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Modelling residential mobility decision and its impact on car ownership and travel mode

Md Bashirul Haque

Choice Modelling Centre and Institute for Transport Studies

University of Leeds, UK

36-40 University Road, Leeds LS2 9JT

Email: tsmbh@leeds.ac.uk

Charisma Choudhury

Choice Modelling Centre and Institute for Transport Studies

University of Leeds, UK

36-40 University Road, Leeds LS2 9JT

Email: C.F.Choudhury@leeds.ac.uk

Stephane Hess

Choice Modelling Centre and Institute for Transport Studies

University of Leeds, UK

36-40 University Road, Leeds LS2 9JT

Email: s.hess@its.leeds.ac.uk

Romain Crastes dit Sourd

Choice Modelling Centre and Institute for Transport Studies

University of Leeds, UK

36-40 University Road, Leeds LS2 9JT

Email: R.CrastesditSourd@leeds.ac.uk

Abstract
Household residential relocation can happen at different scales - local, regional national and international. The impacts of the different scales of residential relocation is likely to have varying impacts on mid-term (e.g. car or transit pass ownership) and day-to-day mobility decisions (e.g. mode choice for a specific trip for example). These mobility changes can be of different levels as well. For example, there are differences between the decision to transition from owning no car to one car and from one car to two cars. Identifying which factors affect the different magnitudes of mobility changes and quantifying the impact of various scales of residential relocation on these changes are crucial to better understanding of travel behaviour. The present study uses discrete choice models on revealed preference data to address these research questions. To complement the travel behaviour models, a residential relocation model has also been developed to predict the probability of a household to stay in the current location vs. to move locally, regionally or nationally at a given point of time.

Given that the residential relocations are rare events, the British household panel survey (BHPS) spanning 18 years has been used to model the choices made by the same households in terms of residential relocation, car ownership and commute mode of the household head. Our results indicate that sociodemographic characteristics, travel behaviour and life events of the households have a significant effect on relocation, car ownership and commute mode choice. As expected, the parameters of the car ownership and commute mode choice models vary significantly with the type of relocation. Further, the socio-demographic factors and life-events also have a varying impact on the scale of relocation. The residential relocation, car ownership and commute mode choice models developed in this research can be used to better predict the medium and long term changes in travel behaviour over course of time.

Keywords: residential mobility, car ownership, commute mode, geographical scale, discrete choice modelling

1. Introduction

Residential relocation is a special biographical moment which affects household daily activities and results changes in the travel behaviour of household members (Scheiner 2006). Household residential relocation can occur at different scales - local, regional, national and international. The different scales of residential relocation are likely to have varying impacts on mid-term (e.g. car or transit pass ownership) and day-to-day mobility decisions (e.g. mode choice for a specific trip for example). For example, local level relocation (moving within the same ward) is an 'adjustment' move typically prompted by better attributes of the dwelling and is unlikely to have a substantial effect on households' transport accessibility and consequently their travel behaviour. Relocating to a different part of the city or country on the other hand is more likely to lead to substantial changes in accessibility and hence car ownership status and daily travel behaviour. For instance, it has been reported that moving in a deprived area having less access to public transport increases the likelihood of car ownership and car use (Clark, Chatterjee and Melia 2016a). In previous studies, researchers have modelled household car ownership levels (e.g. Hanly and Dargay 2000; Dargay and Hanly 2007; Fox *et al.* 2017) and/or the associated changes in two consecutive years (e.g. Cao, Mokhtarian and Handy 2007; Aditjandra, Cao and Mulley 2012; Clark, Lyons and Chatterjee 2012; Clark, Chatterjee and Melia 2016a). However, the effect of the type of the relocation (local, regional, national) on changes in car ownership have not been explored yet. Similarly, though several researchers have focused on changes in residential relocation and commute behaviour (e.g. Oakil *et al.* 2011; Clark, Chatterjee and Melia 2016b), the effect of different geographical scales on commute behaviour remains an unexplored topic. This prompts us to develop econometric models to quantify the effects of different types of residential mobility (local, regional and national) on two critical elements of travel behaviour: car ownership and commute mode choice.

Further, the factors driving the different types of relocation decisions can also differ with the magnitude of the change. For example, local level relocation (within the same ward) is more likely to be driven by factors like demand for larger space, end of contract and local adjustment with the commute distance; regional relocation (within the same city, but a different ward) may be prompted by better transport accessibility, quality of the schools and other attributes of the area; long distance relocation (i.e. migration to a different city) may be prompted by factors like switching to a job in another metropolitan area and/or proximity with the family. Although many studies captured the different aspects of residential mobility decisions such as connections between life course events and residential mobility (e.g. Clark and Huang 2003), role of housing policies on residential mobility (e.g. Sánchez and Andrews 2011), gender role on residential mobility decision (e.g. McCulloch 2010), influence of social network on residential mobility decision (e.g. David, Janiak and Wasmer 2010), residential mobility and travel behaviour (e.g. Krizek 2003), etc., the factors influencing the geographical scale of residential mobility and the associated heterogeneity in sensitivity, remains a largely unexplored area of research. This points to the need for a residential relocation model to make our proposed travel behaviour models suitable for prediction.

The paper therefore also proposes a residential relocation model to predict the probability of a household to stay vs. to move locally, regionally or nationally. This model is aimed to complement the travel behaviour models.

The key applied research questions are thus as follows

- Are there significant differences in the factors that drive the residential mobility in different geographical scales?
- What are the consequences of geographical scale of residential mobility on
  a) household car ownership and
  b) commute mode behaviour?

It may be noted that residential relocation is a rare event which may affect the quality of results obtained from cross sectional data. This has prompted us to use a longitudinal dataset (18 waves of the British Household Panel Survey) for model estimation. The long panel helps us to examine the choices made by the same households over a span of time.

The econometric technique applied in this study allows to quantify the differences between the residential mobility in different geographical scales and the role of geographical scale on car ownership and commute mode switching behaviour. In addition, the panel nature of the data used in this study facilities to capture the correlation of the choices over time and the impact of the dynamic state of the household on their changes in preferences.

The rest of this paper is organised as follows: the next sections discuss the data used for empirical analysis followed by the model structure. The details of the choice set construction and the model formulations are presented next. This is followed by the model results. The concluding section summarizes the study contributions, limitations and direction for future research.

2. Data

2.1 Data source

The British Household Panel Survey Dataset (BHPS) used in this study covers 18 waves from 1991 to 2008. The survey was initially designed for understanding social and economic changes at the individual and household level in the United Kingdom. However, BHPS also contains information on household residential mobility behaviour, travel characteristics and socio-demographic characteristics. The first wave included 5,511 households but a considerable number of households dropped out across the waves and new respondents were added in each of the subsequent waves to retain the sample representativeness. Given our interest to examine how the choices made by the same households evolve over a long span of time, we used the households consistently available in all the 18 waves, 1,455 in total. Further, only household level mobility (when all members of the household relocate) was considered for this study. Therefore, individuals who split-off from the original households and formed new households are not included. Also, it is inevitable that the households are getting older in the later waves.

It may be noted that although the BHPS data has rich panel information about mobility behaviour, demographics and attitudes, because of the discontinuity of some of the variables across the panels, it was not possible to use all variables. Even arranging the data for the analysis, we conducted was a non-trivial task and is indicative of the difficulty of working with such complex data, reflected in the small number of past applications using it.

2.2 Data issues and sample representativeness

The BHPS Using the balanced panel with the observations of the households who have participated in all waves (balanced panel) posed several data issues. In particular, the drop out from the survey can be non-random, making the balanced panel non-representative. For example, if the dropout rate is higher among the renters, the panel may have over-representation of the owners and the estimation results will be dominated by their behaviour. Therefore, the representativeness of the sub sample in relation to the full sample (all households included in wave 1) are investigated using Chi-square test.

Chi square test of goodness of fit is a widely used technique for assessing the sample representativeness that can be applied at the level of attribute to identify the attributes which may make a sample nonrepresentative (e.g. Griffin, J. et al.,2015); Fasbender, D., Devos, W. and Lemajic, S.,2017). The null hypothesis in this case is the distribution of household characteristics in the full sample and the sub-sample are similar and the Chi-square values are calculated using the equation presented below[1]

$$\chi^2(k) = \sum_{i=1}^{J} \frac{(P_{ik} - Q_{ik})^2}{Q_{ik}} \times \frac{N_s}{100} \tag{1}$$

P_{ik} *and* Q_{ik} are percentages of observations is the subsample and the full dataset respectively corresponding to the category *i* of attribute *k*. N_s is the number of households in the subsample. The degree of freedom (DF) is the number of categories under each attribute (J) minus 1.

The results of the Chi-square test for the key household socio-demographic characteristics are presented in Table 1. As seen in the table, the Chi-square stat rejects the null hypothesis for eight out of eleven attributes at 95% confidence interval which implies that the dropout in the BHPS is non-random and requires appropriate corrections.

Review of literature reveals that weighting of the data is a suitable technique to reduce bias due to non-random dropout in the panel survey (Vandecasteele and Debels 2006) and the Raking or iterative technique is the most widely used technique to calculate the sampling weight for each observation (Johnson 2008; Fotini, Evangelia and Michail 2013)[2].

