519	-0.598	0.229	0.550			
Gender x Marital status												
Male, married	0.272	0.140	1.313									
Male, living with partner	0.475	0.110	1.609									
Male, divorced/separated	0.504	0.395	1.655									
Male, Widowed	-10.699	101.537	0.000									
Age x Tenure												
20–24, council rent	-0.919	0.251	0.399									
25–29, council rent	0.315	0.166	1.371									
20–24, rent housing association	-0.501	0.334	0.606									
25–29, rent housing association	0.021	0.219	1.021									
20–24, rent private	-0.034	0.229	0.966									
25–29, rent private	0.038	0.146	1.039									
35–39, council rent				0.334	0.106	1.396						
40–44, council rent				0.078	0.104	1.082						
35–39, rent housing association				0.117	0.133	1.124						
40–44, rent housing association				-0.011	0.126	0.989						

35–39, rent private				$\underline{0.591}$	0.081	1.806						
40–44, rent private				-0.103	0.078	0.902						
Null deviance			18557 on 32367 *df*			30252 on 103902 *df*			24187 on 142864 *df*			9060.6 on 69816 *df*
Residual deviance			17233 on 32315 *df*			28771 on 103854 *df*			23326 on 142821 *df*			8458.9 on 69776 *df*
Improvement (X^2)			$\underline{61.110}$, *df* = 13[a]			$\underline{74.479}$, *df* = 9[a]			$\underline{10.673}$, *df* = 3[a]			$\underline{601.633}$, *df* = 40[b]
AIC			17339			28869			23414			8540.9

*N.B. Model 1 n = 32,368; Model 2 n = 103,903; Model 3 n = 142,865; Model 4 n = 69,817. 95% confidence intervals can be calculated as: coefficient (B) minus 1.96 * SE (lower boundary) and coefficient (B) plus 1.96 * SE (upper boundary) where SE is the standard error. Underlined coefficients are significant at the 95 per cent level. [a] Improvement on main effects only model, [b] improvement on null model.*

Figure 5. Pooled (January 2005-07) Model 1, ages 18-29



N.B. The estimated coefficient for the "Male, widowed" interaction term is not shown due to the size of the standard error (Table 11).

