Transition probabilities, wages and regional human capital stocks

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Abstract

This paper aims to look at regional mobility in the UK and its impact on regional human capital stocks. We estimate regional transitions probabilities from and to regions. We do this using different regional aggregation levels, by demographics characteristics and education status. Our results show that mobility appears heavily concentrated amongst the young and educated populations. The results suggest little changes over recent periods. Using these regional mobility transitions, we find that regional human capital stocks can be misleading if one does not take into account regional mobility of young people.

Keywords: skills, human capital, mobility, migration

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1 Introduction

In 2016 the Office for National Statistics (ONS) produced their first estimates of regional human capital stocks (HCS), using their standard methodology of accumulating lifetime incomes (ONS, 2016). This used a "bottom-up" approach, estimating HCS at the regional level using only information from that region. Therefore, the estimates took account of each region's population size, its demographic characteristics (age and sex), highest qualification as well as regional levels of income, education transition rates, employment rates and mortality rates. However, these estimates did not take account of regional population or employment transition probabilities, i.e. the probability that someone who was resident in a region in the current period moves to another region in the next period.

The purpose of this paper is to explore these regional transition probabilities, and gauge the impact of mobility on lifetime earnings by region. We do so using data from the Understanding Society survey where we tracked individuals across time. We also look at earnings differentials across the regions using data from the Annual Population Survey (APS). The ONS regional estimates are at the ITLS1 broad region level. We also look at a lower level of aggregation, ITLS2, to investigate intra regional population movements.

The next section highlights the relevant literature. Section 3 outlines the general methodology used in constructing human capital stocks and outlines the approach taken by ONS. Section 4 discusses methodology and data sources. Section 5 then presents a series of tables and maps that describe the transition probabilities and some correlations with earnings. Section 6 investigates how the transition probabilities may affect regional capital stocks. Section 7 concludes with an outline on further work we plan to include in a revised version of this paper that simulates the importance of including transition probabilities in HCS estimates. It also includes comments on how we might use information on transition probabilities to construct more refined estimates of regional human capital stocks.

2 Relevant literature

The migration literature is now large and is often discussed by making a distinction between international and internal (i.e. within country) migration (Greenwood, 2015). But both literatures broadly consider the decision to migrate as being determined by expected wage gains by moving to the destination regions/country, the costs of migration (which includes mostly the loss of contacts with friends and family), and the preferences between the origin and host region/country amenities (Dustmann and Okatenko, 2014). Given the expected length of potential gains over the lifetime, and the lower attachment to local amenities and social networks, younger people are nearly always found to be more likely to migrate. Wages (or incomes) are determined by employment growth (past and present) in both the host and origin regions/countries. Unemployment is sometimes included as a push factor but the tightness of local labour markets is often better comprehended by measures of turnover (importance of quits and accessions to jobs)[1].

Education is another key determinant of migration. And most of the literature on graduate migration focuses on short-term migration, due to data limitations. For example, using data for the UK 6 months after graduation, Abreu et al. (2015) find that there is evidence that new entrants to higher education will be likely to favour courses that offer either skills and vocational training suited to specific careers, or very flexible skills suitable to a range of careers, which is particularly good during an economic downturn. Abreu (2018) highlights that there is scope for long-term analysis of graduate migration, career paths and transitions in/out of employment in the UK by combining survey data with administrative data provided by the HMRC and DWP. Another possibility is to look at the existing Longitudinal Education Outcomes (LEO) dataset produced by the Department for Education, which uses a similar methodology.

Internal migration of talent also occurs before the end of educational careers. Kooiman et al. (2018) investigate the spatial redistribution of human capital when individuals leave their parents' home, college-to-work migration and migration around the age of 30 in the Netherlands. The authors find that university graduates moved more than low-educated individuals towards the employment centre of the Netherlands. The spatial distribution is similar across the country of individuals aged 16 who completed a university degree in the future, but after those individuals reached 35 years, the human capital stocks increased in the Randstad. In the UK, while most large cities experience a net inflow of UK students at entry to higher education, London experiences a net outflow of UK students, but attracts a large number of students from abroad (Swinney and Williams, 2016). After graduation, London receives a large proportion of graduates while other large cities experience outflows. Additionally, London attracts a large proportion of top graduates compared to other regions and has a high graduate retention rate.

A very recent strand of the literature focuses on the impact of the localities on economic opportunities (Chetty et al., 2014; Chetty and Hendren, 2018; Bell et al., 2018; Laliberté, 2021; Rothstein, 2019). Chetty et al. (2014) show that children's expected income conditional on their parents' income depends largely on the area where they grow up. The authors argue that the geographical differences in intergenerational mobility could be due to systematic differences in a specific area or it may be that neighbourhoods have a causal impact on economic mobility and that could change children' outcomes. Chetty and Hendren (2018) investigate the effects of neighbourhoods on intergenerational mobility and find evidence that moving at younger age to a region with higher college attendance rates increases the child's likelihood of attending college at any point between ages 18 and 23. For the UK, Bell et al.

[1]See DaVanzo (1978); Pissarides and Wadsworth (1989).

(2018) examine the effects of geography on several dimensions of intergenerational mobility, including education. The authors find substantial differences across regions of England and Wales. For instance, the results for educational mobility indicate that the expansion in higher education has increased the likelihood of a child with non-degree parents going to university. For the cohort born in the late 1970s, early 1980s, the probability of obtain a degree is 79% if at least one parent holds a degree, compared to 35% likelihood if neither parent holds a degree. In areas such as Kent the attainment gap is about 37% and in Inner East London is about 53%. However, the educational expansion seems to have favoured those children whose parents hold a university degree, and overall mobility decreased. Yorkshire and Humberside also present a low mobility in terms of education. Overall, there is scope for observing considerable internal migration within the UK, and this called for more work investigating how this could impact the construction of regional human capital stocks (HCS). We now turn to a short description on the construction of those and their current limitations.

3 Constructing HCS

3.1 General Methodology

A popular method used by many countries in measuring HCS is to consider outcomes from human capital accumulation using information on lifetime labour incomes. The seminal contribution to this literature were the papers by Jorgenson and Fraumeni (1989, 1992), JF from here on. The JF model measures HCS using lifetime earnings in present discounted value that all individuals are expected to earn. This implies the assumption that labour is paid according to its marginal product. The JF approach is consistent with the treatment of assets in the national accounts (Fraumeni et al., 2017) and is the approach recommended by the Atkinson Report (Atkinson, 2005). There are a large number of international efforts to measuring human capital accounts using the JF framework[2] and it is the approach currently used by ONS (see Jones and Chiripanhura (2010) for details of the methodology).

In its original formulation the JF framework calculates lifetime income by sex (s), age (a), and education level (e) and then sums across these dimensions for the total population. In most applications NSIs confine attention to the working age population, e.g. aged 16 to 65 in ONS estimates. This group can be divided into five categories, those in employment, unemployment, retirement, absent due to sickness and economic inactivity other than sickness. For individuals not in employment, we impute potential earnings based on employment earnings for similar demographic groups.[3]

[2]For example: see Atkinson (2005) for an early application to Sweden, and subsequently Wei (2004) for Australia; Gu and Wong (2010) for Canada; Jones and Chiripanhura (2010) for the UK; and Christian (2010) for the US, to name but a few.

[3]In the original JF framework a value based on the average market wage was also imputed to nonworking

Lifetime labour income, $LLI_{(s,a,e)}$, is calculated by using backwards recursion. This implies that market income is zero beyond some age, which in this paper is taken to be 69, and is based on the assumption that people do not receive any earnings once they withdraw from the labour market.

Therefore, lifetime earnings of those aged 69 is given by:

$$LLI_{(s,a=69,e)} = income_{(s,a=69,e)} \tag{1}$$

In the JF method it is standard to assume a fixed discount rate for future income, denoted by δ, and a fixed growth in future income due to general income/productivity increases, denoted by g. The JF methodology assumes that an individual with a given gender, age and education will, in year t+1, have the same labour income and other characteristics (employment and survival rate) as someone in year t, who is one year older and has otherwise the same characteristics (gender and education). Therefore, if someone is aged 68, this person´s LLI equals current income plus discounted future income of someone aged 69 with the same sex and education, conditional on survival, sr. Similar calculations apply to all persons aged above the maximum school enrolment age, which we assume equals 40.

These are given by:

$$\begin{aligned} LLI_{(s,a,e)} &= income_{(s,a,e)} + sr_{(s,a+1)}\frac{(1+g)}{(1+\delta)}LLI_{(s,a+1,e)} \\ &\quad \mid 40 \leq a \leq 69 \end{aligned} \tag{2}$$

For those aged between 16 and 39, LLI needs to take account of changes in educational attainment (school, further education and higher education), measured by education transition probabilities, $ENRR$[4]. Therefore, equation (2) is altered to include the probability of people improving their educational attainment, which is multiplied by the income they are likely to earn given their higher qualification. At the start of each year, everyone has the choice to either work next year so their education level remain at e or, or improve it and move to education level $e+1$, hence receiving a higher income in the next period.

$$\begin{aligned} LLI_{(s,a,e)} = income_{(s,a,e)} + sr_{(s,a+1)}\frac{(1+g)}{(1+\delta)}[ENRR_{(s,a,e)}LLI_{(s,a+1,e+1)} \\ +(1-ENRR_{(s,a,e)})LLI_{(s,a+1,e)}] \qquad \mid 16 \leq a \leq 39 \end{aligned} \tag{3}$$

Total HCS is calculated by aggregating individual LLI across the population, POP:

$$Aggregate\ HCS = \sum_s \sum_a \sum_e LLI_{(s,a,e)}POP_{(s,a,e)} \tag{4}$$

time after adjusting for maintenance (time spent sleeping, eating etc.). This controversial assumption was not widely adopted in subsequent estimates and is not included here, but see Fraumeni et al. (2017) for a recent effort to integrate this broader measure into the US national accounts.

[4]Although the cut-off point is arbitrary here, actual enrolment rates do not show much education activity beyond this age.

The calculations for the productive HCS are similar to equations (2) – (4) except we now multiply incomes by the employment rate, $EMPR$:

$$LLI_{(s,a,e)} = EMPR_{(s,a,e)} income_{(s,a,e)} + sr_{(s,a+1)} \frac{(1+g)}{(1+\delta)} LLI_{(s,a+1,e)} \\ \mid 40 \leq a \leq 69 \tag{5}$$

$$\begin{aligned} LLI_{(s,a,e)} = EMPR_{(s,a,e)} income_{(s,a,e)} + sr_{(s,a+1)} \frac{(1+g)}{(1+\delta)} [& ENRR_{(s,a,e)} LLI_{(s,a+1,e+1)} \\ &+ (1 - ENRR_{(s,a,e)}) LLI_{(s,a+1,e)}] \\ &\mid 16 \leq a \leq 39 \end{aligned} \tag{6}$$

In this case the total productive HCS is given by:

$$productive\ HCS = \sum_s \sum_a \sum_e LLI_{(s,a,e)} EMPR_{(s,a,e)} POP_{(s,a,e)} \tag{7}$$

Calculating the productive HCS is the approach adopted in many countries, e.g. for Canada and the UK, as it measures the human capital being used in the productive process. However, identifying sources of the difference between working population HCS and productive HCS can be useful in understanding labour market effects.

3.2 ONS Methodology for estimating Regional HCS

Regional human capital estimates are produced by ONS using the same approach as the national estimates as outlined in the previous subsection. The main sources of data used in the analysis continue to be the Annual Population Survey (APS), which is an annual version of the Labour Force Survey (LFS) and the longitudinal LFS. A regional variable, based on region of residence, is obtained from the APS. This allows the regional estimation of number of people, earnings (when employed) and enrolment rates for different levels of education. Survival rates, by age, are sourced from ONS mortality, but are only available at the UK country level (England, Wales, Scotland and Northern Ireland). In ONS (2016) estimates of regional human capital by region of work are also provided, rather than region of residence. The difference is largest for London, as expected, given the high number of commuters, mostly from the South East Region.

The main concern in estimating these regional HCS was the small sample size so ONS had to divide into 5 yearly age bands. This required imputing age-band averages onto every age within an age group. This would have created a distorted age-income profile so ONS fitted values of income for each age based on the output of a polynomial regression of order 2 based on the methodology employed by Liu (2013). This better reflects the curved nature of the national age-income profile. The ONS estimates did not, however, attempt to incorporate mobility across regions.

3.3 Mobility and HCS construction

Implicit in equations (4) or (7) is the assumption that a person resident or working in a region will remain there throughout their lifetimes. This is obviously not the case in practice. The assumption is defensible if the numbers of people moving into a region, by age, sex and qualification, match the number moving out. However, if these flows are not close then the approach will overstate HCS in regions losing population and understate it in receiving regions. Taking account of mobility within the lifetime earnings model in section 3.1 is likely to be very complicated, since transitions are required for each age, sex and qualification group. It is beyond the scope of this paper to attempt such a calculation at this stage, although we plan to include some simulations at a later date. In this version we present some descriptive statistics allowing us to gauge how serious an issue this is. Indeed, we find substantial internal migration within the UK and peaking at different stages of life (young age groups) and concentrated in those with high qualification levels. This calls for an inclusion of those migration moves for a more accurate assessment of HCS.

4 Data and methodology

4.1 Data

We examine the transition probabilities of moving from one region (ITLS1 and ITLS2) to another by groups during the years 2009 to 2018. The dataset used in this paper combines individual level records from the UK Household Longitudinal Study (UKHLS), also known as Understanding Society, and the Annual Population Survey (APS). The UKHLS allows us to approach the question within a longitudinal perspective, ie. where we follow the same people through time. We thought this would provide a more stable picture of developments in mobility over time, than the short longitudinal cycle of 5 quarters provided by the LFS.

The UK Household Longitudinal Study covers around 40,000 households in the UK (wave 1) and provides high-quality socioeconomic information on individuals, such as gender, education, age, geographical variables and others, that helps to understand the long-term effects of social and economic changes in the UK population. Our analysis focuses on the adult survey, that is, respondents aged 16 and over using waves 1-10. Overall, this paper follows an average of 36,000 individuals over the period.