[1] The chi-square value needs to be calculated from the actual frequency. The term $\frac{N_s}{100}$ in the equation 1 convers relative frequencies P_{ik} and Q_{ik} into actual frequency.

[2] The sampling weight is the inverse of the selection probability of a sampling unit. In the Raking technique, a weight for each respondent is calculated to force the sample distribution to closely match the population distribution The sampling weights are adjusted using Iterative Proportional Fitting (IPF) algorithm (see Anderson and Fricker Jr 2015 for details).

Table 1: Chi-square goodness of fit test for the sub-sample

Variables	Sample distribution (%) Full sample (wave 1)	Sample distribution (%) Sub sample (wave 1)	Chi-square (category)	Chi-square (total)	Chi-square critical value (95% CI)
Household type					
Single member household	26.7	19.5	28.5	72.1	7.81
Couple without child	27.8	28.5	0.3		
Couple with child	33.5	42.6	35.5		
Lone parents	12.0	9.4	7.9		
Household income in GBP					
Less than £20,000	69.7	59.6	21.5	71.9	5.99
Between £20,000 to £40,000	25.6	33.7	37.5		
More than £40,000	4.7	6.7	12.8		
Education attainment of household head					
Below O level	51.5	40.1	36.8	89.0	7.81
O and A level degree	34.2	39.4	11.4		
Graduate degree	12.5	18.2	39.0		
Post-graduate degree	1.8	2.2	1.8		
Age of household head					
Less equal to 30 years	16	13.8	4.3	147.9	9.49
Between 31 to 40 years	20.2	24.3	12.0		
Between 41 to 50 years	18.9	25.2	30.3		
Between 51 to 60 years	14.2	18.9	22.7		
More than 60 years	30.7	17.8	78.7		
Number of employees in the household					
No employee	34.6	19.6	94.5	152.3	5.99
One employee	28.8	32.4	6.7		
More than one employees	36.7	48.0	51.1		
Tenure type					
Owned house	66.5	79.8	38.6	120.9	5.99
Rented social housing	20.7	14.2	29.1		
Rented private housing	12.8	6.0	53.2		
Presence of senior adult (>75years)					
Yes	12.07	2.5	110.9	126.1	3.84
No	87.9	97.5	15.2		
Length of current job of household head					
Less than 5 years	50.0	55.1	7.3	48.2	5.99
Between 5 to 10 years	19.8	23.0	7.9		
More than 10 years	30.2	21.9	33.0		
Having a child in last one year					
Yes	7.1	7.8	0.9	1.0	3.84
No	92.9	92.2	0.1		
Changed job in last one year					
Yes	15.4	16.0	0.4	0.4	3.84
No	84.6	84.0	0.1		
Residential Location before move					
London	9.0	9.6	0.6	0.6	3.84
Other cities	91.0	90.4	0.1		
Sample size	5511	1454	-	-	-

The initial sampling weights provided with the dataset is also considered here. Therefore, the final weight for each household is the product of the initial weight provided with the dataset and the weight calculated to adjust the sub-sample with the full sample. The weights thus correct the over and under-representation of different population groups in the dataset due to non-random dropouts and ensure that the balanced sample (consisting of respondents who have stayed in all 18 waves) is a representative sample in the base year (wave 1). Consequently, the estimated coefficients are likely to represent the true behaviour of the population.

2.3 Data analyses

2.3.1 Residential mobility behaviour

The residential mobility rate of the households in the BHPS dataset is very low. The number of households that moved in a given year varies between 3% to 6% across the waves (Figure 1). Among all the residential moves, more than 60% occurred locally (within the same ward), around 20-25% happened at the regional level and the remaining 15-20% happened at the national level (Figure 2).

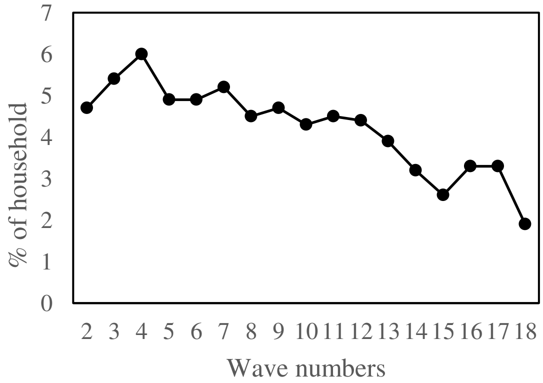


Figure 1: Households that have moved in different waves (full sample)

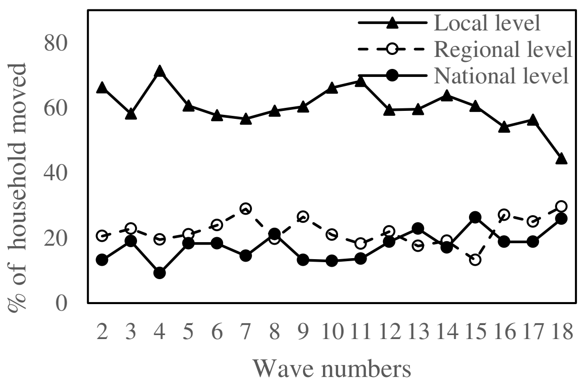


Figure 2: Split of relocation of different geographical scales across the waves

Table 2 presents the distribution of the characteristics of the households who did not move, who moved at local level, who moved at regional level and who moved at national level. The table values represent the household state before the decision has made. The Chi-square test of independence is used to investigate whether the characteristics of different decision-making units are significantly different[3]. Chi-square test results confirm that sociodemographic characteristics and travel behaviour of the households of these four groups (did not move, moved locally, moved regionally and moved nationally) were different from each other before their residential moves. As observed in the table, the group that moved nationally has a considerably higher share of high-income households (annual income above 40,000 GBP) and highly educated people (graduate or postgraduate) compared to the other groups. Similarly, social renters have higher share at local level relocation compared to regional and national level relocation. On the other hand, private renters have the highest share at regional level relocation compared to the other groups. In case of daily travel behaviour, the average commute distance of the households that have moved at a national level is found to be higher than the average commute distance of other groups (stayed, moved at local level and moved at regional level).

[3] For the continuous variables such as length of current job, crowd and travel distance, Chi-square test is inapplicable, therefore, t-stat has been used instead to compare the differences between their mean values.

Households that have made a national-level move are found to be more avid users of public transport compared to the households that have moved at local level, regional level or did not moved.

Table 2: Descriptive statistics of the households that have moved in different geographical scales.

Variables	Residential mobility (%)				Chi square values (category)				Total Chi square values	Chi square critical value (95%
	Stayed (SC)	Moved local level (ML)	Moved regional level (MR)	Moved national level (MN)	Stayed (SC)	Moved local level (ML)	Moved regional level (MR)	Moved national level (MN)		
Sociodemographic characteristics										
Household type										
Single member household	28.2	28.5	29.0	26.7	0.00	0.03	0.06	0.13		
Couple without child	30.8	23.5	34.4	36.3	0.10	10.72	1.02	1.78	34.5	16.9
Couple with child	31.9	34.1	30.0	31.5	0.01	0.98	0.26	0.01		
Lone parents	9.1	13.8	6.5	5.6	0.13	14.93	1.76	2.53		
Household income in GBP										
Less than £20,000	54.3	52.3	51.5	37.3	0.18	0.40	0.30	9.23		
Between £20,000 to £40,000	30.6	33.0	34.9	38.6	0.19	1.04	1.28	3.53	26.0	12.6
More than £40,000	15.1	14.7	13.7	24.1	0.03	0.07	0.33	9.43		
Education attainment of household head										
Below O level	47.2	41.6	26.5	29.5	1.08	3.56	20.07	11.24		
O and A level degree	35.4	37.4	50.6	31.0	0.17	0.62	14.70	1.05	139.6	16.9
Graduate degree	14.7	16.1	18.5	27.4	0.42	0.66	2.08	18.75		
Post-graduate degree	2.7	4.9	4.3	12.1	1.56	8.99	1.69	52.92		
Number of employees in the household										
No employee	38.4	31.2	29.5	28.5	0.72	7.93	4.41	4.27		
One employee	25.5	28.8	34.4	31.7	0.42	2.37	6.87	2.53	32.8	12.6
More than one employees	36.1	40.1	36.1	39.8	0.10	2.52	0.00	0.61		
Tenure type (%)										
Owned house	75.2	52.3	56.3	72.2	1.97	41.98	10.11	0.12		
Rented social housing	19.0	24.4	11.5	7.7	0.00	9.87	6.76	11.78	649.2	12.6
Rented private housing	5.8	23.4	32.2	20.1	22.78	268.95	226.47	48.37		
Presence of senior adult (>75years)										
Yes	16.9	9.1	6.2	15.0	1.42	21.70	15.13	0.28	46.2	7.8
No	83.1	90.9	93.8	85.0	0.28	4.32	3.02	0.06		
Job length of household head (years)										
Mean	9.8	8.8	6.2	8.8	-	-	-	-	*	-
Standard deviation	14.1	13.0	9.3	13.5	-	-	-	-		
Crowd (household size/number of rooms)										
Mean	0.5	0.8	0.6	0.7	-	-	-	-	**	-
Standard deviation	0.4	0.7	0.7	0.6	-	-	-	-		
Life events										
Having a child in last one year										
Yes	3.8	8.2	8.6	6.6	1.8	27.4	12.1	3.0	46.1	7.8
No	96.2	91.8	91.4	93.4	0.1	1.1	0.5	0.1		
Changed job in last one year										
Yes	12.2	18.4	22.2	20.5	1.9	17.7	17.3	9.1	52.6	7.8
No	87.8	81.6	77.8	79.5	0.3	2.5	2.5	1.3		
Travel characteristics										
Travel distance (kilometre)										
Mean	6.3	8.8	7.0	10.3	-	-	-	-	***	-
Standard deviation	18.9	18.9	18.4	24.2	-	-	-	-		
Travel mode										
Car	73.3	56.7	65.1	67.9	1.0	22.5	1.8	0.6		
Public transport (PT)'	10.5	14.6	3.5	28.5	0.6	9.2	11.1	52.5	103.0	12.6
Active travel mode (AT)'	11.9	9.5	10.4	10.1	0.2	2.8	0.4	0.4		
Residential location before move										
London	10.6	12.5	0.9	37.1	0.5	1.8	20.5	115.0	154.4	7.8
Other cities	89.4	87.5	99.1	62.9	0.1	0.2	2.5	13.8		
Number of observations	23675	636	230	177	-	-	-	-	-	-

* t stat for difference between mean of SC-ML, SC-MR,SC-MN, ML-MR,ML-MN, MR-MN are 1.8,5.7,1.0,3.3,0.1,-2.2 respectively.

