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Intergenerational income mobility in England and the importance of education

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Intergenerational income mobility in England and the importance of education *

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Abstract

We use newly linked UK administrative to estimate absolute income mobility for children born in England in the 1980s. We find huge differences across the country, with a strong North-South gradient. Children from low-income families who grew up in the lowest mobility areas - overwhelmingly in the North - are expected to end up around fifteen percentiles lower in the income distribution as adults compared to those from the highest mobility areas - overwhelmingly in the South-East. Differences in average educational achievement across areas can explain 25% of this variation in absolute mobility within the country for men, and more than 45% of the variation for women. This indicates that education policy has an important role to play to equalise opportunities of children from low-income families across the country, though will not be sufficient to fully do so on its own. High mobility is further strongly related to stronger labour markets, more stable families, higher median income and better schools.

JEL Codes: J62, I24, I26, R00

Keywords: social mobility, human capital

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1 Introduction

In recent years, the increasing availability of large scale linked administrative datasets has enabled a new literature to emerge which compares intergenerational mobility across small areas within countries. This work, pioneered by Chetty et al. (2014) has shown substantial heterogeneity within countries both in the outcomes of children from poor backgrounds and in the gap in outcomes between children from poor and rich backgrounds, not only in the US, but also in smaller and more centralized countries such as Italy (Acciari et al., 2019) and Canada (Corak, 2019). Subsequent work (Chetty and Hendren, 2018) has shown that much of these differences in mobility between areas are due to causal effects of place rather than selection. This begs the question what it is about areas that leads to high and low mobility, and hence which policies are most promising to increase mobility. While still little is known on the causal mechanisms driving mobility differences across places, attempts at answering this question have been made by looking at which area characteristics best predict mobility. This work has shown that high mobility areas tend to have better schools, less inequality, stronger labour markets, and more stable families.

This paper adds to this recent and growing literature by providing the first estimates of intergenerational income mobility at a detailed geographical level in England. Previous work in the UK (e.g. Blanden et al., 2004; Gregg et al., 2017) has had to rely on longitudinal surveys, which rely on self-reported earnings, and have samples which are too small to estimate how mobility varies across the country. A recent paper (Bell et al., 2018) uses a 1% sample of the linked census to estimate mobility across broad areas in England, but does not have access to any measures of income and therefore is only able to estimate mobility in terms of occupation, education and homeownership. We use new linked administrative data on the whole population of individuals born in or after September 1985 and educated in England to estimate income mobility for the 1985-1988 birth cohorts for all 152 local authorities in England. We focus on absolute mobility for individuals from low-income backgrounds using two main measures of mobility. The first looks at the average income rank of children on Free School Meals (which indicates that their parents are on means-tested benefits and roughly identifies the children from the 12.5% of families with the lowest incomes), and the second focuses on bottom to top mobility by looking at the proportion of children on FSM who make it to the top 20% of the income distribution. We combine the 1985 to 1988 birth cohorts and measure income as total earned income at age 28, ranking children within their birth cohort.

We first estimate these two measures of absolute mobility at the national level and find that children on Free School Meals are expected to end up at the 37th percentile of their income distribution. This implies that these children move up considerably in the income distribution compared to their parents (who are around the 6th percentile on average), yet do remain substantially below the median. The level of mobility estimated for this group of children from very low-income backgrounds is roughly between that estimated in the US and in Italy.

We then explore how mobility varies according to where a child grows up, focusing on the 152 local authorities in England. We assign children to the local authority where they lived at age 16 and estimate their income rank in the national distribution. Differences across the country are substantial. FSM children in the lowest mobility areas are expected to end up around fifteen percentiles lower on average at age 28 than similar children from the highest mobility areas. This gap in earnings rank is remarkably similar for both men and women. There is a strong North-South gradient in terms of mobility, with the North having the lowest mobility, and virtually all of the highest mobility areas being located in the South-East. There is no clear urban-rural distinction, with areas in and around London performing very well, but Northern cities being among the lowest mobility areas in the country. Geographical patterns of mobility for men and women exhibit some interesting differences, with cities, and particularly Inner London performing relatively much better in terms of absolute mobility for women than for men.

Having estimated how absolute mobility varies across the country, we then ask how much of this variation can be explained by differences in human capital across areas. This is closely related to a recent paper by Rothstein (2019) in the US. There are a few important differences between our work and his. Firstly, we focus on absolute mobility, while Rothstein focuses on explaining differences in relative mobility across areas. Second, unlike Rothstein, we use the same samples to estimate mobility and human capital across areas, and can estimate human capital at the area level. Rothstein combines mobility measures at the Commuting Zone level from Chetty et al. (2014) with a sample of 15,000 indidividuals from the Education Longitidunal Study, which does not enable him to estimate human capital transmission at the area level. Finally, we have much richer measures of educational achievement. Rothstein uses maths scores at age 18 as his main measure of human capital. We instead make use of rich school and university records which give us test scores in individual subjects at ages 11, 16 and 18, as well as subject of study, institution attended, GPA and completion for those who attend university. As we show, using less detailed measures of educational attainment understates the importance of differences in human capital for explaining variation in mobility across areas. Our analysis shows that differences across areas in the educational achievement of children from low-income background can explain 25% of the across-area variation in absolute income mobility for men, and more than 45% for women. This suggests a critical role for improving educational outcomes of children from low-income backgrounds in low mobility areas to equalise opportunities across the country. Despite the important role of education, a substantial part of mobility differences remains even holding educational achievement constant across areas. This suggests the importance of other drivers of mobility.

As a first step in investigating what these other drivers of mobility are likely to be, we correlate our mobility measures with area characteristics. We do this both with overall mobility $\overline{R}_a^{FSM}$ and with differences in income rank across areas when we hold educational achievement constant. Areas with stronger labour markets, more stable families, higher median income and better schools have higher mobility.

The remainder of the paper is organised as follows. We begin in Section 2 by describing the data. Section 3 lays out our national and regional mobility estimates. Section 4 discusses how differences in human capital might explain differences in mobility across areas, and shows the results of our decomposition of the variance in absolute mobility. Section 5 reports correlations of absolute mobility with area characteristics, both before and after accounting for educational differences. Finally, Section 6 concludes.

2 Data

We make use of a new UK linked administrative dataset, the Longitudinal Education Outcomes (LEO) dataset. This dataset consists of three component datasets: school records from the National Pupil Database (NPD), university records from the Higher Education Statistics Agency (HESA) and earnings records from Her Majesty's Revenue and Customs (HMRC). These datasets were linked before we got access to the data by the UK's Department for Work and Pensions. Where National Insurance Numbers[1] were available, these were used to hard link education and tax records. Where no National Insurance Numbers were available fuzzy matching using first name, surname, date of birth, postcode and gender was used. In what follows we briefly summarise the main variables and describe our sample.

[1]National Insurance Numbers are unique person identifiers assigned to individuals at age 16, or upon starting a first job, which are broadly the UK equivalent of US Social Insurance numbers.

2.1 Parental background

Due to the lack of common identifiers, and the absence of up to date address information in UK tax records, it is not possible to reliably link children to their parents in the UK. Fortunately for our purposes however, the NPD school records document whether a child is eligible for Free School Meals (FSM). Children are eligible for FSM when their parents are in receipt of means tested benefits,[2] and have annual gross income below a given threshold, currently £16,190. These eligibility criteria, including the income cutoff, do not vary across the country. In our cohorts of analysis, 12.5% of students are eligible for Free School Meals. FSM eligibility therefore broadly identifies the 12.5% of children coming from the lowest income families. It needs to be kept in mind however, that there may be families with gross income just above the eligibility cut-off but net income (post taxes and benefits) below than that of some of the families who are eligible for FSM. The main focus of this paper will be on the outcomes of children from low-income backgrounds, as defined by children recorded as being eligible for Free School Meals at age 16.

2.2 Child income

Our measure of child income will be earned income at age 28, combining income from employment and self-employment. Data on earnings come from two complementary records, combined in the HMRC tax data: Pay As You Earn (PAYE) records, which record income from employment, and Self Assessment (SA) records, which incorporate income from self-employment. We combine income from both sources and use total earnings in our analysis. We have this data up to the 2016/17 tax year,[3] which means we observe our first cohort (those born between 1st September 1985 and 31st August 1986) up until around age 30. In order to look at earnings as late as possible in the lifecyle, yet have sufficiently large samples to estimate absolute mobility at the the small local area level, we combine three cohorts in our analysis and make use of their earnings at age 28, the last age at which we observe earnings from all three cohorts.

[2]These benefits are: Income Support, income-based Jobseeker's Allowance, income-related Employment and Support Allowance, support under Part VI of the Immigration and Asylum Act 1999, the guaranteed element of Pension Credit and Child Tax Credit (provided the parents are not also entitled to Working Tax Credit).

[3]Tax years in the UK run from 6th April of one year to the 5th of April of the next year.

2.3 Educational attainment

Frequent standardized and externalised marked tests make the UK administrative education records (NPD) extremely comprehensive in detailing the educational trajectory of children. At age 11, the end of primary school, children sit Year 6 Standard Assessment Tests (SATs) in English, maths and science. At age 16, students sit General Certicate for Secondary Education (GCSE) exams. Students in our cohorts of study sat these exams in English, maths, science, and in typically between five and seven additional subjects. We observe each subject taken, and the grade obtained in each exam. At age 18 A-level exams are taken, end of high school exams typically sat in typically between three and four subjects. Students may also sit vocational exams in addition to, or instead of, academic A-levels, in courses such as hospitality or retail. We again have indicators for the subjects taken, as well as grades obtained. Finally, we also have detailed data on higher education attendance from HESA records. We observe subject of study at a granular level, institution attended, as well as whether an individual completes their course, and with what GPA.

For the purposes of our analysis we will use this rich educational data to construct measures of human capital at ages 11, 16, 18 and 21. We combine the information on subjects taken and grades achieved into a continuous measure of human capital as follows. Writing these multiple measures as vector S_i, we first regress individual earnings on S_i:

$$Y_i = \alpha + S_i'\beta + \epsilon_i \tag{1}$$

Using the coefficients obtained in this regression, we then generate our measure of human capital H_i as predicted earnings $\widehat{Y}_i$:

$$H_i = \widehat{Y}_i = \widehat{\alpha} + S_i'\widehat{\beta} \tag{2}$$

We use this method to create human capital measures at different ages 11, 16, 18 and 21, at each age including all educational attainment measures up to that point.