Figure 6. Pooled (January 2005-07) Model 2, ages 30-44

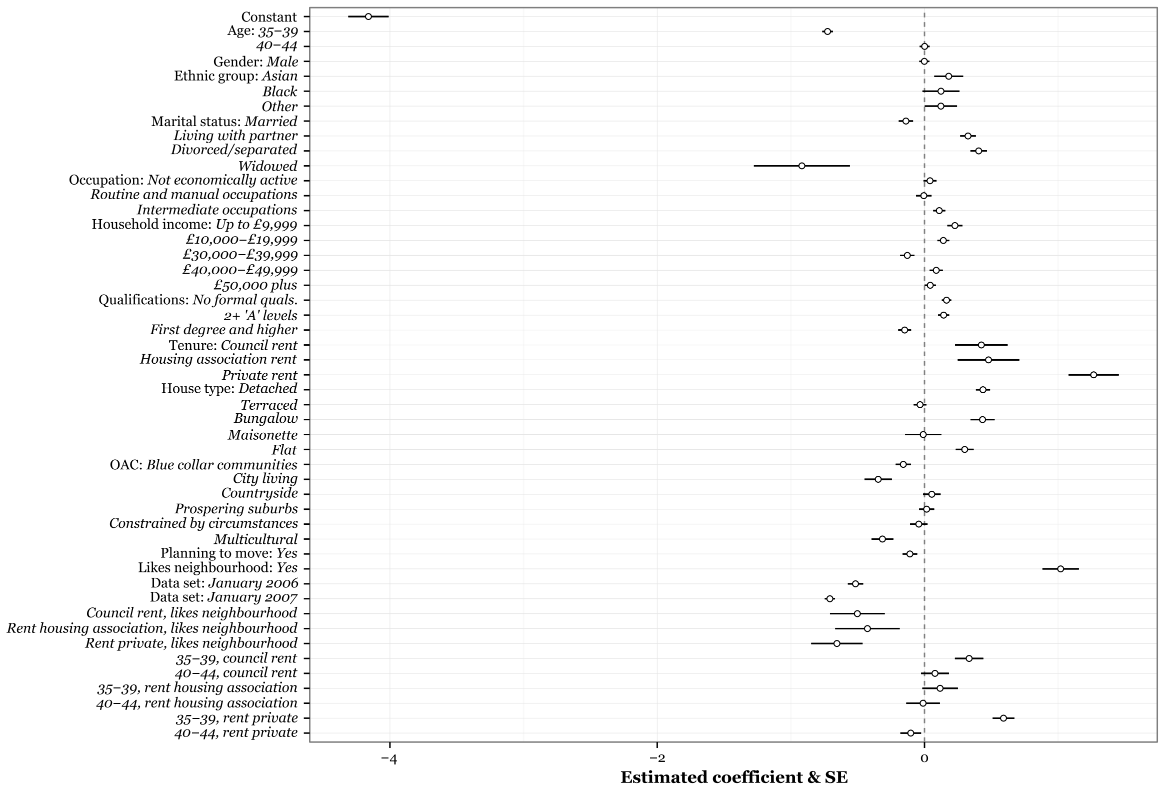


Figure 7. Pooled (January 2005-07) Model 3, ages 45-64

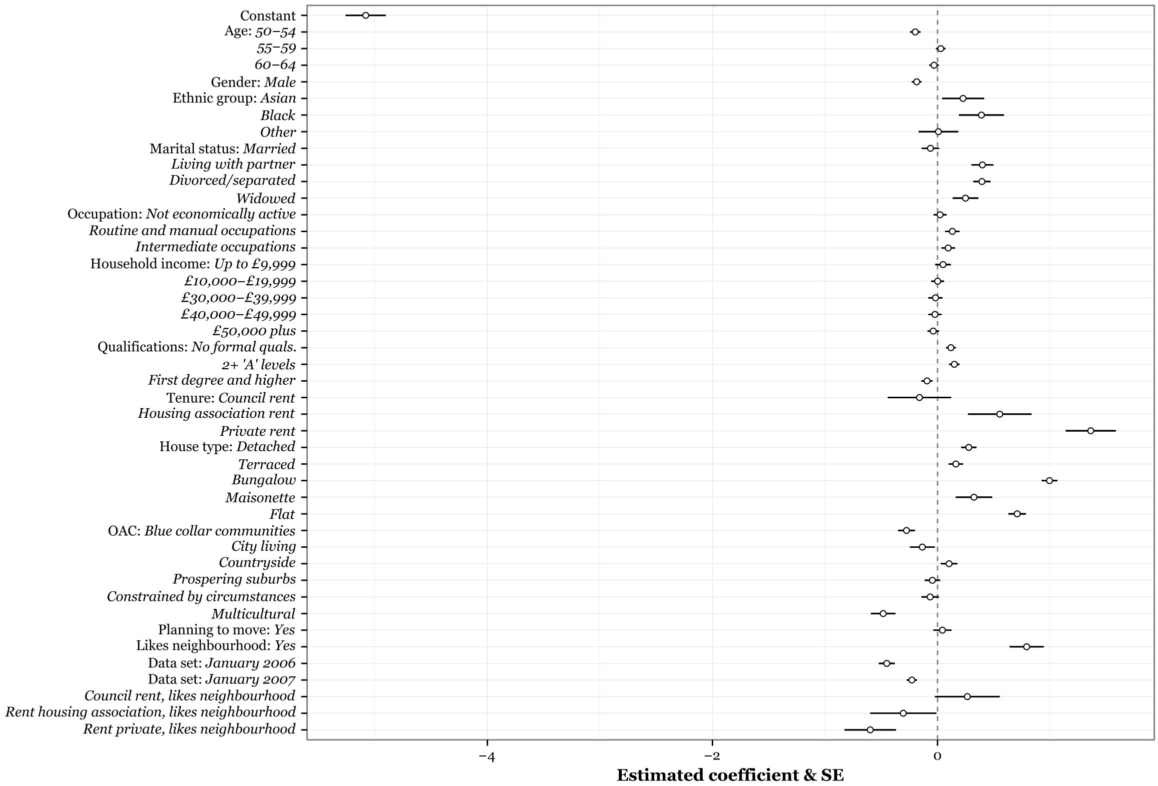
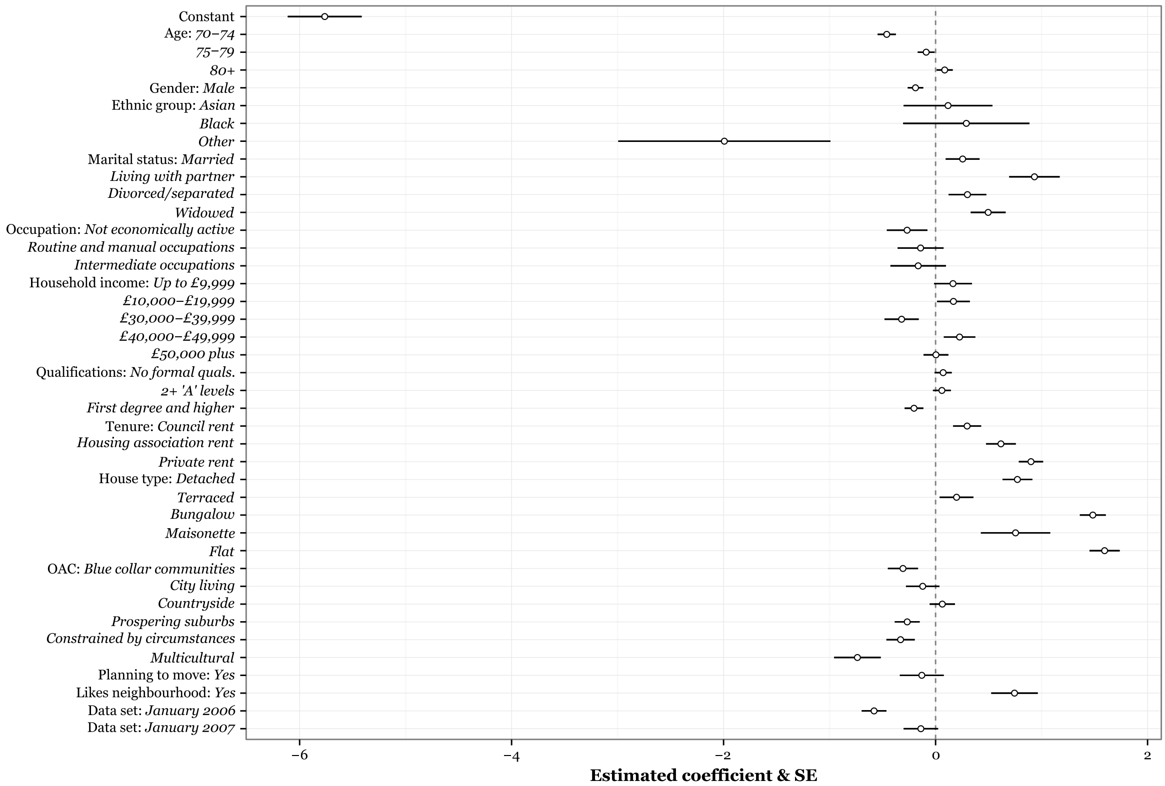