** t stat for difference between mean of SC-ML, SC-MR,SC-MN, ML-MR,ML-MN, MR-MN are -7.8,-1.7,-3.2,2.7,1.4,-1.1 respectively.

*** t stat for difference between mean of SC-ML, SC-MR,SC-MN, ML-MR,ML-MN, MR-MN are -3.3,-0.7,-2.2,1.2-0.8,-1.5 respectively.

' Public transport includes underground/tube, train and bus; active travel includes bicycle and walking.

2.3.2 Changes in car ownership

Car ownership of the households in the weighted dataset is around 75% which is very close to the national average (74%) (Dargay and Hanly 2007). The shares of one, two and three car owning households in the dataset are 44.1%, 24.3% and 6.0% on average respectively. The level of car ownership of each household changes over time. Table 3 presents car ownership level changes from one year to the next between 1991 and 2008. It may be noted that the rate of gaining and losing the second car (3.2% and 2.8% respectively) is found higher compared to the rate of gaining and losing the first car (1.3% and 1.4% respectively).

Table 3: Household car ownership transection pathway in two consecutive years

Car ownership transaction pathway			
Number of car (s) at year t	Number of car (s) at year t+1	Number of cases	Percentage
0 car	0 car	5942	24.0
	1 car	316	1.3
	2 cars	16	0.1
	3+ cars	4	0.0
1 car	0 car	345	1.4
	1 car	9817	39.7
	2 cars	797	3.2
	3+ cars	76	0.3
2 cars	0 car	13	0.1
	1 car	694	2.8
	2 cars	4823	19.5
	3+ cars	455	1.8
3+ cars	0 car	6	0.0
	1 car	79	0.3
	2 cars	381	1.5
	3+ cars	955	3.9
Total		24718	100.0

Car ownership level changes are likely to be triggered by changes in sociodemographic status (e.g. income change, change in household size, etc.) and life events (e.g. moving house, changing job, getting married, etc.) of the households as well as changes in local and national level policies (e.g. insurance cost, fuel price, etc.). Chi-square test of independence is also used here to investigate association between the changes in household state and the changes in car ownership level in two consecutive years and significant level of correlation is observed between them (Table 4). For example, among the households that have acquired their first car, 19.1% gained members in the household and 24% gained increase in employed members. On the other hand, among the households that did not acquire or lose car, only 3.2% gained new members in the household and only 7.4% gained employment. Elderly peoples are found to have higher proportions of decreasing the number of cars than increasing it with the percentage of moving from one car to no car being the highest (21.5%). The correlation between the geographical scale of residential mobility and car ownership change behaviour is also found statistically significant. For instance, the national level movers are found to have higher tendency of owning their first car whereas the local level movers are found to have higher propensity of losing it.

Table 4: Descriptive statistics of the factors driving the car ownership level changes

Parameters	Changes in car ownership level (%)					Chi square values (category)					Total Chi square values	Chi square critical value (95% CI)
	Gained first car	Lost first car	Gained additional car(s)	Lost additional car(s)	No change in car ownership	Gained first car	Lost first car	Gained additional car(s)	Lost additional car(s)	No change in car ownership		
Sociodemographic characteristics												
Changes in household income												
Income increased	39.7	24.1	53.6	32.0	32.4	3.8	9.5	161.1	0.8	7.8		
Income decreased	18.9	36.2	20.9	43.5	20.0	0.9	37.7	0.2	264.8	18.9	760.6	15.5
No change in income	41.4	39.7	25.5	24.5	47.7	1.0	2.4	113.6	108.9	29.1		
Changes in household size												
Household size increased	19.1	6.0	15.2	3.8	3.2	178.8	2.8	385.9	0.4	43.8		
Household size decreased	4.7	22.7	4.7	30.9	3.9	0.4	195.4	1.5	1353.2	99.0	2393.5	15.5
No change in household size	76.3	71.3	80.1	65.3	92.8	7.3	14.5	15.3	80.1	15.0		
Change in number of employment												
Number of employment increased	24.0	10.9	23.5	9.4	7.4	92.1	2.1	342.3	0.8	38.3		
Number of employment decreased	10.1	22.4	9.5	34.3	8.2	0.1	59.8	0.1	717.1	51.4	1470.7	15.5
No change in employment	65.8	66.7	66.9	56.3	84.4	10.2	9.9	35.1	91.1	20.1		
Presence of senior adults (>75 years)												
Yes	9.4	21.5	3.0	3.8	18.1	10.4	5.3	147.6	113.1	31.2	368.7	9.5
No	90.6	78.5	97.0	96.2	81.9	2.1	1.0	29.3	22.5	6.2		
Less educated people (below O level)												
Yes	48.4	54.2	31.1	35.6	47.0	0.5	5.6	62.6	26.0	7.6	188.6	9.5
No	51.6	45.8	68.9	64.4	53.0	0.4	4.7	52.8	22.0	6.4		
Tenure type												
Owned house	47.3	54.5	88.5	88.8	73.4	32.8	19.2	36.0	32.7	2.3		
Rented social housing	38.5	32.6	6.6	7.1	19.8	67.3	35.8	107.3	86.1	8.5	494.7	15.5
Rented private housing	14.2	12.9	4.9	4.1	6.7	27.8	20.6	6.5	11.8	0.0		
Life events												
Household moved house												
Moved at local level	5.5	7.1	4.2	4.0	2.7	7.9	21.8	8.1	5.1	4.8		
Moved at regional level	1.2	0.9	1.9	0.8	0.9	0.2	0.0	11.5	0.4	0.6	109.6.0	21.0
Moved at national level	3.2	2.1	1.6	1.2	0.7	22.4	6.5	9.9	2.2	4.2		
Stayed	90.1	89.9	92.3	93.9	95.7	1.0	1.1	1.3	0.2	0.4		
Householder changed job												
Yes	15.9	14.0	17.9	16.3	11.9	2.9	0.6	30.3	13.1	6.4	61.0	9.5
No	84.1	86.0	82.1	83.7	88.1	0.4	0.1	4.3	1.9	0.9		
Travel characteristics												
Change in travel distance												
Travel distance increased	27.8	32.4	30.0	26.4	25.1	0.6	6.5	10.2	0.3	1.8		
Travel distance decrease	25.1	24.4	23.5	26.7	23.3	0.4	0.1	0.0	5.2	0.4	41.8	15.5
No change in travel distance	47.1	43.3	46.4	46.8	51.6	1.0	4.2	5.3	3.8	2.0		
Number of observations	335	364	1328	1154	21537	-	-	-	-	-	-	-

2.3.3 Changes in commute mode

Table 5 looks at changes in commute mode over time[4]. Only around 6.1% of households are observed to change their commute mode in a given year. We find that the switching between active travel and public transport is considerably low compared to the switching between car and active travel. The association between the changes in household state and travel mode switching behaviour is also investigated using Chi-square test of independence and observed strong correlation (Table 6). As seen in the Table, a large shift is observed towards car from public transport and active travel (25.3%) due to gaining of cars by households. Due to an

[4] This study only includes the commute behaviour of the household head as used also in previous literature (e.g. Ettema, D. 2010)

increase in the commute distance, a high rate of switching is observed, particularly to car and/or public transport (74.8% and 63.2% respectively). On the other hand, a decrease in commute distance results in significant levels of shift towards active travel from both public and private transport (93.3%). Importantly, the correlation between geographical scale of residential mobility and travel mode switching behaviour is also found significant. The share of switching to car is least among the households who moved at regional level (1.0%) compared to the households who moved at local and national level (6.6% and 5.2% respectively). The national level movers are found to have lower switches into active travel (0.5%) compared to the other two groups.

