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The Changing Geography of Intergenerational Mobility

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Abstract

Does the importance of your family background on how far you get in adulthood also depend on where you grow up? For many countries, Britain included, a paucity of data has made this a question with very little reliable evidence to answer. To redress this evidence lacuna, we present a new analysis of intergenerational mobility across three cohorts in England and Wales using linked decennial census microdata. As well as testing the robustness of existing survey evidence on mobility trends over time, this large dataset permits analysis to be undertaken at a more geographically disaggregated level than was previously feasible. Evidence is presented on occupational wages, home ownership and education. Our new analysis shows a slight decline in occupation-wage mobility and a substantial decline in home ownership mobility over the late 20th century in England and Wales, while the picture for educational mobility is less clear. Focusing on the most recent cohort, we find marked geographic differences in mobility. We find that occupation-wage mobility is exceptionally high in London, while ex-industrial and mining areas experience the lowest rates of mobility. Areas with low occupation-wage mobility were more likely to vote to leave the European Union in the 2016 referendum. Home ownership mobility is negatively correlated with house prices and not correlated with occupation-wage mobility, suggesting that geographical comparisons based on one dimension of mobility need not always align with those based on alternative measures.

JEL Codes: J62; R23; R31; I24

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1. Introduction

There is copious evidence showing life chances are affected by family background. Children whose parents went to university are themselves more likely to do so, they are more likely to be higher earners if their parents were, and it is the same story for home ownership.[1] What is far less clear, and for which there is almost no evidence for the UK, is whether the role of family background is attenuated or enhanced by the locality in which you grow up. In other words, is the link between child and parental university attendance the same in Liverpool as in Lambeth? If you father was a low-skilled worker does the probability that you become a high-skilled professional depend on whether you grew up in Oldham or Oxford? Such questions are both intrinsically interesting for academic research and at the same time crucial for policy.

Much of the existing evidence on intergenerational mobility in the UK focusses on small longitudinal studies that follow a group of people born in the same week in a particular year. These cohort studies tend to be infrequent, suffer from significant attrition over time and do not provide a large enough sample to provide estimates at anything other than the aggregate national level. There are some reported estimates of social mobility at a more disaggregated level, but in general these do not directly measure mobility. For example, the Social Mobility Commission publishes an annual report that provides estimates of a social mobility index. Part of this index follows children who receive government-provided free school meals at school and examines their educational outcomes. To the extent that free school meals are a measure of parental disadvantage, this goes some way to measuring mobility. However, the other components of the index focus on wages, employment, occupation and home ownership in an area for all adults, irrespective of background. In other words, they measure the economic outcomes of an area rather than the mobility experienced by individuals in that area. As acknowledged in Social Mobility Commission (2017), this is a limited proxy of spatial differences in intergenerational mobility.

By using linked decennial census data contained in the Longitudinal Study of England and Wales (LS), we are able to make significant progress on measuring geographic levels and trends of intergenerational mobility.[2] The LS data are a 1% cohort sample from the decennial census. They can be used to follow three cohorts of individuals born in 1955-61, 1965-71 and

[1] For reviews of the economic literature on intergenerational mobility see Black and Devereux (2011), the vast sociology literature on social class is discussed in Bukoki and Goldthorpe (2018) and a more populist discussion is given in Elliot Major and Machin (2018).

[2] As the census is administered separately for Scotland and Northern Ireland, these areas are excluded from this dataset. As of 2015, these omitted countries constitute approximately 11% of the UK population.

1975-81 over time. We can observe parental education, occupation and home ownership when the individual cohort members were aged 10-16 and living with their parents. We then examine the same outcomes for the cohort members when aged 30-36.

This dataset therefore allows us to focus explicitly on intergenerational mobility rather than other demographics of an area that may – or may not – be correlated with mobility. And it allows us to focus on the geography of mobility because the sample sizes are an order of magnitude larger than the cohort data used in most previous studies, including the classic study of Blanden et al. (2004) which first drew attention to falling social mobility in Britain. By focusing on a range of outcomes we aim to develop a richer picture of the geography of intergenerational mobility. We show that there are some distinct geographic differences in the various measures.

One potential drawback is that, unfortunately, the UK census does not record wages or income and so we are unable to use this common metric to measure intergenerational mobility. There is in fact no dataset in the UK that would ever be able to generate such estimates at the sub-national level, though the recent availability of computerised income tax records may open up the possibility of using such a measure in the future. On the upside, because we have three successive cohorts, we are able to provide estimates not just of the level of mobility but also changes over time. In addition, we are able to observe a much broader set of characteristics than those commonly available in tax return data.

While the focus of this paper is on providing estimates of mobility at a sub-national level, we are also able to comment on national trends over time. Our analysis based on LS represents a significant improvement on previous evidence based on small surveys, hence we see these national estimates as a valuable additional contribution. Comparing the 1955-61 birth cohort against the 1975-81 cohort we find that occupation-wage mobility has slightly fallen, broadly consistent with the existing evidence based on small surveys. Home ownership mobility, broadly defined as the likelihood of owning a home if your parents did not own a home, has fallen dramatically, again consistent with existing evidence. In terms of education (degree) mobility, this period saw an explosive rise in higher education enrolment, which makes it difficult to make clear comparisons over time. Our analysis based on two different measures suggests that education mobility has risen according to odds-based measures, but has fallen according to coefficient-based measures. While the UK's dramatic higher education expansion led to many more children of non-degree holders attending university, it also led to an increase in enrolment among those whose parents went to university. Overall, the percentage point gap in enrolment probabilities between the two groups actually increased, so in this sense educational mobility fell. However in terms of the number of times more likely the children of degree holders are to attend university than the children of non-degree holders, educational mobility has risen.

Our main analysis points to there being very substantial differences in the levels of mobility across England and Wales. Consider the cohort born in the late 1970s and early 1980s. For this group, the probability that the child obtains a university degree if at least one of their parents had a degree was 79%, compared to 35% if neither parent had a degree. This is an attainment gap of 44% percentage points. But this gap ranged from 42% in the South East of England to 48% in Yorkshire and Humberside. At the even more granulated level, this attainment gap falls to 37% in Kent but is 53% in Inner East London.

Similarly, if we focus on the probability of moving from the bottom tercile of the occupation distribution (ranked according to median wages within occupations) to the top tercile in a generation, the national transition probability for the same cohort is 22%. But this is as high as 30% for those growing up in London and only 17% for those in Yorkshire and Humberside. In terms of home ownership, for those whose parents owned a home, the probability of home ownership is 31 percentage points higher than it is for those whose parents are not homeowners. This gap ranges from 25 percentage points in Wales to 38 percentage points in London.

Our data also allows us to test whether regional differences in mobility have increased over time. How has the dispersion of mobility changed over time across regions of England and Wales? Comparing the cohort born in the late 1950s and early 1960s to that born in the late 1970s and early 1980s, we see that occupation-wage mobility gaps have widened, as have home ownership mobility gaps. The career prospects and chances of owning a home of those from different parental backgrounds for the latest cohort depends more on the region of birth than it did for those born in the mid 20th century. Regional education mobility gaps however have closed over this same time period.

While the existence of variation across geographical areas is interesting in its own right, the real value of producing such estimates is that it allows us to start considering the causes, and implications of variation in intergenerational mobility. While a thorough analysis of the mechanisms leading to different levels of mobility is outside of the realms of this paper, we present correlations of our geographical estimates with several variables. Firstly, we demonstrate that the high occupation-wage mobility experienced by London is not part of a general trend of high mobility in cities. Whatever is driving the exceptional mobility of London is something particular about London rather than a broader urban-rural divide. Secondly, we show that occupation-wage mobility is lowest in ex-industrial and mining areas. Third, we demonstrate that home ownership mobility is related to house prices, such that areas with higher house prices have lower rates of home ownership mobility. Finally, we show that areas experiencing low occupation-wage mobility were more likely to vote to leave the EU in the 2016 referendum.

This paper adds to the growing literature on the geography of opportunity spearheaded by the US administrative data work of Chetty, Hendren, Kline and Saez (2014). Chetty et al. use linked income tax records of more than 40 million children and their parents in the US to examine how intergenerational mobility varies across the country. They show, as we do for England and Wales, that there is substantial geographic variation in mobility across the US. For example, the probability that a child reaches the top quintile of the national income distribution starting from a family in the bottom quintile is 4.4% in Charlotte, North Carolina but 12.9% in San Jose, California. Additionally, they show that high mobility areas have less residential segregation, less income inequality, better primary schools, greater social capital and greater family stability.

Tan (2018) has considered the Chetty et al. spatial estimates in an earlier time period, looking at Census data from the early 20th century in the United States. In a comparative context that is interesting and relevant for our analysis of changes over time in England and Wales, he finds that the geography of intergenerational mobility looked rather different in 1910 and 1940 Census data. Back then, mobility across generations was higher for those growing up in the industrial Midwest and the coastal areas of the US. This contrasts with the more recent spatial patterns in the Chetty et al. study.

In subsequent work on the recent data, Chetty and Hendren (2018a, b) generate casual estimates of the impact of neighbourhoods on intergenerational mobility by exploiting family moves from one area to another that occur at different ages for different children within a family. Provided the selection effect inherent in moving areas is not correlated with the age of the child, this generates a causal estimate. They present evidence that supports the validity of this identification assumption. They also provide estimates of mobility at the county-level for the United States – 3,000 in total. These estimates reinforce the message of their original paper that mobility varies substantially across the country, but also highlights how it varies locally. For example, if a child moved at birth from Cook County (in the city of Chicago) to DuPage County (a western suburb 20 miles from Chicago), they would on average increase their income in adulthood by 30%. To our knowledge, there currently exist few other papers looking at regional aspects of mobility. One exception is Heidrich (2017), who shows evidence of geographic variation in income mobility across Sweden.

Focusing on educational attainment rather than income, Card, Domnisoru and Taylor (2018) use the 1940 census data to examine the intergenerational transmission of human capital for children born in the 1920s. They find lower average mobility rates for blacks than whites, but consistent with Chetty et al., wide variation across states and counties for both races. Perhaps the most striking result in their paper is the strong positive correlation between education mobility for the 1920s cohort and income mobility for the 1980-83 cohort as measured by Chetty et al. across the counties of the US. The correlation coefficient is 0.45, suggesting a high degree of persistence in local factors affecting intergenerational mobility in the US given that the two cohorts were born 60 years apart.

2. Data

The main dataset is the Longitudinal Study of England and Wales (LS). The LS contains linked decennial census and life events data for a 1% sample of the population. It contains records on over 500,000 people at any point in time. Records have been linked at each census since the 1971 Census, for people born on one of four selected dates spread throughout the calendar year. These four dates were used to update the sample at the 1981, 1991, 2001 and 2011 Censuses. Life events data are also linked for LS members, including births to sample mothers, deaths and cancer registrations via the National Health Service (NHS) number, a unique identifier held by almost all residents of England and Wales. New LS members enter the study through birth and immigration (if they are born on one of the four selected birth dates).

Only LS members can be followed over time, not their extended family. However, in each census, data are provided on all individuals in the LS member's household at the time of census enumeration. Importantly this means that to obtain data on parental outcomes we need to first observe the LS member at an age where they are living with their parents. We can then follow the LS member over subsequent years to observe their adult outcomes. Our core sample of cohorts are therefore those individuals aged 10-16 in the 1971, 1981 and 1991 censuses and who have at least one parent in the same household at this age. This corresponds to birth cohorts of 1955-1961, 1965-1971 and 1975-1981. In general, we measure the adult outcome for these cohorts two censuses after we first observe them. For example, the 1975-1981 birth cohort are first observed in 1991 aged 10-16. At this point we extract data on parental outcomes – the median age of parents is 41. We then use the 2011 census to measure adult outcomes for the children who are at that point aged 30-36. We select this age range as it is plausible that by this point, for most individuals occupational maturity has been reached, and most housing and education decisions have been made. We acknowledge however that for housing, the ideal age at which to observe outcomes is possibly greater than that which is possible here. Summary statistics for each cohort are presented in Table 1.

Our empirical analysis of intergenerational mobility focuses on three components: occupation, home ownership and education. As already noted, unlike studies such as Chetty et al. (2014), we do not directly observe individuals' earnings in the census dataset. However, as earnings mobility patterns have been a topic of immense debate and policy interest, we integrate external data on wages into our analysis, producing a hybrid occupation-wage measure. The New Earnings Survey (NES), and later the Annual Survey of Hours and Earnings (ASHE), provide estimates of weekly wages for detailed 3-digit occupation classifications for the period required. These large surveys are thought to be the most reliable source of wage information in the UK. They are based on a 1% sample of UK workers and exclude the self-employed. For the most recent ASHE, there are 494 different occupation codes. For each census, we assign each individual observed in LS the median weekly wage for their occupation from NES / ASHE. As will be discussed in the following section, we do not directly use this median weekly wage data in our analysis, instead using it to form rankings and quantiles on which we base our occupation-wage analysis. Due to low female labour-force participation in the early cohorts, we restrict our occupation-wage analysis to males.

We prefer to think of this simply as a way of ranking occupations by their market price rather than trying to impute earnings to our cohort members (and their parents) since we know that occupation is only one component of an individual's wage. However, cross-section wage regressions using Labour Force Survey data show that 3-digit occupation dummies individually explain 40% of the variation in wages compared to 15% for education, 2% for locality and 25% for industry. Therefore, it is plausible that geographical patterns in wage-ranked occupation measures are similar to those based on actual wage data. One advantage of our approach is that there have been three changes in occupation coding over our sample period. By simply allocating the median wage to each occupation we mitigate the problems involved in trying to generate consistent occupation codes across censuses. Composition changes in the labour market through time cause well-established and understood problems for studying trends in social mobility over time based upon social class measures derived from occupations. This is because of changes in job employment structure and because, as wage inequality has risen over time in the UK, the distribution of wages has also widened within the social class groupings often used in such work. A detailed and very clear analysis of recent Labour Force Survey data by Friedman and Laurison (2016) makes this point clear, showing that studying social class mobility for broadly defined groups is misleading due to occupational shifts within the groups over time, as does the earnings analysis of Blanden, Gregg and MacMillan (2013).[3]

Home ownership measures whether the individual owns their own home, rather than renting or living in public housing. We do not distinguish between whether the home is owned outright or with a mortgage, nor whether the property is freehold or leasehold. The education variable has changed across the census years and we are therefore restricted to focus only on whether the cohort member (and either of their parents) have at least a first degree or not. Fortunately, there is extensive evidence to show that this distinction is the most important in terms of the labour market benefits to educational attainment – the wage premium for a degree relative to leaving school at the compulsory school leaving age was 90% whilst the premium for an additional two years of schooling was only 24% according to calculations from the Labour Force Survey. In the case when we can match to only one parent, we look only at the home ownership status and educational attainment of that parent.