To create the groups of interest we combined individuals by gender, age group and highest qualification. Gender is split into male and female, age group is divided in three categories: young (16-29), middle age (30-49) and older (50-70). Highest qualification is also divided in three categories: high (degree), intermediate (other higher degree, A-levels and other qualification) and low education (GCSE and no qualification). Thus, the combination of these yields 18 gender-age-education groups. To determine whether a worker is a migrant we use the information on the ITLS1 and ITLS2 regions one lives in. Hence, a migrant is defined as a person who lives in a different ITLS1/ITLS2 compared to the previous period (two-year transitions for most individuals).

Additional information on hourly wages is gathered through the Labour Force Survey/Annual Population Survey (LFS/APS). APS provides employment and unemployment information and other socioeconomic information at local levels and covers approximately 360,000 individuals and 170,000 households per year. Our analysis focuses on the average hourly wage for those who are employed by the 18 gender-age-education groups and by region (ITLS1 and ITLS2). Income is deflated using the Consumer Prices Index (CPI) with a base year in 2018.

4.2 Methodology for constructing transition probabilities

In order to examine mobility across regions we calculate the transition probabilities of moving from one region to another (ITLS1 and ITLS2) for each of the 18 gender-age-education groups (k):

$$p_{kij} = Pr(X_{kt} = j \mid X_{k(t-1)} = i) \tag{8}$$

where i is the initial region and j is the final region. So, the probability of moving from region i to region j can be written as:

$$prob_{FROM,ki} = \frac{N_{kij}}{\sum_{j=1}^{n} N_{kij}} \tag{9}$$

where N is the number of people in group k who moved from region i to j and n is the number of regions.

Similarly the probability of moving to region j from region i can be written as:

$$prob_{TO,kj} = \frac{N_{kij}}{\sum_{i=1}^{n} N_{kij}} \tag{10}$$

These transition probabilities are calculated year by year. However, for the ITLS2 regions, due to the small sample size of some regions we report the average transition probabilities across a two 5-year periods, corresponding to waves 1-5 and waves 6-10.

5 Transition Probabilities: Results

5.1 ITLS1 Regions

In this section we summarise the transition probabilities using a series of tables and maps. We divide the population into 18 groups, as noted above, and illustrate probabilities, averaged across the time period, both from the region and to the region. In this analysis we excluded Northern Ireland as the transition probabilities were almost zero for all categories, and may be a reflection of small sample sizes. Given that there are 11 remaining regions and 18 categories we have 198 groups overall. Tables A1.1-A1.6 in the Appendix show these average transition probabilities FROM regions plus their ranking (with 1 having the highest probability of moving), TO regions plus their ranking and the difference between TO and FROM. The maps depict the same information but by characteristic group. Note we label groups by three letters starting with Gender (F=female, M=male), then by Age (Y=16-29, M=30-49, O=50-70) and then by Qualification (H=High, M=Intermediate, L=Low).

To help in summarising this information, Tables 1A and 1B shows the 10 top groups in terms of probabilities of moving TO and FROM regions and Tables 2A and 2B shows the same information for the bottom 10 groups. The top 10 TO region probabilities are all for young persons with High qualifications, and slightly more of these are male than female. These numbers are large, suggesting a great deal of movement for young people who are well qualified. Surprisingly, London is not at the very top of this group but for both males and females the probabilities of moving to London are still quite high. Some of the same groups feature in the top 10 FROM probabilities. For example, highly qualified young males have high probabilities of moving both TO and FROM Wales but the latter dominates so that there is a large attrition from that region. Similar remarks apply to the East Midlands but there is a greater probability of young high skilled males moving to the East of England than from that region.

Table 1A: Average probability of moving TO - Top 10, ITLS1

Rank	Gender	Age group	Qualification	Label group	ITLS1 name	Average
1	Male	16-29	High	MYH	East of England	0.0942
2	Male	16-29	High	MYH	South West (England)	0.0913
3	Female	16-29	High	FYH	East Midlands (England)	0.0855
4	Male	16-29	High	MYH	South East (England)	0.0839
5	Female	16-29	High	FYH	East of England	0.0822
6	Male	16-29	High	MYH	Wales	0.077
7	Male	16-29	High	MYH	East Midlands (England)	0.0758
8	Female	16-29	High	FYH	West Midlands (England)	0.0757
9	Male	16-29	High	MYH	London	0.0661
10	Female	16-29	High	FYH	London	0.0604

Note: excluding Northern Ireland.

Table 1B: Average probability of moving FROM - Top 10, ITLS1

Rank	**Gender**	**Age group**	**Qualification**	**Label group**	**ITLS1 name**	**Average**
1	Male	16-29	High	MYH	Wales	0.1245
2	Male	16-29	High	MYH	East Midlands (England)	0.1041
3	Male	16-29	High	MYH	South West (England)	0.1034
4	Male	16-29	High	MYH	South East (England)	0.0839
5	Male	16-29	High	MYH	Yorkshire and The Humber	0.0824
6	Male	16-29	High	MYH	East of England	0.0788
7	Female	16-29	High	FYH	South West (England)	0.0779
8	Female	16-29	High	FYH	East of England	0.076
9	Female	16-29	High	FYH	East Midlands (England)	0.0756
10	Male	16-29	High	MYH	West Midlands (England)	0.0688

Note: excluding Northern Ireland.

London does not feature in the top 10 FROM regions. Examination of Tables A1.1-A1.6 show that there is a much greater probability of moving TO than FROM London for young high skilled for both males and females.

In Tables 2A and 2B it is clear that low qualifications dominate the bottom of the probability distribution, especially for the TO probabilities. These tables only contain one entry for the 16-29 age group. Tables A1.1-A1.6 show generally low probabilities for those aged 50-70 and also quite low for the age group 30-49, although there are some high numbers for the highly skilled in this age category.

Table 2A: Average probability of moving TO - Bottom 10, ITLS1

Rank	**Gender**	**Age group**	**Qualification**	**Label group**	**ITLS1 name**	**Average**
186	Female	30-49	Low	FML	East Midlands (England)	0.0015
187	Female	30-49	Low	FML	Yorkshire and The Humber	0.0012
188	Female	50-70	Low	FOL	London	0.001
189	Male	50-70	Intermediate	MOI	North East (England)	0.001
190	Male	30-49	Low	MML	East Midlands (England)	0.001
191	Male	50-70	Intermediate	MOI	Scotland	0.001
192	Male	50-70	Low	MOL	London	0.0009
193	Female	50-70	Low	FOL	North East (England)	0.0008
194	Male	16-29	Low	MYL	North West (England)	0.0005

Note: excluding Northern Ireland and other regions where the average probability is zero.

Table 2B: Average probability of moving FROM - Bottom 10, ITLS1

Rank	**Gender**	**Age group**	**Qualification**	**Label group**	**ITLS1 name**	**Average**
187	Female	30-49	Low	FML	Yorkshire and The Humber	0.0018
188	Female	50-70	Intermediate	FOI	North East (England)	0.0017
189	Male	50-70	Intermediate	MOI	Yorkshire and The Humber	0.0015
190	Female	30-49	Low	FML	North West (England)	0.0015
191	Male	30-49	Intermediate	MMI	Yorkshire and The Humber	0.0013
192	Female	30-49	Intermediate	FMI	Yorkshire and The Humber	0.0013
193	Female	30-49	Intermediate	FMI	Scotland	0.0012
194	Female	50-70	Low	FOL	Scotland	0.0009
195	Female	50-70	Low	FOL	North East (England)	0.0007

Note: excluding Northern Ireland and other regions where the average probability is zero.

As discussed in subsection 3.3, from an HCS perspective what matters most is the net TO-FROM probabilities. These are generally quite small with the exception of highly skilled young people. This is clear from the maps. High probabilities in these young age groups will to some extent reflect movement for educational purposes. However, those moving to attend undergraduate university programmes appear in the Intermediate qualified group as they have not yet achieved their degrees. Transition probabilities for those with Intermediate skills are considerably smaller than for the high skilled, suggesting movement for education purposes is not dominating the transitions for young people. The higher probability for low and highly educated is observed for international migration too (see Langella and Manning (2021). And it could similarly be that for internal migration the cost of moving to another region are higher for workers with Intermediate skills. They may exert jobs that require greater use of local knowledge and networks (e.g. surveyors, conveyancers, builders) and greater satisfaction with local amenities (Dustmann and Okatenko, 2014). In a later revision it might be possible to cross classify the data by full-time education status but the sample sizes are likely to be very small.

The net TO-FROM probability is positive for 106 of the 198 groups in Tables A1.1-A1.6. The table also shows that 30 groups, or 15%, have net probabilities greater than plus or minus 1% with only 4% with net probabilities greater than plus or minus 2%. The latter are all in the young highly skilled groups. Since these are transitions from one year to the next, a 1% probability cumulates to a large number over the about 40 years involved in the lifetime earnings calculations of HCS for the younger age groups.

5.2 ITLS2 Regions

We also mapped internal migration transition probabilities in ITLS2 regions by each of the 18 groups (not shown given sizes of the related files). This confirms that the less mobile people are older and less educated, regardless of their gender. For instance, we show that the probabilities of moving TO and FROM ITLS2 regions are less than or equal to 0.025 for low educated females aged 50-70. Conversely, highly educated young people are more mobile than other groups. The pattern is very similar for males and females in the East Midlands (UKF1 - Derbyshire and Nottinghamshire, UKF2 - Leicestershire, Rutland and Northamptonshire, UKF3 - Lincolnshire) and East of England (UKH1 - East Anglia, UKH2 - Bedfordshire and Hertfordshire, UKH3 - Essex), with both probabilities of moving TO and FROM between 0.05 and 0.15. In Herefordshire, Worcestershire and Warwickshire (UKG1) the probabilities of moving TO and FROM are greater than 0.15 for both males and females. Meanwhile, in North Yorkshire (UKE2) the probability of moving FROM is also greater than 0.15, but the probability of moving TO is smaller for both males (less than 0.025) and females (between 0.05 and 0.15).

Additionally, we see that the probability of highly educated young females of moving TO and FROM East Yorkshire and Northern Lincolnshire (UKE1) and of moving TO Cornwall and Isles of Scilly (UKK3) is zero, but the probability of moving FROM Cornwall and Isles of Scilly is considerable (between 0.05 and 0.15). On the other hand, our figures indicate that highly educated young males are slightly more prone to moving TO East Yorkshire and Northern Lincolnshire (between 0.025 and 0.05) than their female counterparts. The same is observed for Cornwall and Isles of Scilly, where the probability of moving TO is more than 0.15 for highly educated young males. Regarding London, the probabilities of moving TO and FROM are significant for highly educated young people, with a higher probability of males and females to move TO and FROM Inner London (UKI3 and UKI4) and Outer London – South (UKI6).

5.3 Transition probabilities through time

One of the advantages of using UKHLS is that we are tracking the same people over time. We investigated to what extent the transition probabilities vary over time during the period 2009-2018. We look at this from more than one dimension and summarise the findings as a series of regression in Table 3, 4 and 5.

First looking at ITLS1, we have annual results so the regression in Table 3 shows the coefficients for each year (including characteristics and NUTS dummies as control). The coefficients can be interpreted as how much the transition (TO and FROM) changes across the years. Some are significant, particularly in mid-period years, but there are no clear trends.

Table 3: Time transitions, ITLS1

	Probability FROM	Probability TO	Net (TO - FROM)
Year 2011	-0.001	0.000	0.001
	(0.40)	(0.09)	(0.043)
Year 2012	0.003	0.003	-0.000
	(1.37)	(1.24)	(0.18)
Year 2013	0.005	0.005	0.000
	(2.28)	(2.43)	(0.02)
Year 2014	0.004	0.004	0.000
	(1.79)	(2.09)	(0.17)
Year 2015	0.006	0.003	-0.003
	(2.83)	(1.69)	(1.09)
Year 2016	0.001	0.003	0.002
	(0.53)	(1.35)	(0.66)
Year 2017	0.000	0.002	0.002
	(0.18)	(1.10)	(0.76)
Year 2018	0.001	0.002	0.002
	(0.38)	(1.20)	(0.67)
R-squared	0.321	0.314	0.012

Notes: t-ratios in parentheses. All regressions include characteristic and regional dummies. *** p<0.01, ** p<0.05, * p<0.1.

We next turn to ITLS2 presented in Tables 4 and 5. As noted above, we average over years to give two periods for our regressions. In this case, we take the difference between the later and the earlier period as our measure of changes and regressed this on our measure of characteristics. The first Table 4 shows the results using broad characteristics group (gender, age and education). The second Table 5 shows the result for the 18 groups detailed above. In this case, the omitted group is older males with intermediate skills. None of the coefficients in 4 are even close to being significant, consistent with the lack of significance for the trends observed in the previous Table 3.

Table 4: Time transitions, ITLS2

	FROM	TO
Male	-0.001	-0.001
	(0.21)	(0.59)
Middle	0.003	0.003
	(0.96)	(1.03)
Old	0.002	0.002
	(0.80)	(0.77)
Intermediate	0.002	0.001
	(0.58)	(0.24)
Low	0.001	0.000
	(0.29)	(0.09)
R-squared	0.115	0.067

Notes: t-ratios in parentheses. All regressions include regional dummies. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: Time transitions by group, ITLS2

	FROM	TO
Male, Young and High education (MYH)	-0.007	-0.009
	(-1.00)	(-1.31)
Male, Young and Intermediate education (MYI)	-0.006	-0.004
	(0.086)	(-0.61)
Male, Young and Low education (MYL)	-0.000	-0.000
	(-0.01)	(-0.05)
Male, Middle aged and High education (MMH)	-0.001	0.002
	(-0.19)	(0.35)
Male, Middle aged and Intermediate education (MMI)	0.000	0.001
	(0.02)	(0.16)
Male, Middle aged and Low education (MML)	0.003	0.001
	(0.43)	(0.12)
Male, Older and High education (MOH)	-0.000	0.000
	(-0.03)	(0.03)
Male, Older and Low education (MOL)	0.000	0.002
	(0.06)	(0.27)
Female, Young and High education (FYH)	-0.000	0.003
	(-0.06)	(0.46)
Female, Young and Intermediate education (FYI)	-0.002	0.001
	(-0.36)	(0.10)
Female, Young and Low education (FYL)	-0.001	-0.002
	(-0.08)	(-0.23)
Female, Middle aged and High education (FMH)	0.001	0.001
	(0.13)	(0.17)
Female, Middle aged and Intermediate education (FMI)	0.001	-0.000
	(0.08)	(-0.00)
Female, Middle aged and Low education (FML)	-0.003	0.001
	(-0.04)	(0.11)
Female, Older and High education (FOH)	-0.003	-0.001
	(-0.04)	(-0.13)
Female, Older and Intermediate education (FOI)	0.001	0.001
	(0.17)	(0.15)
Female, Older and Low education (FOL)	-0.001	-0.000
	(-0.12)	(-0.06)
R-squared	0.0801	0.0721

Notes: t-ratios in parentheses. All regressions include regional dummies. *** p<0.01, ** p<0.05, * p<0.1.