Table 5: Commute mode switching pathway in two consecutive years

Commute mode switching pathway		Number of cases	Percentage
Commute mode in year t	Commute mode at year t+1		
Public transport (PT)	Public transport (PT)	1164	10.9
	Car travel (CT)	117	1.1
	Active travel (AT)	40	0.4
Car travel (CT)	Public transport (PT)	115	1.1
	Car travel (CT)	7731	72.2
	Active travel (AT)	140	1.3
Active travel (AT)	Public transport (PT)	41	0.4
	Car travel (CT)	192	1.8
	Active travel (AT)	1165	10.9
Total		10704	100

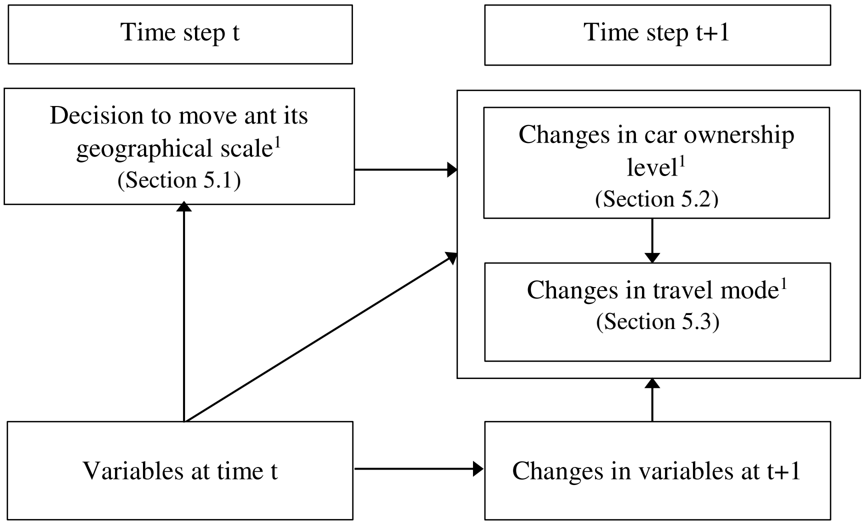
Table 6: Descriptive statistics of the factors driving the travel mode changes.

Parameters	Changes in commute mode (%)				Chi square values (category)				Total Chi square values	Chi square critical value (95% CI)
	Switched to PT from CT & AT	Switched to CT from PT & AT	Switched to AT from PT & CT	No change	Switched to PT from CT & AT	Switched to CT from PT & AT	Switched to AT from PT & CT	No change		
Life events										
Changes in car ownership										
Household acquired car	4.0	25.3	4.8	8.5	4.2	93.0	3.4	1.4		
Household relinquished car	13.1	6.9	16.0	7.1	7.2	0.1	18.6	0.8	139.0	12.6
No change in car ownership	82.9	67.8	79.2	84.4	0.0	9.4	0.4	0.4		
Household moved house										
Moved at local level	2.3	6.6	2.8	3.0	0.3	12.0	0.0	0.3		
Moved at regional level	4.3	1.0	2.5	0.7	25.5	0.3	7.2	1.2	163.0	16.9
Moved at national level	2.9	5.2	0.6	0.5	11.9	97.0	0.0	4.6		
Stayed	90.4	87.2	94.0	95.8	0.4	2.2	0.0	0.1		
Householder changed job										
Yes	17.6	22.0	17.0	16.3	0.1	5.7	0.0	0.2	7.3	7.8
No	82.4	78.0	83.0	83.7	0.0	1.1	0.0	0.0		
Travel characteristics										
Changes in travel distance										
Travel distance increased	74.8	63.2	0.5	23.7	151.7	177.0	43.6	8.9		
Travel distance decreased	13.2	25.5	93.3	22.1	6.8	0.7	378.3	5.8	1002.5	12.6
No change in travel distance	12.0	11.2	6.2	54.1	47.1	97.2	71.6	13.8		
Number of observations	156	309	180	10059	-	-	-	-	-	-

PT-Public Transport, CT-Car Travel and AT-Active Travel

3. Model structure

Households that move in different geographical scales (local, regional and national level) may have different reasons for doing so. In a modelling context, it means that we propose to test if there are significant differences among the parameters depending on whether a household moves at the local, regional or national level. The distinct nature of different categories of residential mobility decisions can influence the household car ownership and travel behaviour in a different manner. Therefore, this study first proposes a modelling framework to investigate the factors that lead to differences in residential mobility decision in different geographical scales and then models their connections with household car ownership and travel mode changing behaviour (Figure 3).



[1] The decision is assumed to be made between time (t) and (t+1) reflected in the observation at time (t+1)

Fig 3: Modelling framework

Random utility based discrete choice modelling techniques are used in this study for analysing different components of the modelling framework (residential mobility decisions, car ownership changes and changes in travel mode) in a sequential manner. In random utility theory, a decision maker chooses the alternative which maximizes his/her utility in a given choice setting. Therefore, the utility equation to choose alternative *i* by individual *n* at year *t* can be expressed as follows:

$$U_{nit} = \beta_i x_{nit} + \alpha_i + \varepsilon_{nit} \quad (2)$$

where x_{nit} is a vector of observed variables and β_i is the corresponding coefficient vector and α_i is the alternate specific constant which capture the mean of the unobserved utility. The error term ε_{nit} is IID (independent and identically distributed) extreme value type I distributed. The multinomial logit (MNL) model formulation for calculating the probability of choosing alternative *i* by individual *n* at time *t* can then be expressed as:

$$P_{nit} = \frac{e^{\beta_i x_{nit} + \alpha_i}}{\sum_{j \in C} e^{\beta_j x_{njt} + \alpha_j}} \quad (3)$$

The logit model formulation has a limitation in terms of not explicitly modelling unobserved random heterogeneity across individuals. Mixed multinomial logit (MMNL) models have added flexibility to capture the random heterogeneity across individuals, both in the alternative specific constants and the marginal utility coefficients. Equation 2 can hence be revised as follows:

$$U_{nit} = \beta_{ni}x_{nit} + \alpha_{ni} + \varepsilon_{nit} \, , \tag{4}$$

i.e. making the constants and marginal utility coefficients person specific. We define a vector α_n grouping together the alternative specific constants for person n and a vector β_n grouping together the marginal utility coefficients for person $n.$ In our mixed logit model, we then assume that $\alpha_n \sim f(\mu_\alpha, \Omega_\alpha)$ and $\beta_n \sim g(\mu_\beta, \Omega_\beta)$. With this notation, we have that μ_α and μ_β are two vectors with parameters for the means of the multivariate α and β in the sample population and Ω_α and Ω_β are covariance matrices. Finally, $f()$ and $g()$ represent the assumed distribution functions.

The random heterogeneity terms α_n and β_n can be exploited to create correlations across time periods for the same individual as well as correlation across the alternatives. The former is accommodated by the fact that the random heterogeneity is at the level of the individual rather than observation. The latter is accommodated by allowing for non-zero off-diagonal elements in Ω_α through a Cholesky decomposition (Walker 2001).

The mathematical expression of the unconditional probability for person n can then be presented as follows.

$$P_{ni} = \int_\beta \int_\alpha \prod_{t=1}^{T} \left[\frac{e^{\beta_{ni}x_{nit}+\alpha_{ni}}}{\sum_{j\in C} e^{\beta_{nj}x_{njt}+\alpha_{nj}}} \right] f(\alpha_n) g(\beta_n) d\alpha_n d\beta_n \tag{5}$$

Since the probability function in above equation contains a multi-dimensional integral and it does not have a closed form solution, probabilities are approximated through simulation (Train 2009).

4. Design of choice alternatives and individual choice set

4.1 Residential mobility decision

Residential mobility decision is a binary choice about the decision to move or not to move. The decision to move can be sub-divided in three geographical scales as explained in the previous sections. Therefore, the joint decision of residential mobility and its geographical scale consists of following four alternatives: stayed in the same place (no move), moved locally, moved at regional level and moved at national level. The full choice set is considered for each individual household.

4.2 Car ownership change model

Four levels of car ownership (having no car, one car, two cars and three cars) are observed in the dataset. Therefore, possible dimensions of switching from one level to another level are 16 (4×4). In the data, the numbers of observations in several directions of switching are very low - specifically switching from zero to two or three cars, one to three cars and in the opposite direction (Table 2). Moreover, this study aims to capture the differences in sensitivity between the first car and additional cars (second or third cars) in terms of gaining and losing. The sensitivity of switching from one to two cars is assumed same as the sensitivity of switching from one to three cars or two cars to three cars. Therefore, the universal choice set consists of seven alternatives which are presented in Table 7 below.

Table 7: Universal choice set of car ownership changes

Alternatives in the universal choice set	Switching pairs under each alternative
Gaining car (s)	
Gaining first car (0-1)	0-1, 0-2,0-3
Gaining additional cars (1-2)	1-2,1-3,2-3
Losing car (s)	
Losing first car (1-0)	1-0,2-0,3-0
Losing additional cars (2-1)	2-1,3-1,3-2
Not gaining or losing car	
Zero car to zero car (0-0)	0-0
One car to one car (1-1)	1-1
Two cars to two cars (2-2)	2-2, 3-3

Note: Each number indicates the number of cars in the household

The choice set consists of a subset of alternatives based on the car ownership level at time *t*. For example, the choice set of a household that owned one car at time *t* consists of the alternatives gaining additional cars (1-2), losing first car (1-0) and remain in the same status (1-1) at time *t+1*. The choice set of households based on the car ownership level at time t are presented in Table 8.