The lowest-level consistent geographical information provided by LS is the local authority, of which there are currently 375 in England and Wales. Local authorities have merged and separated across our period of analysis but using records of these changes we are able to map each observation to its equivalent 2011 census local authority. Local authorities range in population size from several thousand (Isles of Scilly) to over a million (Birmingham). As many of these local authorities do not provide adequate sample sizes for meaningful analyses, we primarily use the European Union's standard geographical classifications (NUTS), which are built on the lower-level local authorities. NUTS1, our highest level of analysis, is equivalent to the ten broad regions of England and Wales. We also perform analysis at the NUTS2 level, of which there are 35 in England and Wales, and the NUTS3 level, of which there are 145.[4]

[3] See also the discussions of 'big' versus 'small' occupation measures and their usefulness or otherwise for studying social mobility, and especially for studying trends over time, in the work by Jonsson, Grusky, Di Carlo, Pollak and Brinton (2009).

[4] To give a sense of sample size, consider the 1975-81 cohort. As show in Table 1, we have data on 34,720 child-parent observations in England and Wales. At the NUTS1 level, the smallest cell is 1,868 (North East) and the largest is 5,297 (South East). At the NUTS2 level, the smallest cell is 323 observations (Cornwall and Isles of Scilly) and the largest is 1,876 (West Midlands). At NUTS3, the smallest cell is Westminster with 20 observations and the largest is Birmingham with 695 observations. In our analysis using NUTS3 results we weight by number of observations to account for the imprecision of estimates based on small sample sizes.

Our main analysis is based on the geographical location of residence for individuals when they are 10-16. Importantly due to migration this will not necessarily be the area in which we observe their adult outcomes aged 30-36. In this paper we do not distinguish between 'movers' and 'non-movers', although in future work we intend to explore this dimension.

Though our core sample are the birth cohorts 1955-61, 1965-71 and 1975-81, we extend these samples when we present sub-national results to increase sample size. For occupation and education measures, we sample children aged 8-17, who are therefore 28-37 when subsequently observed in adulthood. This corresponds to birth cohorts 1954-63, 1964-73, and 1974-83. For homeownership we maintain the core birth cohorts as homeownership tends to occur later in life than educational attainment and occupational choice, so we cannot justify extending the sample. In addition, the distribution of home ownership is such that power is less of a concern. To justify our sample extensions for the regional analyses, we demonstrate that our national results are essentially the same regardless of whether we use the core birth cohorts or the extended cohorts.

Attrition is low, particularly when compared to cohort studies on which previous UK research on mobility are based.[5] For our baseline 10-16 sample, in the 1971 cohort, we start with 53,809 individuals, 45,049 of whom are found at follow-up in 1991. When we restrict those matched to at least one parent in 1971, we are left with 42,907 individuals. Overall then, we retain 80% of our full initial sample. As the census is compulsory and has near-complete coverage, we therefore believe our results to be valid for the full population born in that period. For our 1981 cohort, the equivalent percentage is 76% and for the 1991 cohort it is also 76%. These high rates of follow-up are a key benefit to our study.

3. Methods

In this section, we discuss how we exploit the data described above to generate measures of mobility across our three components.

Intergenerational Mobility in Occupation

These measures are based on the imputed occupational wage data. Each individual is assigned a percentile rank. This rank refers to their position in the national occupational wage distribution within their cohort. For example, a rank of 70 assigned to a father in the 1991 census means that out of the fathers in our sample for that cohort, 70% of fathers work in

[5] While attrition is low on average, it is higher among groups such as younger men.

occupations that paid a median wage less than this particular father's occupation. As discussed previously, occupation-wage measures are based only on fathers and sons, due to low female participation rates in early cohorts.

Using these percentile ranks, we focus on two measures of intergenerational mobility. First, we estimate transition matrices for the probability of moving across percentiles of the occupation distribution. We focus in particular on the probability of the cohort member rising from the bottom group (e.g. quartile) of the occupation distribution (based on the median wage of the parent's occupation) to the top group (based on the median wage of the cohort members adult occupation). Higher values reflect more upward relative mobility at the national level. At the sub-national level, higher values for this measure reflect greater levels of upward absolute occupational wage mobility. An advantage of these transition matrices as opposed to those based on social class is that group proportions are by construction equal and unchanging over time.

Second, we report the mean rank (in the national child occupation distribution) of children whose parents are at the 25th percentile of the national parent occupation distribution. This statistic is derived by regressing child occupation rank on parent occupation rank. Let R_i denote child *i*'s percentile rank in the occupation distribution of children and P_i denote parent *i*'s percentile rank in the occupation distribution of parents. For the various cohorts under study (denoted by *c*), the regression model can be expressed as follows:

$$R_{ic} = \alpha_c + \beta_c P_{ic} + u_{ic} \tag{1}$$

This projection is performed separately for each cohort and geographical unit of interest. Ranks are always defined in relation to the national occupation-wage distribution. The mean rank of children whose parents are at the 25th percentile is given by $\hat{\alpha} + 25\hat{\beta}$, where a hat denotes an estimate. Again, when estimated for sub-national areas, this measure can be thought of as reflecting absolute mobility rather than relative mobility, as the intercept will differ across areas. Differences are then driven by both the change in the overall occupational distribution for those born in an area and the relationship between parent and child occupations in an area.

There are advantages and disadvantages to each of these two measures. The first is non-parametric, not involving any assumptions on the particular functional form of the relationship we seek to model. However, this comes at a cost of sample size. Even in the tercile mobility case, we are discarding two thirds of our sample by building a measure based only on the lowest tercile. On the other hand, the second measure requires more parametric assumptions, but by making these assumptions we are able to leverage information from the entire sample. In our baseline results we present both measures and show the relationship between the two, but for low geographical disaggregation we tend to use the second in the interest of power and consistency with the recent literature.

Intergenerational Mobility in Home Ownership & Education

Home ownership and degree attainment are binary variables for both parent and child. We estimate cohort-specific linear probability models of the determinants of home ownership and possession of a university degree for individual *i* in cohort *c*:

$$Outcome_{ic}^{child} = \gamma_c + \lambda_c Outcome_{ic}^{parent} + \beta_c X_{ic} + u_{ic} \tag{2}$$

In (2), the cohort-specific intergenerational estimate conditional upon a set of control variables is given by $\hat{\lambda}_c = Pr\left[Outcome_{ic}^{child} = 1 \middle| Outcome_{ic}^{parent} = 1 \ \middle| X_{ic}\right]$. Without controls, this is simply the mean gap in home ownership or degree attainment. In our results, we refer to this as the 'correlation' measure, as it is a partial correlation. In our specifications, we control for child age, gender and ethnicity. Higher values of the coefficient correspond to lower mobility. We estimate these models separately for each geographical area of interest.

As will be demonstrated in our results section, over time the levels of home ownership and degree attainment have changed across cohorts. The measure introduced above is only informative on the percentage point difference in the binary outcome between those of one parental status and another. It may be more pertinent to consider the log odds ratio – the (log of the) increased chance of being a home owner (degree recipient) if your parents were owners (degree recipients) compared to the case when they were not. The log odds ratio is given by:

$$log\ (Odds_{ic}) = \log\left(\frac{Pr\left(Outcome_{ic}^{child} = 1 | Outcome_{ic}^{parent} = 1\right) / Pr\left(Outcome_{ic}^{child} = 0 | Outcome_{ic}^{parent} = 1\right)}{Pr\left(Outcome_{ic}^{child} = 1 | Outcome_{ic}^{parent} = 0\right) / Pr\left(Outcome_{ic}^{child} = 0 | Outcome_{ic}^{parent} = 0\right)}\right) \tag{3}$$

If child outcomes are unrelated to parent outcomes, the log odds ratio equals zero. Higher log odds ratios correspond to more (positive) association between parental outcomes and child outcomes, and hence reflect lower mobility. Again, as in the occupational wage case there are arguments for each measure. Both measures are indicators of relative rather than absolute mobility. If parent group sizes are not particularly skewed, as will be shown to be true for home ownership, and controls are not particularly important, the two give broadly similar results. However, when groups are highly imbalanced, as will be shown for degrees, the two give different results. In this case, we argue that both measures have value and opt to discuss both in our analysis.

4. Results

National Results

We begin by showing aggregate results for our various measures of mobility and where possible compare them with extant estimates in the literature, both for Britain and for other countries. We then move on to the key focus of our paper – the geography of mobility.

Table 2 reports the main results for all of England and Wales. Each panel represents a different outcome measure and across the columns we present estimates of mobility for each of our three cohorts. In the final column we estimate the change in the mobility measure from the first to the last cohort to give a sense as to whether mobility has been changing over our sample period. As discussed previously, to avoid issues related to the very substantial change in female labour force participation that has occurred over our sample period, the results for occupation relate only to boys and their fathers. The results for home ownership and degree attainment relate to both sexes for each generation, with controls for gender in the regression-based measures.

Panel A of Table 2 reports estimates for occupational mobility. The probability of moving from the bottom tercile of the occupational wage distribution to the top tercile within a generation was 0.259 for the cohort born in 1955-61. This probability falls over time i.e. occupational mobility declines and stood at 0.223 for the last cohort born in 1975-81. This drop of 0.036 is significant at the 1% level. For robustness, we also present estimates for other percentile groupings – quartile and quintile – and the pattern is very similar. The final row of Panel A presents estimates of the expected rank of the child conditional on the parent being at the 25^{th} percentile. This also shows a decline in mobility, though the magnitude is small and the estimate is statistically insignificant.

Previous studies of intergenerational mobility in the UK have focused on specific cohort studies that follow all children born in a particular week through their childhood and adult life. The two most studied datasets are the 1958 National Child Development Study (NCDS) and the 1970 British Cohort Study (BCS). Our first two cohorts include these birth years and so we can compare our results to published results from these studies. Two points should be borne in mind when comparing these studies to our own. First the NCDS and BCS are both small samples – the useable sample with information on both parents and children tends to be around 2,000 for each survey. This is the key reason why these commonly-used datasets cannot address questions of geographical variation in mobility. Second, the most-recent equivalent cohort study (the Millennium Cohort Study) only began in 2000 and so does not yet provide any substantive evidence on intergenerational mobility. Our estimates therefore present a more up-to-date snapshot of mobility than is possible with cohort studies.

Blanden and Machin (2008) report estimates for the probability of moving from the lowest quartile to the highest quartile based on parent and son's income. For the 1958 cohort this is estimated to be 0.18 and falls to 0.13 in the 1970 cohort. This decline is more pronounced than that shown for occupational wages in Panel A of Table 1, where the bottom to top quartile transition drops from 0.19 to 0.18 – though note that the quintile transition drops more noticeably, from 0.145 to 0.125. In terms of cross-country comparisons, Chetty et al. (2014) report a value of 0.075 for the bottom-to-top quintile transition probability, whilst figures for Denmark (Boserup, Kopczuk and Kreiner, 2013) and Canada (Corak and Heisz, 1999) are 0.117 and 0.134 respectively. Whilst we would caution about comparing transition matrices based on actual household income with our estimates based on occupational median wages, our estimates for the later cohort are clearly in the same ball park as Denmark and Canada. A caveat when interpreting our occupational wage estimates over time is that within-occupation inequality may additionally be changing. In the only other work we are aware of using LS to study mobility, Buscha and Sturgis (2018) present results suggesting a slight increase in broad social class mobility. Sociological measures of broad social class mobility need not align with measures based on finer occupations or wages, as demonstrated in Blanden, Gregg and MacMillan (2013).

Panel B of Table 2 focusses on home ownership. Here there is a very clear and consistent pattern. There has been a large and statistically significant fall in intergenerational mobility across the cohorts – home ownership among children has increasingly depended on the home ownership of their parents. The correlation coefficient was 0.184 for the first cohort, but 0.312 for the last cohort. This means that for the latest cohort, children of homeowners are more than 30 percentage points more likely to own their home than children of non-homeowners. This increase of 0.128 is strongly significant and very substantial. The log-odds ratio paints a very similar picture of a large and significant fall in mobility. Figure 1 shows raw home ownership rates for children and parents. This illustrates large shifts in home ownership rates across generations. Those born in the late 1950s were significantly more likely to own their homes than their parents, but by the 1970s the opposite is true, with home ownership rates falling below 70%. Figure 2 shows home ownership rates for children conditional on parental ownership for all three cohorts. Perhaps the most startling aspect of these figures is the fact that for the first cohort, 67% owned their own home even if their parents did not, whilst this had dropped to 44% for the last cohort. While home ownership rates have fallen for both groups, they have fallen most rapidly for those whose parents did not own their home.

Blanden and Machin (2017) provide evidence on home ownership mobility by analysing data from the two cohort studies referred to above. Using the same empirical approach to that used here, they find that the intergenerational correlation coefficient goes from 0.140 for the 1958 cohort to 0.217 for the 1970 cohort. These are broadly similar to our estimates for the first two cohorts (though their estimates are for when the children are aged 42) and point to a clear decline in mobility along this dimension. Our evidence across more time periods, however, shows that this decline accelerates for the subsequent cohort for which no other extant evidence exists.

The final panel of Table 2 reports mobility estimates for degree attainment. For this outcome, there is a clear difference between the change in the intergenerational correlation coefficient and the log-odds ratio. The log-odds ratio suggests that mobility has risen, whereas the significant positive change in the correlation coefficient corresponds to a fall in mobility over the period. This divergence is driven by the fact that there has been a very substantial increase in the share of the population getting a degree. For the first cohort, only 4% of parents had a degree and 11% of the children. For the final cohort, these figures had risen to 11% and 40% respectively (see Figure 3).