2.4 Sample

Our full sample includes all individuals who 1) are born between 1st September 1985 and 31st August 1988, 2) went to school in England, and 3) were linked to HMRC or DWP records at any point between 2004/05 and 2016/17.[4]

The focus of this paper is on absolute mobility, hence we will mainly focus on the outcomes of children who were on Free Schools Meals at age 16. Table 1 below gives some basic descriptives of children of FSM and compares them to the average characteristics of the entire cohort of students. Children from this group of low-income families are more than twice as likely to have English as an additional language, and are much more likely to be Black or of Asian ethnicity. They perform much worse in school than the average student, and this gap increases between age 11 and age 16. Only around one in four stays in school past age 16, compared to nearly half of all students. Consequently they are also much less likely to attend university and obtain a degree. This lower educational attainment seems to translates into much worse adult outcomes than that of their non-FSM peers. Age 28 earnings of this group are around 35% lower than the average in these cohorts, and they are ten percentage points more likely to have no earned income.

3 Absolute mobility in England

We begin by documenting absolute upward mobility in England at the national level. This will both allow us to compare the English level of mobility with that in other countries, as well as provide a baseline for the regional estimates of mobility. We will then estimate how these measures of mobility vary within England.

3.1 National estimates

We estimate two measures of absolute mobility, one focusing on the average outcomes of children from low-income backgrounds, and one focusing on how many children from low-income backgrounds make it to the top of the income distribution. The first measure, which we will call $\overline{R}_a^{FSM}$, is the average income rank at age 28 of children from low-income families, as defined by being on Free School Meals at age 16. This is equivalent to the r^{25} measure of absolute mobility used for example in Chetty et al. (2014), or the AUM measure used in Acciari et al. (2019), but using a narrower definition of "disadvantage". Where those papers focused on the average outcomes of children from families with below median income, we focus on the average outcomes for those with parental income roughly in the bottom 12.5%

[4] We require individuals to have been in touch with the tax and benefit system at some point between 2004/05 and 2016/17 for them to be recorded in the data. This does not mean individuals have to have had positive earnings at any point in this time frame.

Table 1: Sample descriptives

	Women		Men	
	non-FSM	FSM	non-FSM	FSM
Cohort				
2001/02 GCSE cohort	0.31	0.31	0.32	0.31
2002/03 GCSE cohort	0.33	0.34	0.34	0.34
2003/04 GCSE cohort	0.35	0.35	0.35	0.35
Background characteristics				
English as additional language	0.07	0.20	0.06	0.20
White	0.79	0.70	0.80	0.71
Black	0.02	0.07	0.02	0.06
Asian	0.05	0.14	0.05	0.14
Missing/Other ethnicity	0.14	0.10	0.14	0.10
Educational attainment				
Age 11 test score pctile	52.89	37.57	51.00	37.86
Age 16 test score pctile	56.85	33.50	48.62	26.44
Stay in school past 16	0.56	0.28	0.46	0.20
Start UG	0.48	0.25	0.38	0.19
Graduate from UG	0.41	0.18	0.31	0.12
Age 28 outcomes				
Mean earnings	17700	9900	22300	14700
Median earnings	16000	6600	21200	13500
Self-employment income	0.06	0.03	0.11	0.09
No earned income	0.15	0.31	0.13	0.22
N	710,036	100,709	764,556	108,181

Notes: The first column shows descriptives of the full set of individuals who were born between 1st September 1985 and 31st August 1988, went to school in England, and were linked to HMRC or DWP records at any point between 2004/05 and 2016/17. The second column shows the same descriptives for the subset of those individuals who were eligible for Free School Meals at age 16. "Attend UG" shows the proportion who start a undergraduate degree, while "UG degree" shows the proportion who actually obtain an degree. Mean and median earnings are defined including zero earnings. "Has self-employment income" shows the proportion of people who have any self-employment income at age 28, regardless of whether this is their only source of income, or whether they also have employment income. Not in employment is defined as individuals who report no employment or self-employment income at age 28.

nationally. The second measure of absolute mobility we will use is $P(Q5|FSM)$, the proportion of children on FSM who make it to the top 20% of the income distribution in their cohort at age 28.

Table A4 brings together our estimates of absolute mobility both for the whole sample, as well as for men and women separately. A child on Free School Meals ends up on average at the 37.5 percentile of the income distribution at age 28. As their parental income was on average at the sixth percentile[5] they move up considerably in the income distribution on average, though still end up much below the mean. While there are some differences in our income measures, we can get an idea of how this compares internationally by comparing

[5]Families on FSM broadly correspond to the families with income in the bottom 12.5% nationally.

this to the average income rank of children in the bottom 12% of income in Italy from Acciari et al. (2019) and in the US from Chetty et al. (2014). A child with parents in the bottom 12% of income is expected to end up at the 39th percentile of the child income distribution in Italy, and at the 35th percentile in the US. Absolute upwards mobility for this group in England is hence nearly exactly in between that of Italy and the US.

Turning now to $P(Q5|FSM)$, our measure of bottom-to-top mobility, we see that 8.4% of children on FSM reach the top quintile of the child income distribution. This shows a considerably degree of immobility - this is less than half of the 20% we would see if parental income had no impact on child outcomes. The equivalent figure is the US from Chetty et al. (2014) is even lower at 6.8%.

Men have markedly higher absolute mobility than women. The gender difference is particularly pronounced in terms of the probability of moving to the top quintile of the income distribution. This probability is 5.5% for women, compared to 11% for men. This is likely to be driven to a large extent by differential labour market participation of men and women at this age.[6] Men from low-income families have higher mobility than women from similar backgrounds even when ranking them in their gender-specific earnings distribution. Some of this is likely to be driven by differential patterns of fertility of women from different socio-economic backgrounds at this age.

Table 2: National estimates of absolute mobility

	Overall	Women	Men
$\overline{R}^{FSM}$	37.5	32.3	42.3
$\overline{R}^{FSM}$ - gender specific		36.0	38.3
$P(Q5\|FSM)$	0.084	0.055	0.111
$P(Q5\|FSM)$ - gender specific		0.075	0.087
N	208,915	100,716	108,199

Notes: $\overline{R}^{FSM}$ is the average income rank at age 28 of children from low-income families, as defined by being on Free School Meals at age 16. $P(Q5|FSM)$ shows the proportion of children on FSM who make it to the top 20% of the income distribution in their cohort at age 28. Sample consists of English educated individuals born between 1st September 1985 and 31st August 1988. Income ranks defined within each school cohort (1st September to 31st August of each year). We assign children with zero income the average income rank of that group. For our measure fo relative poverty, we calculate the average earnings among individuals with positive earnings in each cohort, and define individual as being in relative poverty if they earn less than 60% of this amount. In the cohort used in the analysis this broadly corresponds to earnings below £14,000.

[6]We cannot observe hours in our data, but do observe individuals with zero earnings. Among our group of children from low-income families, 31% of women have no earned income, compared to 22% of men.

3.2 Geographical variation

Having looked at the outcomes of children from low-income families at a national level, we now explore how outcomes of low-income children vary depending on where in the country they grow up. We estimate absolute mobility for the 152 Local Authorities in England.[7] The average population of Local Authorities is just over 320,000 individuals, though these vary in size from less than 50,000 individuals for the smallest Local Authorities, to close to 1.3M for the largest Local Authority.[8]

For each area, we estimate the same two measures of absolute mobility as used at the national level. We first estimate for each area the average income rank at age 28 of children on Free School Meals. We call this measure $\overline{R}_a^{FSM}$. In the Appendix we also show the results for $P_a(Q5|FSM)$, the proportion of children on FSM who grew up in area a and make it to the top 20% of the national income distribution at age 28. We always define children's income ranks at the national level and within their cohort, and assign children to the Local Authority where they lived at age 16.

We show the estimates of $\overline{R}_a^{FSM}$ for all local authorities in Figure **??**. The first thing to note is the large differences in average earnings ranks. Both for men and women children on FSM growing up in the highest mobility areas are expected to end up around fifteen percentiles higher in the income distribution than those from the lowest mobility areas. Some broad geographical patterns emerge. There is a clear North to South East gradient for both genders, though there are also some interesting differences across gender. Women in London have the highest levels in mobility, and the lowest in the North. For men, outcomes in the North East are relatively much better, and many areas in Inner London actually do not perform as well in terms of mobility. There seems to be something about these inner city areas that produces bad outcomes for men, but not for women. The overall correlation between absolute mobility for men and women is only 0.66, which suggests that there might be important differences in the characteristics of areas which lead to good outcomes for men, and those that lead to good outcomes for women.

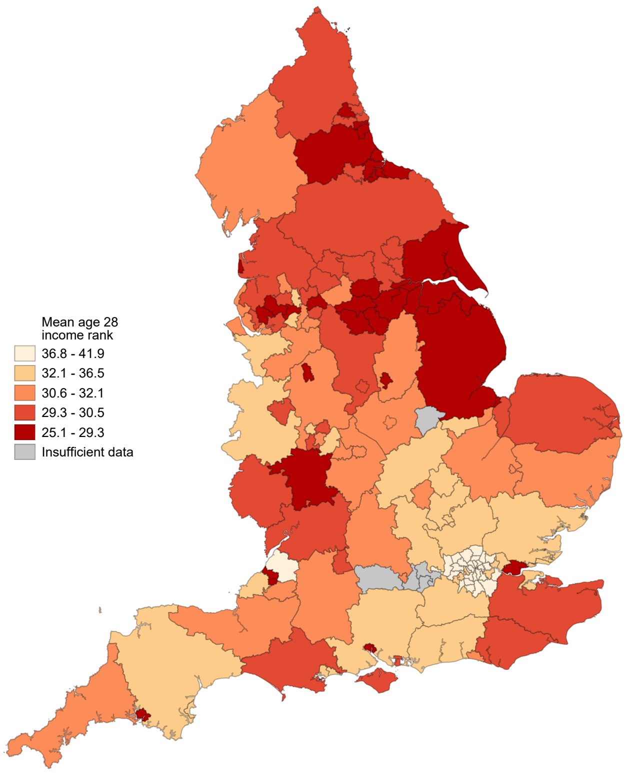
We explore whether these differences between men and women are driven by differences in participation for women. For both genders many rural areas do slightly worse in terms of mobility when we exclude individuals with no earnings, as they have relatively low rates of zero earnings compared to more urban areas. We can see this more clearly in Figure A2 in the Appendix. This is particularly true for men, where zero earnings rates in rural areas

[7] We use upper-tier Local Authorities as defined in the most recent census, which took place 2011.