None of the coefficients are significant in both columns. We observe however that in the second column (TO), the coefficient on young highly skilled males (MYH) is negative, and of opposite sign to young highly skilled women (FYH). In fact the difference between these coefficients is significant at the 10 per cent level. This is suggestive that they might some changes over time comparing the younger cohorts, but this is difficult to pick up given the small sample size. This finding combined with the fact the transition probabilities are only large for younger cohorts calls for additional analysis using alternate data sets (the most obvious being LEO).

Overall the results of this Section suggest an assumption of constant transitions probabilities is reasonable. We will rely on this assumption in Section 6 when we simulate regional Human Capital Stocks (HCS).

5.4 Transition probabilities and wages

It is interesting to examine the extent to which the transition probabilities are correlated with wages. Is there evidence that people move to higher earning regions? We check the correlation between mobility and wages by estimating the following Ordinary Least Square (OLS) model:

$$prob_{grt} = \alpha + \beta_1 log\, w_{grt} + \beta_2 log\, w_{grt} \times T_t + \beta_3 T_t + \beta_4 Group_g + \beta_5 Region_r + \varepsilon_{grt} \qquad (11)$$

where $prob_{grt}$ is the probability of moving to region r, $log\, w_{grt}$ is the logarithm of the hourly wage of group g in region r at time t. Dummy variables for each period, T_t, capture national trends[5]. Dummy variables for each region, $Region_r$, control for regional differences. Additionally, dummies for each gender-age-education group, $Group_g$, account for groups' unobserved heterogeneity. Lastly, ε_{grt} is the idiosyncratic error term.

Tables A2.1-A2.2 show the regression results for ITLS1 and Tables A3.1-A3.3 for ITLS2. First, focusing on ITLS1, one does not see much correlation between the probability of moving TO a region and its wage. Tables A2.1-A2.2 show heterogeneous coefficients on different specifications, but all are not significant at the usual levels. For instance, when controlling for group's fixed effects (column 3) the wage's coefficient is positive, but when regions' dummies are introduced it becomes negative.

Moving to ITLS2, Tables A3.1-A3.3 show a positive coefficient for wage in all 4 specifications. When groups' unobserved characteristics are taken into account (column 3), an increase in wages is associated with an increase in the likelihood of moving TO a certain region, as suggested by the positive and significant coefficient. Additionally, when regional dummies are also controlled for (column 4), the wage coefficient is still positive, but not significant at the usual levels.

Overall, there is some indication of a positive correlation between wages and mobility, particularly for ITLS2 regions. The results may be driven by the fact that people are not moving too far away from the areas where they were initially. Therefore, the relationship between wages and internal migration would be better captured in finer regional levels (ITLS2) than in aggregated regions (ITLS1).

[5] 10 years for ITLS1 and 2 periods for ITLS2, as previously explained.

6 Constructing regional HCS

In this section we investigate how regional human capital stocks might be affected by taking account of transition probabilities. The methodology currently employed by ONS is to replicate equations (5) and (6) but include a regional dimension, r. For example, equation (5) becomes:

$$LLI_{(s,a,e,r)} = EMPR_{(s,a,e,r)} income_{(s,a,e,r)} + sr_{(s,a+1)} \frac{(1+g)}{(1+\delta)} LLI_{(s,a+1,e,r)} \tag{12}$$

Note the survival rate, sr, does not vary by region or level of education. The final term in equation (12) assumes that the individual will remain in region r throughout their working life time. This is obviously not the case, especially for young people, as shown in the previous results. Therefore, it is necessary to incorporate regional mobility, through adjusting the 2nd term in (12). This requires a number of assumptions. First we assume that the transition probabilities do not change over time. The survival, growth and discount rates are assumed to not vary by region, so for simplicity we write:

$$\lambda_{(s,a)} = sr_{(s,a)} \frac{(1+g)}{(1+\delta)} \tag{13}$$

Let PF denote the transition probability of moving from region r to any other region, and let PT denote the probability of moving to region r, from any other region. For each gender, age and education group we need to incorporate the transition probabilities group in the recursive calculations that make up the LLI for that group. For any group j of gender s and education level e, at the final age at which they earn income, assumed to be 69, their lifetime earnings are given by equation (1), reproduced as:

$$LLI_{(s,a=69,e)} = income_{(s,a=69,e)} \tag{14}$$

For an individual aged 68, including transition probabilities, lifetime income in region r for those who stay is given by:

$$LLI_{(s,a=68,e)} = EMPR_{(s,a=68,e)} income_{(s,a=68,e)} + \lambda_{(s,a+1)}[(1 - PF_{(s,a=68,e)})LLI_{(s,a=69,e)}] \tag{15}$$

At the same time as individuals in gender, age and education groups move out of a region, some individuals will move in at a later date than the current period. These can be seen as replacing the lifetime labour income of those leaving to some extent. Therefore, we should include a term in the recursive calculation:

$$\lambda_{(s,a+1)}[(PT_{(s,a=68,e)})LLI_{(s,a=69,e)}] \tag{16}$$

Suppose we assume individuals moving into a region command the same salary as the average for that region by gender, age and education. Adding (15) and (16) gives:

$$\begin{aligned} LLI_{(s,a=68,e)} =& EMPR_{(s,a=68,e)} income_{(s,a=68,e)} + \lambda_{(s,a+1)}[LLI_{(s,a=69,e)}] \\ &+ \lambda_{(s,a+1)}[(PT_{(s,a=68,e)} - PF_{(s,a=68,e)})LLI_{(s,a=69,e)}] \end{aligned} \tag{17}$$

The final term is the adjustment to each group's HCS to take account of future labour mobility and it shows that only the net transition probabilities matter in this calculation. Denote this adjustment as $adjLLI$. This equation is then calculated recursively for each age back to age 16.

We may also need an adjustment to the aggregate total capital stocks, given by equation (7) above for employment numbers. This requires further assumptions. For simplicity assume that the employment rate is the same for movers and stayers, and let EMP denote employment numbers (EMP=EMPR*POP for each group). Then we can calculate the numbers moving from the region for each group as PF EMP and for those moving into the region by PT EMP. Therefore, the aggregate HC becomes:

$$
\begin{aligned}
HCS = &\sum_r \sum_s \sum_a \sum_e LLI_{(s,a,e,r)} EMP_{(s,a,e,r)} \\
&+ \sum_r \sum_s \sum_a \sum_e adjLLI_{(s,a,e,r)} (PT_{(s,a=68,e)} - PF_{(s,a=68,e)}) EMP_{(s,a,e,r)}
\end{aligned}
\tag{18}
$$

An ideal next step in our analysis would be to attempt to ascertain the extent to which adding transition probabilities will impact on estimates of regional HCS. This could use the data series underlying the ONS ITLS1 HCS estimates but there are a number of modelling choices to make before this could be attempted. Most important is that the numbers discussed above aggregate to only three age groups and only three qualification groups.

Instead we resort to simulations to get a handle on how much using the above estimates of transition probabilities might matter. To do so we use national HCS data for males for one year that underlie the work on health and human capital for the UK in (O'Mahony and Samek, 2021). We calculate HCS for two 'constructed' sample regions that vary according to the assumptions underlying the calculations. Therefore, we assume two regions, Region 1 where there is significant movement into the region, and Region 2 where the flows are mostly from that region. We use the actual transition probabilities calculated above for the East and York and the Humber regions to illustrate the results, as these two most fit this mostly to and mostly from distinction. We also change the populations in the calculations to mirror the share of aggregate population of these two regions in England - the East region is slightly larger in terms of population than York and Humberside but not by much. We then construct and compare regional HCS with and without the regional transition adjustments.

We present three different scenarios in Table 6. The first shows the change in HCS if we just vary the transition probabilities across two regions, leaving all other variables in the HCS calculation unchanged. The second scenario assumes region 1 is a high wage region and region 2 is low wage. In this calculation we assume that region 1 wages are 10% above the national average for low and Intermediate skilled workers and 33% above for high skilled workers. Similarly, we assume region 2 wages are 10% below the national average for low and Intermediate and 33% below for the high skilled. Finally, we maintain this distinction between high and low wage regions but also assume that the proportion of skilled workers is 20% higher than the national average in the high wage region and 20% below the national average in the low wage region. Note that other variables in the dataset, such as employment rates are assumed constant.

In Table 6, the numbers in the table are the percent change in the HCS through taking account of transition probabilities as described above. The first row of Table 3 estimates that HCS in Region 1 would be about 1.5% higher and that of region 2, 5.9% lower if transition probabilities were taken into account. Taking account of wages and high skill proportions raises the Region 1 HCS but dampens the impact of transitions on region 2, as most mobility is within the high skill group. The final row shows the adjustment to HCS for the total potential HCS if employment rates are not taken into account. Recent ONS figures suggest HCS in the East region is about 33% higher than in York and the Humber. If the simulated changes in the table were applied to this difference then HCS would be between 52% and 41% higher suggesting that these adjustments are quite large. Note also that these calculations assume constant transition probabilities through time, consistent with the findings above. If Region 2 net outward transitions were increasing over time, the adjustments would be greater than this one off change to levels of HCS. We leave consideration of this aspect to future work.

Table 6: Simulations of changes to regional capital stocks

	Region 1	Region 2
Transition probabilities only	1.46	-5.92
plus wage adjustment	1.75	-5.22
plus wages and skills adjustments	2.17	-4.37
Population plus wages and skills adjustments	1.82	-5.71

7 Conclusion

In this paper we have attempted to investigate the impact of mobility on regional Human Capital Stocks (HCS). Our analysis suggest that mobility is concentrated mostly among the young highly skilled population and that taking into account regional mobility affects the relative values of regional HCS. Our analysis was constrained by the small sample size of the data sets used. In particular, it would have been beneficial to break out the school age groups, 16-21, from those most likely to be in work 22-29. We did investigate this possibility but the cell size fell below the reporting threshold. These are crucial ages where young people transition from education to careers that in turn determine their future choice of labour market location.

The results presented here suggest that the greatest mileage might be had from looking at alternative data sources that concentrate on younger populations and follow the same people through time. The LEO data sets is an obvious choice as is Growing Up in England (GUIE). As well as providing more robust estimates that could be combined with actual regional labour market data, it would enable us to also look at other aspects of regional mobility such as the impact of localities on economic opportunities and its relationship to families moving while children are in school.

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Appendix A

Table A1.1: Females aged 16-29

Gender	Age group	Qual	Label group	Region name	TO	Rank	FROM	Rank	TO - FROM
Female	16-29	High	FYH	North East	0.0525	14	0.0336	22	0.019
Female	16-29	High	FYH	North West	0.0369	22	0.0543	15	-0.0174
Female	16-29	High	FYH	Yorkshire/Humber	0.0399	19	0.0543	14	-0.0144
Female	16-29	High	FYH	East Midlands	0.0855	3	0.0756	9	0.0099
Female	16-29	High	FYH	West Midlands	0.0757	8	0.0614	12	0.0143
Female	16-29	High	FYH	East of England	0.0822	5	0.076	8	0.0062
Female	16-29	High	FYH	London	0.0604	10	0.0328	23	0.0276
Female	16-29	High	FYH	South East	0.0452	17	0.0619	11	-0.0166
Female	16-29	High	FYH	South West	0.0541	12	0.0779	7	-0.0238
Female	16-29	High	FYH	Wales	0.046	16	0.0452	16	0.0008
Female	16-29	High	FYH	Scotland	0.011	64	0.0216	37	-0.0106
Female	16-29	Intermediate	FYI	North East	0.0285	23	0.0239	31	0.0046
Female	16-29	Intermediate	FYI	North West	0.0222	35	0.0146	57	0.0075
Female	16-29	Intermediate	FYI	Yorkshire/Humber	0.0253	29	0.0192	44	0.0061
Female	16-29	Intermediate	FYI	East Midlands	0.0256	28	0.0169	51	0.0087
Female	16-29	Intermediate	FYI	West Midlands	0.0142	52	0.0234	33	-0.0092
Female	16-29	Intermediate	FYI	East of England	0.0186	45	0.0346	21	-0.0161
Female	16-29	Intermediate	FYI	London	0.022	36	0.0205	41	0.0015
Female	16-29	Intermediate	FYI	South East	0.0233	32	0.0248	30	-0.0015
Female	16-29	Intermediate	FYI	South West	0.0233	31	0.0294	27	-0.0061
Female	16-29	Intermediate	FYI	Wales	0.0208	42	0.0191	45	0.0018
Female	16-29	Intermediate	FYI	Scotland	0.0113	62	0.0079	92	0.0034
Female	16-29	Low	FYL	North East	0.0392	20	0.0044	138	0.0348
Female	16-29	Low	FYL	North West	0.0068	114	0.0043	142	0.0025
Female	16-29	Low	FYL	Yorkshire/Humber	0.0059	127	0.0081	91	-0.0022
Female	16-29	Low	FYL	East Midlands	0.0065	120	0.0106	74	-0.004
Female	16-29	Low	FYL	West Midlands	0.009	83	0.0068	107	0.0022
Female	16-29	Low	FYL	East of England	0.0088	85	0.0123	62	-0.0036
Female	16-29	Low	FYL	London	0.0128	56	0.0078	94	0.005
Female	16-29	Low	FYL	South East	0.0123	59	0.0214	38	-0.0091
Female	16-29	Low	FYL	South West	0.0099	70	0.0088	82	0.0011
Female	16-29	Low	FYL	Wales	0.0025	175	0.0071	103	-0.0046
Female	16-29	Low	FYL	Scotland	0	195	0.0044	140	-0.0044

Note: excluding Northern Ireland.