Table 8: Choice set of the individual had different car ownership levels at time t

Car ownership level at time t	Choice set at time (t+1)
0 car	0-0, 0-1
1 car	1-1,1-2,1-0
2+ cars	2-2,2-1

4.3 Commute mode change model

The most commonly used commute modes reported by the respondents in the BHPS data are Rail/train, underground/tube, bus/coach, car, cycle and walk. The possible dimensions of switching explode with the number of alternative modes available. Since the number of switching is very small for some pairs, it is infeasible to capture all possible directions of switching. Therefore, the alternatives are grouped into public transport (PT), car travel (CT) and active travel (AT). This reduces the total number of alternatives to 9 (3×3). The individual choice set consists of a subset of them depending on the travel mode in the year *t*[5]. Household-specific choice sets are presented in Table 9[6].

[5] Since the households travel mode switching behaviour between the year *t* and *t+1* have been investigated here, travel mode at year *t* is used as the basis of defining the choice set. Though travel mode at year *t+1* is observed in the data as well, since it is the state after the decision has been made by the household, it could not be used to define the choice set.

Table 9: Household-specific choice set based on travel mode at time t

Travel mode at time t	Choice set at time (t+1)
CT	CT-CT, CT-PT, CT-AT
PT	PT-PT, PT-CT, PT-AT
AT	AT-AT, AT-CT, AT-PT

5. Estimation results

Residential mobility, car ownership changes and travel mode switching behaviours are modelled separately. Although, the decisions households made are likely to be correlated to each other, the simultaneous estimation was not feasible in this case due to the nature of the choices and the data. Since we have modelled relatively rare events, the number of observations for several composite choices (moved house and change travel mode) in the simultaneous modelling approach are very low. In addition, modelling the directionalities of each decision (for example moved at different geographical scale, switched to a different level of car ownership, etc.) further reduced the number of observations for each composite choice (e.g. move at the national level and switched travel mode from car to public transport). The number of observations for many joint choice alternatives are either zero or very low. It may be noted that although several studies in literature (Lerman 1976; Ben-Akiva and Bowman 1998; Salon 2006; Habib and Kockelman 2008; Pinjari *et al.* 2011) have adopted joint estimation technique for modelling residential location and travel related decisions, none of these studies dealt with the changes in the household behaviour and hence did not have estimation issues. The estimation problems in the simultaneous formulation forced use to consider

a) residential mobility as an exogenous variable in car ownership change model and
b) Residential mobility and car ownership levels as exogenous variables in the travel mode switching model.

We acknowledge that this sequential decision structure can under/overestimates the correlations among the decisions neglecting the inherent trade-offs and simultaneity in choice (Habib and Kockelman 2008).

The mixed multinomial logit (MMNL) model framework is considered for these analyses. In addition, the panel nature of the data provides an opportunity to capture the correlation across the choices over time and unobserved taste heterogeneities across individual households. The estimation results are summarized in Tables 10-12 and discussed in the following sections.

5.1 Modelling residential mobility decision and its geographical scale

Household residential mobility decision (decision to stay or move) and joint decision of residential mobility and its geographical scales are modelled in this section. Joint estimation captures the differences in the parameter sensitivity of the households who have moved in different geographical scales. Household sociodemographic characteristics, life events and travel characteristics are considered as explanatory variables. MNL and MMNL models are estimated. As presented in Equation (4), in the MMNL model, we tried making the constants (α_{ni}) and the marginal utility coefficients (β_{ni}) person specific. However, heterogeneity in the marginal utility components are found insignificant after capturing the random heterogeneity in the constant terms. Therefore, the final models include the random term in the constants only. Correlations across the alternatives (using both nesting structure and Cholesky decomposition) are found statistically insignificant.

The likelihood ratio test value is used to evaluate the goodness of fit of the MMNLs estimation over the MNL estimation. The null hypothesis of the MNL models are rejected by the Chi-square statistics for 99.9 % confidence interval revealing significant level of taste heterogeneity and correlation across the choices over time.

5.1.1 Residential mobility decision

Estimation results of residential mobility decision to move or stay are presented in Table 10. Household level characteristics are found to influence the residential mobility decision significantly. As seen in Table 10, single member households are observed to have the highest disposition to move compared to the other groups. The propensity to move is less for larger households possibly as higher the number of members, typically higher is the connection with the local neighbourhood and lower is the flexibility, capacity and appeal to move. The probability of moving is higher for people with higher level of income. This may be due to inclination for better lifestyle preferences and affordability to change tenure type (i.e. switch from renting to owning) of the middle and higher income people. Highly educated people are also found to have higher propensity to move. This phenomenon (also observed by Kortum *et al.* (2012)), may be due to their higher access to opportunities (specifically in the job market). Presence of senior adults (more than 75 years of old) in the household is found to reduce the likelihood of moving. (see Kortum *et al.* (2012) for similar finding). This may be due to the fact that most of the elderly people are more settled in their place and their physical condition constrain to move frequently. Working with the same employer for a long time is found to reduce the propensity of moving home. The role of dwelling characteristics on residential mobility decision is also found significant. For instance, households living in rented private housing are found to be more likely to move compared to households living in rented social housing or owned houses (also observed by Eluru *et al.* (2009) and Tatsiramos (2009)). Due to a large investment and high relocation cost owners, are less likely to move frequently. On the other hand, social renters do not have free choice to move in another social house and they are also less likely to move in privately rented house or owing a house ultimately leading to less likelihood of relocation. Higher crowding level (denoted as the ratio of number of household members and number of rooms) is also found to increase the likelihood of move. Life events such as having a child is found to increase the likelihood of moving home significantly (also reported by Clark and Davies Withers (1999)) whereas the impact of job change on residential relocation is also positive but statistically insignificant at 90% confidence interval.

5.1.2 Joint estimation of residential mobility and its geographical scale

Estimation results of residential mobility and its geographical scale are also presented in Table 10. Considerable level of differences has been observed in preferences depending on the geographic scale of the relocation. *t*-difference tests have been used in order to investigate whether the differences are statistically significant or not. Most of the parameters demonstrate a certain level of sensitivity differences from one to another scale of relocation, however, ten

Table 10: MMNL estimation results of the decision to move

Parameters	Residential mobility decision		Joint decision of residential mobility and its scale						t difference test		
			Local level (LL)		Regional level (RL)		National level (NL)		LL & RL	LL & NL	RL & NL
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat			
Alternative specific constants											
(not moved is the base alternative)											
Mean	-4.9985	-27.3	-5.6400	-25.5	-6.6415	-30.3	-6.7952	-17.8	3.1	2.3	0.5
Standard deviation	-0.7719	-14.7	-0.7894	-12.1	1.0096	8.4	0.9223	5.7	-13.2	-9.2	0.4
Household level characteristics											
Household type (base is couple with child)											
Single member household	0.7926	5.6	0.8536	5.0	0.8756	4.1	0.5353	1.8	-0.1	0.9	1.1
Couple without child	0.4900	4.5	0.3953	3.0	0.7186	4.2	0.5448	2.5	-1.6	-0.6	1.2
Lone parents	0.2843	2.1	0.4832	3.1	0.0417	0.1	-0.3728	-1.1	1.4	2.5	0.9
Household income (base is less than £20,000)											
Between £20,00 to £40,000	0.2336	2.5	0.1778	1.6	0.2000	1.0	0.4564	2.2	-0.1	-1.2	-0.8
More than £40,000	0.1568	1.2	0.0572	0.4	0.1570	0.6	0.5921	2.3	-0.3	-1.9	-1.0
Education attainment of household head											
O and A level degree	0.2980	3.1	0.1791	1.6	0.7410	3.9	0.1474	0.7	-2.7	0.1	2.2
Graduate degree	0.4001	3.2	0.2566	1.7	0.7530	3.1	0.7576	3.3	-1.9	-2.1	0.0
Post-graduate degree	1.1325	5.6	0.9846	4.0	1.1217	2.9	1.4780	4.6	-0.3	-1.4	-0.9
Number of employees in the household (base is no employee)											
One employee	0.0298	0.3	0.0450	0.4	0.0677	0.4	-0.1324	-0.5	-0.1	0.7	0.8
More than one employees	0.1101	0.9	0.3254	2.3	-0.2119	-1.0	-0.3334	-1.2	2.0	2.2	0.4
Length of current job of household head	-0.0141	-2.8	-0.0071	-1.2	-0.0321	-2.7	-0.0166	-1.5	2.0	0.8	-1.2
Presence of senior adult (>75 years)	-0.4397	-3.4	-0.5982	-3.7	-0.7175	-2.2	0.2877	1.1	0.3	-3.4	-3.3
Dwelling level characteristics											
Tenure type (base is owned house)											
Rented social housing	0.3967	3.5	0.6570	5.1	0.0537	0.2	-0.6642	-2.2	2.1	4.4	1.8
Rented private housing	1.9368	18.1	1.9209	15.1	2.1278	11.2	1.3763	6.4	-1.0	2.6	3.7
Crowd (household size\number of rooms)	1.2721	9.2	1.3908	8.6	1.0380	4.1	1.0070	3.6	1.5	1.3	0.2
Life course events											
Having child in last one year	0.3916	2.8	0.3506	2.1	0.6260	2.5	0.4402	1.3	-0.9	-0.3	0.4
Changed job in last one year	0.1289	1.4	0.1443	1.2	0.0837	0.4	0.2133	1.1	0.3	-0.3	-0.5
Location characteristics											
Metropolitan area (base is other than London)											
London	0.3038	2.6	0.0011	0.0	-2.6171	-4.2	1.6700	8.7	4.4	-8.3	-8.4
Measures of model fit											
Number of observations	24718		24718								
Initial LL	-17133.21		-34266.40								
Final LL	-4256.64		-5210.83								

out of the eighteen parameters are found significantly different in at least one pairs (e.g. local level vs. regional level relocation, local level vs. nation level relocation or regional level vs. national level relocation) based on t difference test results. Although the single member households and couples without child are likely to move at the local, regional and national level, the lone parents are not significantly interested to move beyond the local area.