Figure 4 shows that children of degree holders are in all cohorts significantly more likely to obtain a degree themselves than children of non-degree holders. The increased correlation coefficient reflects that this gap has actually increased. We see this as a fairly novel and important contribution of this paper. The large expansion in UK higher education has actually, according to one measure, increased the link between parent and child university education, almost guaranteeing a university education for those whose parents received one. Children of degree holders in the most recent cohort now have an 80% probability of going to university, compared to a probability of approximately 35% for those whose parents did not attend university. The gap between the raw probability of a child getting a degree if at least one of the parents did have a degree compared to if they did not actually rose from 0.408 to 0.444, but the ratio of that gap declined.

Regional Results

We next present results at the level of standard region, which coincide with the NUTS1 classification. There are 10 regions in England and Wales, each with a population averaging approximately 6 million individuals. Tables 3A and 3B present estimates using our two primary occupational wage measures – the bottom-to-top tercile transition probability and the expected child rank at the 25th percentile of the parent distribution. As with Table 2, the first three columns report estimates for each successive cohort while the final column reports the change from first to last cohort. As discussed in Section 2, we expand the cohorts to include those aged 8-17 when first observed in the census to give us larger samples with which to estimate more precisely at the sub-national level. We present the national results with this extended sample at the bottom of each table. The extension of sample does not dramatically change these national results. Figures 5 and 6 present the mobility estimates graphically, for easier visual interpretation.

The data show very substantial and statistically significant differences across regions in occupational mobility. For the most recent cohort, the probability of moving from the bottom to the top tercile is 0.302 in London and only 0.167 in Yorkshire and Humberside. The expected rank measure in Table 3B shows the same pattern, with these two regions also at the top and bottom. When we look at the changes in mobility across the cohorts, Yorkshire and Humberside stands out as a region that has seen a very substantial decline in occupational mobility over time. Indeed, for the cohort born in 1954-63, only two regions (London and the South East) had higher mobility, whereas for the most recent birth cohort mobility is lowest in this region. This decline in mobility is strongly significant for Yorkshire and Humberside and is about three times larger in magnitude than for the country as a whole. All regions except the North East have seen a decline in mobility, though the picture is more mixed when looking at the expected rank and most changes are not statistically significant. Two regions in fact experience an increase in mobility over this period according to the expected rank measure.

The results in Table 3B suggest that an individual growing up in the most recent cohort in London whose father works in a 25th-percentile wage occupation is expected to work in an occupation in which median wages are 7 percentiles higher than someone of an equivalent background growing up in Yorkshire and Humberside. This latter region contains many former industrial areas, including cities such as Hull and Grimsby, heavily associated with post-industrial decline in the north of England. Parts of this region have in the past been synonymous with energy production and coal mining, and it is still home to Europe's second-biggest power station. In sub-regional analysis following this section we will investigate whether the region's low mobility rates are indeed driven by these ex-industrial areas. The other clear pattern in these results is that London has an exceptionally high rate of occupational mobility in every cohort. London is a large and heterogeneous city. In our sub-regional analysis we will inspect whether this is driven by inner London or by the expansive suburbs surrounding the city centre. It is pertinent also to ask whether this high mobility is reflective of a broader trend of high mobility in cities. We come to this in Section 5 below.

In terms of dispersion across regions, both tables 3A and 3B show an increase in dispersion from the earliest to the most recent cohort. While London has remained highly mobile according to both measures, other areas have fallen behind. For the final cohort, those growing up with fathers in the bottom tercile of occupations in London are almost twice as likely to reach the top tercile themselves than those with fathers of similar occupations in Yorkshire and Humberside.

Tables 4A and 4B and Figures 7 and 8 show the regional results for home ownership mobility indicators. In stark contrast to the pattern for occupational mobility, London is now the area with the lowest mobility and the largest fall in mobility. The intergenerational correlation coefficient for the most recent cohort is 0.381 for London, compared to the national average of 0.312. For the most recent cohort, the highest housing mobility estimate is found in Wales, which has a coefficient estimate of only 0.245. Looking at changes over time, all regions have seen a significant decline in mobility, with London and Yorkshire and Humberside exhibiting the largest changes. The same is true when we focus on the log-odds ratio instead (Table 4B), though here some of the changes are not statistically significant, and mobility in Yorkshire and Humberside actually deteriorates marginally more than in London. As was the case for occupation-wage mobility, we see that regional dispersion in home ownership mobility has increased over time.

The fact that areas with very different estimates for occupational wage mobility exhibit similar housing mobility suggests that the link between these two measures is likely to be complex. It is immediately clear that patterns based on occupational wage mobility (and likely income mobility) need not reflect differences in housing mobility. We view this as another key contribution of this paper - that different measures of mobility need not be aligned when making geographical comparisons. We explore this further in the sections below using sub-regional estimates.

Results for degree attainment are presented in Tables 5A and 5B and Figures 9 and 10. Focusing on the most recent cohort, the ranking of regions in terms of mobility is approximately the same irrespective of which measure is used. Degree mobility is lowest in

London, with a correlation coefficient of 0.486 and highest in the South East, with a correlation coefficient of 0.418. Yorkshire and Humberside again has low mobility on both measures. In terms of changes over time, the results depend more on the precise measure used. Areas such as the North East and North West which had relatively low proportions of individuals obtaining degrees in the earliest cohort have seen significant increases in log-odds mobility. Yorkshire and Humberside and the East of England show the largest decline in mobility according to correlation coefficients, and no statistically significant improvement in the log-odds. In contrast to the occupation and housing mobility results on dispersion, areas have converged in terms of degree mobility. The increased probability of obtaining a degree associated with having degree-holding parents has become more similar across regions over time

Sub-regional Results

Moving to estimates based on smaller areas, we first present estimates at the sub-regional NUTS2 level, all of which have a population of at least 800,000 individuals. This level is an appropriate aggregation for producing maps. The downside of moving to lower geographies is that estimates are inherently less precise. At the NUTS2 level, each region contains several hundred observations. We present choropleth maps of England and Wales for the first and last cohort as well as the change between these two cohorts. As with the Regional results, for occupation and degree measures we use the extended (8-17) sample and for home ownership measures we use the baseline (10-16) sample.

Table 6 shows correlations between all measures at the NUTS2 level. We see that alternative measures for each type of mobility are strongly correlated. However, when looking across types of mobility, for example comparing the two housing mobility measures with the two degree mobility measures, there is rarely any significant correlation. There exists a correlation between one occupation-wage measure and one degree measure. Given the high returns to degrees discussed in the data section earlier, it is natural to expect some relationship between these two types of mobility. However, housing mobility is notably uncorrelated with both degree and occupation-wage mobility. Areas which are successful in propelling under-privileged kids towards degrees and high-earning occupations are not the same as those in which similar kids are able to get onto the housing ladder.

Figures 11A-11C show results using the expected rank measure of occupational mobility. Darker areas have higher expected occupational wage ranks for those starting at the 25th percentile, and hence higher mobility. There is a clear tendency for areas in the south of the country to have higher levels of mobility along this dimension. For the most recent cohort, the figures range from 38.7 for South Yorkshire to 52.9 for West and North West Outer

London. All areas in the region constituting Yorkshire and Humberside see low rates of mobility.

One interesting dimension that becomes clear when looking at the sub-regional level is the difference between inner and outer London. The three outer London areas are the most mobile areas for the most recent cohort, all having an expected rank above the median. In contrast, the two inner London areas are amongst the five lowest mobility areas, with an average expected rank of only 41. This difference between inner and outer London is much less pronounced in earlier cohorts. Though outer London has always been the most mobile on this measure, inner London was above the national average for the first cohort and has become substantially less mobile. This echoes the results from Chetty et al. (2014), finding that mobility tends to be higher in suburban areas outside of major population centres. In Section 5 we explore patterns for cities using lower geographies. For brevity, we do not report separate maps for the tercile transition probability measure, but the cross-section correlation for the most recent cohort between this transition probability and the expected rank is 0.89 and is 0.74 for the change across cohorts. Therefore, the picture looks approximately the same if this measure is used.

It is useful at this stage to compare our measure on occupational mobility that ranks occupations by their median wage with the alternative approach favoured particularly by sociologists that rank occupations by their social class. Social class groupings tend to focus on the skill-level of the occupation. We follow standard practice and divide occupations into three categories: Professional and Technical occupations, Skilled occupations and Semi-Skilled/Unskilled occupations. For the 1974-83 cohort, the percentage of working fathers in each of these three groupings was 40%, 43% and 17% respectively. For the children it was 47%, 39% and 14% respectively. For each NUTS2 area, we calculate the probability of moving from the bottom to the top social class in a generation and compare this with the expected rank for the same cohort. Figure 12 shows the scatterplot of these two alternative measures for the most recent cohort. There is a strong positive correlation between the two measures (0.74). This suggests that our approach is consistent with this alternative approach to "valuing" occupations. Again though, we would emphasise that our approach avoids the inevitable value judgements of assigning changing occupation groupings to particular social classes and avoids the significant problems associated with changing group size, and shifts in the composition of work over time.

Figures 13A-13C present the sub-regional estimates for the home ownership correlation coefficient. Darker areas here correspond to lower mobility. Again, for brevity we do not report the log-odds estimates separately, but the picture looks identical as the cross-sectional correlations are 0.97 for the most recent cohort, and 0.95 for the change across cohorts. As was clear from the regional estimates, for the most recent cohort London and Yorkshire and Humberside have poor mobility on this measure. However, for the most recent cohort, East Inner London has an estimated coefficient below the national average (0.276 compared to 0.312). Once again, inner and outer London exhibit substantial differences. We see that after the London areas, Greater Manchester has the lowest housing mobility, suggesting a link between cities and low housing mobility. We explore this further in the following section.

Finally Figures 14A-14C give estimates for degree attainment for the correlation coefficient measure. Several patterns are clear in the figures for the most-recent cohort. Similar to the results for occupational and housing mobility, there is a noticeable divide between inner and outer London. Inner London areas have the lowest mobility on this measure, with an average correlation coefficient of 0.558, compared to the three outer London areas with an estimated average coefficient of 0.425, below the national average. For the educational attainment of children born in inner London in the late 1970s and early 1980s, it really mattered whether your parents went to university or not.

South Yorkshire and North Yorkshire rank in the top five areas in terms of low intergenerational education mobility. To put these numbers into context, a child in the most recent cohort born in South Yorkshire has only a 29% chance of getting a degree if neither of their parents had a degree, whilst this rises to 45% in West and North West Outer London. The educational prospects of those born to non-graduates really varies by the area in which they grow up. Interestingly, there is also substantial variation in the probability of attending university conditional on parental attendance, from 70% in Kent to 100% in Inner West London. The areas in which those from educated backgrounds are more likely to attend university do not coincide with areas in which those from less educated background are more likely to attend university.

5. Correlates of Mobility

While time trends and geographical patterns of intergenerational mobility across England and Wales may be of interest in their own right, the deeper intention in generating these estimates is that they can be used to shed light on causal mechanisms. Understanding underlying mechanisms is crucial if we are to move from descriptive patterns to policy implications. As a first step towards this, in this section we explore correlates of our mobility measures. To do so, we use the lowest-level geographical estimates possible. This is necessary to obtain a decent number of areas required for estimating even the simplest of relationships. But it comes at the expense of precision in each estimate. We follow standard practice (Saxonhouse 1977, Card and Lemieux 2011) and use regression weights which are inversely proportional to the standard error of the mobility estimate. This up-weights areas where mobility is estimated more precisely. We also exclude estimates based on very small numbers of observations (under 50), resulting in the loss of 19 of our 145 NUTS3 areas in the occupation-based regressions.

These relationships are entirely correlational, and as such can be seen as the first step to understanding both the causes of differences in intergenerational mobility across areas and how intergenerational mobility can affect other outcomes. All the analysis in this section refers only to the most recent cohort born in the late 1970s / early 1980s. To aid interpretation, mobility estimates are standardised to have mean 0 and variance 1, and where necessary have been transformed such that higher numbers correspond to higher mobility. We use correlation coefficient-based measures rather than odds-based measures to maximize the sample size used to create each measure.

Cities and mobility: The ‘London’ effect?

The results of Section 4 demonstrated that London is often substantially more or less mobile than other regions, depending on the measure. A pertinent question then is whether this is due to the fact that London is a city, whereas other regions are combinations of urban and rural areas, or whether this is something particular about London. NUTS3 geographies are detailed enough to test this, as many cities are assigned unique NUTS3 codes. Figure 15 shows a map of NUTS3 areas of England and Wales, with city areas highlighted. We regress each of our mobility measures on an indicator for ‘city’ and an indicator for ‘London’. Coefficients are presented in Table 7. Something to be aware of when interpreting these results is that the UK essentially has only a single very large city, so we are inevitably comparing London to substantially smaller cities.

The first key result from the third column of Table 7 is that high occupation-wage mobility appears to reflect more of a ‘London’ effect, rather than a broader city effect. The estimated coefficient on London is positive and highly significant whereas the estimated coefficient on City is negative and insignificant. This suggests that if one is hoping to understand the mechanisms driving high occupation-wage mobility, one must look at policies, populations and institutions of London rather than those of cities in general. These results also show that home ownership mobility is typically lower in cities, and exceptionally low in London.

Industrial decline and mobility

The UK experienced particularly strong declines in manufacturing employment in the latter 20th century, which is thought to have devastated some communities. It was observed in Section 4 that occupation-wage mobility is particularly low and has fallen dramatically in regions containing ex-industrial areas. Next, we use our lower-level geographical estimates, along with external data on the geography of industrial decline, to assess this pattern more formally. Our external data comes from the Office for National Statistics 'SuperGroup' classifications, in which areas of the UK are divided into groups based on economic, demographic and historical characteristics. We define ex-industrial areas as those labelled as 'Manufacturing Legacy', 'Industrial and Multi-ethnic' and 'Mining Legacy' areas. These industrial groupings are mapped in Figure 16.

The first row of Table 8 shows that regressing occupation-wage mobility on this ex-industrial indicator gives a statistically significant coefficient estimate of -0.56. Ex-industrial areas are less mobile in terms of occupations than other areas. This relationship is robust to the inclusion of an indicator for London. There exists no significant relationship between the ex-industrial indicator and other measures of mobility. The mobility patterns found here are consistent with the US income mobility results found in Chetty et al. (2014), in which mobility was found to be low in industrial 'rust-belt' areas such as Michigan and Illinois. While of course much differs between these and other areas, the evidence here is consistent with mobility falling in areas suffering from industrial decline.