Table A1.2: Females aged 30-49

Gender	Age group	Qual	Label group	Region name	TO	Rank	FROM	Rank	TO - FROM
Female	30-49	High	FMH	North East	0.008	91	0.015	55	-0.0071
Female	30-49	High	FMH	North West	0.0067	116	0.0107	72	-0.004
Female	30-49	High	FMH	Yorkshire/Humber	0.0154	48	0.0077	96	0.0077
Female	30-49	High	FMH	East Midlands	0.0215	39	0.0121	65	0.0094
Female	30-49	High	FMH	West Midlands	0.0108	66	0.0067	108	0.0041
Female	30-49	High	FMH	East of England	0.0174	46	0.0154	54	0.002
Female	30-49	High	FMH	London	0.0082	87	0.0256	28	-0.0173
Female	30-49	High	FMH	South East	0.021	40	0.0135	59	0.0075
Female	30-49	High	FMH	South West	0.0219	37	0.0093	78	0.0126
Female	30-49	High	FMH	Wales	0.0068	115	0.014	58	-0.0072
Female	30-49	High	FMH	Scotland	0.0049	139	0.0037	153	0.0012
Female	30-49	Intermediate	FMI	North East	0.0018	182	0.002	183	-0.0002
Female	30-49	Intermediate	FMI	North West	0.0053	132	0.0084	87	-0.0031
Female	30-49	Intermediate	FMI	Yorkshire/Humber	0.0042	156	0.0013	192	0.0029
Female	30-49	Intermediate	FMI	East Midlands	0.0064	122	0.0044	139	0.002
Female	30-49	Intermediate	FMI	West Midlands	0.0043	152	0.0046	133	-0.0003
Female	30-49	Intermediate	FMI	East of England	0.0112	63	0.0029	166	0.0082
Female	30-49	Intermediate	FMI	London	0.0045	148	0.023	34	-0.0185
Female	30-49	Intermediate	FMI	South East	0.0091	80	0.0059	114	0.0032
Female	30-49	Intermediate	FMI	South West	0.0026	172	0.0046	132	-0.002
Female	30-49	Intermediate	FMI	Wales	0.0068	113	0.004	147	0.0028
Female	30-49	Intermediate	FMI	Scotland	0.0076	99	0.0012	193	0.0064
Female	30-49	Low	FML	North East	0.0042	155	0	196	0.0042
Female	30-49	Low	FML	North West	0.0021	180	0.0015	190	0.0006
Female	30-49	Low	FML	Yorkshire/Humber	0.0012	187	0.0018	187	-0.0006
Female	30-49	Low	FML	East Midlands	0.0015	186	0.0028	170	-0.0012
Female	30-49	Low	FML	West Midlands	0.0023	177	0.0032	162	-0.0009
Female	30-49	Low	FML	East of England	0.005	135	0.0074	99	-0.0024
Female	30-49	Low	FML	London	0.0029	169	0.0087	83	-0.0058
Female	30-49	Low	FML	South East	0.0092	78	0.0055	121	0.0037
Female	30-49	Low	FML	South West	0.0036	162	0.0026	175	0.001
Female	30-49	Low	FML	Wales	0.0055	130	0.0025	178	0.0029
Female	30-49	Low	FML	Scotland	0.0046	147	0.0031	163	0.0015

Note: excluding Northern Ireland.

Table A1.3: Females aged 50-70

Gender	**Age group**	**Qual**	**Label group**	**Region name**	**TO**	**Rank**	**FROM**	**Rank**	**TO - FROM**
Female	50-70	High	FOH	North East	0.0082	88	0.0073	100	0.001
Female	50-70	High	FOH	North West	0.0037	161	0.0049	128	-0.0012
Female	50-70	High	FOH	Yorkshire/Humber	0.0023	178	0.0107	73	-0.0084
Female	50-70	High	FOH	East Midlands	0.0217	38	0.0119	69	0.0098
Female	50-70	High	FOH	West Midlands	0.0079	92	0.0099	77	-0.002
Female	50-70	High	FOH	East of England	0.0066	119	0.0105	75	-0.0039
Female	50-70	High	FOH	London	0.0046	145	0.0123	63	-0.0077
Female	50-70	High	FOH	South East	0.0074	102	0.007	105	0.0004
Female	50-70	High	FOH	South West	0.0143	51	0.0058	115	0.0085
Female	50-70	High	FOH	Wales	0.0127	58	0.0069	106	0.0058
Female	50-70	High	FOH	Scotland	0.0089	84	0.0072	101	0.0016
Female	50-70	Intermediate	FOI	North East	0.0063	124	0.0017	188	0.0046
Female	50-70	Intermediate	FOI	North West	0.0016	184	0.0039	149	-0.0023
Female	50-70	Intermediate	FOI	Yorkshire/Humber	0.0058	129	0.0039	150	0.0019
Female	50-70	Intermediate	FOI	East Midlands	0.0063	125	0.0071	104	-0.0008
Female	50-70	Intermediate	FOI	West Midlands	0.0047	142	0.0044	141	0.0004
Female	50-70	Intermediate	FOI	East of England	0.0061	126	0.0084	86	-0.0023
Female	50-70	Intermediate	FOI	London	0.0044	151	0.0126	61	-0.0082
Female	50-70	Intermediate	FOI	South East	0.0095	75	0.0075	98	0.002
Female	50-70	Intermediate	FOI	South West	0.0097	74	0.0046	134	0.0051
Female	50-70	Intermediate	FOI	Wales	0.0077	96	0.0047	130	0.0029
Female	50-70	Intermediate	FOI	Scotland	0.0025	174	0.0028	169	-0.0003
Female	50-70	Low	FOL	North East	0.0008	193	0.0007	195	0.0002
Female	50-70	Low	FOL	North West	0.0034	164	0.0026	177	0.0009
Female	50-70	Low	FOL	Yorkshire/Humber	0.0035	163	0.0026	176	0.0009
Female	50-70	Low	FOL	East Midlands	0.0046	144	0.0034	157	0.0012
Female	50-70	Low	FOL	West Midlands	0.0066	118	0.0033	159	0.0033
Female	50-70	Low	FOL	East of England	0.0047	143	0.0056	118	-0.0009
Female	50-70	Low	FOL	London	0.001	188	0.0086	84	-0.0076
Female	50-70	Low	FOL	South East	0.0092	79	0.0091	79	0.0001
Female	50-70	Low	FOL	South West	0.0077	95	0.006	112	0.0017
Female	50-70	Low	FOL	Wales	0.0027	171	0.004	146	-0.0014
Female	50-70	Low	FOL	Scotland	0.0016	185	0.0009	194	0.0006

Note: excluding Northern Ireland.

Table A1.4: Males aged 16-29

Gender	**Age group**	**Qual**	**Label group**	**Region name**	**TO**	**Rank**	**FROM**	**Rank**	**TO - FROM**
Male	16-29	High	MYH	North East	0.0536	13	0.0366	20	0.0171
Male	16-29	High	MYH	North West	0.05	15	0.0543	13	-0.0043
Male	16-29	High	MYH	Yorkshire/Humber	0.0391	21	0.0824	5	-0.0433
Male	16-29	High	MYH	East Midlands	0.0758	7	0.1041	2	-0.0283
Male	16-29	High	MYH	West Midlands	0.0581	11	0.0688	10	-0.0107
Male	16-29	High	MYH	East of England	0.0942	1	0.0788	6	0.0153
Male	16-29	High	MYH	London	0.0661	9	0.0393	19	0.0268
Male	16-29	High	MYH	South East	0.0839	4	0.0839	4	0
Male	16-29	High	MYH	South West	0.0913	2	0.1034	3	-0.0121
Male	16-29	High	MYH	Wales	0.077	6	0.1245	1	-0.0475
Male	16-29	High	MYH	Scotland	0.0409	18	0.041	17	-0.0001
Male	16-29	Intermediate	MYI	North East	0.0208	43	0.0222	36	-0.0014
Male	16-29	Intermediate	MYI	North West	0.0134	54	0.017	50	-0.0036
Male	16-29	Intermediate	MYI	Yorkshire/Humber	0.0257	27	0.0171	48	0.0087
Male	16-29	Intermediate	MYI	East Midlands	0.027	25	0.0158	53	0.0112
Male	16-29	Intermediate	MYI	West Midlands	0.0135	53	0.0122	64	0.0014
Male	16-29	Intermediate	MYI	East of England	0.0127	57	0.0299	25	-0.0171
Male	16-29	Intermediate	MYI	London	0.021	41	0.0253	29	-0.0043
Male	16-29	Intermediate	MYI	South East	0.0258	26	0.0235	32	0.0022
Male	16-29	Intermediate	MYI	South West	0.0273	24	0.021	39	0.0063
Male	16-29	Intermediate	MYI	Wales	0.0147	50	0.0194	43	-0.0047
Male	16-29	Intermediate	MYI	Scotland	0.0101	69	0.0055	122	0.0046
Male	16-29	Low	MYL	North East	0.0109	65	0.004	148	0.0069
Male	16-29	Low	MYL	North West	0.0005	194	0.0039	151	-0.0034
Male	16-29	Low	MYL	Yorkshire/Humber	0.0077	94	0.002	184	0.0057
Male	16-29	Low	MYL	East Midlands	0.0071	106	0.0048	129	0.0024
Male	16-29	Low	MYL	West Midlands	0.008	90	0.0036	154	0.0044
Male	16-29	Low	MYL	East of England	0.0071	108	0.003	165	0.0041
Male	16-29	Low	MYL	London	0.0073	103	0.0169	52	-0.0095
Male	16-29	Low	MYL	South East	0.0049	140	0.0083	88	-0.0035
Male	16-29	Low	MYL	South West	0.0105	67	0.0121	66	-0.0015
Male	16-29	Low	MYL	Wales	0.0039	158	0.0031	164	0.0008
Male	16-29	Low	MYL	Scotland	0	195	0	196	0

Note: excluding Northern Ireland.

Table A1.5: Males aged 30-49

Gender	**Age group**	**Qual**	**Label group**	**Region name**	**TO**	**Rank**	**FROM**	**Rank**	**TO - FROM**
Male	30-49	High	MMH	North East	0.0099	71	0.011	70	-0.0011
Male	30-49	High	MMH	North West	0.0103	68	0.0105	76	-0.0002
Male	30-49	High	MMH	Yorkshire/Humber	0.0148	49	0.0199	42	-0.005
Male	30-49	High	MMH	East Midlands	0.0169	47	0.0396	18	-0.0227
Male	30-49	High	MMH	West Midlands	0.0113	61	0.0171	49	-0.0057
Male	30-49	High	MMH	East of England	0.0227	33	0.0208	40	0.0019
Male	30-49	High	MMH	London	0.0077	93	0.0182	46	-0.0105
Male	30-49	High	MMH	South East	0.0224	34	0.0322	24	-0.0098
Male	30-49	High	MMH	South West	0.0207	44	0.0298	26	-0.0091
Male	30-49	High	MMH	Wales	0.0074	101	0.0227	35	-0.0153
Male	30-49	High	MMH	Scotland	0.0082	89	0.0035	155	0.0047
Male	30-49	Intermediate	MMI	North East	0.0028	170	0.0033	158	-0.0005
Male	30-49	Intermediate	MMI	North West	0.0037	160	0.0053	126	-0.0015
Male	30-49	Intermediate	MMI	Yorkshire/Humber	0.0043	153	0.0013	191	0.003
Male	30-49	Intermediate	MMI	East Midlands	0.0093	76	0.0056	119	0.0037
Male	30-49	Intermediate	MMI	West Midlands	0.0071	109	0.0043	143	0.0028
Male	30-49	Intermediate	MMI	East of England	0.0065	121	0.0054	124	0.0011
Male	30-49	Intermediate	MMI	London	0.005	136	0.0179	47	-0.0129
Male	30-49	Intermediate	MMI	South East	0.0099	72	0.012	68	-0.0021
Male	30-49	Intermediate	MMI	South West	0.0121	60	0.006	113	0.0061
Male	30-49	Intermediate	MMI	Wales	0.0059	128	0.0057	116	0.0001
Male	30-49	Intermediate	MMI	Scotland	0.0071	107	0.005	127	0.0021
Male	30-49	Low	MML	North East	0	195	0.0063	109	-0.0063
Male	30-49	Low	MML	North West	0.0074	100	0.0045	137	0.003
Male	30-49	Low	MML	Yorkshire/Humber	0.0033	165	0.0029	167	0.0004
Male	30-49	Low	MML	East Midlands	0.001	190	0.0027	174	-0.0017
Male	30-49	Low	MML	West Midlands	0.0044	150	0.0038	152	0.0007
Male	30-49	Low	MML	East of England	0.0042	154	0.0043	144	0
Male	30-49	Low	MML	London	0.0025	176	0.0149	56	-0.0124
Male	30-49	Low	MML	South East	0.009	82	0.0034	156	0.0055
Male	30-49	Low	MML	South West	0.003	168	0.0023	181	0.0007
Male	30-49	Low	MML	Wales	0.003	167	0.0028	172	0.0003
Male	30-49	Low	MML	Scotland	0.0049	137	0	196	0.0049

Note: excluding Northern Ireland.