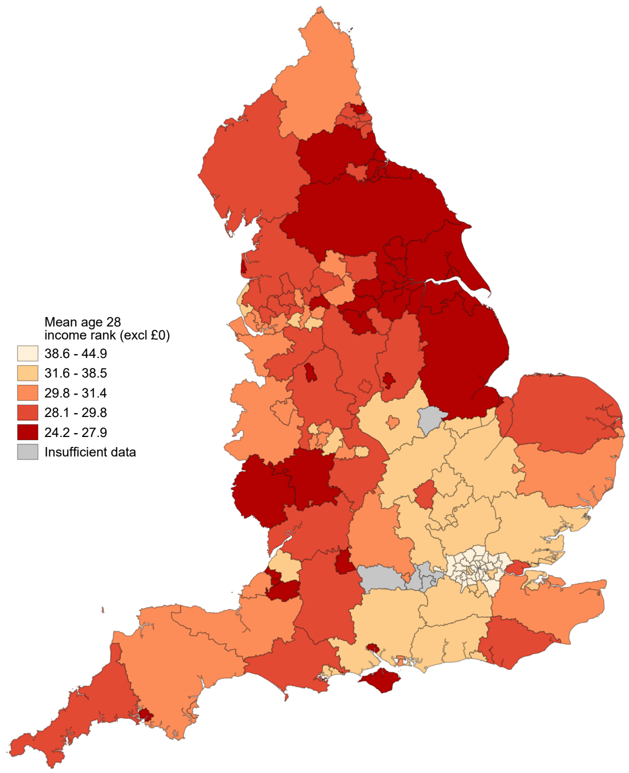
[8] We measure population size from the 2001 population census, which is the closest census to when we measure location of residence of our sample (2002-2004).

such as Cornwall are around 10 percentage points lower than in London or many Northern cities. Removing individuals with zero earnings does not seems to substantially change the overall geographical patterns for either gender and does not seem to drive the differences across genders.

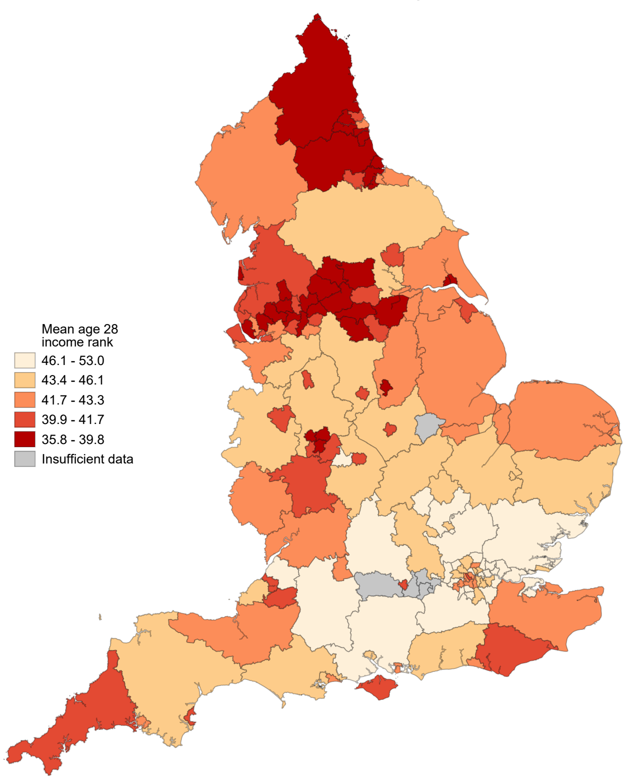
Figure 1: Average earnings rank age 28 - by gender



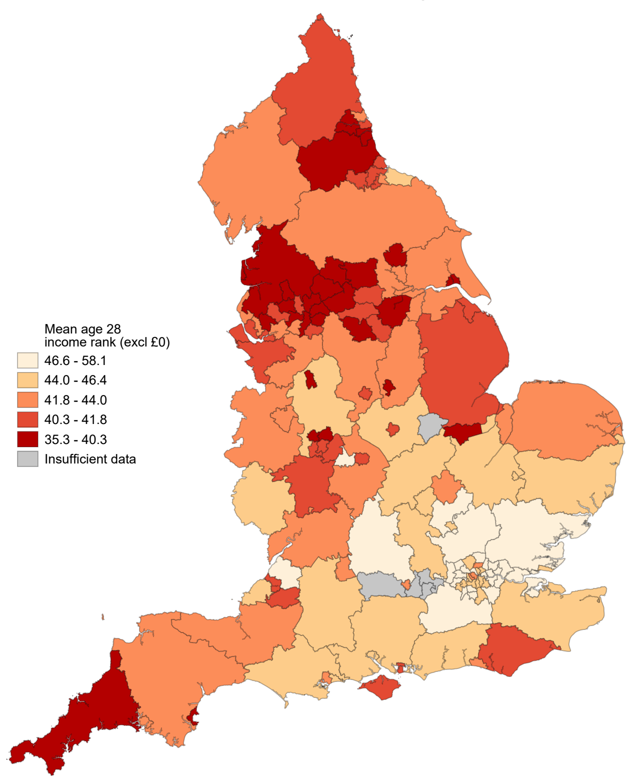
Women - including £0



Women - excluding £0



Men - including £0



Men - excluding £0

If we look at mobility to the top, as measured by $P_a(Q5|FSM)$, we see a very similar pattern, as shown in Figure A1 in the Appendix. London is even more of an outlier in this measure of mobility with virtually London boroughs in the top quintile in terms of the proportion of FSM children reaching the top 20% of the income distribution. Across all areas, the correlations between the two measures of absolute mobility, $\overline{R}_a^{FSM}$ and $P_a(Q5|FSM)$, is very high at 0.88. This indicates that areas where FSM children have the best average outcomes are also those where these children have the best chance of making it to the top of the income distribution.

4 The importance of education

In the previous section, we established that substantial variation exists in the earnings outcomes of children from low-income backgrounds, depending on where in the country they grew up. In this section, we investigate whether differences in educational attainment can explain this variation. If differences in educational attainment are an important driver of differences in absolute income mobility across areas, we would expect children from areas with high absolute income mobility to have high levels of human capital. Conversely, if we find that the average income ranks and human capital levels of individuals across areas are not highly correlated, or if these human capital differences do not matter much in the labour market, we would expect other mechanisms, such as labour market policies, to be more important in driving the differences in income mobility across areas. We investigate this more formally by decomposing the variance in absolute income mobility across areas in a component which can be explained by differences in human capital accumulation and the return to this human capital in the labour market, and a remainder which cannot be explained by human capital differences across areas. This decomposition helps inform us as to the potential for educational interventions to equalise opportunities for children from low-income backgrounds across the country.

We discuss this decomposition in Section 4.1, before showing the results in Section 4.2.

4.1 Methodology

Write the adult income rank of FSM eligible child i who grew up in area a as $R_{i,a}^{FSM}$. We can then write their earnings as a function of their human capital $H_{i,a}^{FSM}$, and of the earnings impact of the location they grew up in η_l, controlling for their level of human capital:

$$R_{i,a}^{FSM} = \beta H_{i,a}^{FSM} + \eta_a + w_{i,a} \tag{3}$$

We can also write their level of human capital as a function of the average human capital in the area they grew up in, and an individual level error term:

$$H_{i,a}^{FSM} = \overline{H}_a^{FSM} + v_{i,a} \tag{4}$$

Plugging in equation 4 into equation 3 and rearranging, we get:

$$R_{i,a}^{FSM} = (\beta \overline{H}_a^{FSM} + \eta_a) + (\beta v_{i,a} + w_{i,a}) \tag{5}$$

In the previous section, we estimated $\overline{R}_a^{FSM}$, the average adult income rank of FSM children in each area. We can write individual earnings rank of individual i who is on Free School Meals and grows up in area a as:

$$R_{i,a}^{FSM} = \overline{R}_a^{FSM} + u_{i,a} \tag{6}$$

Comparing equations 6 and 5 we can then see that $\overline{R}_a^{FSM} = (\beta \overline{H}_a^{FSM} + \eta_a)$, hence we can decompose the average earnings rank in an area, $\overline{R}_a^{FSM}$, into a part which is explained by the level of human capital in an area ($\overline{H}_a^{FSM}$) and the return to this in the labour market (β), and a remainder which is not explained by human capital levels in the area.

We can use this to decompose the variance in absolute mobility (as defined by $\overline{R}_a^{FSM}$) across areas into a part which is explained by differential human capital accumulation across areas, and a part which cannot be explained by differences in human capital accumulation. Using $\overline{R}_a^{FSM} = (\beta \overline{H}_a^{FSM} + \eta_a)$ we get:

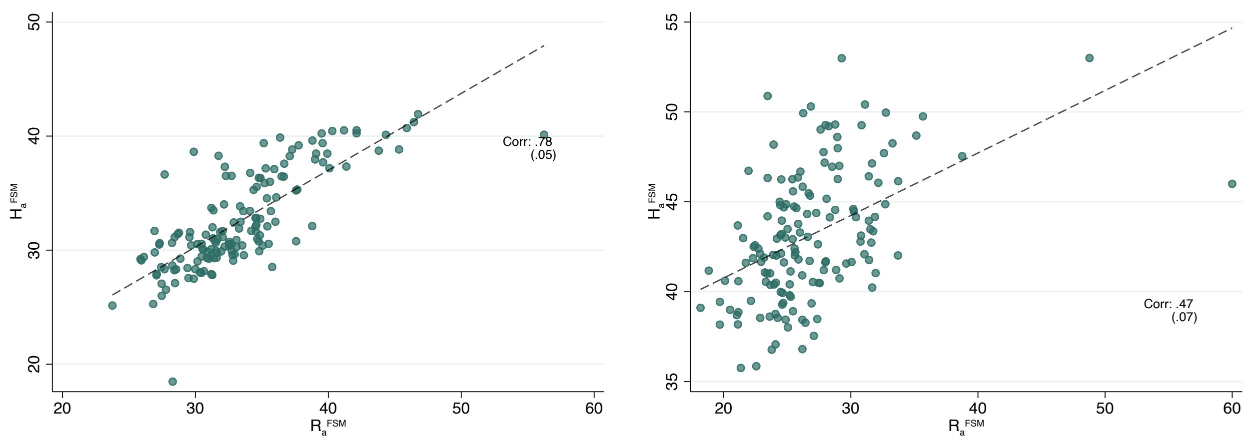
$$Var(\overline{R}_a^{FSM}) = \beta^2 Var(\overline{H}_a^{FSM}) + Var(\eta_a) + 2\beta Cov(\overline{H}_a^{FSM}, \eta_a) \tag{7}$$

The ratio $(\beta^2 Var(\overline{H}_a^{FSM}))/Var(\overline{R}_a^{FSM})$ hence tells us what proportion of the variation in absolute income mobility can be explained by differences in human capital accumulation across areas. This will inform us as to the importance of education policy in improving earnings outcomes of children from disadvantaged background across the country.