Households with high income (>£40,000) have higher likelihood of moving nationally. The likelihood of high-income households to move locally or regionally are not found to be statistically different from 0 as 90% level of confidence. Highly educated (post graduate) people are found to have the highest propensity to move at the national level than regional and local level, whereas, less educated people (O and A level degree holder) are more likely to move at the regional level. This difference may be due to limited access and knowledge about the job markets in different regions or metropolitan areas. Households having more than one employed members are found to be more likely to move at the local level. This may be due to the complexity in adjustment of the commute distances and/or job-relocation issues of multiple working members in the households arising from the regional and national moves. The coefficient of the length of current employment of the household held denotes that if the job-tenure is longer, less likely are they inclined to move. The coefficient is however statistically significant in case of regional level move only. Households having senior adults are found to be less likely to move in general with the propensity to move being less for the regional level and statistically insignificant for national level. Private renters are more likely to move at local, regional and national level while social renters are only inclined to move locally. The influence of life events on moving home are not found to be significantly different across the different geographical scales. Londoners are found more likely to move out from the greater London area (GLA) but they are unlikely to move within the GLA.

5.2 Modelling car ownership changes

As mentioned in section 3, models have been estimated to explore the factors driving the changes of car ownership level in two consecutive years with a special focus on the impact of geographical scale of residential mobility on car ownership level changes. An MMNL model is estimated to capture the taste heterogeneities and potential correlation structures. The goodness of fit of the MMNL model is then compared with the MNL model using the likelihood ratio (LR). The Chi-square statistic rejects the null hypothesis of the MNL model at 99.9% confidence interval. The MMNL model also captures significant level of heterogeneities in the unobserved component. However, taste heterogeneity in the observed utility and correlation across the alternatives are found insignificant. Models are estimated without residential mobility parameters to investigate their contribution on the model fit. The chi-square statistic indicates that the model without residential mobility parameters is significantly worse (LR=55.21, Chi-square stat=32.91 degree of freedom=12, confidence interval = 99.9%). Estimated results are presented in Table 11 and discussed in the next sections based on the MMNL outcomes.

Household sociodemographic characteristics, dwelling characteristics, life events and travel characteristics are considered in the model as independent variables. Changes in household state (sociodemographic, life event and travel behaviour are added) are also added as dummy variables to capture dynamics in the life course. From the estimation results (Table 11), household income is found to have a strong influence on car ownership level changes. High-income people are more likely to own a second (or third) car while unlikely to relinquish a car. This finding is in agreement with previous studies (e.g. Clark, Chatterjee and Melia (2016a)).

An increase in household income also increases the likelihood of acquiring an additional car and a decrease in household income significantly increases the likelihood of disposing of a car. In terms of number of members in the household, inspired by literature (e.g. Krizek 2003; Clark, Chatterjee and Melia 2016a; Fatmi and Habib 2017) we use three variables to capture this effect: household size, increase in household size and decrease in household size. Size of the household is found to have a positive impact on gaining cars as expected (see Clark, Chatterjee and Melia (2016a) for similar result). However, the positive effect of household size on losing a car (1-0) is unexpected. This is may be due to the fact that the households lost the only member having a driving licence or maintaining a car becomes unaffordable due to the large household size. The variable 'Change in household size' captures the likelihood of gaining or losing car due to recent increase of decrease in the number of members in the household (e.g. childbirth, death, marriage, divorce, etc.)[7]. An increase in the size of the household in the following year is found to increase the propensity of gaining cars and a decrease in household size increases the probability of reducing the number of cars.

Similarly, the effect of number of employed persons in the household are captured by three variables, the latter two capturing the change in the number of employed person in the immediate past. As seen in Table 11, the number of employed persons in the household significantly influences the gain in household car ownership level. The likelihood of gaining a car increases when an additional household member gets a job and, similarly, the likelihood of losing a car increase if a household member loses her/his job. The presence of senior adults decreases the likelihood of gaining and increases the chance of losing cars. Less educated people have lower propensity to gain car and higher propensity of losing it. Households living in rented social housing facilities are found to have the lower propensity of acquiring cars and the higher propensity of relinquishing cars compared to the households living in owned houses.

Importantly, as seen in Table 11, the changes in car ownership levels of households are found to be vary significantly depending on the residential relocation and the associated geographical scale. The propensity of owning the first car is found to be significant for the households who moved at national level and insignificant for the other two groups. Moving to a different metropolitan area can adversely affect household accessibility to the public transport and other facilities which may increase the propensity to own a car. Likelihood of gaining a second car is found significant for the households that move at local, regional and national level. However, the likelihood of losing cars are found significant only among the local level movers. The association between job changing and changes in car ownership level is found insignificant. Householders that reported a longer daily commute are more likely to buy their first car but unlikely to buy additional cars. A change in commute distance is not found significantly correlated with household car ownership change.

[7] The variables "Household size" and "Change in household size" provide different insights with the latter capturing the dynamic effect of gaining or losing cars due to adding or losing a new member in the family in the recent year.

Table 11: MMNL estimation results of household car ownership changes

Variables	Changes in household car ownership							
	Gained car				Lost car			
	0 to 1		1 to 2		1 to 0		2 to 1	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Alternative specific constants								
(no changes in car ownership is the base alternative)								
Mean	-4.2721	-14.2	-5.7862	-26.5	-5.2464	-18.7	-1.3025	-8.6
Standard deviation	1.8227	11.2	1.9966	20.7	-1.7297	-11.9	-0.7793	-11.2
Household level characteristics								
Household income	-0.0006	-0.1	0.0358	9.9	-0.0127	-1.7	-0.0133	-5.7
Change in household income (base is no change)								
Income increased	0.0733	0.5	0.5896	6.9	-	-	-	-
Income decreased	-	-	-	-	0.3401	2.1	0.3134	3.6
Household size	0.4860	5.8	0.3813	7.3	0.1333	2.0	-0.1112	-2.6
Change in household size (base is no change)								
Household size increased	1.9219	7.1	1.2508	8.5	-	-	-	-
Household size decreased	-	-	-	-	1.6497	7.6	1.9587	15.3
No of employees in the household	0.4053	3.3	1.0301	14.4	-0.1148	-1.0	-0.1012	-1.9
Change in number of employment (base is no change)								
Number of employment increased	1.0696	5.0	1.2502	10.3	-	-	-	-
Number of employment decreased	-	-	-	-	0.6938	3.3	0.6415	5.9
Presence of senior adults	-0.8817	-3.2	-1.3171	-4.9	1.0062	4.9	-0.1117	-0.5
Less educated people (below O level)	-0.6298	-2.7	-0.4953	-3.1	0.3008	1.6	0.4103	3.9
Dwelling characteristics								
Tenure type (base is owned house)								
Rented social housing	-0.7471	-3.1	-0.7720	-3.2	1.6463	7.4	0.9518	4.5
Rented private housing	0.1908	0.6	-0.8275	-3.4	1.1186	4.3	0.2570	1.1
Life course events								
Moved house								
Moved at local level	0.0432	0.1	0.4545	2.1	0.9578	3.4	0.5401	2.5
Moved at regional level	0.5232	0.8	0.6885	2.0	-0.3130	-0.5	-0.1602	-0.4
Moved at national level	2.1839	4.1	0.9818	2.3	0.8732	1.4	0.1844	0.5
Householder changed employer	-0.1082	-0.5	0.1380	1.2	0.0584	0.3	0.0068	0.1
Travel characteristics								
Travel distance	0.0184	3.3	-0.0060	-1.8	0.0039	0.7	-0.0026	-1.1
Change in travel distance (base is no change)								
Travel distance increased	0.3761	1.3	0.0992	0.8	-	-	-	-
Travel distance decreased	-	-	-	-	-0.0498	-0.2	0.1763	1.5
Measures of model fit								
Number of observations					24718.000			
Initial LL					-21985.800			
Final LL					-7852.630			

5.3 Modelling commute mode changes

Switching travel mode in two consecutive years has been modelled in this section to investigate the factors driving household commute behaviour changes. One of the core aims is to look at the influences of geographical scales of residential mobility and car ownership changes on mode choice behaviour. The MMNL model that we estimate allows for randomness in the unobserved component to capture inter and intra respondent heterogeneity (potential correlation across the alternatives and taste heterogeneity in the observed component are also tested and found insignificant). The goodness of fit of the MMNL model over the MNL model is investigated using likelihood ratio test and the Chi-square statistic rejects the null hypothesis of the the MNL model at 99.9% confidence interval. Similar to the car ownership models, the impact of residential mobility parameters on the goodness of fit of the models are also tested here. The model without residential mobility parameters is worse compared to the model with residential mobility parameters (LR=30.62, Chi-square stat=27.88, degree of freedom=9, confidence interval=99.9 %). Estimated results are presented in Table 12 and results are discussed in the following section based on the MMNL outcomes. It may be noted that the choice set at time *t* has been generated based on travel mode at time *t* for the reasons mentioned in footnote 4 For example, households who used car at *t*, the options available for them are switching from car to public transport and car to active travel.