Table A1.6: Males aged 50-70

Gender	Age group	Qual	Label group	Region name	TO	Rank	FROM	Rank	TO - FROM
Male	50-70	High	MOH	North East	0.0133	55	0.0076	97	0.0057
Male	50-70	High	MOH	North West	0.0048	141	0.0082	90	-0.0034
Male	50-70	High	MOH	Yorkshire/Humber	0.0052	133	0.0108	71	-0.0056
Male	50-70	High	MOH	East Midlands	0.0086	86	0.0056	117	0.003
Male	50-70	High	MOH	West Midlands	0.0076	97	0.0091	80	-0.0015
Male	50-70	High	MOH	East of England	0.009	81	0.0086	85	0.0004
Male	50-70	High	MOH	London	0.0053	131	0.0055	123	-0.0002
Male	50-70	High	MOH	South East	0.0051	134	0.0062	111	-0.001
Male	50-70	High	MOH	South West	0.0098	73	0.009	81	0.0008
Male	50-70	High	MOH	Wales	0.0244	30	0.0129	60	0.0115
Male	50-70	High	MOH	Scotland	0.0073	104	0.0062	110	0.001
Male	50-70	Intermediate	MOI	North East	0.001	189	0.0021	182	-0.0011
Male	50-70	Intermediate	MOI	North West	0.0032	166	0.0024	180	0.0009
Male	50-70	Intermediate	MOI	Yorkshire/Humber	0.0026	173	0.0015	189	0.0011
Male	50-70	Intermediate	MOI	East Midlands	0.0022	179	0.0053	125	-0.0031
Male	50-70	Intermediate	MOI	West Midlands	0.0069	111	0.0028	171	0.0041
Male	50-70	Intermediate	MOI	East of England	0.0049	138	0.0046	131	0.0002
Male	50-70	Intermediate	MOI	London	0.0019	181	0.012	67	-0.0102
Male	50-70	Intermediate	MOI	South East	0.007	110	0.0055	120	0.0014
Male	50-70	Intermediate	MOI	South West	0.0063	123	0.0029	168	0.0035
Male	50-70	Intermediate	MOI	Wales	0.0038	159	0.0024	179	0.0014
Male	50-70	Intermediate	MOI	Scotland	0.001	191	0.0027	173	-0.0018
Male	50-70	Low	MOL	North East	0	195	0.0019	185	-0.0019
Male	50-70	Low	MOL	North West	0.0017	183	0.0041	145	-0.0024
Male	50-70	Low	MOL	Yorkshire/Humber	0.0076	98	0.0071	102	0.0005
Male	50-70	Low	MOL	East Midlands	0.0066	117	0.0032	161	0.0034
Male	50-70	Low	MOL	West Midlands	0.0041	157	0.0045	136	-0.0005
Male	50-70	Low	MOL	East of England	0.0069	112	0.0078	93	-0.0009
Male	50-70	Low	MOL	London	0.0009	192	0.0083	89	-0.0074
Male	50-70	Low	MOL	South East	0.0072	105	0.0078	95	-0.0005
Male	50-70	Low	MOL	South West	0.0092	77	0.0046	135	0.0046
Male	50-70	Low	MOL	Wales	0.0046	146	0.0032	160	0.0014
Male	50-70	Low	MOL	Scotland	0.0045	149	0.0019	186	0.0026

Note: excluding Northern Ireland.

Table A2.1: Transition probabilities and wages, ITLS1 (part 1)

	(1)	(2)	(3)	(4)
Variables	**probto1**	**probto2**	**probto3**	**probto4**
lnwageh	-0.00134	0.00154	0.00797	-0.00081
	(0.00124)	(0.00275)	(0.00567)	(0.0118)
2011.year#c.lnwageh		-0.00305	-0.00245	-0.00269
		(0.00372)	(0.00323)	(0.00316)
2012.year#c.lnwageh		-0.00386	-0.00254	-0.0028
		(0.00425)	(0.00382)	(0.00377)
2013.year#c.lnwageh		-0.00212	-0.000915	-0.00104
		(0.00459)	(0.00378)	(0.00375)
2014.year#c.lnwageh		-0.00666	-0.00565	-0.00594
		(0.0065)	(0.00628)	(0.00623)
2015.year#c.lnwageh		-0.00192	-0.000207	-0.000376
		(0.00482)	(0.00429)	(0.00431)
2016.year#c.lnwageh		-0.00555	-0.00344	-0.00392
		(0.00425)	(0.00375)	(0.00379)
2017.year#c.lnwageh		-0.0031	-0.00111	-0.00187
		(0.00419)	(0.00378)	(0.00382)
2018.year#c.lnwageh		0.000638	0.00153	0.000549
		(0.0049)	(0.00415)	(0.00445)
year = 2011	-0.000168	0.00778	0.00649	0.00678
	(0.00201)	(0.00977)	(0.00848)	(0.00832)
year = 2012	0.00268	0.0127	0.00967	0.00987
	-0.00245	-0.0116	-0.0104	-0.0103
year = 2013	0.00531**	0.0109	0.00828	0.00798
	(0.00257)	(0.0121)	(0.00991)	(0.00981)
year = 2014	0.00434*	0.0215	0.0194	0.0195
	(0.00235)	(0.0175)	(0.0168)	(0.0167)
year = 2015	0.00322	0.0083	0.00427	0.00421
	(0.00243)	(0.0131)	(0.0115)	(0.0116)
year = 2016	0.00256	0.0169	0.0118	0.0127
	(0.00238)	(0.0114)	(0.00996)	(0.01)
year = 2017	0.00116	0.00923	0.00437	0.00599
	(0.00227)	(0.0117)	(0.0103)	(0.0104)
year = 2018	0.00222	0.000686	-0.00137	0.00083
	(0.00246)	(0.0128)	(0.0108)	(0.0114)
grp = 2, FML			-0.00543	-0.0108
			(0.00367)	(0.00729)
grp = 3, FMI			-0.00436	-0.00844
			(0.00296)	(0.00565)
grp = 4, FOH			-0.00438**	-0.00390**
			(0.00175)	(0.00173)
grp = 5, FOL			-0.00499	-0.0105
			(0.00374)	(0.00749)
grp = 6, FOI			-0.00448	-0.0083
			(0.0028)	(0.0053)
grp = 7, FYH			0.0433***	0.0394***
			(0.00482)	(0.00662)
grp = 8, FYL			0.00306	-0.0052
			(0.00545)	(0.0113)
grp = 9, FYI			0.0133***	0.00617
			(0.00489)	(0.00977)

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A2.2: Transition probabilities and wages, ITLS1 (part 2)

Variables	(1) probto1	(2) probto2	(3) probto3	(4) probto4
grp = 10, MMH			-0.000304	0.00141
			(0.00208)	(0.00282)
grp = 11, MML			-0.00670**	-0.0101**
			(0.00264)	(0.00486)
grp = 12, MMI			-0.00496***	-0.00689**
			(0.00188)	(0.00293)
grp = 13, MOH			-0.00568**	-0.003
			(0.00252)	(0.004)
grp = 14, MOL			-0.00577**	-0.00917*
			(0.00259)	(0.00477)
grp = 15, MOI			-0.00812***	-0.00978***
			(0.00174)	(0.0026)
grp = 16, MYH			0.0556***	0.0524***
			(0.00548)	(0.00669)
grp = 17, MYL			-0.00173	-0.00908
			(0.00504)	(0.0102)
grp = 18, MYI			0.0103**	0.00448
			(0.00419)	(0.00809)
ITLS1 = 2, UKD				-0.00426*
				(0.00237)
ITLS1 = 3, UKE				-0.00265
				(0.00255)
ITLS1 = 4, UKF				0.00409
				(0.00282)
ITLS1 = 5, UKG				-0.000196
				(0.00247)
ITLS1 = 6, UKH				0.00409
				(0.00309)
ITLS1 = 7, UKI				-0.000654
				(0.00353)
ITLS1 = 8, UKJ				0.00375
				(0.00324)
ITLS1 = 9, UKK				0.00433
				(0.00275)
ITLS1 = 10, UKL				-0.000338
				(0.00288)
ITLS1 = 11, UKM				-0.00684***
				(0.00254)
Constant	0.0156***	0.00804	-0.0126	0.0136
	(0.00354)	(0.00727)	(0.0168)	(0.0343)
Observations	1,782	1,782	1,782	1,782
R-squared	0.005	0.006	0.433	0.451

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3.1: Transition probabilities and wages, ITLS2 (part 1)

Variables	(1) probto1	(2) probto2	(3) probto3	(4) probto4
lnwageh	0.00233	0.00259	0.0396***	0.00836
	(0.00184)	(0.00247)	(0.00947)	(0.0145)
1.period#c.lnwageh		-0.000543	0.00282	0.00121
		(0.00369)	(0.00291)	(0.00298)
period = 1, Waves 6-10	0.00119	0.0026	-0.0054	-0.00181
	(0.00192)	(0.00964)	(0.0077)	(0.00787)
grp = 2, FML			0.0088	-0.0102
			(0.00614)	(0.00894)
grp = 3, FMI			0.00708	-0.0071
			(0.00477)	(0.00695)
grp = 4, FOH			-0.0115***	-0.00985***
			(0.00254)	(0.00247)
grp = 5, FOL			0.00767	-0.0117
			(0.00617)	(0.00921)
grp = 6, FOI			0.0028	-0.0107
			(0.00452)	(0.00652)
grp = 7, FYH			0.0756***	0.0620***
			(0.00818)	(0.00861)
grp = 8, FYL			0.0288***	-0.000339
			(0.00919)	(0.0137)
grp = 9, FYI			0.0456***	0.0205*
			(0.00877)	(0.0122)
grp = 10, MMH			-0.00456	0.00155
			(0.00335)	(0.00379)
grp = 11, MML			0.00152	-0.0105*
			(0.0045)	(0.0059)
grp = 12, MMI			-0.0011	-0.00765**
			(0.00306)	(0.00365)
grp = 13, MOH			-0.0205***	-0.0113**
			(0.00374)	(0.00492)
grp = 14, MOL			-0.00107	-0.0129**
			(0.00419)	(0.00581)
grp = 15, MOI			-0.00857***	-0.0143***
			(0.00269)	(0.00331)
grp = 16, MYH			0.0934***	0.0826***
			(0.00841)	(0.00896)
grp = 17, MYL			0.0214**	-0.00446
			(0.00867)	(0.0124)
grp = 18, MYI			0.0344***	0.0138
			(0.00743)	(0.01)
ITLS2 = 2, UKC2				-0.0067
				(0.0054)
ITLS2 = 3, UKD1				0.00386
				(0.00585)
ITLS2 = 4, UKD3				-0.00636
				(0.00451)
ITLS2 = 5, UKD4				-0.00399
				(0.00527)
ITLS2 = 6, UKD6				0.012
				(0.0103)
ITLS2 = 7, UKD7				-0.0118**
				(0.00598)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3.2: Transition probabilities and wages, ITLS2 (part 2)

Variables	(1) probto1	(2) probto2	(3) probto3	(4) probto4
ITLS2 = 8, UKE1				-0.00615
				(0.00615)
ITLS2 = 9, UKE2				0.00508
				(0.00701)
ITLS2 = 10, UKE3				-0.00860*
				(0.00516)
ITLS2 = 11, UKE4				-0.00302
				(0.00475)
ITLS2 = 12, UKF1				9.28E-05
				(0.00507)
ITLS2 = 13, UKF2				-0.00194
				(0.00506)
ITLS2 = 14, UKF3				0.00698
				(0.00601)
ITLS2 = 15, UKG1				0.0173**
				(0.00838)
ITLS2 = 16, UKG2				-0.00637
				(0.00499)
ITLS2 = 17, UKG3				-0.00332
				(0.00534)
ITLS2 = 18, UKH1				-0.00185
				(0.00492)
ITLS2 = 19, UKH2				0.000941
				(0.00572)
ITLS2 = 20, UKH3				-0.000775
				(0.0059)
ITLS2 = 21, UKI3				0.0357***
				(0.0101)
ITLS2 = 22, UKI4				0.00868
				(0.00624)
ITLS2 = 23, UKI5				0.00175
				(0.00586)
ITLS2 = 24, UKI6				0.0134
				(0.00915)
ITLS2 = 25, UKI7				-0.00215
				(0.00559)
ITLS2 = 26, UKJ1				0.00118
				(0.0056)
ITLS2 = 27, UKJ2				0.00446
				(0.00572)
ITLS2 = 28, UKJ3				0.00425
				(0.00566)
ITLS2 = 29, UKJ4				-0.00391
				(0.00593)
ITLS2 = 30, UKK1				0.00237
				(0.0054)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

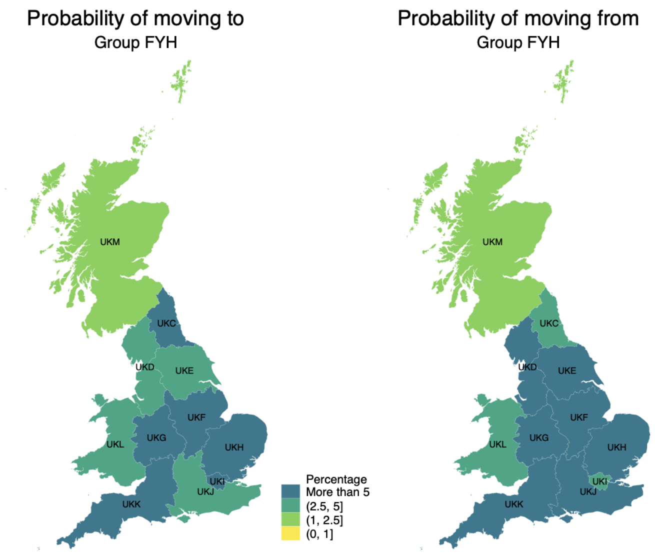
Table A3.3: Transition probabilities and wages, ITLS2 (part 3)

Variables	(1) probto1	(2) probto2	(3) probto3	(4) probto4
ITLS2 = 31, UKK2				-0.00107
				(0.00547)
ITLS2 = 32, UKK3				0.0123
				(0.00796)
ITLS2 = 33, UKK4				0.00264
				(0.00516)
ITLS2 = 34, UKL1				-0.00636
				(0.00491)
ITLS2 = 35, UKL2				0.00793
				(0.00708)
ITLS2 = 36, UKM5				-0.00732
				(0.00691)
ITLS2 = 37, UKM6				0.00668
				(0.00636)
ITLS2 = 38, UKM7				-0.0043
				(0.00495)
ITLS2 = 39, UKM8				-0.00658
				(0.00534)
ITLS2 = 40, UKM9				0.00413
				(0.00591)
Constant	0.0170***	0.0163***	-0.0949***	-0.00388
	(0.00478)	(0.0063)	(0.0279)	(0.0422)
Observations	1,438	1,438	1,438	1,438
R-squared	0.001	0.001	0.507	0.554