4.2 Results

We first look at the variation in average human capital across areas, and how this relates to variation in average income rank across areas. We plot the average value of the human capital index in each area[9] against the average income rank in each area for FSM eligible children in Figure 2. We can see a strong positive correlation between the average human capital index and the average income rank in an area, but we also note that the variation in income ranks is much larger than than in the human capital, or predicted income, ranks. This appears to suggest differences in human capital across areas play an important role in explaining variation in absolute income mobility, though will not be able to explain all of the variation.

Figure 2: Correlation of $\overline{R}_a^{FSM}$ mobility measure and human capital index $\overline{H}_a^{FSM}$



Women

Men

Notes: $\overline{H}_a^{FSM}$ shows the average level of the human capital index in an area, which is created by predicting income rank of FSM eligible children based on their educational achievement at ages 11, 16, 18 and in university. $\overline{R}_a^{FSM}$ represents for each area the average income rank of FSM children who grew up in that area. The dotted line shows the results from an anweighted regressions of $\overline{H}_a^{FSM}$ on $\overline{R}_a^{FSM}$.

Table 3 shows the results of the decomposition of the variance in $\overline{R}_a^{FSM}$ more formally. The top rows of Table 3 show that if we include all measures of educational achievement from age 11 to university, for women 46% and for men 25% of the variation in absolute income mobility across areas can be explained by variation in the educational achievement of children from low-income backgrounds across areas. This points towards a meaningful role for improving educational achievement of low-income students in low mobility areas

[9]As described in the Data section, the human capital index is predicted earnings rank based on test scores and educational attainment at ages 11, 16, 18 and in university.

in order to equalise opportunities across the country, yet other channels, for example differences in labour market practices across areas, are clearly at least as important in explaining variation in mobility across the country. In the rest of the Table, we look at the impact of including fewer measures of educational achievement, respectively only including student achievement up to age 11, 16 and 18 in the human capital index. This shows the importance of including rich measures of educational achievement. Only including measures at younger ages considerably understates the proportion of variation in absolute mobility which can be explained by differences in educational achievement. Sections A2.1 and A2.2 in the Appendix show that these findings are robust to relaxing our implicit assumption of constant returns to human capital across areas, and to changing how we construct measures of human capital.

Table 3: Decomposition of $Var(\overline{R}_a^{FSM})$

		Share of $Var(\overline{R}_a^{FSM})$					
		Men			**Women**		
		Main	Excl. London	Excl. £0s	Main	Excl. London	Excl. £0s
HC index	$\beta^2 Var(\overline{H}_a^{FSM})$	0.25	0.12	0.18	0.46	0.28	0.30
	$Var(\eta_a)$	0.75	0.80	0.73	0.27	0.53	0.33
	$2\beta Cov(\overline{H}_a^{FSM}, \eta_a)$	0.00	0.08	0.09	0.30	0.19	0.37
HC index - up to age 11 only	$\beta^2 Var(\overline{H}_a^{FSM})$	0.04	0.04	0.03	0.04	0.09	0.02
	$Var(\eta_a)$	0.92	0.95	0.96	0.89	0.95	0.96
	$2\beta Cov(\overline{H}_a^{FSM}, \eta_a)$	0.04	0.01	0.01	0.07	-0.04	0.02
HC index - up to age 16 only	$\beta^2 Var(\overline{H}_a^{FSM})$	0.20	0.12	0.12	0.23	0.24	0.12
	$Var(\eta_a)$	0.79	0.88	0.82	0.45	0.65	0.58
	$2\beta Cov(\overline{H}_a^{FSM}, \eta_a)$	0.01	0.00	0.06	0.33	0.11	0.30
HC index - up to age 18 only	$\beta^2 Var(\overline{H}_a^{FSM})$	0.22	0.12	0.13	0.30	0.24	0.16
	$Var(\eta_a)$	0.80	0.89	0.82	0.38	0.63	0.51
	$2\beta Cov(\overline{H}_a^{FSM}, \eta_a)$	-0.02	0.00	0.05	0.32	0.12	0.34
	Total $Var(\overline{R}_a^{FSM})$	12.6	10.3	11.9	17.9	7.1	22.7
	Number of areas	143	112	139	145	113	140

Notes: Local Authorities with fewer than 250 individuals included in the analysis are dropped from the analysis of that gender. Results are shown for multiple measures of human capital, using educational attainment up to age 11, and up to age 16, up to age 18 and up to age 21. Results are shown for men and women separately and human capital measures and area fixed effects are constructed completely separately by gender.

5 What do mobile areas look like?

We have shown that some areas in England exhibit much higher absolute mobility than others, and that part, but not all of this, can be explained by low-income children in high mobility areas having better educational achievement. As a further step in trying to explain why certain areas have higher mobility than others, we correlate our measures of mobility with area characteristics. While these correlates cannot be interpreted as causal determinants of mobility, they can help guide future research towards potential policies which may help improve mobility.

We look at different sets of area characteristics which have been suggested as important for mobility in previous work in economics or sociology. The first column in Tables 4 and 5 show, for women and men respectively, the unweighted correlations of the $\overline{R}_a^{FSM}$ measure of mobility and area characteristics at the Local Authority level for all areas with at least 250 FSM eligible children in our sample. Columns (2) to (4) add in an indicator for being a London LA, regional fixed effects, and controls for median income in the LA respectively. Most of our correlations follow the expected direction. Labour market characteristics seem to play an important role, with areas with a stronger labour market having higher mobility, as well as areas with a higher share of skilled jobs. Areas with lower family stability, as measured by the share of single parent families and the divorce rate, have lower mobility. We do not have those measures at the individual level, so cannot disentangle whether this relationship is driven by children of single parents families having lower mobility, or all children in areas with lower family stability having lower mobility. Median income and school quality are also strongly positively associated with mobility. Interestingly, and contrary to previous work in other countries, we find a positive relationship between inequality and mobility. This positive correlation seems to be driven by the good performance of London LA, where inequality is relatively high. Once we add an indicator for being in London this correlation disappears. When we control for median income, the relationship actually reverses, and we find a strong negative relationship between inequality and mobility.

Comparing the factors which predict mobility for men and women, we find significant differences in terms of immigration and ethnic make up of areas. There is a much stronger positive relationship between a higher share of immigration and non-white population for women than for men. Controlling for region fixed effect does not change this for women, but reverses the relationship for men. We also find a stronger association between mobility and the share of skilled jobs, median income and population density, and a weaker association with measures of labour market strength, for women than for men. These differences

Table 4: Correlations of areas characteristics and mobility (women)

	Raw area effects				Controlling for education			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Labour market								
Economically	0.363***	0.246***	0.129**	0.010	0.446***	0.370***	0.255***	0.247**
active	(0.082)	(0.046)	(0.049)	(0.062)	(0.079)	(0.066)	(0.075)	(0.080)
Unemployment	0.026	-0.198***	-0.066	0.084	-0.157	-0.324***	-0.169*	-0.118
	(0.088)	(0.049)	(0.053)	(0.055)	(0.087)	(0.070)	(0.081)	(0.074)
Professional	0.726***	0.321***	0.238***	0.132	0.496***	0.214*	0.115	0.009
jobs	(0.061)	(0.060)	(0.064)	(0.125)	(0.077)	(0.096)	(0.105)	(0.167)
Manufacturing	-0.674***	-0.178*	-0.044	-0.292***	-0.519***	-0.234*	-0.074	-0.280**
share	(0.065)	(0.069)	(0.079)	(0.068)	(0.076)	(0.102)	(0.124)	(0.094)
Immigration and ethnicity								
Share white	-0.781***	-0.365***	-0.325***	-0.479***	-0.406***	0.056	0.126	-0.099
	(0.055)	(0.070)	(0.062)	(0.057)	(0.081)	(0.112)	(0.107)	(0.095)
Share Asian	0.567***	0.249***	0.231***	0.371***	0.279**	0.033	-0.018	0.130
	(0.073)	(0.051)	(0.043)	(0.048)	(0.085)	(0.082)	(0.075)	(0.077)
Share Black	0.672***	0.087	0.107	0.297***	0.368***	-0.173	-0.118	0.033
	(0.065)	(0.078)	(0.078)	(0.066)	(0.082)	(0.114)	(0.122)	(0.096)
Share foreign	0.825***	0.450***	0.373***	0.546***	0.440***	-0.100	-0.241	0.068
born	(0.050)	(0.081)	(0.074)	(0.067)	(0.079)	(0.131)	(0.125)	(0.111)
Family stability								
% single parent	0.055	-0.225***	-0.185***	0.021	-0.038	-0.239**	-0.128	-0.063
families	(0.088)	(0.049)	(0.048)	(0.055)	(0.088)	(0.074)	(0.078)	(0.074)
% married	-0.223**	0.165**	0.104*	-0.104	-0.020	0.276***	0.165*	0.067
families	(0.086)	(0.054)	(0.052)	(0.055)	(0.088)	(0.077)	(0.082)	(0.075)
Income distribution								
Median earnings	0.781***	0.357***	0.246**		0.551***	0.280*	0.147	
	(0.055)	(0.072)	(0.076)	(0.055)	(0.074)	(0.112)	(0.122)	(0.074)
90:10 ratio	0.329***	0.127*	0.076	-0.070	0.156	-0.001	-0.061	-0.186
	(0.098)	(0.063)	(0.062)	(0.074)	(0.108)	(0.093)	(0.095)	(0.100)
90:50 ratio	0.330***	0.050	0.046	-0.312***	0.056	-0.155	-0.152	-0.477***
	(0.097)	(0.060)	(0.059)	(0.077)	(0.099)	(0.084)	(0.089)	(0.098)
Urbanity								
Urban	0.232**	-0.065	-0.015	0.092	0.134	-0.074	-0.012	0.034
	(0.086)	(0.053)	(0.048)	(0.056)	(0.088)	(0.078)	(0.074)	(0.075)
Share rural	-0.303***	0.034	0.000	-0.095	-0.218*	0.012	-0.032	-0.072
	(0.084)	(0.055)	(0.049)	(0.057)	(0.086)	(0.080)	(0.076)	(0.077)
Segregation								
Segregation by	0.390***	0.178***	0.103*	0.089	0.327***	0.186*	0.093	0.124
KS4 score	(0.081)	(0.050)	(0.045)	(0.060)	(0.084)	(0.074)	(0.070)	(0.080)
Index of dissim	-0.041	0.132**	0.090*	-0.035	0.044	0.165*	0.100	0.048
- FSM	(0.088)	(0.050)	(0.044)	(0.055)	(0.088)	(0.073)	(0.069)	(0.074)
Index of dissim	-0.375***	-0.058	0.081	-0.048	-0.340***	-0.138	-0.020	-0.127
- ethnicity	(0.082)	(0.054)	(0.051)	(0.061)	(0.083)	(0.079)	(0.080)	(0.081)
School quality								
% schools rated	0.368***	0.168***	0.146***	0.076	0.169	0.026	0.003	-0.053
outstanding	(0.082)	(0.050)	(0.042)	(0.060)	(0.087)	(0.076)	(0.069)	(0.080)
Avg school	0.084	0.175***	0.070	0.044	0.147	0.210**	0.058	0.118
value-added	(0.088)	(0.048)	(0.048)	(0.055)	(0.087)	(0.071)	(0.076)	(0.073)
Population weights	No	No	No	No	No	No	No	No
London dummy	No	Yes	No	No	No	Yes	No	No
Region FE	No	No	Yes	No	No	No	Yes	No
Control for median inc	No	No	No	Yes	No	No	No	Yes

Notes: Each column shows the coefficients univariate regressions of Local Authority level mobility measures separately on each area characteristics listed in the rows. Both mobility and area characteristics are standardized and coefficients can therefore be interpreted as correlations. Area characteristics are described in more detail in the Appendix.