As observed in Table 12, households have significant levels of inertia to switch from one type of mode to another type. Across the possible dimensions of switching, all else being equal, moving from public transport to car travel is found to be the least preferred option. Car ownership is found to have strong association with travel mode change. Households that own cars are more likely to switch from public transport and active mode to car travel and unlikely to switch in other directions (switching from car to PT and AT). The likelihood of moving from PT and AT to car further increases if the household has gained a car in the preceding year. Losing a car in a given year on the other hand makes people more likely to switch to public transport or active travel in the following year.

The commute mode switching behaviour of the head of the households that have relocated is found to be significant in some but not all cases. In particular, estimation results indicate that local level relocation does not result statistically significant change in the likelihood to switch modes. This is probably due to the fact that moving in the same neighbourhood is unlikely to affect household transport circumstances (transport accessibility, commute distance), therefore households are found to use the same commute mode after a local level relocation. Estimation results indicate that regional level movers are more inclined to shift to public transport from car and active travel modes. This may be indirectly related to the fact that while making a regional move, households tend to move to an area with good public transport accessibility and consequently there is an increase in the likelihood of using public transport. In case of relocations at the national level, there is a significant increase in switches both to car and public transport. This may be due to more significant changes in transport and work accessibility after national level relocation. The connection between the change of employer and changing travel mode is found statistically insignificant. Travel distance is found to have a strong association with the travel mode changing behaviour for switches to public transport and active travel. This may be due to the fact that driving a long distance on a regular basis increases the anxiety level and adversely affects personal stress level and work efficiency; consequently, car is a less preferred option for the long-distance commuters. The effect of increase or decrease in travel distance however has a larger and more significant effect. An increase in travel distance makes people more likely to switch to public transport and car while a decrease in commute distance results significant increase in the probability to shift to active travel. Some other sociodemographic characteristics such as income, education level, household size, etc. have also been tested but found to have insignificant effect and hence dropped from the final model.

Table 12: MMNL estimation results of travel mode switching behaviour

Variables	Travel mode switching behaviour					
	Switched to CT (from PT & AT)		Switched to PT (from CT & AT)		Switched to AT (from CT & PT)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Alternative specific constants						
(no changes in travel mode is the base alternative)						
Mean						
Switched from car travel (CT)	-	-	-6.0397	-7.4	-5.8760	-7.1
Switched from public transport (PT)	-7.3598	-13.9	-	-	-3.8629	-8.7
Switched from active travel (AT)	-6.9939	-7.8	-5.7866	-16.1	-	-
Standard deviation						
Switched from car	-	-	2.2887	7.1	1.6919	6.9
Switched from public transport	2.6795	8.3	-	-	0.1265	0.1
Switched from active travel	2.6628	4.1	1.1433	5.5	-	-
Household owns car	1.9458	7.3	-2.6965*	-4.5	-0.6512*	-0.9
Changes in car ownership						
Household acquired car	2.4394	8.5	-2.8584*	-3.3	-0.9686*	-1.7
Household relinquished car	0.4306	1.1	0.8842*	2.6	1.2170*	3.9
Moved house						
Moved at local level	-0.0936	-0.2	-0.2974	-0.5	-0.3640	-0.7
Moved at regional level	0.2378	0.2	2.3575	3.7	1.0994	1.4
Moved at national level	1.6951	2.5	1.5369	1.9	-0.1043	-0.1
Householder changed employer	0.1802	0.8	-0.0931	-0.3	0.0024	0.0
Travel distance	-0.0033	-0.4	0.0291	5.2	-0.0669	-7.7
Changes in travel distance						
Travel distance increased	4.0742	14.5	3.3362	10.3	-1.8339	-1.6
Travel distance decreased	3.4740	10.5	1.2165	3.0	3.9887	11.2
Measures of model fit						
Number of observations	10704					
Initial LL	-11759.5					
Final LL	-1784.3					

* parameters represent switching from car travel only

6. Validation results

The MMNL models using the full dataset outperform their MNL counterparts in the estimation context. However, there is a risk that the MMNL model overfits the estimation data. To check for potential overfitting issue, we test the performances of both the MNL and MMNL models using a holdout sample validation (as used by other researchers: de Luca and Cantarella 2016; Bwambale et al. 2017 for example) where we randomly select 60% of the households for estimation (who are consistently available in the panel) and the other 40% of households for out of sample prediction). Models are re-estimated again using the estimation subsets of the data from the different random draws. Interpretation of the estimation results of the models remains same as the interpretation of the model estimated using the full dataset (explained in the previous sections). The estimated model parameters are then applied on the validation sample to investigate the predictive performance of each of the models. The same procedure is repeated for three times to check whether the performance is consistent over the different split of the dataset based on different independent random draws.

The predictive power of the models are evaluated in terms of improvement in goodness-of-fit (log likelihood in prediction sample and predictive rho-square). The results are presented in Table 13. It is observed that the MMNL models of residential mobility decision, car ownership change and travel mode change perform better than the corresponding MNL models in the estimation sample and hold consistent performance in the hold-out sample.

Table 13: Out-of-sample prediction results of residential mobility decision, car ownership change and travel mode change models

Models	Draws	Number of observations	Initial log likelihood	Final log likelihood		Predictive rho-square	
				MNL	MMNL	MNL	MMNL
Estimation sample							
Residential mobility decision	D1	14824	-20550.4	-3066.9	-3044.8	0.848	0.849
	D2	14824	-20550.4	-3090.9	-3058.4	0.846	0.848
	D3	14824	-20550.4	-3165.4	-3143.0	0.843	0.844
Changes in car ownership level	D1	14824	-13123.9	-5334.3	-5004.7	0.588	0.613
	D2	14824	-13091.3	-4845.8	-4538.1	0.625	0.648
	D3	14824	-13104.9	-5119.6	-4789.8	0.604	0.629
Changes in travel mode	D1	6418	-7050.9	-1177.2	-1122.6	0.828	0.835
	D2	6416	-7048.7	-1156.0	-1095.9	0.831	0.839
	D3	6416	-7048.7	-1143.9	-1085.9	0.833	0.840
Validation sample							
Residential mobility decision	D1	9894	-13716.0	-2253.1	-2226.0	0.831	0.833
	D2	9894	-13716.0	-2225.3	-2208.3	0.833	0.834
	D3	9894	-13716.0	-2159.6	-2131.7	0.838	0.840
Changes in car ownership level	D1	9894	-8659.2	-3100.7	-2909.4	0.634	0.656
	D2	9894	-8688.8	-3580.7	-3377.0	0.580	0.603
	D3	9894	-8676.8	-3309.1	-3134.4	0.611	0.630
Changes in travel mode	D1	4286	-4708.7	-754.4	-703.1	0.832	0.842
	D2	4288	-4710.8	-772.2	-744.6	0.828	0.833
	D3	4288	-4710.8	-790.2	-771.3	0.825	0.827

Further, to demonstrate the value of the developed models in the context of forecasting, we compare the model performance in prediction of future years. To demonstrate the performance of the MNL and MMNL models in the context of forecasting, we use only the data from waves 1-14 for estimation and apply the model estimates for predicting the decisions made in the last three years (waves 15-17). The results are presented in Table 14.

Table 14: Performance of the models for forecasting the decisions made in the last three waves

Models	Predictive rho-square	
	MNL	MMNL
Residential mobility decision	0.880	0.880
Changes in car ownership level	0.591	0.599
Changes in travel mode	0.789	0.790

As seen in Table 14, the models perform well in terms of forecasting the decisions of the last three waves and for the car ownership and commute mode choices, the MMNL models perform substantially better than the MNL counterparts. However, for the residential relocation model, both models have similar performances. The forecasting results indirectly indicate that capturing the panel effect is more important in the context of the latter two decisions.

7. Conclusions and direction of future research

Three different models are estimated in this paper for better understanding residential relocation decisions and their impact on travel behaviour. These are:

- A residential relocation choice model to quantify the relative sensitivity of different factors affecting the decision to move at the local, regional or national level or stay in the current location
- A car ownership model to investigate the relative impact of residential relocation on the changes in car ownership levels (i.e. increase or decrease in number of cars)
- A mode choice model to investigate the relative impact of residential relocation and car ownership on the changes in mode switch (i.e. shifts between car, public transport and active travel modes)

For our analysis, the BHPS data is used where the same households have been observed over 18 years of time. MMNL techniques are used to capture the panel effect of the data.