House prices and mobility

One might expect the relative prospects of buying a home for the children of homeowners and non-homeowners to vary with local house prices. In areas with high house prices, homeowners may be able to assist their children with the purchase of a home by downsizing. Children of non-homeowners will not receive such support. On the other hand, areas with high house prices are also likely to be areas of strong economic growth, possibly aiding those whose parents do not own a home. To test for a relationship between prices and mobility measures, we use data from the UK Land Registry on 1995 median house prices at the local authority level, aggregated to the NUTS3 level by taking a population-weighted mean across local authorities.

We find a negative relationship between house prices and housing mobility, consistent with the first mechanism discussed above. This relationship is significant at the 1% level. A one standard-deviation increase in mobility corresponds to a drop of £3,641 in local house prices, relative to an average price of £54,000. While there is then evidence of a negative link, housing mobility is clearly determined by more than house prices alone. There exist many outliers such as Tower Hamlets, an area in Inner East London which has relatively high house prices and high housing mobility. Also evident from Table 8 is that house prices are strongly positively related to areas with high occupation-wage mobility. Much of this is driven by outer London, an area with high occupation-wage mobility and high house prices.

Political voting behaviour and mobility

The UK's vote to leave the European Union in 2016 exposed a wide divide in public opinion on key political issues. As with recent political events in the United States, there were significant differences in voting patterns across regions. In general, younger metropolitan areas of the UK voted to remain in the EU, whereas older, poorer and rural areas voted to leave. In the media, this pattern has been linked to geographical differences in social mobility. The argument frequently made is that some areas have been 'left behind', that people living in these regions see little prospect of improving their position in life under the current system, so are more likely to vote for radical changes to the status quo as represented by Brexit in the UK and President Trump in the US. This correlation has been shown for the US in Rothwell and Diego-Rosell (2016) but has not been tested for the UK due to the prior lack of regional estimates.

To test for a relationship between voting patterns and mobility, we obtain publicly-available data on 2016 referendum voting shares at the local authority level. We aggregate to NUTS3 and investigate how these shares relate to occupation-wage mobility. The third row of Table 8 and the scatter plot provided in Figure 17 demonstrate that consistent with the above story of 'left-behind' areas, occupation-wage mobility is negatively related to the share voting to leave the EU. The relationship is significant at the 5% level. Areas with low occupation-wage mobility, such as the northern areas of Barnsley, Doncaster and Rotherham, tended to vote to leave the EU. High mobility areas, such as the outer London areas of Harrow, Hillingdon and Barnet voted to remain in the EU. It is clear from the figure however that there are some significant outliers. Several urban areas such as Hackney and Newham voted to remain despite having low mobility. It is worth noting that many of these urban areas changed (gentrified) substantially throughout the 1990s and early 2000s. Interestingly, in terms of other measures of mobility, areas which voted to leave the EU had higher rates of mobility than those which voted to remain. This is particularly true for our measure of degree mobility. Again, this is partially driven by London being an outlier in both measures, however the result holds if London is excluded.

6. Conclusions

This paper presents the first evidence on the geography of intergenerational mobility in the UK using decennial census data. These data allow us to explore various dimensions of mobility and present estimates of both the differences in mobility across areas, but also offer the opportunity to map changes over time. In addition, we present some preliminary evidence that points to factors likely to be important in explaining differences across areas in mobility and how differences in mobility may impact other outcomes that we are interested in understanding.

Our key finding is that across all dimensions of mobility there are stark differences across the regions of England and Wales. A national intergenerational mobility measure hides much of this spatial variation. In terms of occupational movements, London stands out as an area that exhibits high mobility – being born to a low-skilled parent does not stand in the way of moving into the professions to the same extent that it does in other areas. Ex-industrial and mining areas have the opposite tendency, with particularly poor results for Yorkshire and Humberside. By contrast, home ownership mobility points to a worrying trend for London – increasingly those born to parents who are homeowners are the most likely to themselves get onto the housing ladder. Finally, our educational mobility estimates point to an intriguing result. The mass expansion of higher education has dramatically improved the chances of a child from a non-degree household going to university. But this expansion has actually marginally favoured those whose parents have a university education, so mobility has declined. Again, Yorkshire and Humberside perform poorly in terms of educational mobility.

These results suggest that it may be over-simplistic to think in terms of high and low mobility areas. On some measures an area may be highly mobile whilst on another measure it is substantially less so. Unless we are willing to make value judgements on the relative importance of various dimensions of mobility, it will generally be difficult to rank areas in terms of overall mobility.

We also present some indicative analysis of correlates with mobility. London appears different than other cities in terms of improving occupational mobility, whereas it looks more similar to other cities in terms of housing and educational mobility. Ex-industrial and mining areas appear to consistently have poor outcomes for intergenerational mobility, particularly in terms of occupation. And, finally, these mobility patterns seem important for understanding political disenchantment and how it has risen over time.

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TABLE 1. SUMMARY STATISTICS BY COHORT

	Birth Cohort Sample		
	1955-1961	1965-1971	1975-1981
Baseline			
Female (%)	50.1 (50.0)	51.7 (50.0)	51.6 (50.0)
Age at baseline	12.90 (2.0)	13.07 (2.0)	12.90 (2.0)
White (%)	97.4 (16.0)	91.7 (27.6)	91.8 (27.5)
Parent homeowner (%)	48.4 (50.0)	63.9 (48.0)	76.2 (42.6)
Missing mother (%)	1.8 (13.2)	3.0 (17.0)	3.5 (18.4)
Missing father (%)	7.1 (25.6)	10.2 (30.3)	15.8 (36.5)
Age of mother at baseline	41.1 (6.2)	40.1 (6.1)	39.9 (5.4)
Age of father at baseline	43.9 (6.8)	42.9 (6.9)	42.7 (6.2)
Parents have degree (%)	4.0 (19.6)	8.2 (27.4)	11.2 (31.6)
Mother has degree (%)	0.8 (9.0)	2.8 (16.5)	4.3 (20.4)
Father has degree (%)	4.0 (19.63)	7.8 (26.8)	11.3 (31.7)
Follow-up			
Age at follow up	32.90 (2.4)	33.14 (2.8)	32.90 (2.4)
Owns house at follow up (%)	76.1 (42.6)	76.7 (42.3)	67.9 (46.7)
Degree at follow up (%)	10.6 (30.8)	21.9 (41.3)	40.0 (49.0)
Number of observations	42,907	44,683	34,720

Notes: Statistics are based on the core sample of 10-16 year-olds at baseline year who were successfully followed up two censuses later and matched with at least one parent. Values correspond to means and percentages, depending on the variable. Standard errors in parentheses. *Source*: ONS Longitudinal Study

TABLE 2. INTERGENERATIONAL MOBILITY ESTIMATES AT THE NATIONAL LEVEL

	Birth Cohort Sample			
	1955-1961	1965-1971	1975-1981	Change
Panel A: Median Occupational Wage				
1. Bottom-to-Top Tercile	0.259	0.257	0.223	-0.036***
	(0.005)	(0.006)	(0.006)	(0.005)
2. Bottom-to-Top Quartile	0.193	0.181	0.158	-0.035***
	(0.006)	(0.006)	(0.006)	(0.004)
3. Bottom-to-Top Quintile	0.145	0.125	0.120	-0.025***
	(0.006)	(0.006)	(0.006)	(0.004)
4. Expected rank of 25th percentile	44.98	44.99	44.87	-0.110
	(0.277)	(0.295)	(0.326)	(0.428)
No of Observations	18,355	16,125	13,163	
Panel B: Owner Occupier				
1. Correlation Coefficient	0.184	0.217	0.312	0.128***
	(0.004)	(0.004)	(0.004)	(0.007)
2. Log odds Ratio	1.050	1.168	1.355	0.305***
	(0.024)	(0.023)	(0.026)	(0.035)
No of Observations	43,427	44,862	34,771	
Panel C: University Degree				
1. Correlation Coefficient	0.408	0.447	0.447	0.039***
	(0.007)	(0.007)	(0.008)	(0.011)
2. Odds Ratio	2.309	2.024	1.967	-0.341***
	(0.051)	(0.037)	(0.041)	(0.065)
No of Observations	42,907	44,609	34,705	

Notes: Each cohort are aged 10-16 when observed in the family home with at least one parent present and observed again after 20 years. Correlations coefficients control for sex, age and ethnic origin. Standard errors in parentheses. Number of observations for variables vary due to restriction to males for occupation-wage estimates and a small number of missing values. *** = 1% significance, ** = 5% significance, * = 10% significance. *Source*: ONS Longitudinal Study.

TABLE 3A. INTERGENERATIONAL OCCUPATION MOBILITY ESTIMATES (TERCILE TRANSITIONS) AT THE REGIONAL LEVEL

	Birth Cohort Sample			
	1954-1963	1964-1973	1974-1983	Change
North East	0.233	0.226	0.255	0.022
	(0.016)	(0.020)	(0.023)	(0.030)
North West	0.247	0.232	0.218	-0.029
	(0.010)	(0.013)	(0.014)	(0.019)
Yorkshire & Humberside	0.265	0.216	0.167	-0.098***
	(0.012)	(0.015)	(0.014)	(0.022)
East Midlands	0.259	0.220	0.220	-0.039
	(0.015)	(0.017)	(0.017)	(0.024)
West Midlands	0.251	0.264	0.235	-0.016
	(0.012)	(0.014)	(0.015)	(0.021)
East of England	0.238	0.270	0.226	-0.012
	(0.013)	(0.016)	(0.016)	(0.022)
London	0.303	0.329	0.302	-0.001
	(0.011)	(0.015)	(0.017)	(0.022)
South East	0.271	0.260	0.239	-0.032*
	(0.012)	(0.013)	(0.015)	(0.019)
South West	0.229	0.239	0.227	-0.002
	(0.014)	(0.016)	(0.018)	(0.024)
Wales	0.253	0.251	0.237	-0.016
	(0.016)	(0.020)	(0.021)	(0.029)
England and Wales	0.258	0.253	0.231	-0.027***
	(0.004)	(0.005)	(0.005)	(0.004)

Notes: Each cohort are aged 8-17 when observed in the family home with at least one parent present and observed again after 20 years. Estimates show the probability of moving from the bottom tercile to the top tercile. Standard errors in parentheses. *** = 1% significance, ** = 5% significance, * = 10% significance. *Source*: ONS Longitudinal Study.

TABLE 3B. INTERGENERATIONAL OCCUPATION MOBILITY ESTIMATES (EXPECTED RANK AT 25TH PERCENTILE) AT THE REGIONAL LEVEL

	Birth Cohort Sample			
	1954-1963	1964-1973	1974-1983	Change
North East	42.75	40.96	44.88	2.13
	(0.94)	(1.04)	(1.18)	(1.33)
North West	44.10	43.77	42.62	-1.48*
	(0.59)	(0.66)	(0.73)	(0.83)
Yorkshire & Humberside	45.35	42.33	41.29	-4.06***
	(0.7)	(0.8)	(0.83)	(0.99)
East Midlands	43.98	43.36	44.39	-0.41
	(0.8)	(0.82)	(0.85)	(1.13)
West Midlands	44.77	45.63	44.88	0.11
	(0.7)	(0.72)	(0.79)	(0.99)
East of England	43.71	46.73	45.54	1.83*
	(0.76)	(0.79)	(0.83)	(1.08)
London	48.34	48.19	48.44	0.10
	(0.62)	(0.79)	(0.85)	(0.88)
South East	46.65	46.66	46.10	-0.55
	(0.65)	(0.68)	(0.75)	(0.92)
South West	43.85	45.09	45.57	1.72*
	(0.81)	(0.84)	(0.93)	(0.86)
Wales	44.27	44.60	45.10	0.83
	(0.98)	(0.98)	(1.09)	(1.39)
England and Wales	45.02	44.97	44.85	-0.17
	(0.28)	(0.30)	(0.33)	(0.43)

Notes: Each cohort are aged 8-17 when observed in the family home with at least one parent present and observed again after 20 years. Estimates show the mean expected rank of sons in the son occupation-wage distribution conditional on the father being at the 25th percentile of the parent occupation-wage distribution. Standard errors in parentheses. *** = 1% significance, ** = 5% significance, * = 10% significance. *Source*: ONS Longitudinal Study.

TABLE 4A. INTERGENERATIONAL HOME OWNERSHIP MOBILITY ESTIMATES (COEFFICIENTS) AT THE REGIONAL LEVEL

	Birth Cohort Sample			
	1955-1961	1965-1971	1975-1981	Change
North East	0.227	0.227	0.288	0.061**
	(0.019)	(0.018)	(0.023)	(0.030)
North West	0.188	0.230	0.322	0.135***
	(0.010)	(0.011)	(0.015)	(0.018)
Yorkshire & Humberside	0.162	0.214	0.329	0.167***
	(0.013)	(0.013)	(0.018)	(0.022)
East Midlands	0.179	0.227	0.280	0.101***
	(0.014)	(0.014)	(0.020)	(0.024)
West Midlands	0.187	0.214	0.315	0.128***
	(0.012)	(0.012)	(0.017)	(0.021)
East of England	0.193	0.209	0.297	0.103***
	(0.013)	(0.013)	(0.019)	(0.023)
London	0.195	0.243	0.381	0.186***
	(0.011)	(0.012)	(0.015)	(0.019)
South East	0.192	0.224	0.297	0.105***
	(0.011)	(0.011)	(0.016)	(0.019)
South West	0.147	0.172	0.295	0.147***
	(0.014)	(0.014)	(0.021)	(0.025)
Wales	0.154	0.169	0.245	0.091***
	(0.017)	(0.016)	(0.023)	(0.029)
England and Wales	0.184	0.217	0.312	0.128***
	(0.004)	(0.004)	(0.004)	(0.007)

Notes: Each cohort are aged 10-16 when observed in the family home with at least one parent present and observed again after 20 years. Correlations coefficients control for sex, age and ethnic origin. Standard errors in parentheses. *** = 1% significance, ** = 5% significance, * = 10% significance. *Source*: ONS Longitudinal Study.