Table 5: Correlations of areas characteristics and mobility (men)

	Raw area effects				Controlling for education			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Labour market								
Economically	0.553***	0.495***	0.282***	0.365***	0.516***	0.512***	0.312***	0.522***
active	(0.073)	(0.065)	(0.067)	(0.079)	(0.075)	(0.076)	(0.081)	(0.087)
Unemployment	-0.347***	-0.485***	-0.257***	-0.282***	-0.460***	-0.513***	-0.293***	-0.435***
	(0.082)	(0.068)	(0.072)	(0.069)	(0.078)	(0.078)	(0.086)	(0.077)
Professional	0.414***	0.197*	0.073	-0.324*	0.113	0.082	-0.018	-0.488**
jobs	(0.080)	(0.100)	(0.093)	(0.151)	(0.087)	(0.114)	(0.111)	(0.173)
Manufacturing	-0.435***	-0.217*	0.020	-0.129	-0.163	-0.182	-0.011	0.004
share	(0.079)	(0.107)	(0.112)	(0.095)	(0.086)	(0.121)	(0.133)	(0.112)
Immigration and ethnicity								
Share white	-0.254**	0.195	0.283**	0.134	0.130	0.450***	0.560***	0.454***
	(0.085)	(0.114)	(0.092)	(0.091)	(0.087)	(0.123)	(0.102)	(0.099)
Share Asian	0.191*	-0.020	-0.073	0.022	-0.109	-0.191*	-0.268***	-0.207*
	(0.086)	(0.087)	(0.068)	(0.077)	(0.087)	(0.096)	(0.078)	(0.087)
Share Black	0.138	-0.488***	-0.499***	-0.325***	-0.204*	-0.646***	-0.652***	-0.578***
	(0.087)	(0.110)	(0.099)	(0.088)	(0.086)	(0.120)	(0.116)	(0.095)
Share foreign	0.322***	-0.167	-0.344**	-0.138	-0.081	-0.487***	-0.682***	-0.520***
born	(0.083)	(0.134)	(0.107)	(0.102)	(0.087)	(0.145)	(0.117)	(0.111)
Family stability								
% single parent	-0.336***	-0.531***	-0.345***	-0.359***	-0.442***	-0.524***	-0.292***	-0.453***
families	(0.082)	(0.067)	(0.066)	(0.066)	(0.078)	(0.079)	(0.083)	(0.075)
% married	0.294***	0.584***	0.424***	0.370***	0.478***	0.625***	0.441***	0.518***
families	(0.083)	(0.068)	(0.065)	(0.066)	(0.077)	(0.078)	(0.080)	(0.072)
Income distribution								
Median earnings	0.554***	0.482***	0.348**		0.254**	0.428**	0.325*	
	(0.073)	(0.113)	(0.108)	(0.073)	(0.084)	(0.130)	(0.130)	(0.084)
90:10 ratio	0.292**	0.187	0.127	0.064	0.124	0.115	0.091	0.070
	(0.102)	(0.098)	(0.081)	(0.106)	(0.106)	(0.110)	(0.103)	(0.121)
90:50 ratio	0.093	-0.073	0.021	-0.263**	-0.104	-0.155	-0.025	-0.300**
	(0.099)	(0.092)	(0.085)	(0.094)	(0.098)	(0.103)	(0.104)	(0.108)
Urbanity								
Urban	-0.088	-0.278***	-0.159*	-0.201**	-0.219*	-0.287**	-0.166*	-0.278***
	(0.087)	(0.079)	(0.065)	(0.072)	(0.085)	(0.089)	(0.078)	(0.083)
Share rural	0.053	0.279***	0.179**	0.227**	0.200*	0.284**	0.186*	0.296***
	(0.087)	(0.081)	(0.067)	(0.073)	(0.086)	(0.092)	(0.080)	(0.085)
Segregation								
Segregation by	0.269**	0.153	0.005	0.052	0.150	0.132	-0.016	0.055
KS4 score	(0.084)	(0.080)	(0.065)	(0.080)	(0.086)	(0.090)	(0.077)	(0.093)
Index of dissim	0.050	0.111	0.069	-0.013	0.044	0.058	0.006	0.015
- FSM	(0.087)	(0.078)	(0.062)	(0.073)	(0.087)	(0.088)	(0.074)	(0.085)
Index of dissim	-0.339***	-0.204*	-0.015	-0.145	-0.283***	-0.282**	-0.149	-0.217*
- ethnicity	(0.082)	(0.081)	(0.072)	(0.078)	(0.084)	(0.090)	(0.085)	(0.090)
School quality								
% schools rated	0.228**	0.126	0.062	0.058	0.021	-0.002	-0.071	-0.066
outstanding	(0.085)	(0.079)	(0.062)	(0.077)	(0.087)	(0.090)	(0.074)	(0.089)
Avg school	0.464***	0.502***	0.307***	0.413***	0.449***	0.459***	0.247**	0.428***
value-added	(0.077)	(0.064)	(0.063)	(0.064)	(0.078)	(0.078)	(0.079)	(0.077)
Population weights	No	No	No	No	No	No	No	No
London dummy	No	Yes	No	No	No	Yes	No	No
Region FE	No	No	Yes	No	No	No	Yes	No
Control for median inc	No	No	No	Yes	No	No	No	Yes

Notes: Each column shows the coefficients univariate regressions of Local Authority level mobility measures separately on each area characteristics listed in the rows. oth mobility and area characteristics are standardized and coefficients can therefore be interpreted as correlations. Area characteristics are described in more detail in the Appendix.

suggests that the policies and institutions which are most effective at promoting mobility for men may not always be those most effective for women. Heterogeneity in mobility patterns and in the drivers of those across groups is an important area for further study.

We also look at correlations between area characteristics and the income rank of FSM children, holding educational achievement constant (η_a in equation 5) in Columns (5) to (8) in Tables 4 and 5. For many area characteristics this does not meaningfully alter their correlation with mobility. The largest changes can be found in terms of immigration and ethnicity. Controlling for education significantly reduces the strength of association between higher immigration and a higher non-white share of the population and mobility. Once we control for region fixed effects or median income of the area, there is no relationship for women, while for men we now see strong negative correlations with the share of non-white children and the share of immigration in the area. This suggest that the strong performance of areas with high shares of immigration and a high share of non-white individuals is largely due to the strong educational performance of children in those areas. This aligns with the findings from previous work which find that in England, unlike in many other countries, ethnic minority children outperform their white counterparts in school (though not always in the labour market).

Many of the areas characteristics we have looked at so far will be highly correlated with each other. In Table A7 and A8 we therefore run multivariate regressions where we include all area characteristics[10] to assess which characteristics are the strongest predictors of absolute mobility. Columns (1) to (3) show this for absolute upwards mobility as measured by $\overline{R}_a^{FSM}$. The next three columns do the same thing with the absolute mobility measure controlling for differences in educational achievement (η_a in equation 5).

Higher immigration, more stable families, lower inequality and higher share of professional jobs all are strong predictors of absolute mobility, but most other factors lose their significance. Controlling for education differences gives very similar results, but the share of foreign born loses its significance for women, and becomes negative for men, in line with the univariate correlations shown above.

6 Conclusion

This is the first paper which estimates intergenerational income mobility at the detailed geographical level in England. It finds considerable differences in absolute upwards mobility

[10]Closely related area characteristics are combined into indices as described in the Appendix.

across the country. Children from low-income families who grew up in the highest mobility areas end up on average fifteen percentiles higher up the income distribution than those from similar backgrounds who grew up in the lowest mobility areas.

More than 45% of this variation in absolute mobility across areas can be explained by differences in educational attainment of children from low-income backgrounds across areas for women, while the equivalent for men is 25%. This suggests that current government policies aimed at improving mobility through improving educational outcomes, such as the Opportunity Areas, are promising interventions to equalise opportunities across areas. For a government truly committed to 'levelling-up' across areas however, solely focusing on education will not be enough. While we cannot interpret these as causal drivers, local labour market conditions, average incomes in an area, and stable families are strong predictors of mobility, and those would be a promising area to look for other potential policies aimed at increasing mobility.

Our work also tentatively suggests that the factors promoting mobility for men from low-income backgrounds may not be the same as those which are most effective at promoting mobility for women from the same backgrounds. Investigating heterogeneity in mobility patterns, and in the mechanisms driving those, across different groups is an important direction for future research.

References

Acciari, P., A. Polo, and G. L. Violante (2019). "And yet, it moves": Intergenerational mobility in Italy. *IZA Discussion Papers*, No. 12273.

Bell, B., J. Blundell, and S. Machin (2018). The changing geography of intergenerational mobility. *CEP Discussion Paper*, No. 1591.

Blanden, J., A. Goodman, P. Gregg, and S. Machin (2004). Changes in intergenerational mobility in britain. *In M. Corak (Ed.), Generational income mobility in North America and Europe, Cambridge University Press*, pp. 122–46.

Chetty, R. and N. Hendren (2018). The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates*. *The Quarterly Journal of Economics 133*(3), 1163–1228.

Chetty, R., N. Hendren, P. Kline, and E. Saez (2014). Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States *. *The Quarterly Journal of Economics 129*(4), 1553–1623.

Corak, M. (2019). The Canadian Geography of Intergenerational Income Mobility. *The Economic Journal 130*(631), 2134–2174.

Gregg, P., L. Macmillan, and C. Vittori (2017). Moving towards estimating sons' lifetime intergenerational economic mobility in the uk. *Oxford Bulletin of Economics and Statistics 79*(1), 79–100.

Rothstein, J. (2019). Inequality of educational opportunity? Schools as mediators of the intergenerational transmission of income. *Journal of Labor Economics 37*(S1), S85–S123.