The key findings are as follows:

- Significant levels of heterogeneity are observed among the different geographical scales of relocation. Eleven out of the eighteen parameters are found to be significantly different among different scales of relocation (local vs. regional level, local vs. nation level, regional vs. national level). We therefore conclude that analysing the residential mobility decisions without considering geographical scale may produce biased estimates.
- Geographical scales of residential mobility lead to differences in the car ownership level changes. Estimation results indicate that household car ownership level changes between two consecutive years are significantly affected by residential mobility decisions (i.e. do not relocate, relocate locally, regionally or nationally) alongside the household sociodemographic characteristics and dwelling characteristics. For example, households that have moved locally are found to be less likely to gain a car whereas

households that have moved at the regional or national level are found to be more inclined to acquire a car.

- Household travel mode choice is also found to be significantly affected by the geographical scale of relocation. Households that have moved at the national level are more likely to switch to public transport while households that have moved at the regional level are more inclined to switch from car to public transport and active travel (or vice versa). Local movers on the other hand are observed to have higher inertia and lower probabilities of mode switch.
- Household travel mode choice is also found to be significantly affected by changes in car ownership level. For instance, an increase in car ownership is found to increase the propensity of shifting to car and decrease the probability of switching to other modes.

As with most empirical studies, out work has several limitations. The panel nature of the data has the potentiality to capture the dynamics in the household behaviour. Although this study has captured the correlation among the household choices over time and how changes in household circumstances influence their behaviour, the modelling technique used in this research did not allow us to capture the dynamic nature of the decision process (influences of the past decision on the current decision). An in-depth analyses of the extent of state-dependence in the data have been included in the Appendix. We recommend that future studies should further focus on dynamic modelling approaches (e.g. hazard based model or Marcov chain model) to capture the full range of behavioural dynamics.

This study is also limited in terms of capturing the correlation across the residential mobility decision, car ownership change and travel mode switching behaviour. These decisions are likely to be correlated in their unobserved component, however, the sequential estimation did not allow to capture this. Although the nature of the decisions (rare events) does not offer flexibility for joint estimation, the future work should aim to find a suitable way of dealing this issue.

Our study captured the influence of household residential mobility on their car ownership and travel mode switching behaviour. However, this relation may have reverse causality (e.g. changes in car ownership can influence residential change) which has not been investigated in this research. This issue can also be addressed in future research.

The residential mobility and other decisions are likely to be affected by neighbourhood characteristics such as public transport accessibility, parking availability, land use pattern etc. These parameters are not available in the dataset and cannot be tested in the current models due to the absence of low-level geographical identifiers in the unrestricted version of BHPS data.

The households have been getting older through the survey. Since, this study aims to examine how the choices made by the same households over a long span of time, the households getting older is unavoidable. However, corrections to adjust the weights for estimation to ensure the representativeness of the balanced panel is expected to reduce the extent of the issue. There are few new "spin-off households in the survey as well. Due to the small number of such spin-offs (1.1%), we were unable to investigate these households using the BHPS data. However, we acknowledge that observing the behaviour of the newly formed households can be an interesting direction for future research.

However, the findings of our study have important policy implications. Metropolitan cities in the UK have different levels of intra and inter-regional residential mobility. Our findings will help understanding how internal mobility and mobility from other cities affect the aggregate level car ownership and commute behaviour of the cities differently leading to the differences in the policy formulation. For example, high rate of internal mobility may result larger shift to active travel which has important policy implications.

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Appendix
Discussion on state-dependence
we have conducted detailed data analyses to see the extent of state-dependence. We have also cross-compared our findings with those reported by other researchers who have used longitudinal data and potentially encountered similar issues. Our findings are summarized below.

Firstly, In our data, we have investigated the likelihood of changing behaviour in a row and observed that indeed a very few respondents have changed their residential location, car ownership and travel mode in two consecutive years (Table A).

Table A: Percentage of respondents who changed their behaviour in two subsequent years

Model components	Behaviour		Respondents in %
	Year t	Year t+1	
Residential mobility	Moved	Moved at the local level	0.3%
		Moved at the regional level	0.1%
		Moved at the national level	0.1%
Car ownership change	Gained car	Gained car	0.3%
	Lost car	Lost car	0.1%
Travel mode switching	Changed travel mode	Changed to public transport	0.3%
		Changed to car	0.9%
		Changed to active travel	0.1%

We evaluated two potential approaches to capture this effect is in the model:
1. Using the lagged dependent variable as an explanatory variable in the model
2. Using 'stay length' as an explanatory variable

Using lagged dependent variable refers to directly acknowledging that the impact of the decision at t affects the decision at t+1. A review of literature revealed that in case of modelling residential relocation, the lagged dependent variable has rarely been used in literature. To the best of our knowledge, only McHugh, Gober and Reid (1990) used lagged variable (recent movers as a dummy) in residential relocation choice modelling and found counter-intuitive result that recent movers are likely to move again. We have considered using a series of lagged variables in order to capture behaviour at time t-1, t-2, etc, but this has led to well-known issues related to multicollinearity, driven by the fact that we are modelling rare events.

The duration of stay has been used as an independent variable in several previous papers on residential location choice (e.g. Davies and Pickles 1985; McHugh, Gober and Reid 1990; Habib 2009; Clark and Lisowski 2017). We have tested duration of stay (as in common practice in literature) as an independent variable in the model of residential mobility decision. The parameter of stay duration gave a negative estimation which is consistent with the finding in the literature (Davies and Pickles 1985; McHugh, Gober and Reid 1990; Habib 2009; Clark and Lisowski 2017). The results are presented below:

Table B: MMNL estimation results of the residential mobility decision

Parameters	Household behaviour					
	Moved at Local level (LL)		Moved at regional level (RL)		Moved at national level (NL)	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Alternative specific constants						
(not moved is the base alternative)						
Mean	-4.9070	-18.8	-5.8119	-14.8	-5.8242	-11.0
Standard deviation	-0.5939	-6.5	0.8362	6.7	0.6173	3.2
Household level characteristics						
Household type (base is couple with child)						
Single member household	0.8130	4.9	0.8045	2.9	0.4464	1.3
Couple without child	0.3699	2.9	0.7161	3.3	0.5127	2.1
Lone parents	0.5184	3.4	0.0172	0.1	-0.3526	-1.0
Household income (base is less than £20,000)						
Between £20,00 to £40,000	0.1868	1.6	0.1890	1.0	0.4449	2.1
More than £40,000	0.1373	0.9	0.1813	0.7	0.5986	2.3
Education attainment of household head (base is below O level)						
O and A level degree	0.1152	1.1	0.6619	3.5	0.0722	0.4
Graduate degree	0.1153	0.8	0.5966	2.4	0.6058	2.6
Post-graduate degree	0.6935	2.9	0.9187	2.2	1.1954	3.6
Number of employees in the household (base is no employee)						
One employee	0.0094	0.1	-0.0095	-0.1	-0.1995	-0.9
More than one employees	0.2512	1.7	-0.3074	-1.3	-0.4132	-1.6
Length of current job of household head	-0.0044	-0.8	-0.0269	-2.3	-0.0126	-1.1
Presence of senior adult (>75 years)	-0.4600	-2.8	-0.5639	-1.7	0.3207	1.3
Dwelling level characteristics						
Tenure type (base is owned house)						
Rented social housing	0.5314	4.3	-0.0753	-0.3	-0.7224	-2.3
Rented private housing	1.7415	13.3	1.9428	10.5	1.2013	5.6
Crowd (household size\number of rooms)	1.2011	7.9	0.8225	3.2	0.8360	2.5
Life course events						
Having child in last one year	0.3062	1.8	0.5366	1.9	0.3276	1.0
Changed job in last one year	0.1146	1.0	0.0700	0.4	0.2123	1.0
Location characteristics						
Metropolitan area (base is other than London)						
London	0.0710	0.5	-2.5246	-3.6	1.5921	9.1
Stay length						
Linear	-0.0331	-2.7	-0.0318	-1.5	-0.0487	-2.7
Square	0.0001	0.4	0.0001	0.1	0.0006	1.7
Measures of model fit						
Number of observations	24718					
Initial LL	-34266.4					
Final LL	-5178.5					

However, the results indicate that inclusion of the stay-length variable reduces the explanatory power of other important variables which represent the behaviour of the larger community. Further, though supported by literature, we believe that the negative sign indicating the longer one stays, less likely he/she is to move is misleading. Because, on average, households in England change their home in every 8 years (Randall 2011). Therefore, we have added this table in the appendix of the revised paper as opposed to the main text.

In case of car ownership change and travel mode switching, we did not find any literature where lagged variable (changed at t and impact on the utility of changing at t+1) has been used to capture the behavioural dynamics. However, in the literature, the number of cars at time t has been used in car ownership change models (Oakil et al. 2014) and travel mode at time t has been used in travel mode switching model (Fatmi and Habib 2017). This has already been captured in our models as we have investigated the directionalities of the behavioural changes which depends on the car ownership or travel mode at year t (for example we have captured the behaviour of shifting from non-car ownership to car ownership state for the households who did not have a car in year t).

It should also be noted that the inclusion of state dependence has a potentially detrimental impact on models that is often ignored by analysts. Indeed, by including past choices in the utility for behaviour at time t, we are explaining the behaviour on the basis of past behaviour rather than explanatory variables. This creates issues with endogeneity (as the past behaviour is driven by the same underlying factors) and also removes explanatory power from the remaining variables in the model. The key question that an analyst needs to ask is whether he/she wants to explain behaviour on the basis of variables that could be used as policy levers or on the basis of past behaviour. In our view, it should be the former.