Figure 8. Pooled (January 2005-07) Model 4, ages 65+



While the models are themselves broken down according to rather broad life-course stages, each stand-alone model was designed to accommodate the potential effects of age at the smaller intervals found *within* the specific life-course groupings. The results are presented in Table 11 and Figures 5-8, and provide evidence that marked differences according to age *within* these broad stages of life are apparent and, to a large extent, further highlight some of the demographic themes considered above. For instance, the greatest mobility within the early adulthood stage is associated with those in the 18-19 age group, that conventionally associated with move away from home to university (Champion, 2005b; Duke-Williams, 2009; Smith, 2009). While at the opposite end of the life-course there is significantly greater immobility for those in their 70s compared to individuals in the immediate years following retirement. Of course, beyond the expected increase in immobility for more elderly cohorts, we have come to expect the ages associated with retirement, as with those associated with moves to university, to reflect increased mobility behaviour (Evandrou *et al*., 2010).

The results strengthen the case that females are more migratory than males, one of Ravenstein's (1885) original laws of migration. Mobility premiums are observed for women of all stages of the life-course apart from those in their 30s and early 40s. Indeed, the absence of evidence in support of Ravenstein's theory for the 30-44 age group, is an interesting empirical observation. However, given the common theme of family formation and childbearing at this life-stage, it is perhaps not so unexpected. After all, the relative plateauing of the female mobility premium can be thought of as linked to the ways in which the social and cultural norms associated with such household and family based phenomena affect mobility behaviours and propensities differently according to gender (Boyle *et al.*, 2001; Magdol, 2002; Boyle *et al.*, 2009).

The influence of ethnicity on mobility and immobility in Britain has been the focus of increasing interest in recent years (Simpson and Finney, 2009; van Ham and Clark, 2009; Stillwell and Hussain, 2010). According to research by Stillwell and Hussain (2010), almost all ethnic minority groups in Britain (bar certain Asian groups) are characterised by higher rates of residential mobility than the White-British majority. However, this is to a large extent tied to the fact that the White-British majority is, on average, an older population and therefore a seemingly less mobile one (Stillwell and Hussain, 2010). With this in mind, the analysis presented in Table 11 and Figures 5-8 is useful in showing the remaining effect of the individual's ethnic background once it is sufficiently disentangled from their age/stage in life-course. The findings suggest that there are clear patterns in mobility and immobility according to ethnicity which vary through the life-course, with particularly interesting results associated with those in early adulthood. Indeed, Table 11 and Figure 5 actually reveal a greater likelihood of mobility for individuals from the White majority background than those in the non-White groups, with a particularly strong, and statistically significant, reduction in mobility found for individuals from Asian ethnic backgrounds. However, this relationship reverses as we move through the stages of the life-course with those from White ethnic backgrounds in the 30-44, 45-64, and 60+ age groups seen to be less mobile than those in the other ethnic groups. The exception to this rule is for those who are classified as 'Other' in the post-retirement/elderly (aged 60+) stages, where a substantial level of immobility is evident when compared to the White reference group. That said, the size of the standard error, perhaps best observed in Figure 8, would suggest that this estimate is open to a particularly wide degree of variability and so should be treated with a good deal of caution.

Moving beyond the typical demographic characteristics uncovers further patterns. For instance, while a change in marital status cannot be inferred, given the cross-sectional nature of the ROP data, a focus on the current marital status of movers and non-movers does reveal some patterns that appear to vary across the life-course. When focussing on those in early adulthood, the sole substantive and statistically significant difference is found between individuals who live with a partner and individuals who class themselves as single, with the former suggesting greater mobility than the latter. Given that by its very nature, living with partner suggests cohabitation, we can expect a change of residence to be necessary for at least one, and possibly both, of the partners, with an increased likelihood of the moves being relatively recent given the age group we are studying. Applying Wald tests to the model parameters suggests that the interaction of gender and marital status, at least at this stage in the life-course, significantly contributes to the multivariate model (Wald $X^2 = 19.0$; $df = 4; p < 0.01$) and, as a result, should be included. With the added gender-marital status interaction term, we can observe that this relationship is further amplified for men; in other words, there is a positive and additional effect for men who live with their partners when compared to women who live with theirs[7]. Therefore, men living with their partners are 2.03 ($\exp^{0.71}$) times more likely to have undertaken a residential move within the last 12 months than the reference group, women who are single[8]. This compares to women living with their partners who are 1.64 times more likely to have moved than single women. Given that cohabitation would necessitate at least one individual changing residence, these findings perhaps suggest a slightly greater propensity for men to do the moving in. Interestingly, this interaction is not found to be significant for any of the later stages in the life-course.