TABLE 4B. INTERGENERATIONAL HOME OWNERSHIP MOBILITY ESTIMATES (LOG-ODDS RATIOS) AT THE REGIONAL LEVEL

	Birth Cohort Sample			
	1955-1961	1965-1971	1975-1981	Change
North East	1.231	1.165	1.289	0.058
	(0.108)	(0.096)	(0.094)	(0.151)
North West	1.096	1.256	1.431	0.335***
	(0.063)	(0.062)	(0.072)	(0.096)
Yorkshire & Humberside	0.911	1.179	1.472	0.561***
	(0.074)	(0.075)	(0.083)	(0.111)
East Midlands	1.128	1.208	1.268	0.140
	(0.093)	(0.079)	(0.094)	(0.132)
West Midlands	1.030	1.148	1.384	0.354***
	(0.071)	(0.079)	(0.079)	(0.106)
East of England	1.094	1.118	1.261	0.167
	(0.079)	(0.073)	(0.086)	(0.117)
London	1.106	1.304	1.659	0.553***
	(0.067)	(0.069)	(0.073)	(0.099)
South East	1.096	1.198	1.277	0.181*
	(0.066)	(0.061)	(0.072)	(0.098)
South West	0.846	0.922	1.246	0.400***
	(0.083)	(0.077)	(0.093)	(0.125)
Wales	0.838	1.006	1.080	0.242*
	(0.098)	(0.098)	(0.107)	(0.145)
England and Wales	1.050	1.168	1.355	0.305***
	(0.024)	(0.023)	(0.026)	(0.035)

Notes: Each cohort are aged 10-16 when observed in the family home with at least one parent present and observed again after 20 years. Standard errors in parentheses. *** = 1% significance, ** = 5% significance, * = 10% significance. *Source*: ONS Longitudinal Study.

TABLE 5A. INTERGENERATIONAL DEGREE MOBILITY ESTIMATES (COEFFICIENTS) AT THE REGIONAL LEVEL

	Birth Cohort Sample			
	1954-1963	1964-1973	1974-1983	Change
North East	0.405	0.490	0.440	0.035
	(0.027)	(0.027)	(0.033)	(0.043)
North West	0.452	0.467	0.450	-0.002
	(0.018)	(0.016)	(0.019)	(0.026)
Yorkshire & Humberside	0.397	0.459	0.479	0.082***
	(0.021)	(0.020)	(0.022)	(0.030)
East Midlands	0.438	0.494	0.466	0.028
	(0.022)	(0.021)	(0.024)	(0.033)
West Midlands	0.400	0.434	0.448	0.048*
	(0.020)	(0.020)	(0.021)	(0.029)
East of England	0.365	0.425	0.447	0.082***
	(0.017)	(0.016)	(0.019)	(0.025)
London	0.430	0.451	0.486	0.056**
	(0.017)	(0.016)	(0.019)	(0.025)
South East	0.368	0.455	0.418	0.050**
	(0.014)	(0.013)	(0.015)	(0.021)
South West	0.383	0.459	0.454	0.071***
	(0.022)	(0.020)	(0.021)	(0.030)
Wales	0.410	0.463	0.444	0.034
	(0.030)	(0.025)	(0.029)	(0.042)
England and Wales	0.402	0.457	0.452	0.050***
	(0.006)	(0.006)	(0.007)	(0.009)

Notes: Each cohort are aged 8-17 when observed in the family home with at least one parent present and observed again after 20 years. Correlations coefficients control for sex, age and ethnic origin. Standard errors in parentheses. *** = 1% significance, ** = 5% significance, * = 10% significance. *Source*: ONS Longitudinal Study.

TABLE 5B. INTERGENERATIONAL DEGREE MOBILITY ESTIMATES (LOG-ODDS RATIOS) AT THE REGIONAL LEVEL

	Birth Cohort Sample			
	1954-1963	1964-1973	1974-1983	Change
North East	2.470	2.223	1.935	-0.535**
	(0.211)	(0.147)	(0.172)	(0.272)
North West	2.442	2.077	1.972	-0.470***
	(0.120)	(0.087)	(0.101)	(0.157)
Yorkshire & Humberside	2.313	2.081	2.090	-0.223
	(0.144)	(0.110)	(0.116)	(0.194)
East Midlands	2.506	2.265	2.041	-0.465**
	(0.158)	(0.118)	(0.128)	(0.203)
West Midlands	2.337	1.919	1.948	-0.390**
	(0.113)	(0.103)	(0.110)	(0.181)
East of England	2.183	1.973	1.987	-0.196
	(0.124)	(0.088)	(0.102)	(0.161)
London	2.337	1.999	2.215	-0.122
	(0.113)	(0.091)	(0.108)	(0.156)
South East	2.080	2.035	1.831	-0.249**
	(0.091)	(0.069)	(0.075)	(0.118)
South West	2.194	2.053	2.028	-0.166
	(0.154)	(0.104)	(0.114)	(0.192)
Wales	2.205	2.091	1.951	-0.254
	(0.197)	(0.135)	(0.152)	(0.249)
England and Wales	2.284	2.051	1.993	-0.291***
	(0.042)	(0.031)	(0.035)	(0.055)

Notes: Each cohort are aged 8-17 when observed in the family home with at least one parent present and observed again after 20 years. Standard errors in parentheses. *** = 1% significance, ** = 5% significance, * = 10% significance. *Source*: ONS Longitudinal Study.

TABLE 6. CORRELATION BETWEEN MOBILITY MEASURES AT NUTS2 LEVEL, FINAL COHORT

	Housing (coefficient)	Housing (odds)	Degree (coefficient)	Degree (odds)	Occupation-wage (terciles)	Occupation-wage (exp 25th)
Housing (coefficient)	1					
Housing (odds)	0.97*	1				
Degree (coefficient)	0.16	0.09	1			
Degree (odds)	0.12	0.08	0.92*	1		
Occupation-wage (terciles)	-0.14	-0.18	0.26	0.13	1	
Occupation- wage (exp 25th)	0.00	-0.03	0.39*	0.25	0.89*	1

Notes: Pairwise correlations. * signifies significance at the 5% level. Measures transformed such that higher numbers correspond to greater mobility. *Source*: ONS Longitudinal Study

TABLE 7. 'LONDON EFFECT' VS 'CITY EFFECT' REGRESSION COEFFICIENTS

	Housing (coefficient)	Degree (coefficient)	Occupation-wage (exp 25^{th})
London	-.51*	-.07	1.16***
City	-.34*	-.21	-.17
Observations	141	145	126

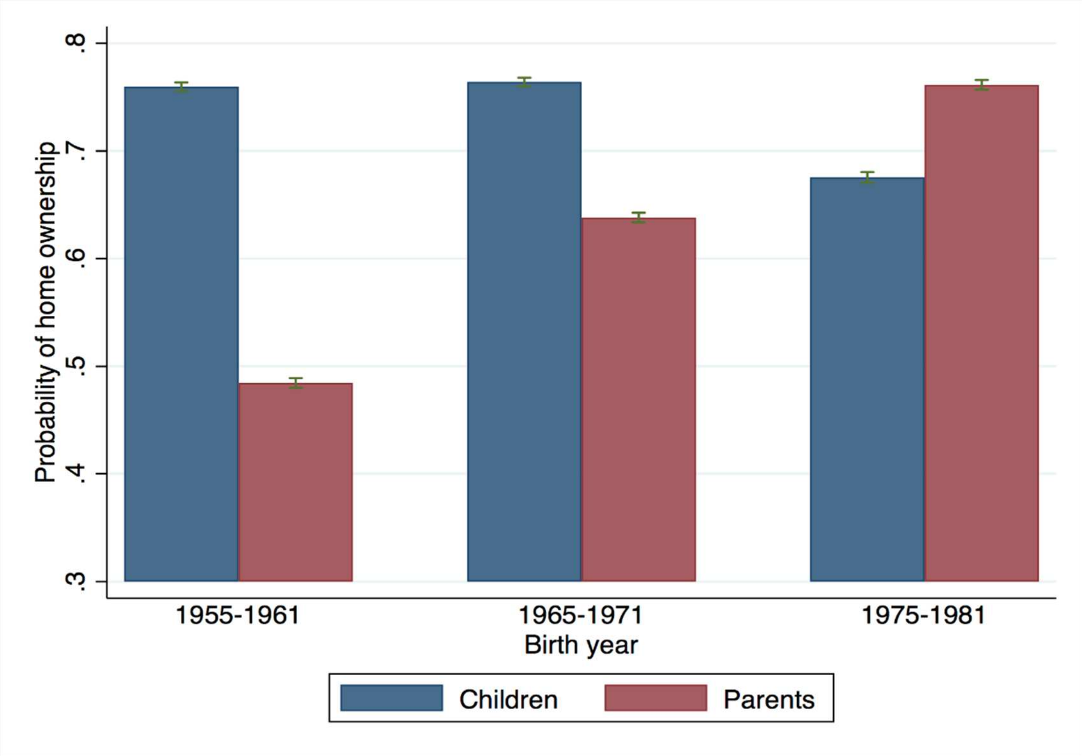
Notes: Values are coefficients from linear regression of each mobility measure on a 'London' indicator and a 'City' indicator at the NUTS3 level for the most recent cohort. Observations weighted by inverse of standard error of mobility estimate. Mobility estimates based on fewer than 50 observations omitted. Measures standardized to have standard deviation 1, mean 0 and transformed such that higher values correspond to higher mobility. *** = 1% significance, ** = 5% significance, * = 10% significance. *Source*: ONS Longitudinal Study

TABLE 8. EX-INDUSTRIAL, HOUSE PRICES AND LEAVE VOTE REGRESSION COEFFICIENTS

	Housing (coefficient)	Degree (coefficient)	Occupation-wage (exp 25th)
Ex-Industrial	-.00	-.10	-.56***
House prices (£)	-3,641***	411	7,610***
Leave vote (%)	.02**	.02***	-.02**
Observations	141	145	126

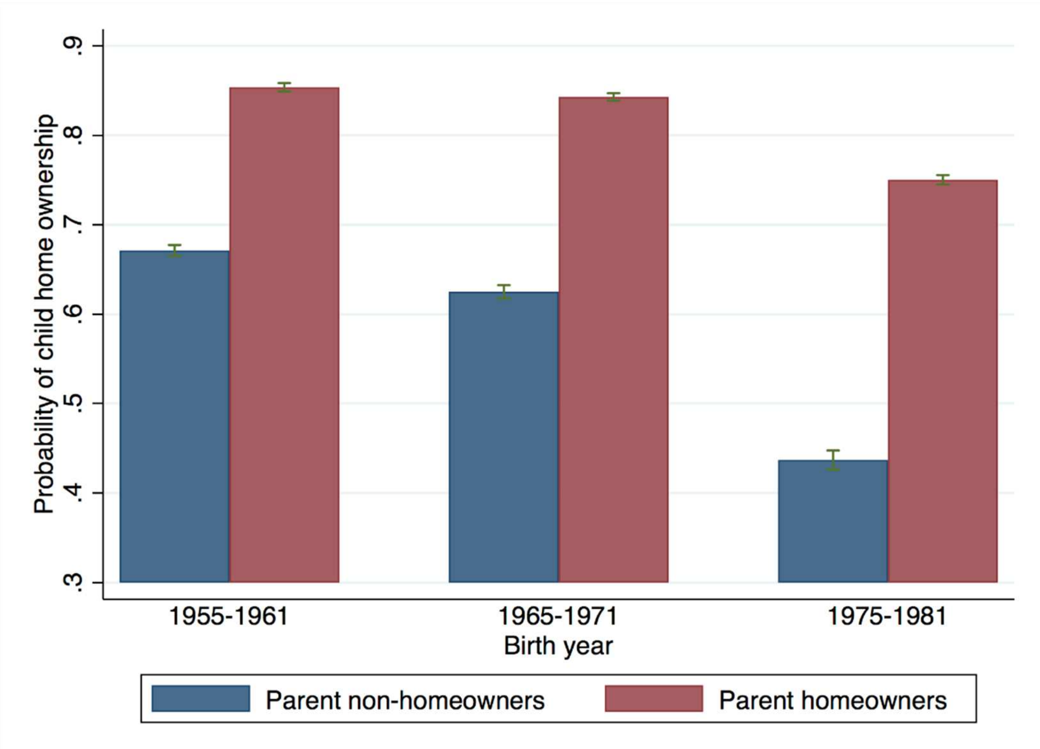
Notes: Each predictor entered individually in simple regressions. Observations weighted by inverse of standard error of mobility estimate. Mobility estimates based on fewer than 50 observations omitted. Measures standardized to have standard deviation 1, mean 0 and transformed such that higher values correspond to higher mobility. *** = 1% significance, ** = 5% significance, * = 10% significance. *Source*: ONS Longitudinal Study, UK Land Registry, UK Electoral Commission, ONS Area classification.