Appendix

A1 Additional mobility results

Table A1: Top 10 - women

	Region	R_c^{FSM}	$P(Q5|FSM)$
Redbridge	London	41.9	0.14
Kensington and Chelsea	London	41.2	0.14
Tower Hamlets	London	40.7	0.13
Ealing	London	40.5	0.13
Harrow	London	40.5	0.15
West Berkshire	South East	40.4	0.11
Hackney	London	40.2	0.12
Wandsworth	London	40.2	0.12
Newham	London	40.1	0.12
Bexley	London	39.9	0.15

Notes:

Table A2: Top 10 - men

	Region	R_c^{FSM}	$P(Q5|FSM)$
Havering	London	53.0	0.25
Wokingham	South East	50.9	0.17
Bracknell Forest	South East	50.3	0.12
Kingston upon Thames	London	50.0	0.22
Hillingdon	London	49.9	0.20
Tower Hamlets	London	49.8	0.19
Surrey	South East	49.3	0.17
Sutton	London	49.3	0.20
Barking and Dagenham	London	49.3	0.19
Hertfordshire	East	49.2	0.19

Notes:

Table A3: Bottom 10 - women

	Region	R_c^{FSM}	$P(Q5\|FSM)$
Lincolnshire	East Mid	27.8	0.03
County Durham	North East	27.8	0.02
Stoke-on-Trent	West Mid	27.6	0.02
Wakefield	Yorkshire	27.5	0.02
Middlesbrough	North East	27.1	0.03
Nottingham	East Mid	27.1	0.03
Stockton-on-Tees	North East	26.5	0.02
North East Lincolnshire	Yorkshire	26.0	0.03
Barnsley	Yorkshire	25.3	0.01
Kingston upon Hull, City of	Yorkshire	25.1	0.02

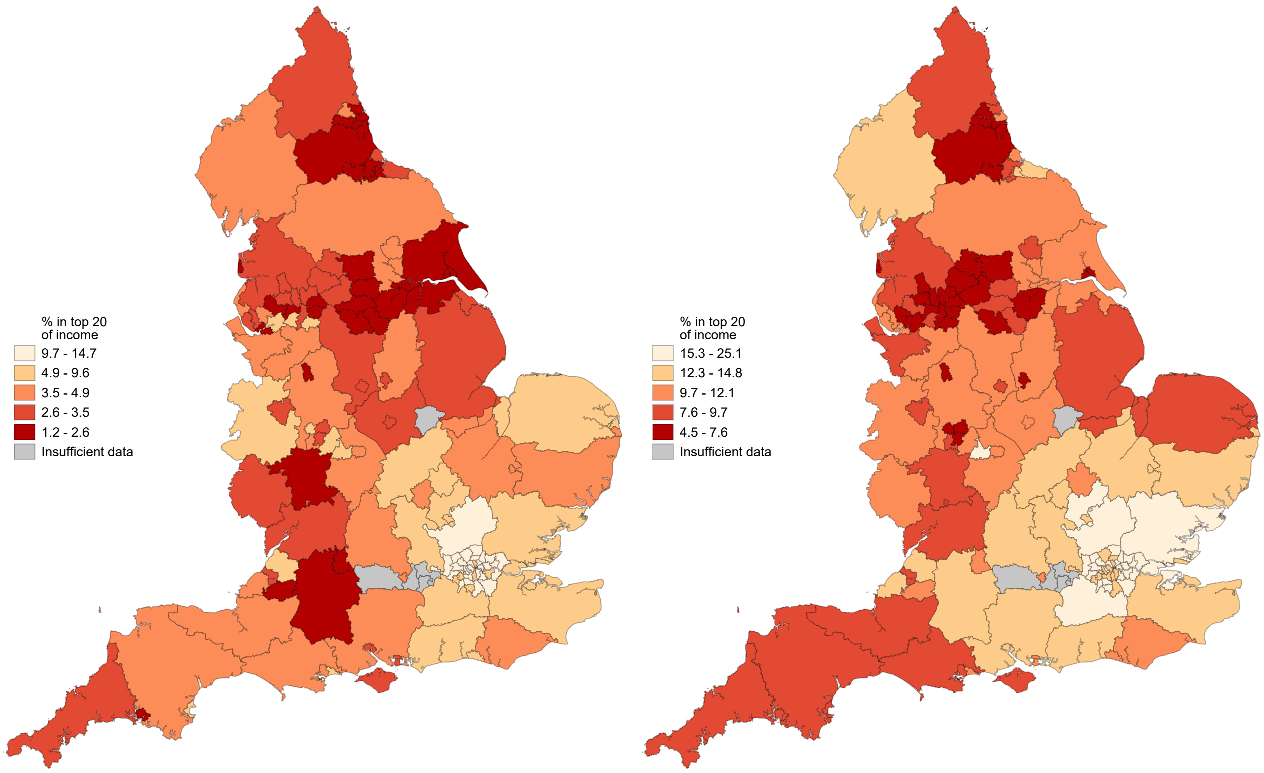
Notes:

Table A4: Bottom 10 - men

	Region	R_c^{FSM}	$P(Q5\|FSM)$
Calderdale	Yorkshire	38.3	0.05
Newcastle upon Tyne	North East	38.2	0.07
County Durham	North East	38.2	0.07
Bolton	North West	38.0	0.07
Manchester	North West	37.5	0.06
Bradford	Yorkshire	37.1	0.06
Gateshead	North East	36.8	0.05
Blackpool	North West	36.8	0.05
Sheffield	Yorkshire	35.9	0.05
Nottingham	East Mid	35.8	0.06

Notes:

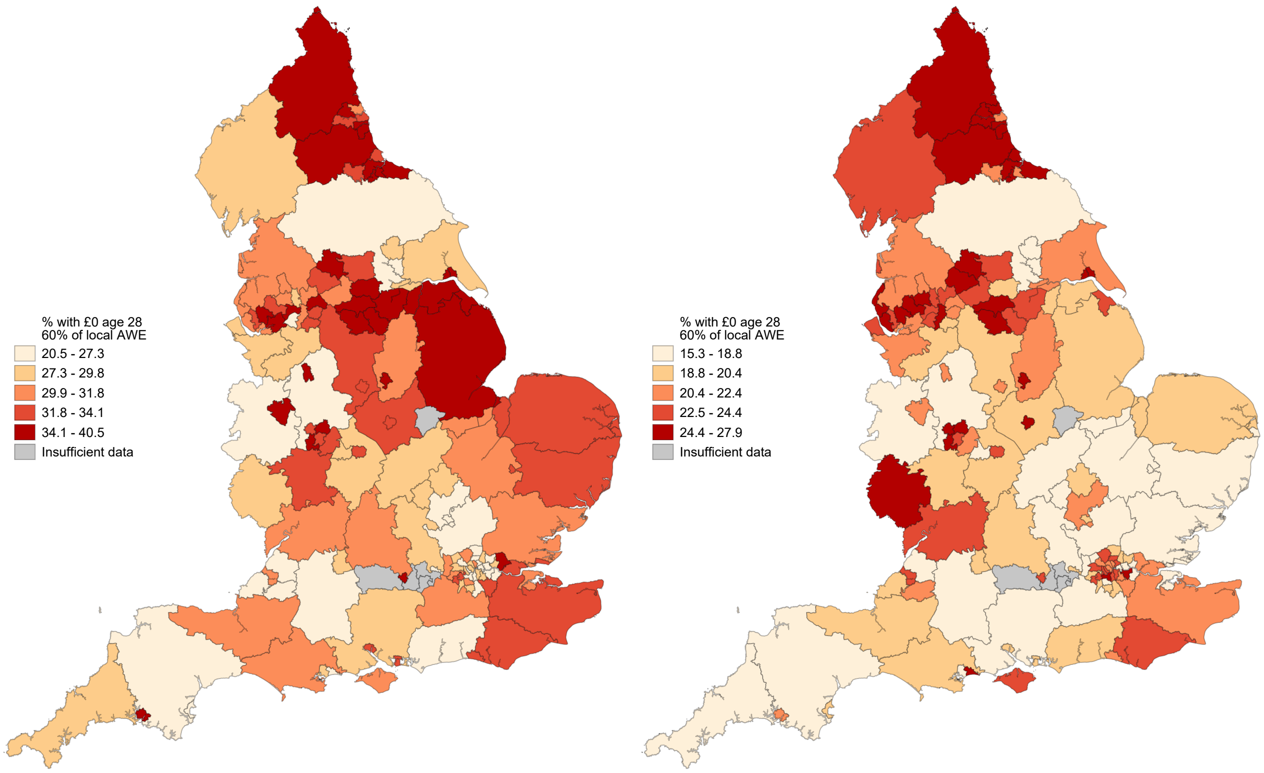
Figure A1: Probability of reaching top 20% of income for children on FSM



Women Men

Notes: See notes to Figure **??**.

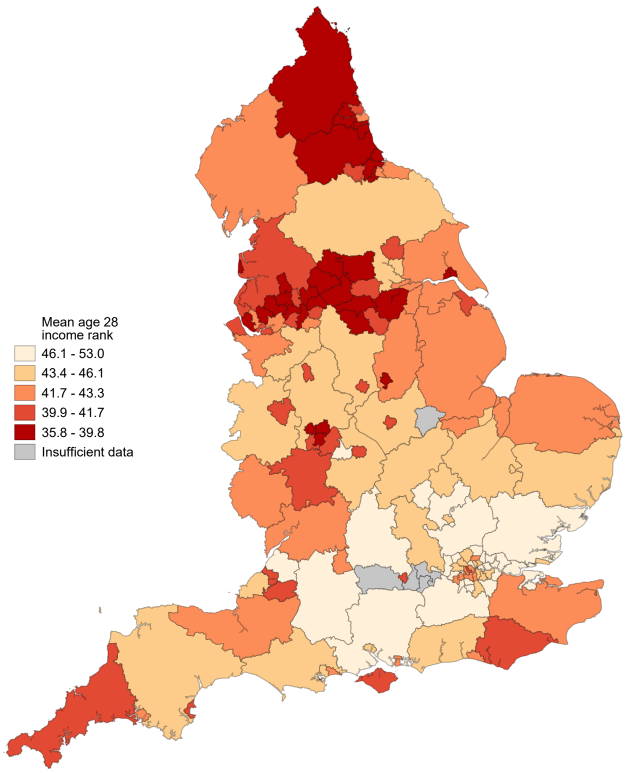
Figure A2: Zero earnings rates by area and gender