[7] The main effect for marital status is interpreted to be the effect for women (the reference category in the gender variable) while the interaction terms reflect the additional effect of being male.
[8] The total effect for men living with a partner in this model is: $-0.258 * 1 + 0.493 * 1 + 0.475 * (1 * 1) = 0.71$.

The significance of marital status increases somewhat in the more stable family forming/childrearing stages of life. Married people, perhaps reflecting this apparent stability, are found to be 0.71 times as likely to move as those who are single. However, those living with their partner experience higher rates of mobility than singles (odds ratio, 1.36). Divorced/separated people also have greater mobility than single people. Indeed, as with family/household formation, the breakdown of relationships will in most cases also necessitate the move of one, and possibly both, of the individuals (Geist and McManus, 2008; Mulder and Wagner, 2010). Being widowed in this group is also found to have a substantial effect with widowers having far greater levels of immobility when compared to singles; however, again the magnitude of the standard error calls into question the reliability of this estimate (Figure 6). The relationship roughly follows the same pattern in the later stages of the life-course, with the exception being the rather unsurprising increase in mobility associated with widowhood, something known to influence greater rates of residential mobility (Chevan, 2005; Evandrou *et al.,* 2010).

The literature suggests that both occupational class and gross annual household income play important selective roles in residential mobility (Borjas *et al.*, 1992; Fielding, 1992; 1998; 2007; Poston and Bouvier, 2010). However, once we control for the additional demographic, socio-economic and lifestyle/behavioural characteristics of the individual, a substantively important relationship between the various occupational or income groups and residential mobility/immobility is lacking. For instance, while the appearance of greater mobility for the intermediate occupational groups in the 18-29 and 30-44 age groups, when compared to the higher level occupations, is statistically significant, the magnitude of the effect is comparatively small, with odds ratios of 1.15 and 1.12 respectively. Likewise, those with routine and manual occupations between the ages of 45 and 64 also experience a statistically significant, yet seemingly small increase in mobility when compared to the highest occupational groups (odds ratio, 1.14). While it remains relatively trivial compared to the other characteristics included in the life-course models, the income dimension is perhaps a little more interesting. For instance, for those in early adulthood, there is *some* evidence of a relatively linear relationship, with greater household income associated greater mobility. This is a commonly theorised relationship with greater financial resources, indicated by a higher income, leading to improved choice within the housing market as well as an increased ability to cover the financial costs associated with changing residence. Yet for those in the 30-44 and 65+ age groups, we see this admittedly slight association shift into more of a U-shaped relationship with small increases in mobility for those in the lower and upper income groups, when compared to the middling income levels (Figures 6 and 8). It should be said that other studies focussed on specific stages in the life-course have also suggested the relative irrelevance of household income on residential mobility/immobility patterns; for instance, the study of the mid-life stage by Wulff *et al*. (2010) and the analysis of migration in later life by Evandrou *et al.* (2010). While this may be so, it is important to keep this study in context. Indeed, the analysis concentrates on variations in the associational patterns of demographic, socio-economic and lifestyle/behavioural characteristics for all movers, as opposed to non-movers, with no differentiation for the distance moved; for which the average across all residential movers modelled here, is assumed to be relatively short given the well-known frictional effect of distance on mobility (Stillwell, 1991). If residential movers were to be modelled separately as short-distance movers, which are typically thought to be more strongly associated with the economics of housing markets and longer-distance migrants, which are again theorised to be more closely tied to the economics of the labour market, the expectation might be to find the latter group to vary considerably, in terms of income and occupation, from those in the former short-distance group (Gordon, 1982). While distance moved is not modelled here, future research will address this.

This argument also holds weight when applied to what is observed with the highest qualification characteristic. Educational attainment, as with the occupational and income characteristics of individuals, is found again to be of quite marginal importance when exploring the variations in movers and non-movers. For the small effects we do see, relative stability is observed across the life-course with small mobility premiums seen for individuals with no formal qualifications or qualifications equivalent to two or more 'A' levels and small increases in immobility associated with individuals educated to the level of first degree or higher. Generally speaking, these findings contradict the conventional theories which suggest, in a similar way to the interrelated income and occupational factors, that we should expect residential mobility to increase with educational attainment. However, as has been alluded to already, it is probable that a separate analysis of movers, according to distance travelled, would likely increase the relevance and effect of such a variable. Indeed, beyond the labour market dynamics that we would associate with educational attainment, highly educated individuals have been suggested to have weaker social ties to their locality and therefore less of an instinct to remain within them (van Ham and Feijten, 2008). All things considered then, we should perhaps expect those with higher levels of educational attainment to move greater distances than those with comparatively lower educational attainment. However, as the models presented here suggest, when strictly looking at residential mobility *per se*, our educational attainment appears to be a relatively minor influence.

Following Gordon's (1982) suggestions, if the proposed effects of the more labour-market relevant variables are suppressed in these models, due to the greater likelihood of movers being short-distance movers, it can be forgiven for supposing that the effects of the housing-market orientated characteristics will be amplified. The findings from the models presented here do, to a large extent, encourage such a supposition. Tenure for example, regardless of one's age/stage in life-course, is found to be a one of the most substantively important and highly significant characteristics. Across the board, from those in the stages of early adulthood right through to the post-retirement stages of life, there appears to be greater mobility for individuals who rent their accommodation than those who own it, an observation that is by no means new (Rossi and Shlay, 1982; Boyle, 1993; Champion *et al*., 1998; Bailey and Livingston, 2005; van Ham and Feijten, 2008).