FIGURE 1. HOME OWNERSHIP RATES FOR CHILDREN AND PARENTS



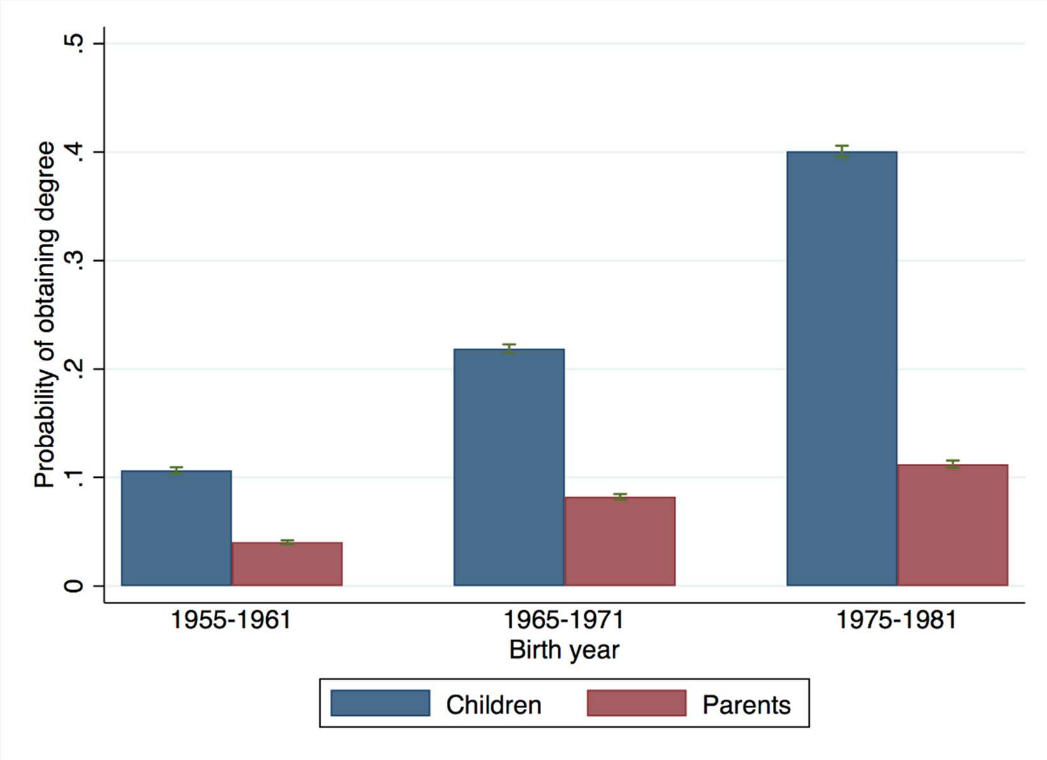
Notes: Parents observed when children age 10-16, children observed age 30-36. Error bars reflect 95% confidence intervals. *Source*: ONS Longitudinal Study

FIGURE 2. HOME OWNERSHIP RATES FOR CHILDREN OF HOMEOWNERS AND NON-HOMEOWNERS



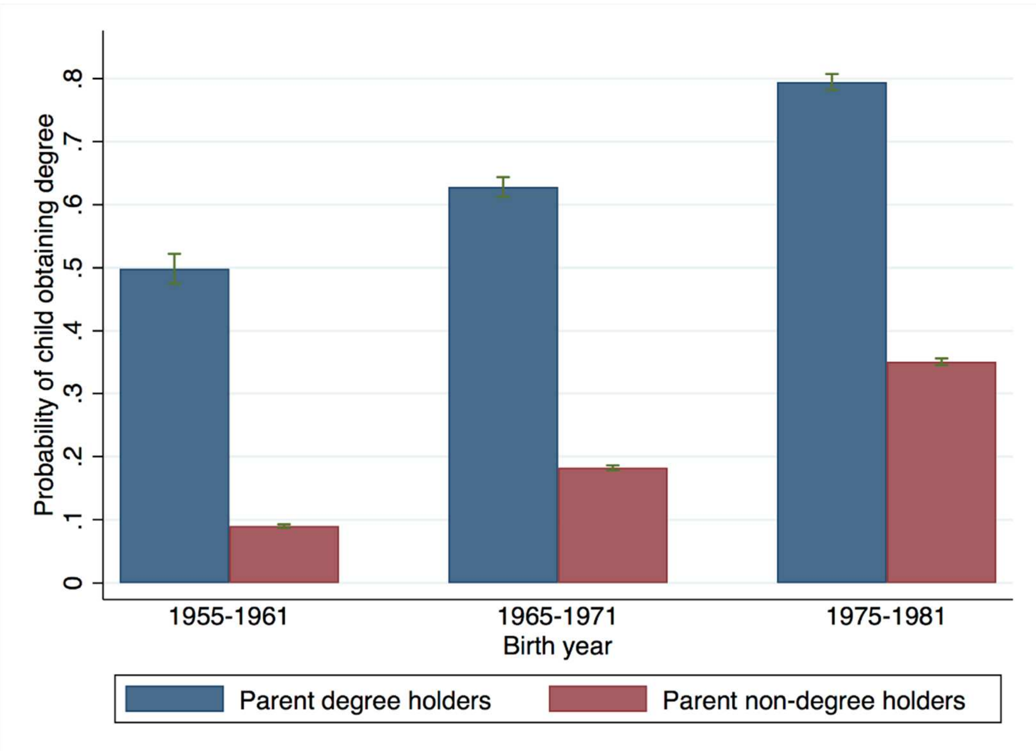
Notes: Parents observed when children age 10-16, children observed age 30-36. Error bars reflect 95% confidence intervals. *Source*: ONS Longitudinal Study

FIGURE 3. DEGREE RATES FOR CHILDREN AND PARENTS



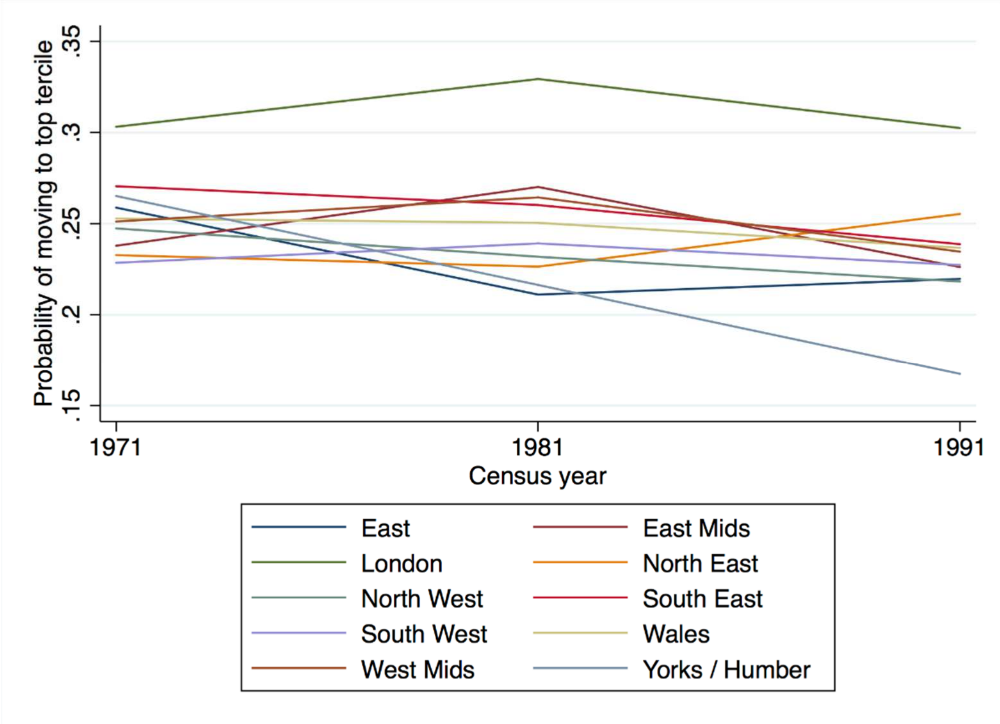
Notes: Parents observed when children age 10-16, children observed age 30-36. Error bars reflect 95% confidence intervals. *Source*: ONS Longitudinal Study

FIGURE 4. DEGREE RATES FOR CHILDREN OF DEGREE HOLDERS AND NON-DEGREE HOLDERS



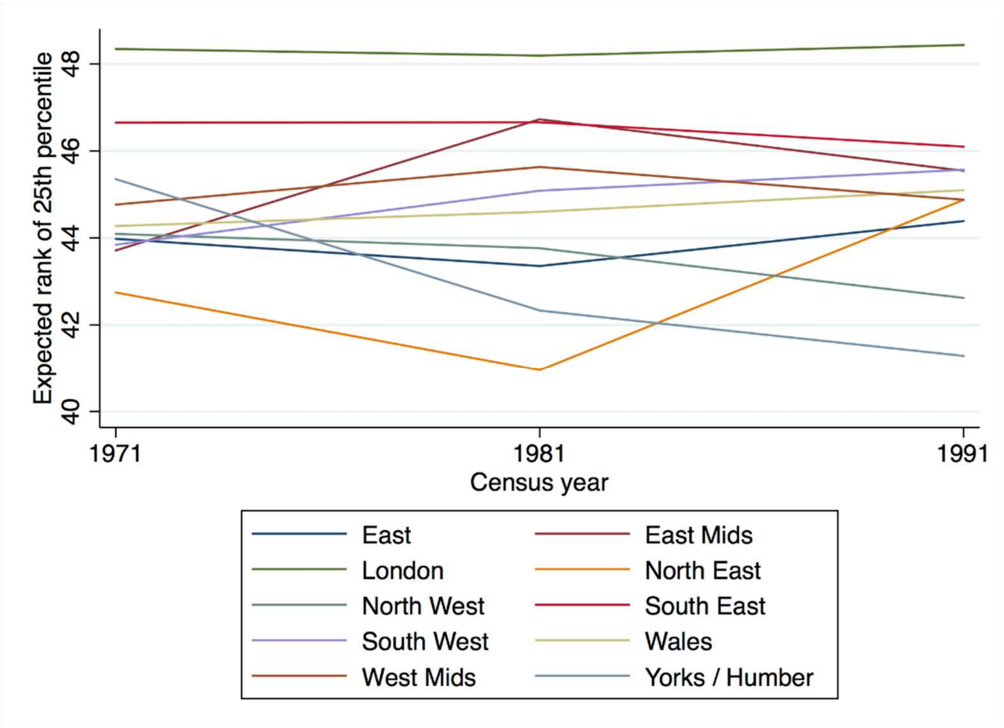
Notes: Parents observed when children age 10-16, children observed age 30-36. Parents defined as degree holders if at least one parent holds a university degree. Error bars reflect 95% confidence intervals. *Source*: ONS Longitudinal Study

FIGURE 5. OCCUPATION-WAGE MOBILITY ESTIMATES (BOTTOM TO TOP TERCILE) AT REGIONAL LEVEL



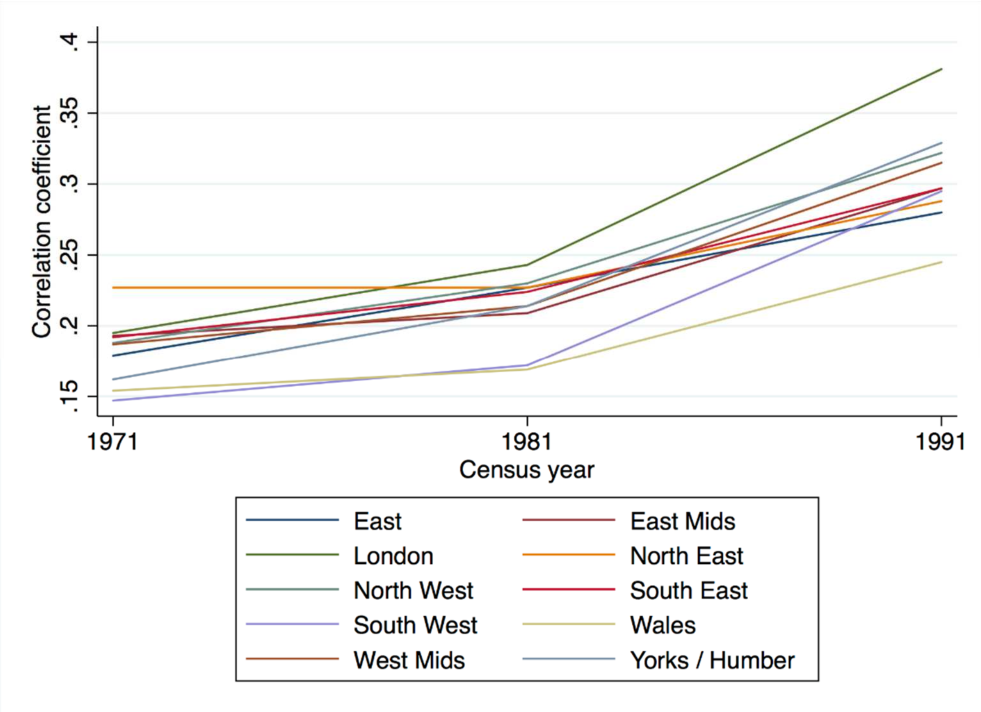
Notes: Parents observed when children age 8-17, children observed age 28-37. *Source*: ONS Longitudinal Study

FIGURE 6. OCCUPATION-WAGE MOBILITY ESTIMATES (EXPECTED RANK OF 25TH PERCENTILE) AT REGIONAL LEVEL



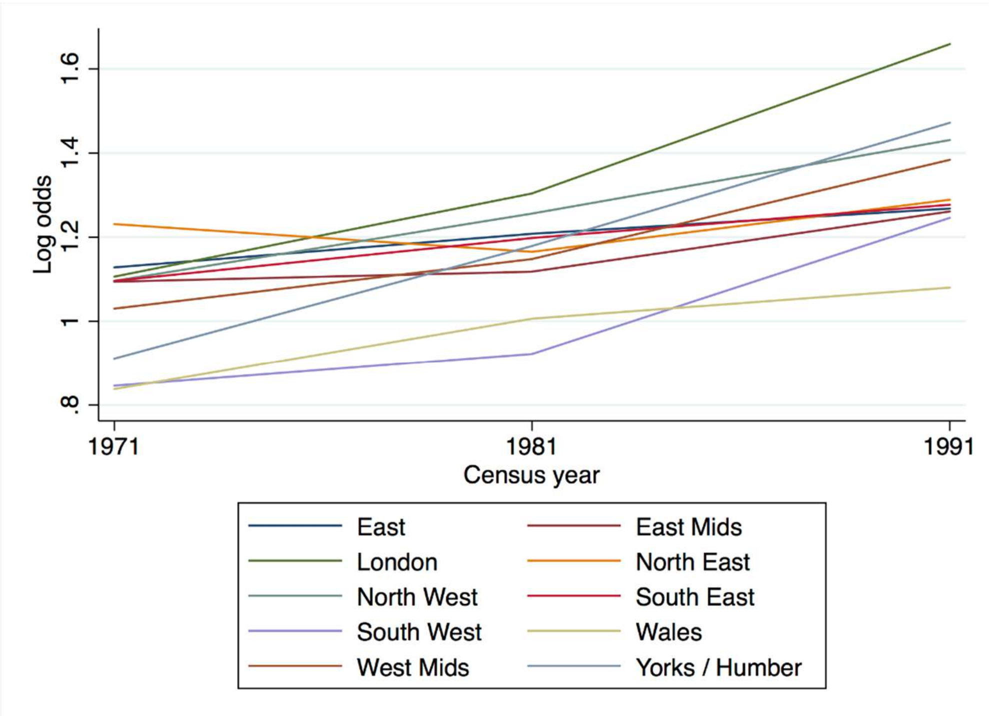
Notes: Parents observed when children age 8-17, children observed age 28-37. *Source*: ONS Longitudinal Study