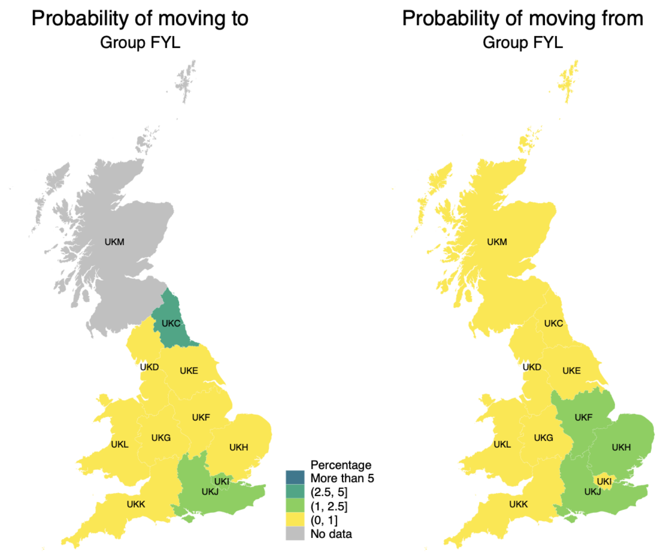
Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1.1: Regional probability of moving (part 1)

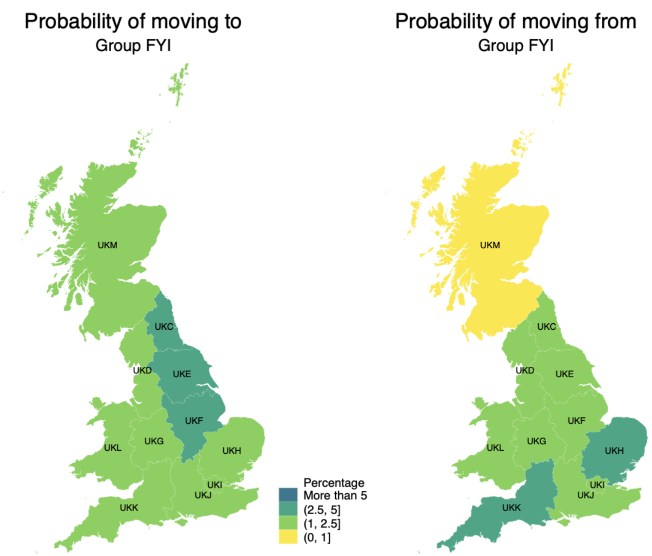
(A) Female-Young-High education, ITLS1



(B) Female-Young-Intermediate education, ITLS1



(C) Female-Young-Low education, ITLS1



(D) Female-Middle age-High education, ITLS1

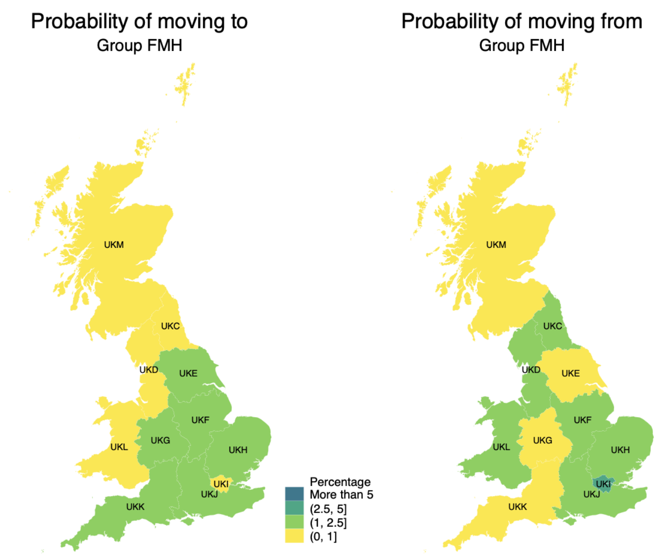
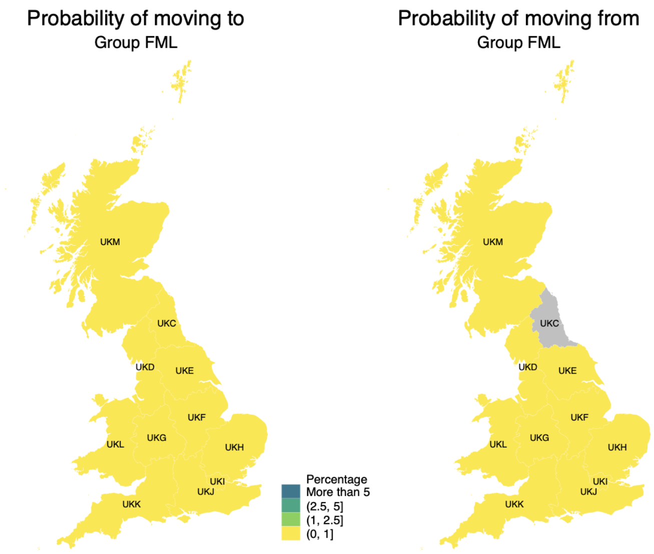
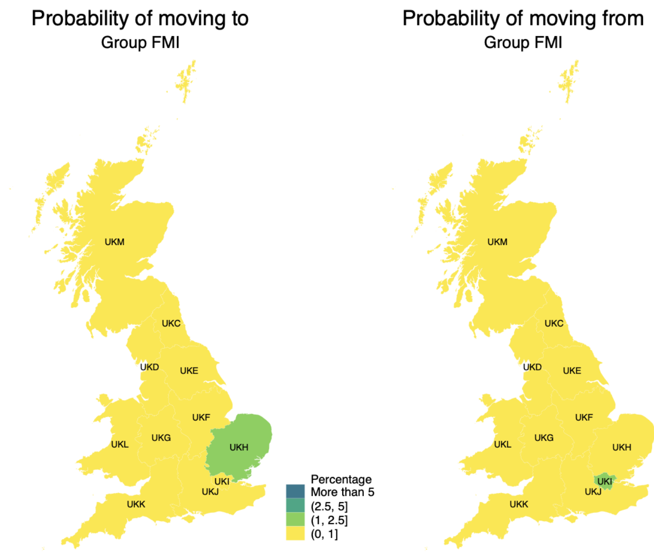


Figure 1.2: Regional probability of moving (part 2)

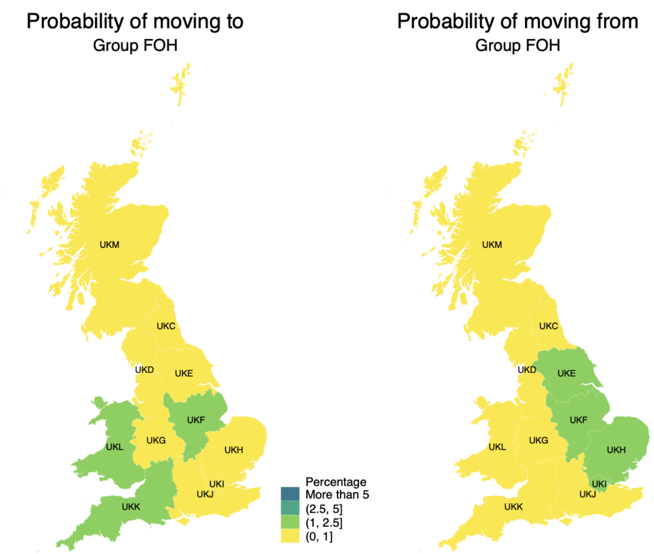
(A) Female-Middle age-Intermediate education, ITLS1



(B) Female-Middle age-Low education, ITLS1



(C) Female-Older-High education, ITLS1



(D) Female-Older-Intermediate education, ITLS1

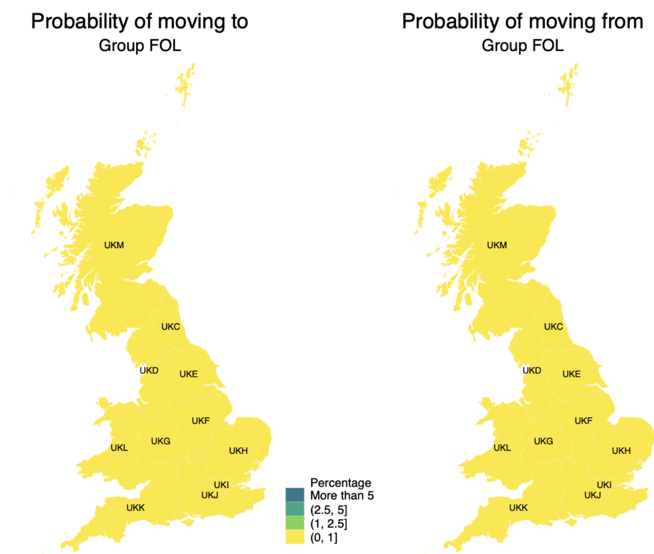
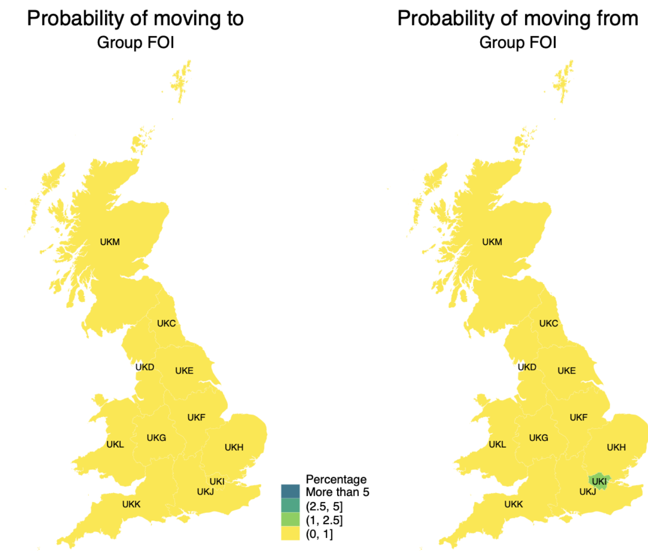
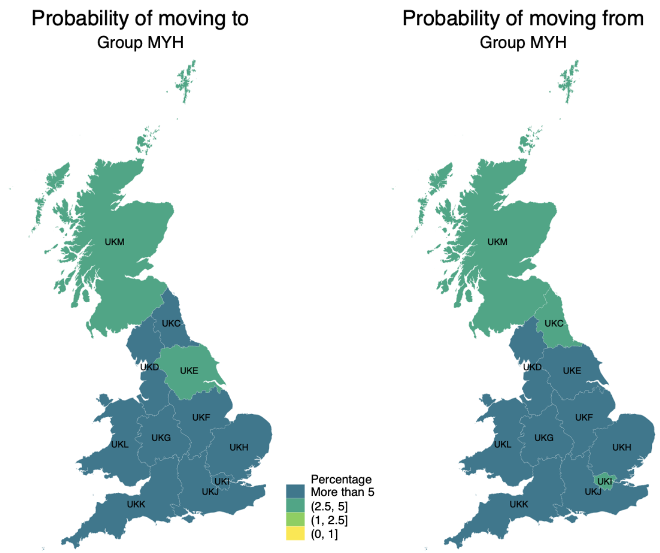


Figure 1.3: Regional probability of moving (part 3)

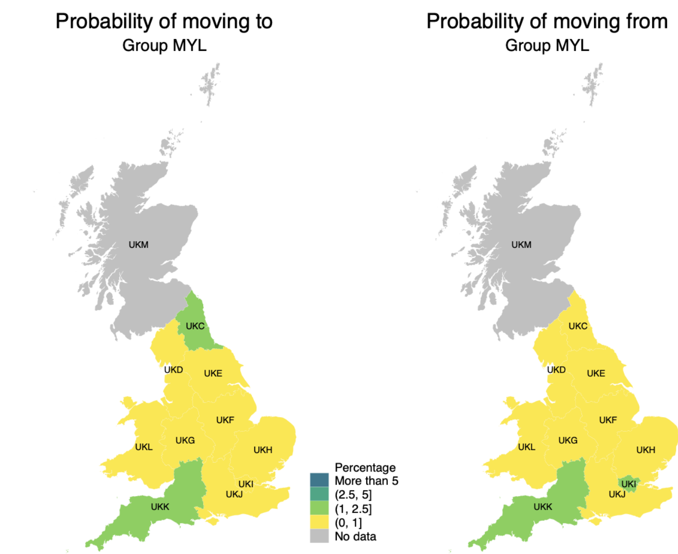
(A) Female-Older-Low education, ITLS1



(B) Male-Young-High education, ITLS1



(C) Male-Young-Intermediate education, ITLS1



(D) Male-Young-Low education, ITLS1

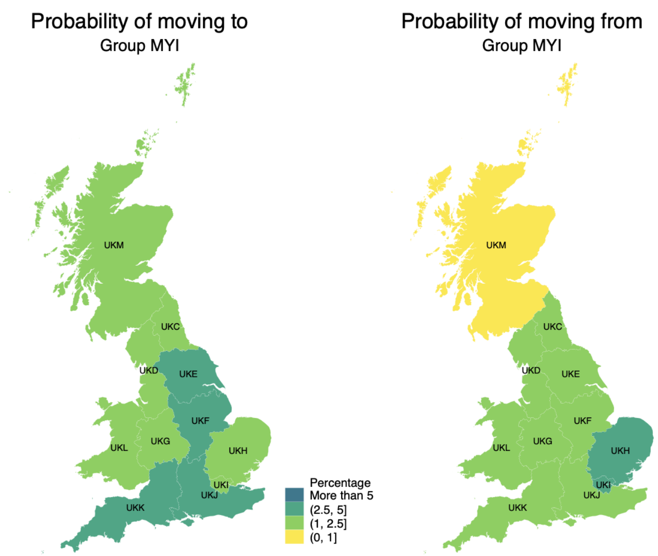
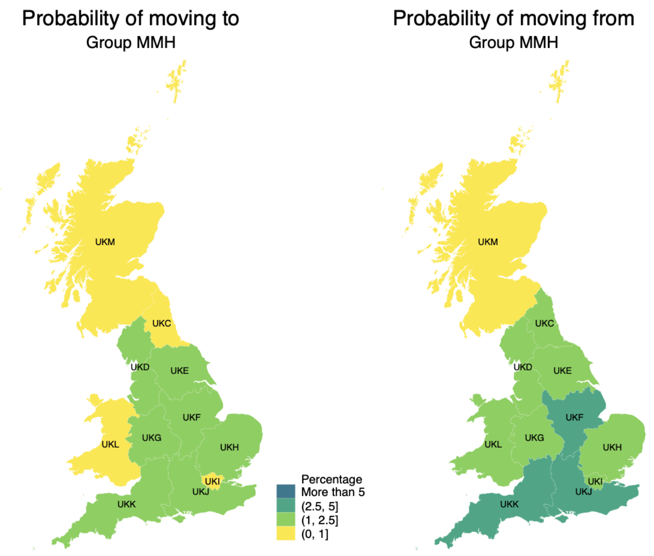
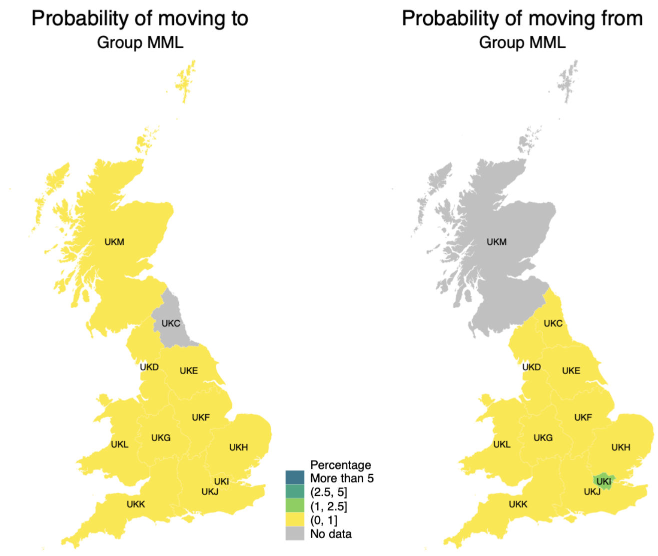