The greatest disparity can be seen between private renters and homeowners. Indeed, private renters are found to be almost two-times more likely to move than homeowners in the early stages of adulthood, with the magnitude of the relationship increasing in the 30s and early 40s (3.5 times more likely), and again in the middle-age/pre-retirement stage where the likelihood of moving is almost four times greater for private renters. The mobility premium associated with private renters depreciates somewhat (odds ratio 2.46) in the final stage of post-retirement and old age, but remains strongly predictive of greater mobility. Increased mobility is also observed for those who rent from the council, with the non-significant exception of individuals aged 45-64, and those who rent from housing associations. Interestingly, Wald tests suggest that the mobility rates associated with private renters and council tenants significantly vary according to age within the broad stages of the life-course, but only for those associated with early adulthood and, more specifically for this stage, only council tenants (Model 1, Table 11; Figure 5) (Wald $X^2 = 29.5$; $df = 6; p < 0.01$) and those in the family forming/childrearing stage (Model 2, Table 11; Figure 6) (Wald $X^2 = 61.4$; $df = 6; p < 0.01$).

Given the inclusion of the interaction terms, the main effects of tenure for those in the 18-29 and 30-44 groups should be interpreted as the effects for individuals in the reference age brackets, 18-19 in Model 1 and 30-34 in Model 2 (Table 11; Figures 5 and 6). With this being the case, it should be noted that those who record themselves as homeowners at the age of 18-19 are in fact quite probably living in their parents (owned) home. Looking at these finer age group variations, council tenants aged 18-19 are estimated to be 1.68 times more likely to have moved than the reference group, homeowners aged 18-19, whereas council tenants aged 20-24 actually buck the general trend with the likelihood of having moved estimated to be 0.61 times that of the reference group. Conversely, council tenants in the 30-44 stage are found to have the same directional associations, with greater mobility found when compared to homeowners, although the magnitude of the relationship is significantly weaker for those aged 35-39 who are in fact only 1.13 times more likely to have moved than those in the reference group, homeowners aged 30-34. This pattern for individuals aged 30-34 is also significant for private renters where again, *ceteris paribus*, we see them being slightly less likely to have moved than private renters aged 30-34, when compared to homeowners of the same age. In terms of the bigger picture, the greater mobility for council tenants is particularly interesting as they have traditionally been associated with lower rates of mobility, although more specifically at the inter-regional level, partly linked to the rather rigid allocation system employed in the UK (Hughes and McCormick, 2000; Bailey and Livingston, 2005). However, such structural restrictions are greatly reduced for localised moves and therefore, given the likelihood that most of the recorded moves will be short-distance in nature, the higher mobility associated with council tenants, in comparison to homeowners, is not as unexpected as perhaps first thought.

Continuing the housing related trend, house type is also found to be highly influential for patterns of mobility/immobility, although the type-specific relationships vary depending on the stage of life-course. For the youngest stage (early adulthood), mobility is significantly higher for those in flats (odds ratio, 1.90), maisonettes (odds ratio, 1.37) and terraced housing (odds ratio, 1.24) and significantly lower for those in detached housing (odds ratio, 0.83), when compared to those in semi-detached housing. Given that we are talking about people at the start of their housing/occupational careers, it is perhaps unsurprising that individuals in the housing types we generally associate with lower transaction costs reflect a greater likelihood of moving. The picture becomes a little more mixed in the middle stages of life (Models 2 and 3, Table 11; Figures 6 and 7) with individuals from detached accommodation now reflecting, on average, a greater propensity for residential mobility than those in semi-detached housing. This relative increase in mobility associated with detached housing, and the relative decrease in the mobility witnessed for those in flats when compared to semi-detached accommodation, is likely to reflect the importance of family formation, especially for those aged 30-45, and the necessary housing adjustments that changes to family composition are known to entail (Rossi and Shlay, 1982; Boyle, 1993; Champion *et al.,* 1998; Bailey and Livingston, 2005; van Ham and Feijten, 2008; Fielding, 2012). For those in the final stages of the life-course, the substantive importance of housing-type increases still further with rather pronounced rates of mobility associated with bungalows (odds ratio, 4.41) and flats, the latter suggestive of a mobility premium almost five times greater than that of the reference category, semi-detached (Figure 12). Indeed, while change to family composition, though family formation, can be thought to influence the increased mobility rates observed for the larger accommodation types, the increase in the substantive importance of the smaller accommodation types, for this stage in the life-course, can also be understood to reflect such factors. For instance, it might be assumed that the housing needs for retired and elderly individuals, in terms of space, are somewhat reduced when compared to individuals in earlier stages of life. Moreover, given the onset of old age and the physical problems that this can bring, it is of no surprise that a rather substantial shift towards single-level accommodation types is apparent.

While it is measured in a rather simplistic manner here, the effect of the individual's current neighbourhood type can, to a certain extent, be seen to further condition the likelihood of undertaking a residential move. All things being equal, and irrespective of stage in the life-course, individuals living in multicultural areas are found, on average, to have the lowest levels of mobility. Similarly, individuals living in blue collar communities, excluding those in early adulthood, can also be seen to have significantly reduced rates of mobility, when compared to individuals living in areas classified as typical traits. However, aside from these rather consistent findings, the remaining effects associated with neighbourhood type, as observed in previous studies (for example: Kearns and Parkes, 2003; van Ham and Feijten, 2008; van Ham and Clark, 2009; Rabe and Taylor, 2010), are fairly trivial when compared to the individual's demographic, socio-economic and behavioural/lifestyle characteristics. Yet it is possible that the technical and analytical limitations associated with the inclusion of neighbourhood type in the manner presented here, as a series of fixed effects dummy term variables within a single-level modelling framework, are working to obscure substantively interesting neighbourhood characteristic/context influences on residential mobility/immobility.