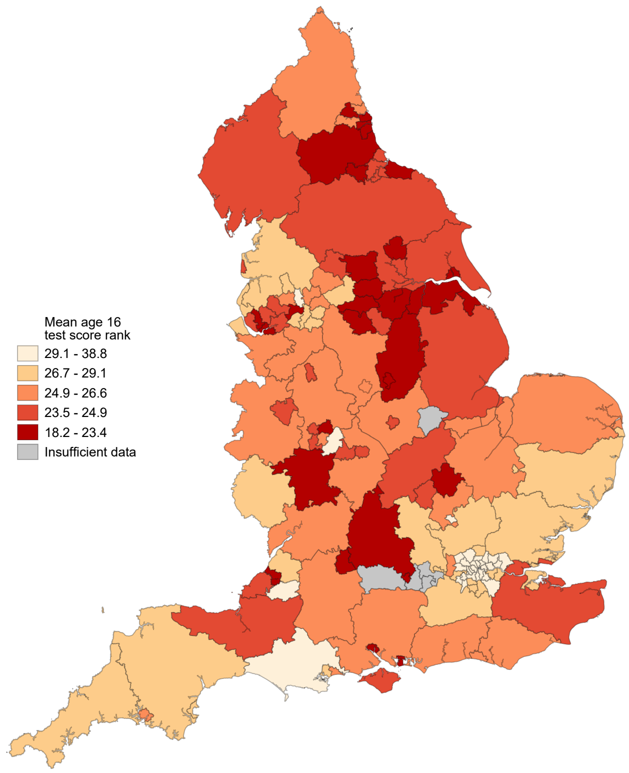
Women Men

Notes: Figure shows share of FSM individuals with zero earned income recorded at age 28. Only areas with at least 100 children on FSM in our analysis sample are shown. Local authorities are split into quintiles based on the share of individuals with zero earnings. The darkest colour shows the areas with the highest share of individuals with zero earnings.

Figure A3: Comparing earnings and education outcomes for children on FSM (men)

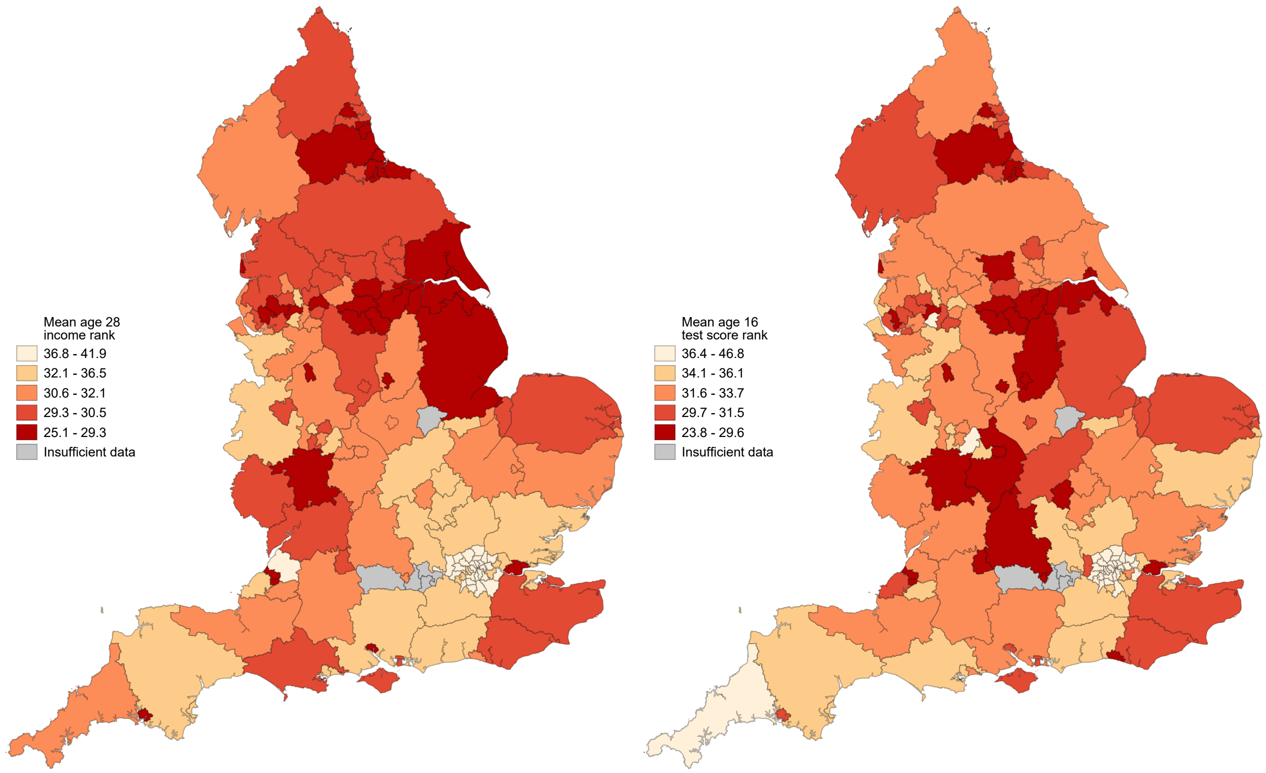


Earnings



Age 16 education

Figure A4: Comparing earnings and education outcomes for children on FSM (women)



Earnings | Age 16 education

A2 Robustness

A2.1 Decomposition robustness

In our main specification for decomposing the variance of $R_{i,a}^{FSM}$, we assume the return to education, β is constant across areas. In this section we relax that assumption and consider the robustness of our findings to allowing the return to education to vary across the area where an individual grew up. Instead of Equation 3 we estimate the equation below:

$$R_{i,a}^{FSM} = \beta_a H_{i,a}^{FSM} + \eta_a + w_{i,a} \tag{8}$$

This means that our decomposition becomes:

$$\overline{R}_a^{FSM} = (\beta_a \overline{H}_a^{FSM} + \eta_a) \tag{9}$$

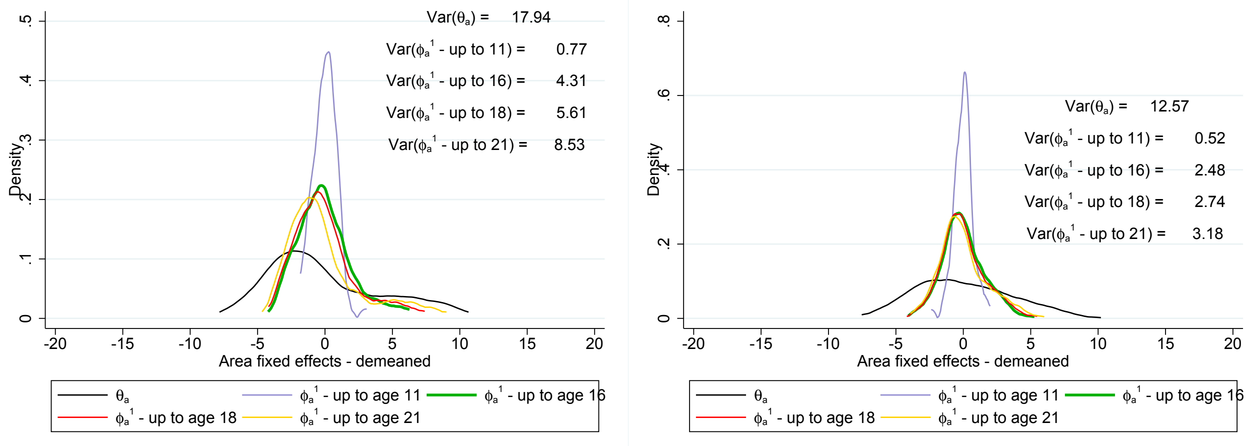
We hold β_a and η_a constant, allowing only $\overline{H}_a^{FSM}$ to vary across areas. We then estimate the variance of the resulting distribution of area effects to determine how much of the variance in mobility rates $R_{i,a}^{FSM}$ across areas can be explained by the variance of human capital $\overline{H}_a^{FSM}$ across areas. As before, we show this both for a comprehensive measure of human capital which includes measures of educational attainment up to age 21, and measures of human capital which only include attainment up to 11, 16 or 18. The results of this exercise are shown in Table A5 and Figure A5 shows the shape of the resulting distributions. The share of variance in mobility across areas which can be explained by differences in human capital across areas are virtually identical to those in our main specification, indicating the robustness to our main findings to relaxing our assumption of constant returns to education.

Table A5: Decomposition of $Var(\overline{R}_a^{FSM})$ - β varying across area

	Share of $Var(\overline{R}_a^{FSM})$	
	Men	**Women**
HC index	0.25	0.48
HC index - up to age 11 only	0.04	0.04
HC index - up to age 16 only	0.20	0.24
HC index - up to age 18 only	0.22	0.31
Total $Var(\overline{R}_a^{FSM})$	12.6	17.9

Notes: Table shows the variance of distribution where we only allow $\overline{H}_a^{FSM}$ to vary, as a proportion of total variance of $\overline{R}_a^{FSM}$. Local Authorities with fewer than 250 individuals included in the analysis are dropped from the analysis of that gender. Results are shown for multiple measures of human capital, using educational attainment up to age 11, and up to age 16, up to age 18 and up to age 21. Results are shown for men and women separately and human capital measures and area fixed effects are constructed completely separately by gender.

Figure A5: Decomposing the variance of R_a^{FSM}



Women Men

Notes:

A2.2 Robustness to alternative definitions of human capital

Table A6 shows the results of our decomposition when, instead of measuring human capital at each age as the predicted earnings rank based on educational achievement up to that point, we create human capital measures using a principal component analysis. We run a principal component analysis on educational achievement at each age, and take the first component of this analysis. The human capital index at each age is then constructed by taking the first component of a further PCA analysis, combining all de indices up to the given age. We can explain slightly less of the variation in mobility across areas by variation in human capital across areas, than using our main measure of human capital. as this measure is much less flexible than our main measure, this is unsurprising. The overall message remains the same however: the results point towards a meaningful role for improving educational achievement of low-income students in low mobility areas in order to equalise opportunities across the country, yet other channels, for example differences in labour market practices across areas, are clearly at least as important in explaining variation in mobility across the country. Educational achievement differences seem also more important in explaining mobility differences for women than for men. Again, the results highlight the importance of including a rich set of measures of educational achievement at different ages. Only including measures at younger ages considerably understates the proportion of variation in absolute mobility which can be explained by differences in educational achievement.