Figure 1.4: Regional probability of moving (part 4)

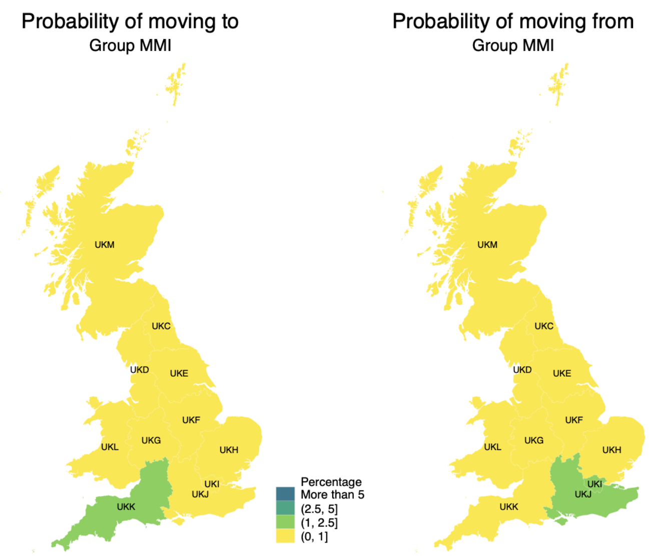
(A) Male-Middle age-High education, ITLS1



(B) Male-Middle age-Intermediate education, ITLS1



(C) Male-Middle age-Low education, ITLS1



(D) Male-Older-High education, ITLS1

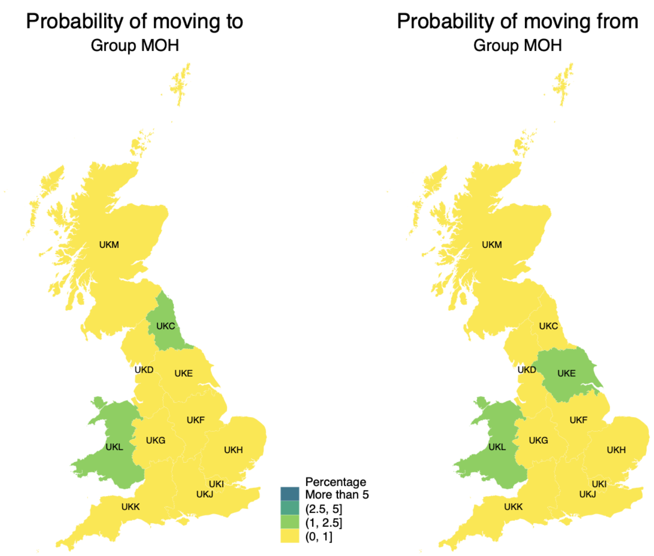
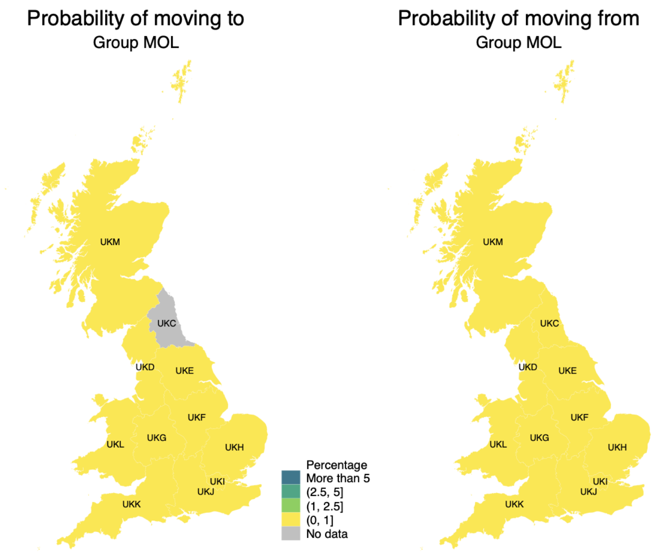
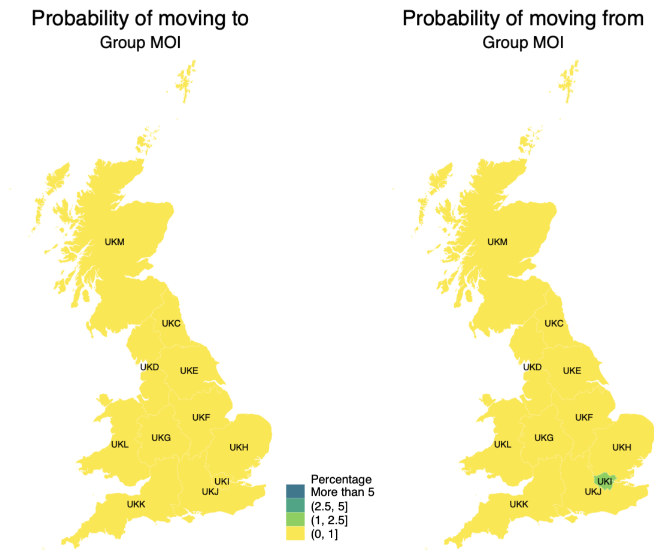


Figure 1.5: Regional probability of moving (part 5)

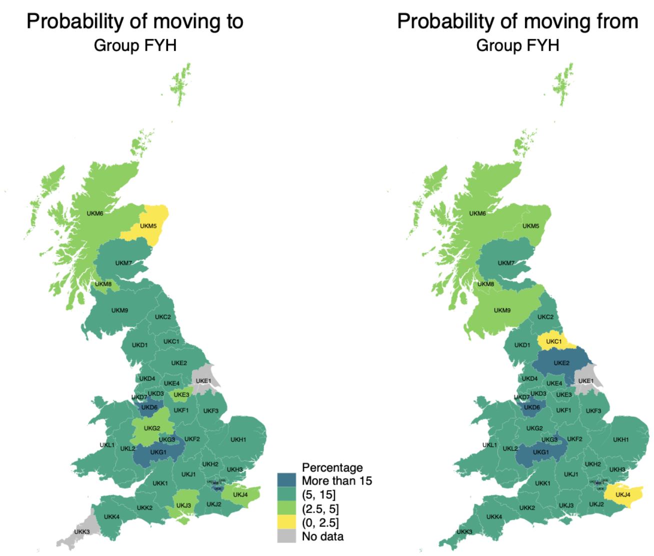
(A) Male-Older-Intermediate education, ITLS1



(B) Male-Older-Low education, ITLS1



(C) Female-Young-High education, ITLS2



(D) Female-Young-Intermediate education, ITLS2

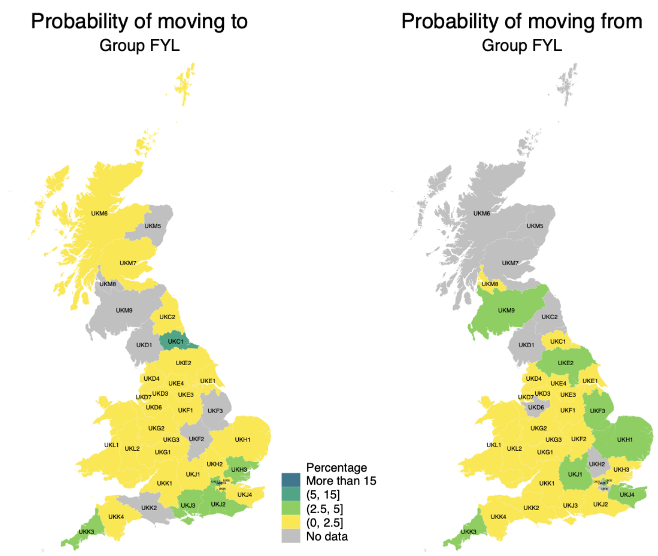
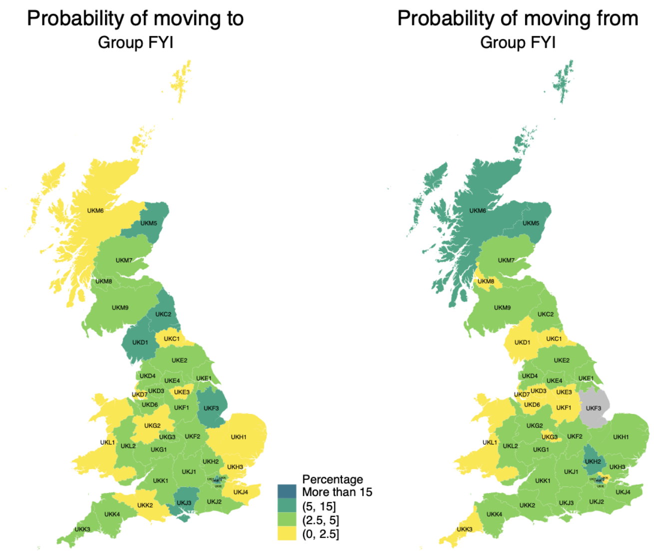
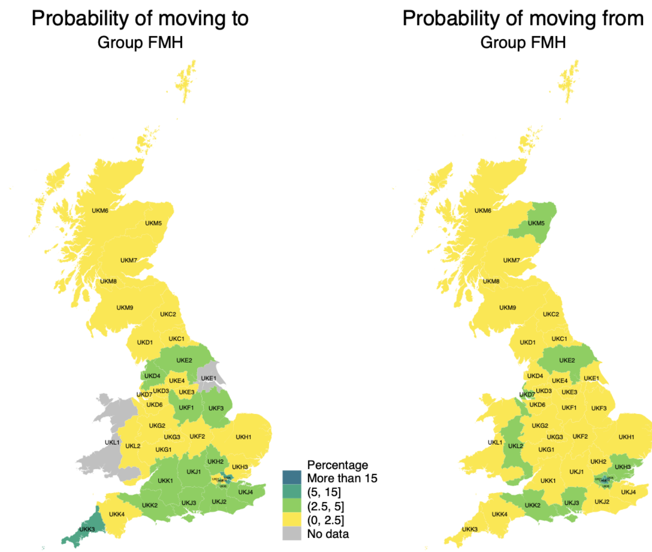


Figure 1.6: Regional probability of moving (part 6)