Finally, we are left with the seemingly more nuanced characteristics of movers and non-movers, namely those associated with greater conjecture and subjectivity. Individuals' moving desires, expectations and plans are of clear importance to the study of residential mobility and immobility. However, from an empirical perspective, the focus on such factors remains surprisingly lacklustre. That said, research in this area is increasing, with key contributions focussing on the interrelationship between pre-move desires and subsequent moving behaviour (Lu, 1998; Kley and Mulder, 2010; Kley, 2011; Coulter *et al*., 2011; 2012). Unfortunately, the nature of the ROP makes it impossible to study the relationship between pre-move desires and subsequent mobility. However, in spite of the lack of longitudinal data, we are able to uncover whether, in fact, individuals who have moved within the last 12 months are more/less likely to be planning a further move within the next 12 months. Looking at the results from the life-course models, the directional relationships, aside from those in the 45-64 stage, appear to suggest that individuals are less likely to be planning a future move if they have already recently moved.

This observation is particularly significant, and statistically more stable, for those in the early adulthood phase, where individuals planning to move are on average, 0.81 times as likely to have already moved in the 12 months prior to the survey. At first sight, this appears to contradict the cumulative inertia hypothesis, wherein individuals with the shortest durations of residence are thought to be the most likely to move again, a theory that has been important in explaining the high correlation between out-migration and in-migration rates at the aggregate levels (Cordey-Hayes and Gleave, 1974). However, micro-level studies, with their notable inclusion of important covariates such as age, have shown that the relationship between residence duration and the likelihood of considering a future move does not follow a simple monotonic relationship, that is, with probabilities of moving decreasing as duration increases. For instance, micro-level analysis by Gordon and Molho (1995: 1970) suggests that the likelihood of considering a move peaks at approximately seven years, with those in their first 12 months of residence being the least likely to consider a further move. Could it be therefore, that the residential moves already performed by individuals, particularly in the early adulthood stage, are to a certain extent successful in fulfilling the factors that motivated their move in the first place? Indeed, at this stage in the life-course for instance, interrelated events such as leaving the parental home, going to university, starting a career and forming relationships resulting in cohabitation, are all factors that stimulate residential mobility. And it follows therefore, that they are all factors that can be satisfied, to varying degrees, by residential mobility. Additionally, given that a mover would, by definition, have lived at their address for fewer than 12 months, the financial requirements of a further move, within such a short timeframe, would undeniably weigh heavy on their plans for a future move. Of course, planning to move is a more definitive statement than simply desiring a move and would suggest that more serious practical considerations of the residential move, such as the financial implications, had been made (Lu, 1998; Coulter *et al.,* 2011).

The importance of the neighbourhood, in terms of subjective measures of satisfaction, has become an increasingly interesting area within the residential mobility literature (see for instance, Clark and Ledwith, 2006; Feijten and van Ham, 2009; Permentier *et al.*, 2009; Hedman, 2011). The analyses presented in this literature suggest that, aside from household needs and preferences, (dis)satisfaction with the wider neighbourhood is fundamental in motivating a decision to move/stay, with greater neighbourhood satisfaction tied closely to a greater likelihood to remain in place. However, the processes behind neighbourhood satisfaction are clearly complex and dynamic in nature; with variations likely to be driven by differences operating at the level of the individual as well as the household (Parks *et al*., 2001). Therefore, it is perhaps not surprising that the relationship between neighbourhood satisfaction and residential mobility is found to vary significantly according to tenure type, although only for those aged 18-29 (Wald $X^2 = 10.2; df = 3; p < 0.05$), 30-44 (Wald $X^2 = 12.6; df = 3; p < 0.01$) and 45-64 (Wald $X^2 = 10.8; df = 3; p < 0.05$). Overall, greater neighbourhood satisfaction is found to be consistently and rather strongly associated with residential mobility. Across the various stages of the life-course, people who are satisfied with their neighbourhood are more likely to have recently moved than not. However, allowing for this relationship to vary according to tenure uncovers further and perhaps more interesting findings. In fact, all things being equal, for the relationship between neighbourhood satisfaction and residential mobility, there is a positive additional effect associated with homeowners and conversely a negative additional effect for renters (be they council, housing association or private). In other words, the higher level of neighbourhood satisfaction associated with residential movers is lessened somewhat if their tenure type is renter, be it council, housing association, or private, as opposed to homeowner. Such findings are perhaps to be expected given that movers who own their home are more likely to have invested for the long-term, and subsequently, one would imagine, are more likely to have chosen an area/neighbourhood that fits their housing, lifestyle and consumption desires more comfortably. After all, the difference is particularly pronounced when comparing homeowners to private renters, the latter being the tenure group most closely associated with short-term residential durations (Bailey and Livingston, 2005).