Table A6: Decomposition of $Var(\overline{R}_a^{FSM})$ - different measures of HC

		Share of $Var(\overline{R}_a^{FSM})$ Men	Women
PCA HC index	$\beta^2 Var(\overline{H}_a^{FSM})$	0.24	0.36
	$Var(\eta_a)$	0.83	0.32
	$2\beta Cov(\overline{H}_a^{FSM}, \eta_a)$	-0.07	0.32
PCA HC index - up to age 11 only	$\beta^2 Var(\overline{H}_a^{FSM})$	0.03	0.04
	$Var(\eta_a)$	0.92	0.92
	$2\beta Cov(\overline{H}_a^{FSM}, \eta_a)$	0.04	0.04
PCA HC index - up to age 16 only	$\beta^2 Var(\overline{H}_a^{FSM})$	0.09	0.11
	$Var(\eta_a)$	0.79	0.63
	$2\beta Cov(\overline{H}_a^{FSM}, \eta_a)$	0.12	0.26
PCA HC index - up to age 18 only	$\beta^2 Var(\overline{H}_a^{FSM})$	0.15	0.21
	$Var(\eta_a)$	0.79	0.45
	$2\beta Cov(\overline{H}_a^{FSM}, \eta_a)$	0.06	0.34
	Total $Var(\overline{R}_a^{FSM})$	12.6	17.9

Notes: Local Authorities with fewer than 250 individuals included in the analysis are dropped from the analysis of that gender. Results are shown for multiple measures of human capital, using educational attainment up to age 11, and up to age 16, up to age 18 and up to age 21. Results are shown for men and women separately and human capital measures and area fixed effects are constructed completely separately by gender.

A3 Description of correlates

We use the following area characteristics from the 2001 population census in England:

- **Unemployment**: the share of the economically active population between the ages of 16 and 74 who were looking for work in the wek preceding the census.
- **Professional jobs**: the share of the usual resident population who provided a vaild occupation and are working in professional jobs according to the ONS' Social Class based on Occupation classification.
- **Manufacturing share**: the share of individuals aged 16 to 74 in employment who provide a valid industry of work, who work in the manufacturing industry.
- **Share foreign born:** the share of individuals who list a country outside of the United Kingdom as their country of birth.

- **Share Black, Asian and white**: the share of individuals who self-report as each ethnic group. "Asian" includes Indian, Pakistani, Bangladeshi, Chinese and other Asian.
- **% single parent families:** the share of families with dependent children where the head of the household is a single parent.
- **% of married families:** share of families with dependent children headed by a married couple.
- **Urban**: whether the area is classified as "urban" as defined by the ONS classification of areas.
- **Share rural**: the share of the population who live in rural areas (including large market towns), as defined by the settlement type and population density.

Aggregate data on annual gross pay in 2002 by Local Authority published by ONS based on the Annual Survey of Hours and Earnings (ASHE) allows us to construct measures of earnings and earnings inequality:

- **Median income**: 50th percentile of annual gross pay.
- **90-10 and 50-10 ratio**: ratio of the 90th (50th) percentile of gross annual pay in the area to the 10th percentile of gross annual pay in the same area. Due to disclosivity this data is not available for certain small areas. Those areas are excluded when estimating the correlation of mobility and the 90-10 or 50-10 ratios.

From the analysis dataset we obtain from the of students attending state school in England who took their GCSEs in 2002:

- **Index of dissimilarity for ethnicity and FSM**: measures the evenness with which white and non-white students (for ethnicity) and FSM and non-FSM students (for FSM) across state secondary schools within each local authority.
- **Average school value-added**: constructed for each school in the local authority by regressing overall KS4 scores on quadratics in KS2 maths, English and sciences scores, gender, FSM status, English as an Additional Language (EAL) status and ethnic group. Value added is then averaged over all state secondary schools in the local authority. Segregation by KS2 and KS4 score: KS2 and KS4 scores in the local authority among state school students are regressed on indicators for all local state secondary schools. As measure of segregation we take the degree of variance in KS2 or KS4 scores explained by schools (R squared).

The percentage of schools rated outstanding is calculated based on the share of state schools in the area which were rated outstanding by Ofsted in 2002.

A4 Additional correlation results

Table A7: Conditional multivariate correlations of areas characteristics and mobility (women)

	Raw area effects			Controlling for education		
	(1)	(2)	(3)	(4)	(5)	(6)
Strong labour market	-0.006	0.075	0.070	0.238	0.345**	0.389**
	(0.088)	(0.088)	(0.102)	(0.155)	(0.159)	(0.192)
Good jobs	0.262***	0.197**	0.101	0.326*	0.241	0.105
	(0.097)	(0.095)	(0.109)	(0.172)	(0.172)	(0.204)
Immigration	0.607***	0.518***	0.477***	0.174	0.058	-0.058
	(0.068)	(0.071)	(0.076)	(0.121)	(0.129)	(0.142)
Stable families	0.269***	0.240***	0.157	0.146	0.108	-0.126
	(0.090)	(0.086)	(0.115)	(0.158)	(0.155)	(0.216)
Median earnings	0.339***	0.142	0.182	0.370*	0.112	0.190
	(0.109)	(0.121)	(0.127)	(0.192)	(0.220)	(0.238)
Inequality	-0.253***	-0.185***	-0.129*	-0.472***	-0.382***	-0.294**
	(0.062)	(0.063)	(0.072)	(0.109)	(0.114)	(0.135)
Segregation by KS4	0.051	0.068	0.052	0.058	0.080	0.031
score	(0.054)	(0.052)	(0.051)	(0.095)	(0.093)	(0.095)
Urban	-0.061	-0.044	-0.037	-0.009	0.012	0.036
	(0.059)	(0.057)	(0.059)	(0.105)	(0.103)	(0.110)
Index of dissim -	-0.103*	-0.072	-0.015	-0.189**	-0.148	-0.040
ethnicity	(0.053)	(0.051)	(0.056)	(0.093)	(0.093)	(0.105)
School quality	0.045	0.043	0.032	-0.048	-0.051	-0.031
	(0.056)	(0.053)	(0.052)	(0.098)	(0.096)	(0.098)
London dummy	No	Yes	No	No	Yes	No
Region FE	No	No	Yes	No	No	Yes
R-squared	0.841	0.858	0.884	0.546	0.572	0.629
Adj R-squared	0.822	0.839	0.854	0.490	0.514	0.532
N	93	93	93	93	93	93

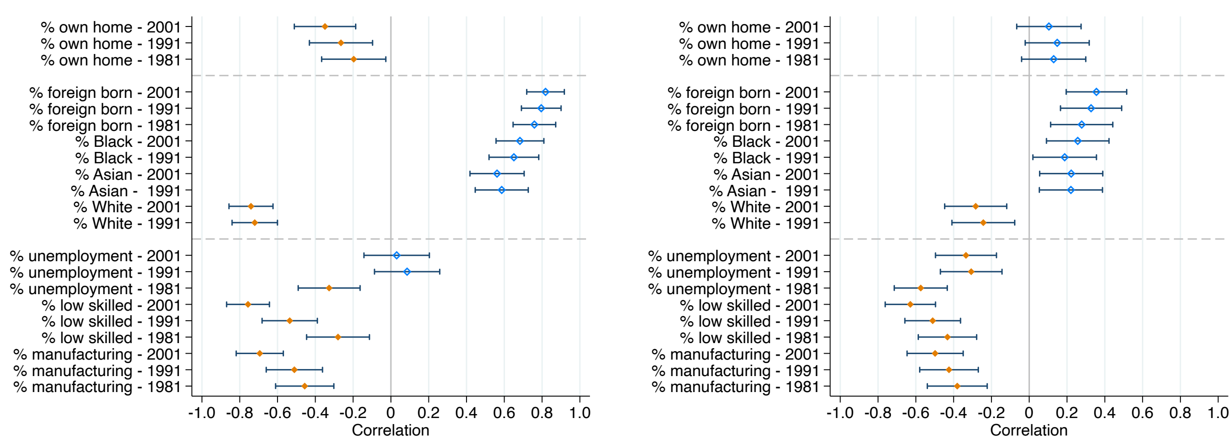
Notes: Each column shows the coefficients from a multivariate regression of Local Authority level mobility measures on the area characteristics listed in the rows.oth mobility and area characteristics are standardized and coefficients can therefore be interpreted as correlations. Area characteristics are described in more detail in the Appendix.

Table A8: Conditional multivariate correlations of areas characteristics and mobility (men)

	Raw area effects			Controlling for education		
	(1)	(2)	(3)	(4)	(5)	(6)
Strong labour market	-0.022	0.119	0.016	0.017	0.142	0.065
	(0.152)	(0.153)	(0.159)	(0.168)	(0.173)	(0.191)
Good jobs	0.052	-0.049	-0.182	-0.085	-0.175	-0.209
	(0.166)	(0.162)	(0.164)	(0.183)	(0.183)	(0.197)
Immigration	0.246**	0.105	-0.147	-0.063	-0.188	-0.477***
	(0.116)	(0.121)	(0.114)	(0.129)	(0.137)	(0.137)
Stable families	0.547***	0.500***	0.305*	0.547***	0.505***	0.261
	(0.155)	(0.149)	(0.177)	(0.171)	(0.168)	(0.212)
Median earnings	0.346*	0.049	0.176	0.249	-0.015	0.085
	(0.175)	(0.196)	(0.179)	(0.193)	(0.222)	(0.215)
Inequality	-0.203*	-0.092	-0.021	-0.156	-0.057	0.018
	(0.107)	(0.110)	(0.111)	(0.119)	(0.124)	(0.133)
Segregation by KS4 score	0.026	0.053	-0.046	0.054	0.078	-0.030
	(0.095)	(0.092)	(0.079)	(0.105)	(0.103)	(0.095)
Urban	-0.076	-0.047	0.065	-0.065	-0.040	0.069
	(0.101)	(0.098)	(0.089)	(0.112)	(0.110)	(0.107)
Index of dissim - ethnicity	-0.328***	-0.280***	-0.068	-0.401***	-0.358***	-0.146
	(0.090)	(0.088)	(0.085)	(0.100)	(0.099)	(0.102)
School quality	0.072	0.066	0.066	-0.056	-0.061	-0.059
	(0.094)	(0.090)	(0.078)	(0.105)	(0.102)	(0.093)
London dummy	No	Yes	No	No	Yes	No
Region FE	No	No	Yes	No	No	Yes
R-squared	0.543	0.586	0.738	0.441	0.475	0.624
Adj R-squared	0.488	0.530	0.671	0.374	0.404	0.527
N	94	94	94	94	94	94

Notes: Each column shows the coefficients from a multivariate regression of Local Authority level mobility measures on the area characteristics listed in the rows. oth mobility and area characteristics are standardized and coefficients can therefore be interpreted as correlations. Area characteristics are described in more detail in the Appendix.

Figure A6: Correlation of $\overline{R}_a^{FSM}$ mobility measure and area characteristics - comparing with historical measures



Women Men

Notes: Figures shows (unweighted) correlations of area characteristics with $\overline{R}_a^{FSM}$ measure of absolute mobility at the Local Authority level. Bars represent 95% confidence intervals. Correlates are described in Appendix A3.