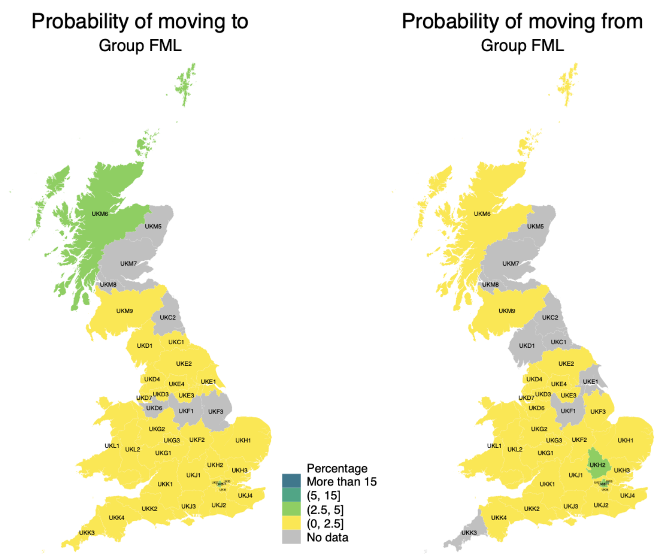
(A) Female-Young-Low education, ITLS2



(B) Female-Middle age-High education, ITLS2



(C) Female-Middle age-Intermediate education, ITLS2



(D) Female-Middle age-Low education, ITLS2

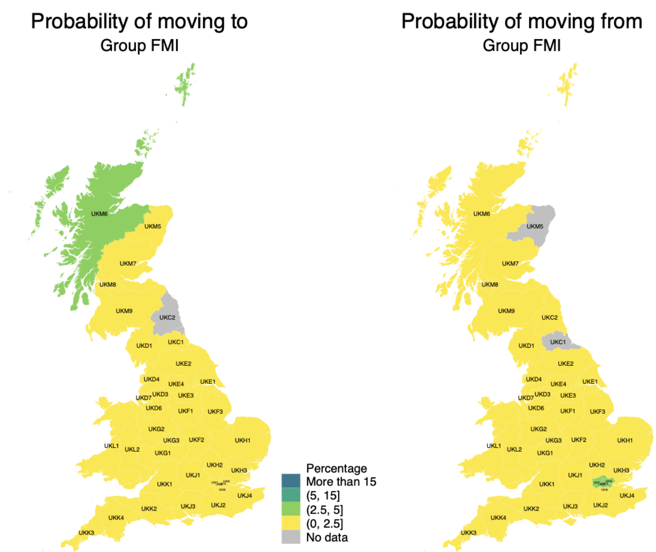
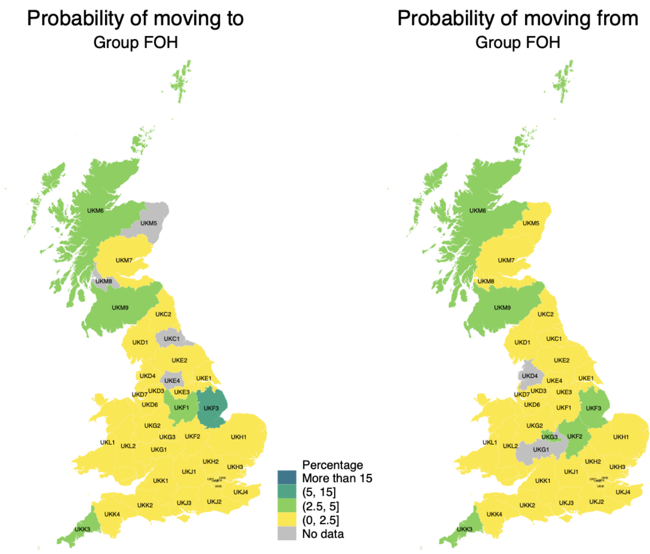
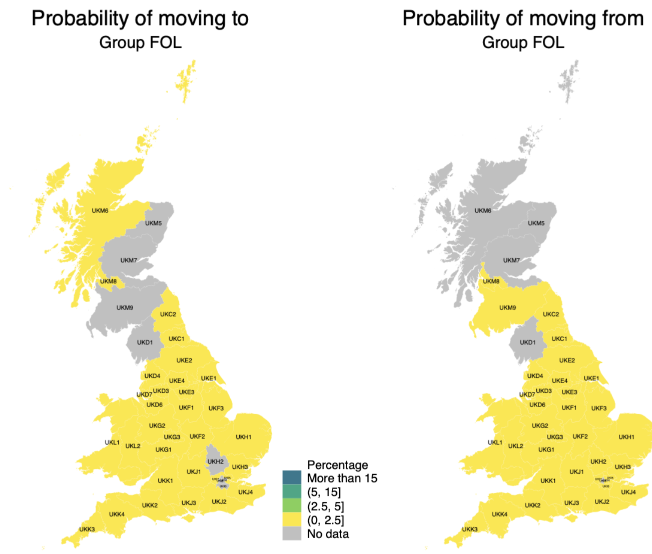


Figure 1.7: Regional probability of moving (part 7)

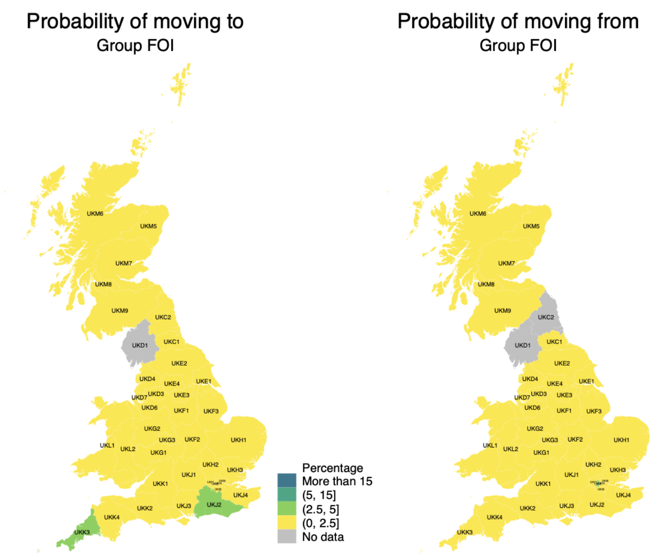
(A) Female-Older-High education, ITLS2



(B) Female-Older-Intermediate education, ITLS2



(C) Female-Older-Low education, ITLS2



(D) Male-Young-High education, ITLS2

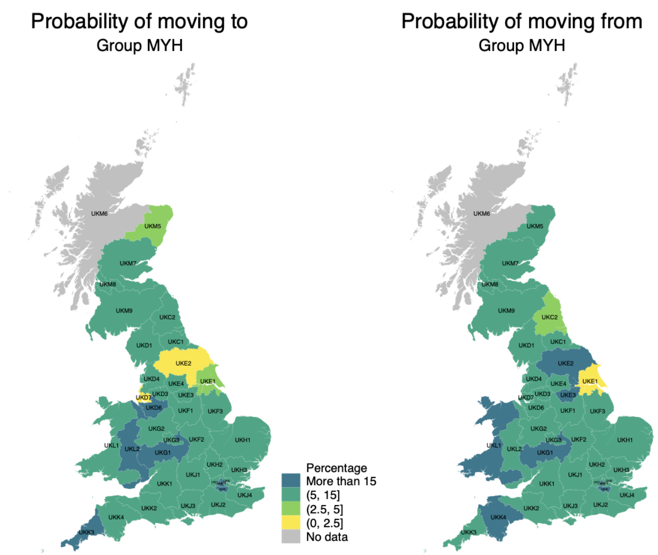
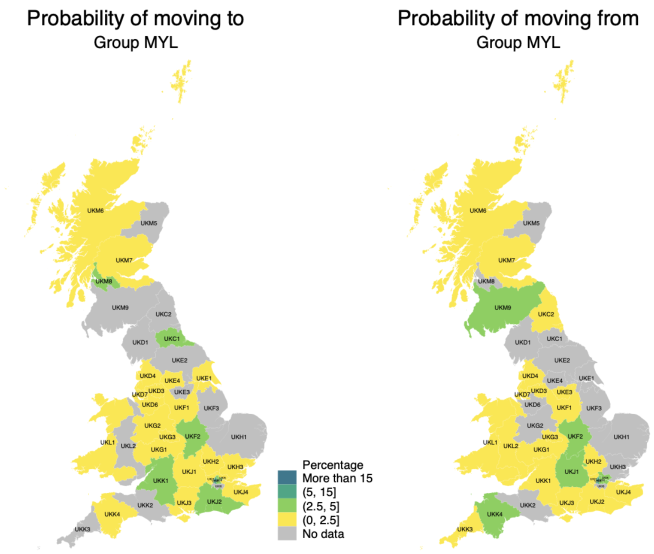
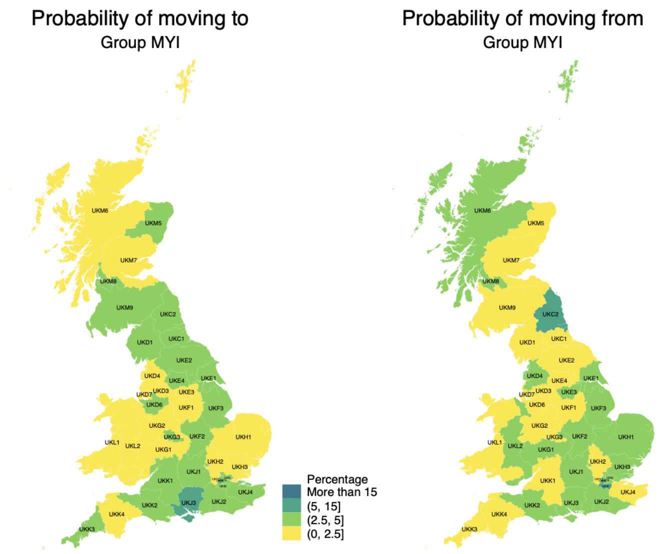


Figure 1.8: Regional probability of moving (part 8)

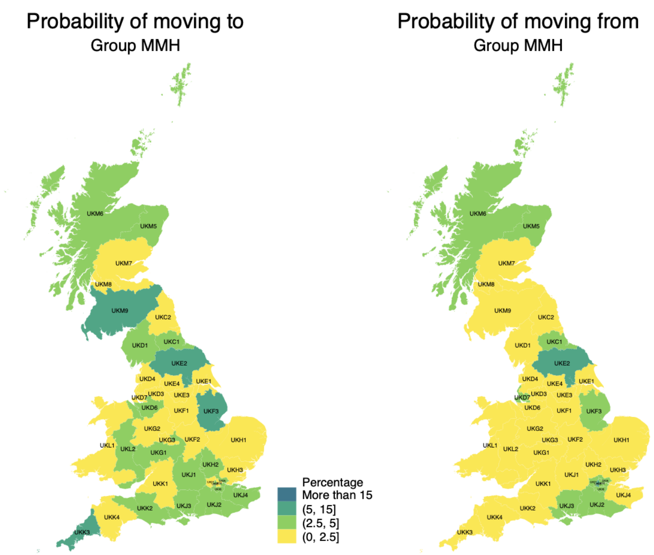
(A) Male-Young-Intermediate education, ITLS2



(B) Male-Young-Low education, ITLS2



(C) Male-Middle age-High education, ITLS2



(D) Male-Middle age-Intermediate education, ITLS2

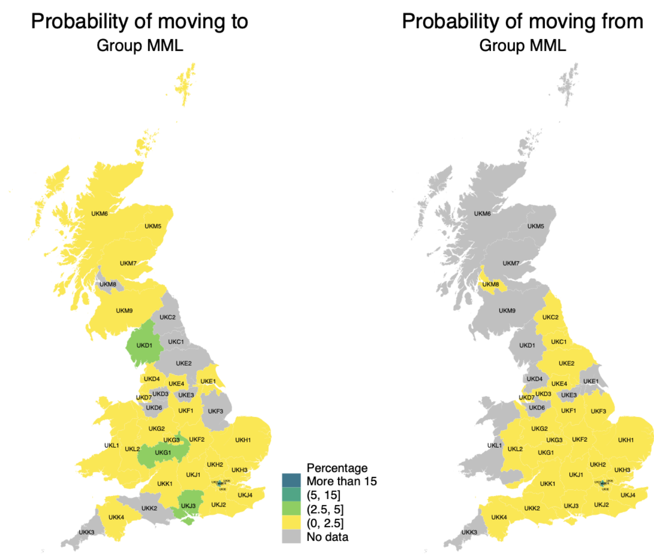
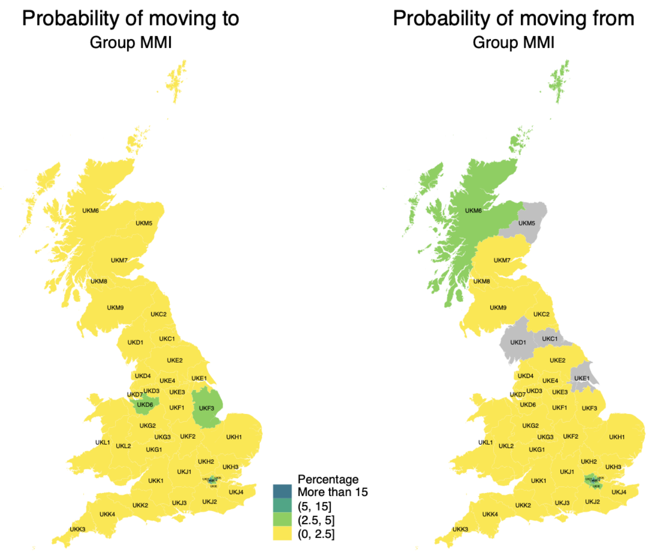
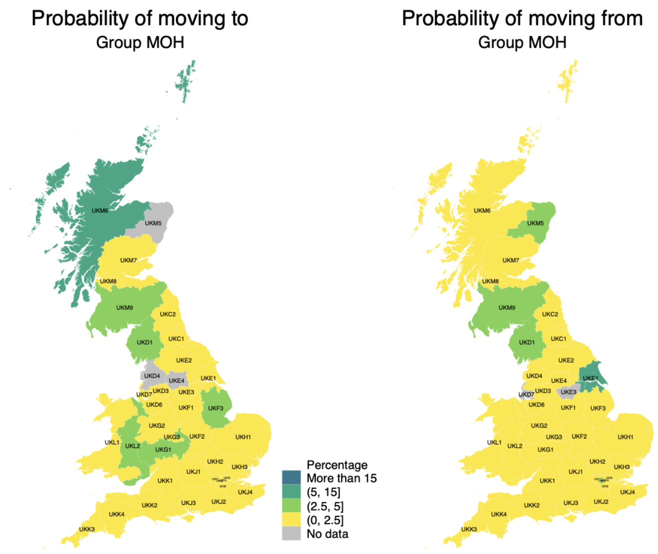


Figure 1.9: Regional probability of moving (part 9)

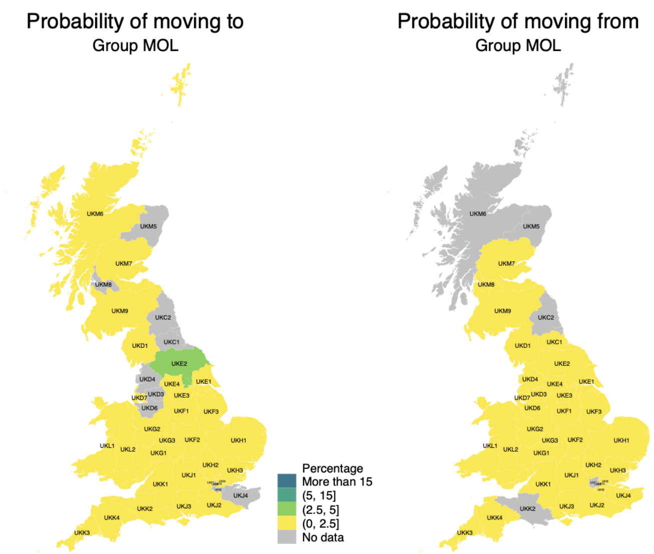
(A) Male-Middle age-Low education, ITLS2



(B) Male-Older-High education, ITLS2



(C) Male-Older-Intermediate education, ITLS2



(D) Male-Older-Low education, ITLS2