6 Conclusion and next steps

This paper aimed to address two issues, one of technical and methodological relevance and the other of more substantive analytical importance. From a methodological perspective, the paper has set out a way in which survey raking (or IPF) can be used as a means for providing some degree of protection against potential distortions in model-based estimates; that is, by accounting for the unequal probabilities of selection in a sample for which the user has no prior information on the sampling design/strategy employed. Through the use of like-for-like weighted and unweighted binary logistic regression models, it has been possible to compare the relative difference of the estimated odds ratios (in percentage terms) for each model pairing (weighted and unweighted), as well as the differences/similarities in the effect sizes and the direction of associations both between *and* across all pairs of models for individual ROP surveys (2005, 2006, 2007) and the pooled data. The findings of this comparison suggest a good deal of stability and reliability across all of the eight models involved, but particularly for the model estimates derived from the *pooled* ROP data. Given such findings, it is suggested that further analytical research on the pooled data can be performed with greater confidence; however, care must be taken not to discount the influence of nonresponse bias altogether.

The substantive analytical focus in the second part of the paper capitalised on the confidence demonstrated in utilising pooled data, and the associated practical advantages gained with increased sample size and an inherently flexible data source, to explore how the complex and interlinked micro-level characteristics of movers and non-movers vary according to an individual's life-course stage. Separating the life-course into four major stages – 18-29, 30-44, 45-64, and 65+ – did uncover some interesting patterns, some of which varied across the life-course (for instance, the effects of ethnic background) and others of which remained constant throughout (for instance, the effects of neighbourhood type).

One important conclusion to be drawn from the life-course models is the relative unimportance of what can be thought of as the labour market characteristics of individuals. Indeed, occupational class, gross annual household income and education levels are all found to play marginal roles in influencing an individual's likelihood to have moved. In contrast, however, the characteristics that can be thought of as tied more closely to the housing market, i.e. tenure, house type, neighbourhood satisfaction, are found to be of great substantive relevance. Interestingly, such findings do appear to contradict much of the literature, at least that which highlights the supposed influence of occupational class, income and educational attainment on an individual's propensity to move. However, as mentioned above, it is important to think carefully about what we are measuring here. The primary focus is to explore variations in movers and non-movers; however, as with all categorisations at such broad levels, it would be foolish to assume that all moves are driven by the same processes, influences and dynamics. In fact we know that the motivations behind moves tend to vary substantially depending on the spatial distance involved, with short-distance moves theorised to be more strongly associated with the economics of housing markets and long-distance moves thought to be more closely tied to the economics of the labour market (Gordon, 1982). Given that we know the vast majority of moves in the population are short-distance in nature (Stillwell, 1991; Bailey and Livingston, 2007), when analysing movers and non-movers as two dichotomous groups, we are in fact more accurately describing the differences between short-distance movers and non-movers. This could well explain, if Gordon (1982) is indeed correct in his theory, the apparent marginality found for occupational class, household income and educational attainment, and the apparent substantive importance of household tenure, house type and neighbourhood satisfaction, in our models. A theme for future research is to explore this in a multilevel context by modelling distance moved as a response while allowing for differential heterogeneity for different individual characteristics.

While accepting that our findings could be influenced by aforementioned issues, a focus on the more subjective behaviours/characteristics of movers and non-movers did uncover results worthy of further discussion. Future plans to move are found to be negatively associated with mobility, especially for those in their early adulthood. It is suggested therefore that individuals, particularly in the young adulthood stage, who undertook a residential move within the 12 months prior to the survey were largely successful in fulfilling the factors that motivated their move in the first place, be it university, cohabitation or career driven. However, beyond this, it is also highly likely that recent movers are comparatively less likely to plan a further move given the various forms of additional investment (in terms of time, emotion, and finance) that would be required, a feeling that would likely increase if we were to shrink the timeframe between the last move and the proposed future move still further. It was also suggested that the definition of planning a move was more definitive as a statement than, for instance, desiring a move would be. As a result it is thought highly likely that individuals who are planning to move within the next 12 months have taken these more practical, investment related considerations into account. Shifting to the dynamic role of neighbourhood satisfaction for mobility and immobility, we observed some rather interesting (and to the knowledge of the authors) previously unobserved findings. Indeed, the role of neighbourhood satisfaction is found to be a complex one, wherein it would appear to be linked rather strongly to the individual's housing tenure. Primarily, across the various stages of the life-course, people who are satisfied with their neighbourhood are more likely to have recently moved than remained *in situ*. Yet, all things being equal, a positive additional effect is associated with homeowners and a negative additional effect for renters regardless of type. In other words, the higher level of neighbourhood satisfaction associated with residential movers is lessened somewhat if their tenure type is renter, be it council, housing association, or private, as opposed to homeowner. It is thus suggested that movers who own their home are, for varying reasons, more likely to have chosen a neighbourhood that more closely fits their housing, lifestyle and consumption desires.