FIGURE 7. HOUSING MOBILITY ESTIMATES (COEFFICIENTS) AT REGIONAL LEVEL



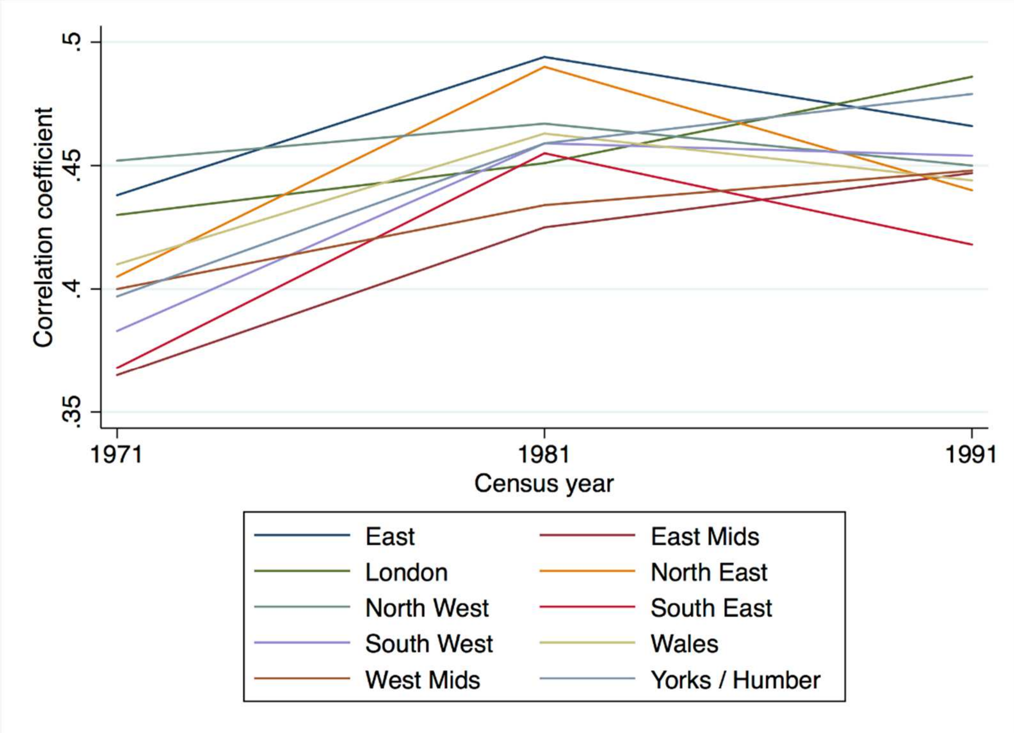
Notes: Parents observed when children age 10-16, children observed age 30-36. *Source*: ONS Longitudinal Study

FIGURE 8. HOUSING MOBILITY ESTIMATES (LOG ODDS RATIOS) AT REGIONAL LEVEL



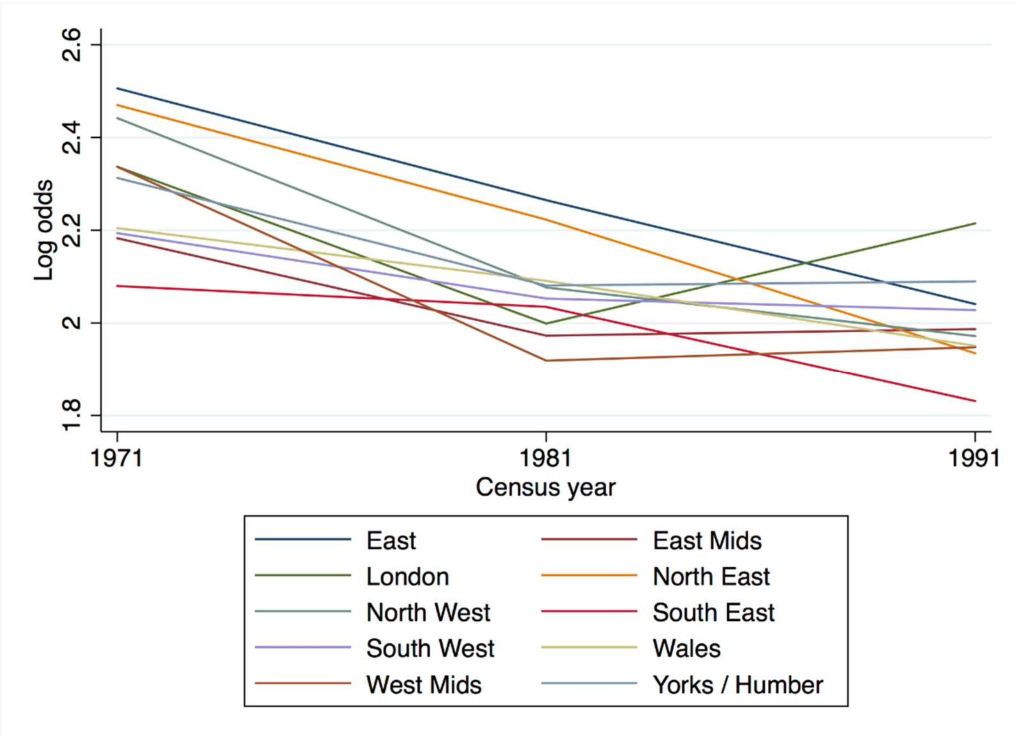
Notes: Parents observed when children age 10-16, children observed age 30-36. *Source*: ONS Longitudinal Study

FIGURE 9. DEGREE MOBILITY ESTIMATES (COEFFICIENTS) AT REGIONAL LEVEL



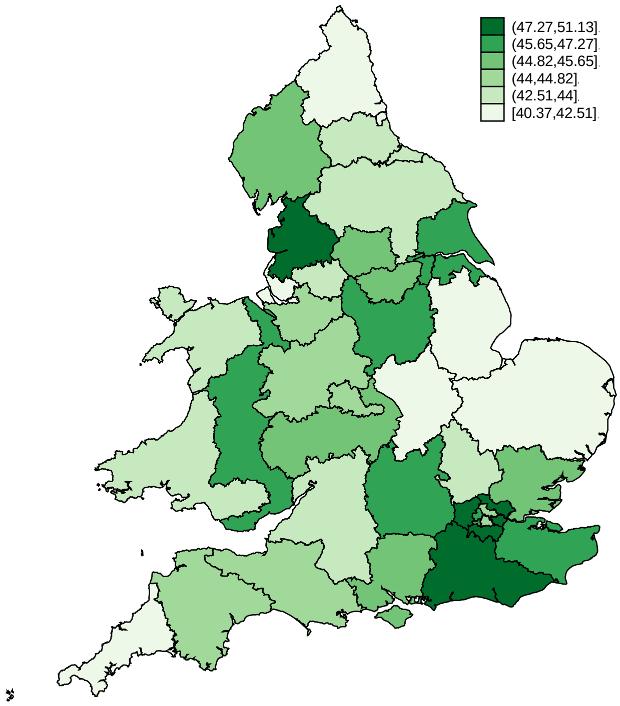
Notes: Parents observed when children age 8-17, children observed age 28-37. *Source*: ONS Longitudinal Study

FIGURE 10. DEGREE MOBILITY ESTIMATES (LOG ODDS RATIOS) AT REGIONAL LEVEL



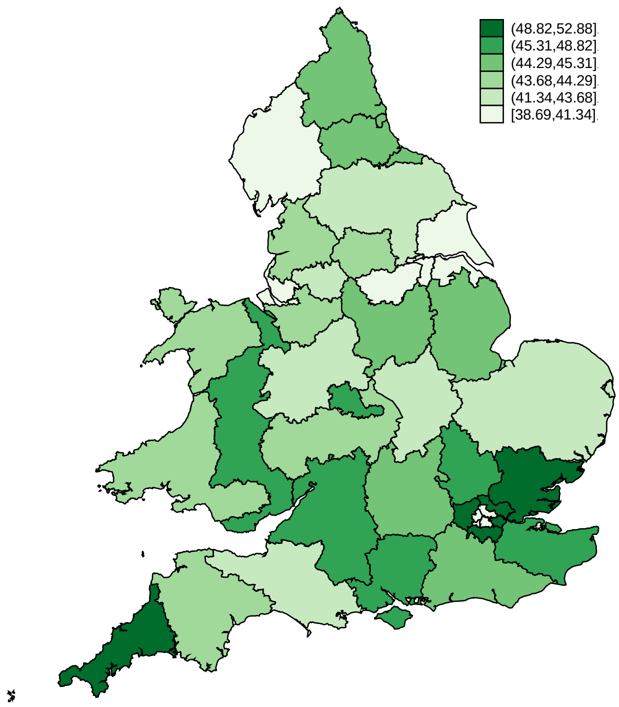
Notes: Parents observed when children age 8-17, children observed age 28-37. *Source*: ONS Longitudinal Study

FIGURE 11A. OCCUPATION-WAGE MOBILITY ESTIMATES (EXPECTED RANK OF 25TH PERCENTILE) AT NUTS2 LEVEL, 1954-63 COHORT



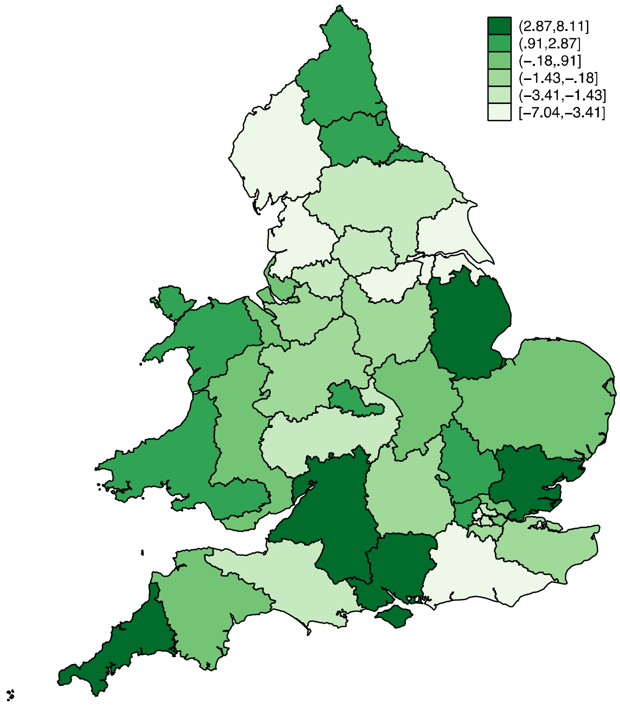
Notes: Parents observed when children age 8-17, children observed age 28-37.
Source: ONS Longitudinal Study

FIGURE 11B. OCCUPATION-WAGE MOBILITY ESTIMATES (EXPECTED RANK OF 25TH PERCENTILE) AT NUTS2 LEVEL, 1974-83 COHORT



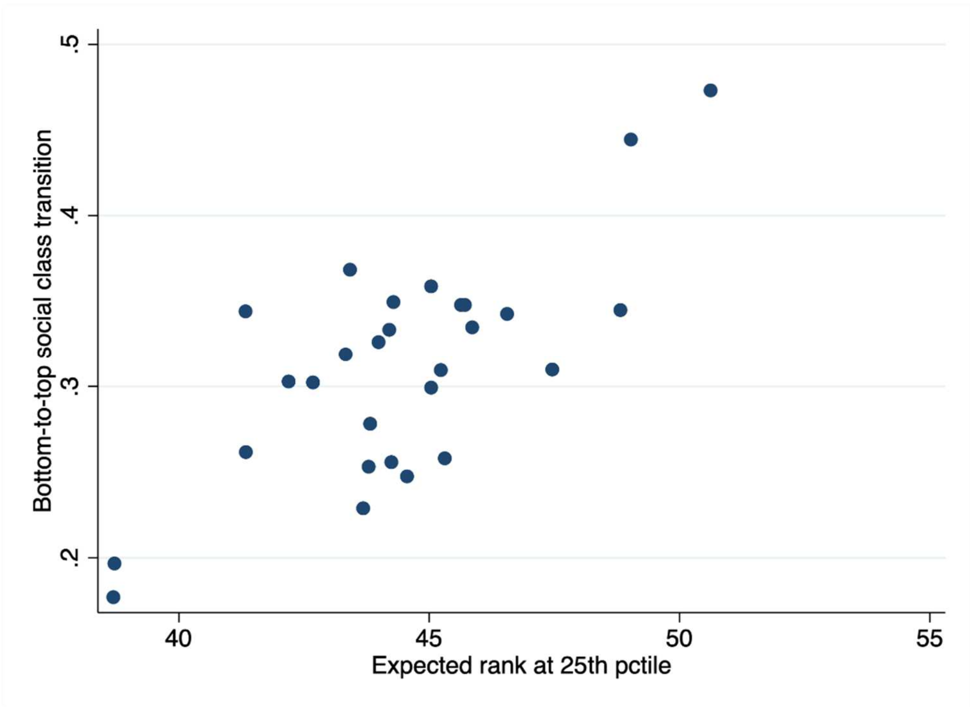
Notes: Parents observed when children age 8-17, children observed age 28-37.
Source: ONS Longitudinal Study

FIGURE 11C. OCCUPATION-WAGE MOBILITY ESTIMATES (EXPECTED RANK OF 25TH PERCENTILE) AT NUTS2 LEVEL, CHANGE BETWEEN 1954-63 COHORT AND 1974-83 COHORT



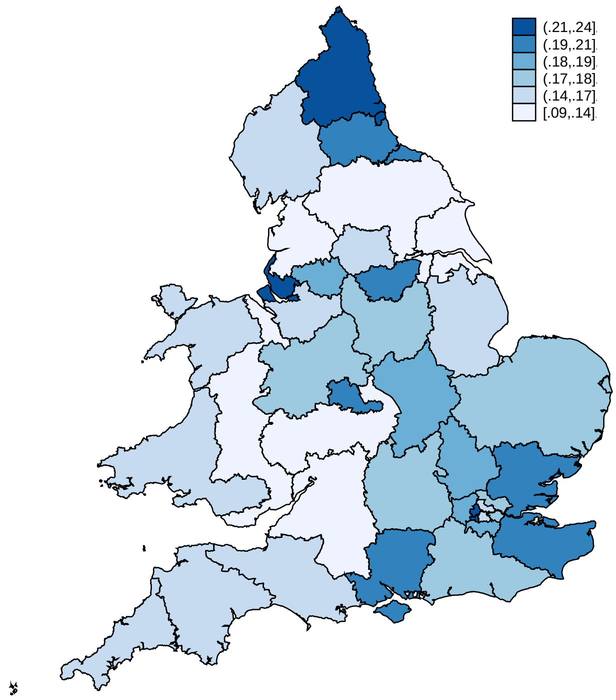
Notes: Parents observed when children age 8-17, children observed age 28-37.
Source: ONS Longitudinal Study

FIGURE 12. MEASURES OF OCCUPATIONAL MOBILITY AT NUTS2 LEVEL, 1974-83 COHORT



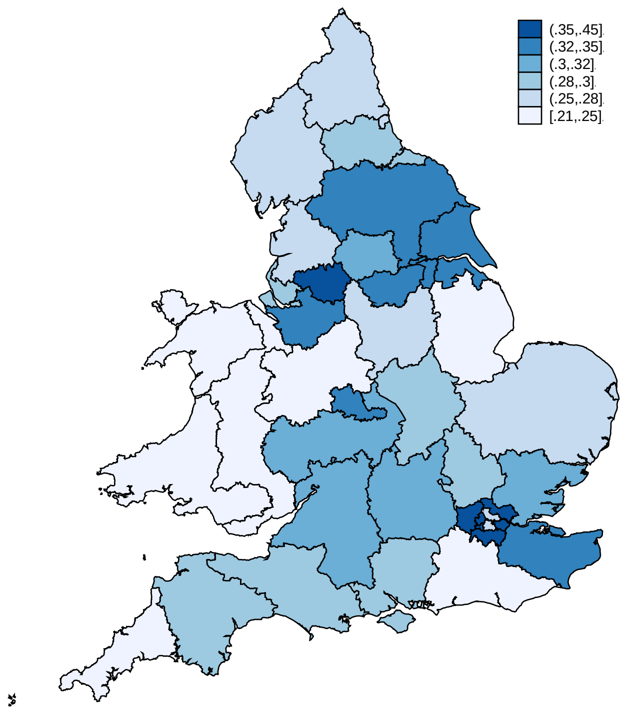
Notes: Parents observed when children age 8-17, children observed age 28-37. Three social class groups are Professional and Technical occupations, Skilled occupations and Semi-Skilled/Unskilled occupations. *Source*: ONS Longitudinal Study

FIGURE 13A. HOUSING MOBILITY ESTIMATES (COEFFICIENTS) AT NUTS2 LEVEL, 1955-61 COHORT



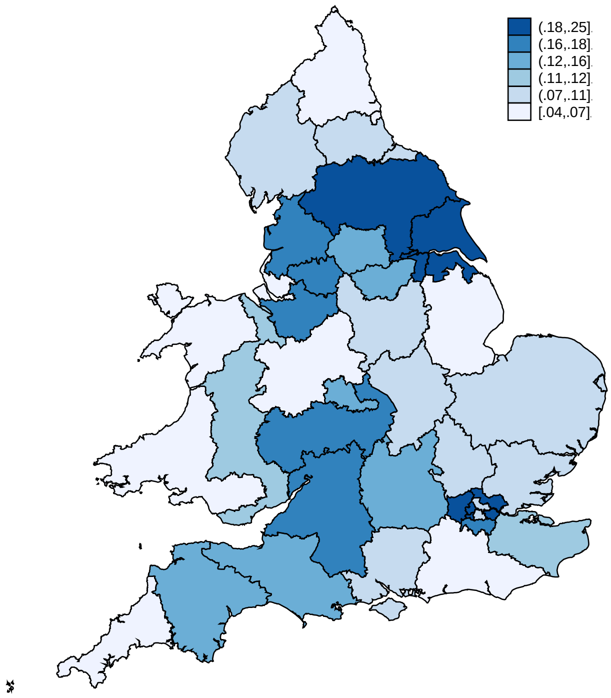
Notes: Parents observed when children age 10-16, children observed age 30-36.
Source: ONS Longitudinal Study

FIGURE 13B. HOUSING MOBILITY ESTIMATES (COEFFICIENTS) AT NUTS2 LEVEL, 1975-81 COHORT



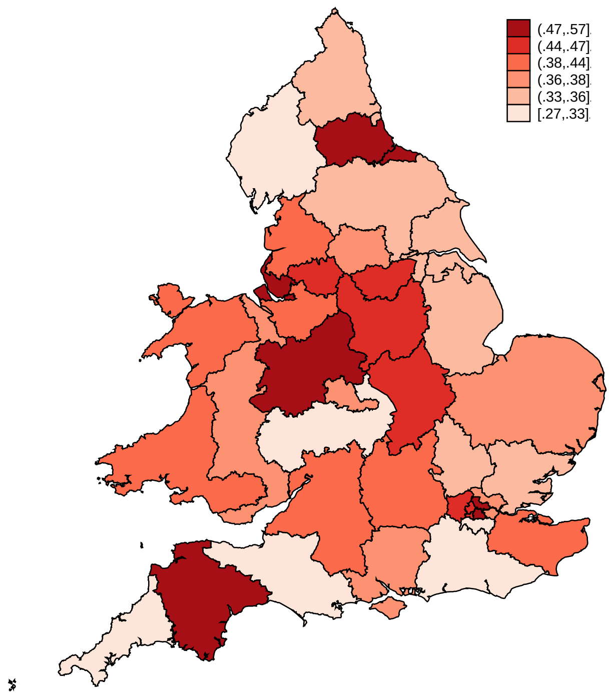
Notes: Parents observed when children age 10-16, children observed age 30-36.
Source: ONS Longitudinal Study

FIGURE 13C. HOUSING MOBILITY ESTIMATES (COEFFICIENTS) AT NUTS2 LEVEL, CHANGE BETWEEN 1955-61 COHORT AND 1975-81 COHORT



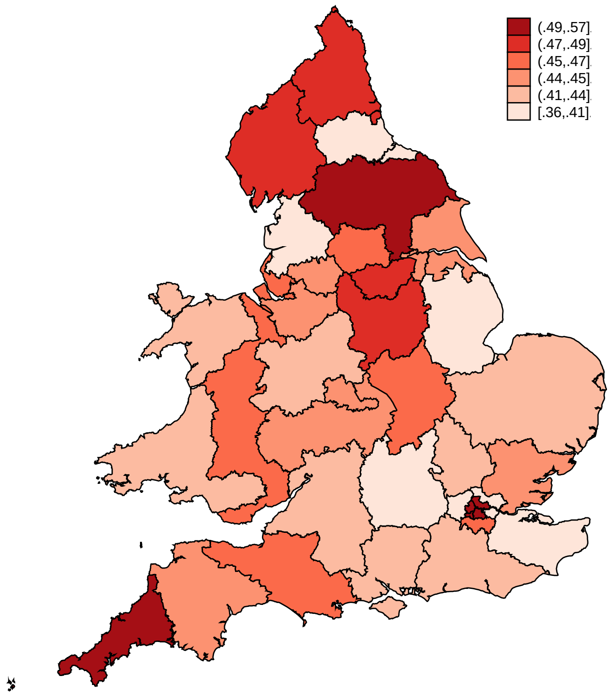
Notes: Parents observed when children age 10-16, children observed age 30-36.
Source: ONS Longitudinal Study

FIGURE 14A. DEGREE MOBILITY ESTIMATES (COEFFICIENTS) AT NUTS2 LEVEL, 1954-63 COHORT



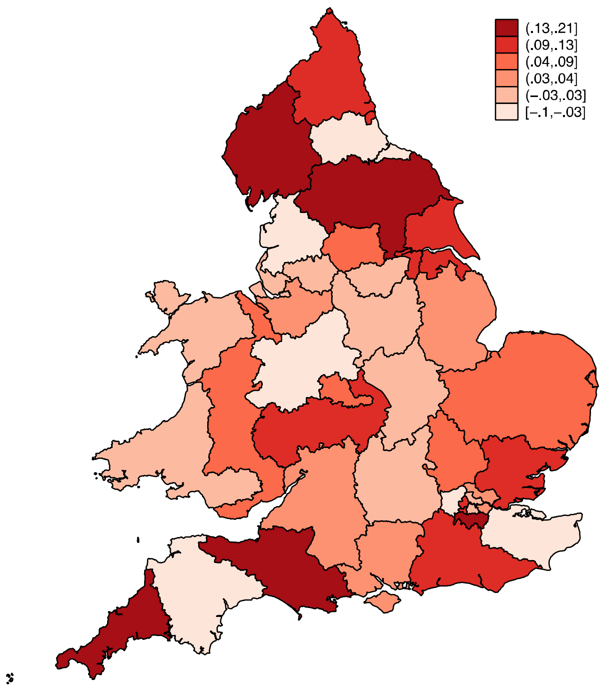
Notes: Parents observed when children age 8-17, children observed age 28-37.
Source: ONS Longitudinal Study

FIGURE 14B. DEGREE MOBILITY ESTIMATES (COEFFICIENTS) AT NUTS2 LEVEL, 1974-83 COHORT



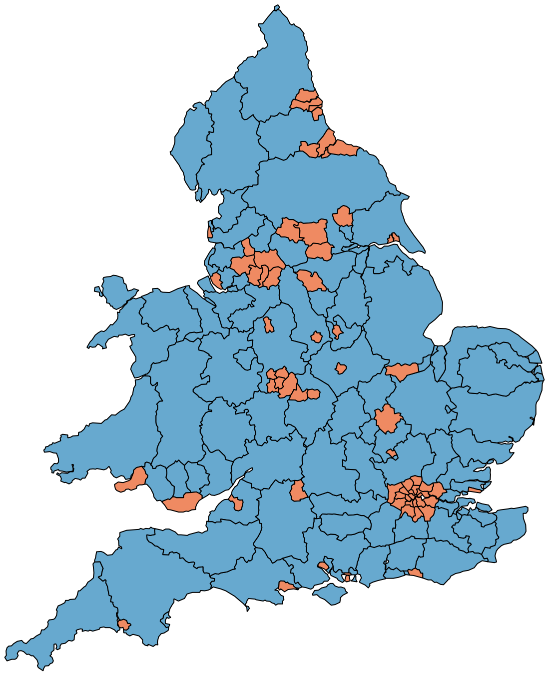
Notes: Parents observed when children age 8-17, children observed age 28-37.
Source: ONS Longitudinal Study

FIGURE 14C. DEGREE MOBILITY ESTIMATES (COEFFICIENTS) AT NUTS2 LEVEL, CHANGE BETWEEN 1955-61 COHORT AND 1974-83 COHORT



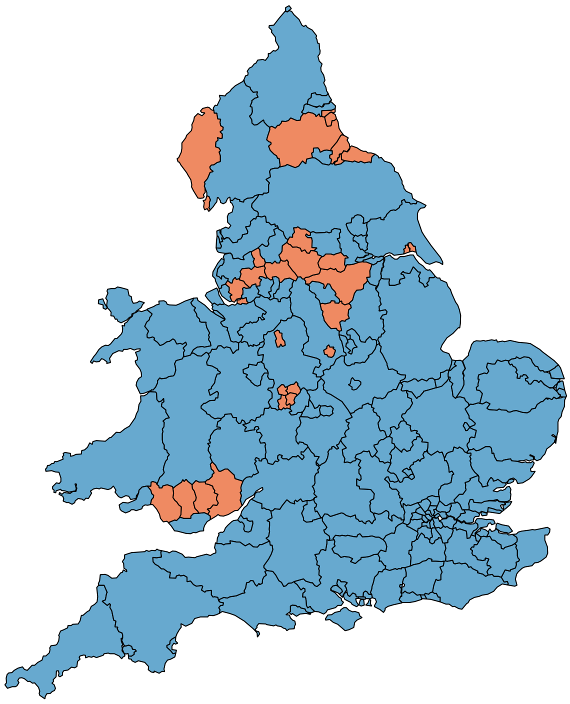
Notes: Parents observed when children age 8-17, children observed age 28-37.
Source: ONS Longitudinal Study

FIGURE 15. CITIES IN ENGLAND AND WALES



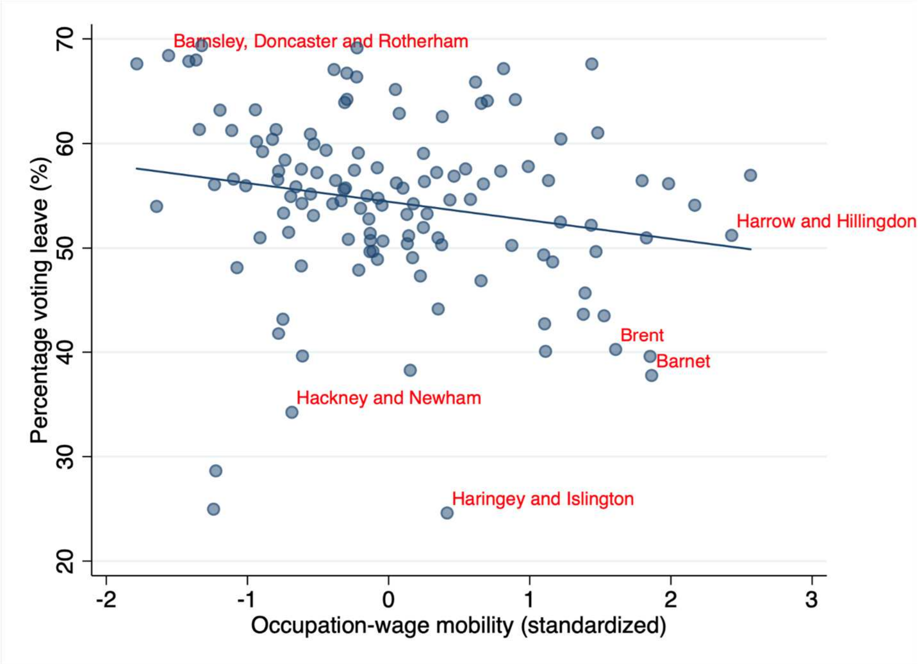
Notes: NUTS3 areas corresponding to cities highlighted in red.
*Source***:** Eurostat NUTS3 classifications. Cities identified by authors.

FIGURE 16. EX-INDUSTRIAL AREAS IN ENGLAND AND WALES



Notes: NUTS3 areas corresponding to ONS classifications 'Manufacturing Legacy', 'Industrial and Multi-ethnic' and 'Mining Legacy' highlighted in red.
*Source***:** ONS Area Classifications

FIGURE 17. OCCUPATION-WAGE MOBILITY AND EU REFERENDUM VOTING PATTERNS



Notes: Parents observed when children age 8-17, children observed age 28-37. Mobility estimates based on cohort born 1984 – 1973. Mobility measure standardized such that higher values correspond to higher mobility.
Source: ONS Longitudinal Study, UK Electoral Commission

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