While the findings here do help in highlighting how the complex and interlinked micro-level behaviours and characteristics of movers and non-movers vary or not, as may be the case according to the stage in the life-course. The single-level framework employed does restrict what analysis can be undertaken with these data. As was mentioned in the background section, our own personal experiences of residential mobility, coupled with a substantial volume of theoretical and empirical research, would suggest that residential mobility and immobility are inextricably linked to complex structural processes that interact across various scales. As such our analysis of residential mobility should be able to recognise that "*people make a difference and places make a difference*" (Gregory, 1995, cited in Jones and Duncan, 1996: 81). The findings that have been presented in this paper have shown some effect related to an individual's neighbourhood type (as measured by the OAC), however, while such indicators of aggregate phenomena can be incorporated into a single-level model as fixed effects, as they are here, they cannot account for the possibility of residual correlation between individuals within shared spatial contexts, for instance their neighbourhood. At the same time they are further limited by not being able to properly account for inter-contextual variability or the underlying factors behind it (Diez-Roux, 2002). Such technical and analytical restrictions can be addressed, however, through the use of a multilevel statistical framework (Paterson and Goldstein, 1991; Gould *et al*., 1997; Snijders and Bosker, 2012). Fundamentally, multilevel modelling would allow for the exploration of both individual and area level effects (and their interactions) simultaneously and in a statistically reliable manner thanks to its technical advantages (the use of 'shrunken estimation', using Empirical Bayes and/or Markov Chain Monte Carlo estimation) which control for concerns surrounding heterogeneity and (spatial) autocorrelation (Jones, 1991; Goldstein, 2003). However, beyond the advantages associated with the traditional hierarchical structure, cross-classified designs also pose a great deal of potential. For instance, as Bailey *et al.* (2013: 33) argue "[if] *we wish to study mobility outcomes, we need data that links people to places they lived some time earlier*". As such with the flexibility allowed for by the ROP, it is a possibility to nest individuals within, for instance, their neighbourhood of origin and their neighbourhood of destination simultaneously in order to tease out any compositional, contextual or compositional/contextual interactions associated with the origin and/or destination. For instance, when exploring the distance of a residential move, are certain neighbourhood characteristics more influential at the origin than they are at the destination? Do some origin/destination types lose/attract ('send'/'receive') longer/shorter distance movers than others? Do subjective evaluations of (destination) neighbourhood satisfaction vary according to individual (level-1) and origin and/or destination neighbourhood-level (level-2) characteristics? Are there cross-level interactions between individual-level and area-level characteristics? This flexibility, once combined with the unique characteristics of the ROP data, including the allowance for postcode-to-postcode distance travelled, points the way to some potentially quite interesting analyses in the future.

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Appendix A: Marginal population totals

N.B. All subtotals are later adjusted to meet the 18+ Mid-2005 Population Estimates for Great Britain ($N = 45{,}775{,}200$) which themselves reflect ONS revisions due to improved migration measures.

Totals used for the model estimates:

Government Office Region (GOR) totals:

GOR	Population
North East A	2,074,000
North West B	5,503,900
Yorkshire D	4,124,800
East Midlands E	3,503,600
West Midlands F	4,282,800
East of England G	4,472,800
London H	6,046,000
South East J	6,591,200
South West K	4,158,400
Wales W	2,384,500
Scotland X	4,165,800
GB total (16+)	47,307,800

Source: Table 8 Mid-2005 Population Estimates: Selected age groups for local authorities in the United Kingdom; estimated resident population.

Age group totals:

Age	Population
18-24	5,345,300
25-29	3,651,700
30-34	4,051,100
35-39	4,511,800
40-44	4,475,300
45-49	3,926,300
50-54	3,566,800
55-59	3,812,400
60-64	3,030,100
65-69	2,641,800
70+	6,762,600
GB total (18+)	45,775,200

Source: Table 2 Mid-2005 Population Estimates: Great Britain; estimated resident population by single year of age and sex; reflecting revisions due to improved migration. Office for National Statistics, General Register Office for Scotland.

Sex group totals:

Sex	Population
Male	22,118,300
Female	23,656,600
GB total (18+)	45,774,900

Source: Table 2 Mid-2005 Population Estimates: Great Britain; estimated resident population by single year of age and sex; reflecting revisions due to improved migration. Office for National Statistics, General Register Office for Scotland.

Mover/non-mover group totals:

Length of residence	Population
Less than 12 months	4,032,346
More than 12 months	39,344,060
GB total (18+)	43,376,406

Source: Quarterly Labour Force Survey Household Dataset, April - June, 2005. Weight: Person household weight. Crown copyright material is reproduced with the permission of the Controller of HMSO and the Queen's Printer for Scotland.

Totals used in the worked example of the raking procedure:

Income group totals:

Approx. Gross Annual Household Income	% of valid responses
Less than £5,200	1.4
£5,200 less than £10,400	6.1
£10,400 less than £15,600	10.5
£15,600 less than £20,800	9.4
£20,800 less than £26,000	8.8
£26,000 less than £31,000	9.6
£31,000 less than £36,000	9.2
£36,000 less than £42,000	10.1
£42,000 less than £47,000	7.8
£47,000 less than £52,000	7.3
£52,000 and above	19.9
Total	100

Source: Survey of English Housing, 2006-2007. Weight: Household weight. Crown copyright material is reproduced with the permission of the Controller of HMSO and the Queen's Printer for Scotland.

N.B. Refusal to answer the question in the SEH counts as an invalid and is removed from the weighted estimate for the gross annual household income distribution for the English population. It was decided to use the SHE income estimates, despite the non-coverage of Scotland and Wales, because the categorisation was the closest fit to the ROP. The categories were aggregated so as to fit with the ROP income brackets.

Tenure group totals:

Home ownership	Population
Own your Own Home/ buying on mortgage	41,808,186
Rent Council	6,123,636
Rent Housing Association	4,237,787
Rent Private	5,871,681
GB total (all)	58,041,290

Source: General Household Survey, 2006. Weight: Weight. Crown copyright material is reproduced with the permission of the Controller of HMSO and the Queen's Printer for Scotland.