Brexit and intergenerational mobility over time and space

Tzvetan Moev*

Abstract

There has been a lot of debate about whether intergenerational mobility has deteriorated over time in the UK by comparing estimates for just two cohorts. However, little is known about how intergenerational mobility varies over a longer period of time and across space. Using the Labour Force Survey, I provide a time series for the evolution of *national* intergenerational mobility over time for cohorts born between 1958 and 1997 as well as some of the first estimates of *regional* intergenerational mobility in the UK. I utilise my regional estimates to explore whether they are related to the share of Brexit voters in each region. Surprisingly, *no* evidence is found that regions with low intergenerational mobility are more likely to support Brexit.

Keywords: Brexit, Regional Intergenerational Mobility, Multilevel Modelling, TSTSLS

*Tzvetan Moev, *UCL School of Public Policy* and *UCL Institute of Education.* This paper is based on my undergraduate dissertation at UCL School of Public Policy. I would like to thank Prof. Lindsey Macmillan for her continued support on this project as well as Dr. Catherine Dilnot, and Prof. Paul Gregg for introducing me to the literature on intergenerational mobility in the UK. I am also grateful to Dr. Jack Blumenau for excellent supervision.

1 Introduction

Inequality has increased considerably in the UK since the 70s (Piketty et al., 2019). Why should we be concerned about this increase? Even John Rawls (1971) accepted a certain level of inequality in a just society so long as it benefits the worse-off. However, if one introduces a temporal element into this story, inequality in one generation can worsen inequality in the next due to the transmission of advantage across generations (Blanden et al., 2007). For this reason, as shown by the Great Gatsby Curve, countries with high inequality have lower social mobility, suggesting that high inequality worsens the prospects for social mobility (Corak, 2013). Given this increase in inequality, it is no surprise that intergenerational *earnings* mobility, arguably the most common measure of social mobility, is found to have deteriorated over time in the UK (Blanden et al., 2004; Gregg et al., 2018). However, this conclusion has been drawn on the basis of comparing mobility estimates in only two points in time for the cohorts born in 1958 and 1970.

Few studies have examined the change in earnings mobility over a longer period because estimating mobility imposes heavy data requirements: both parents' earnings and children's earnings should be available. Unfortunately, parental earnings are rarely available in surveys that are sufficiently big to explore the long-term trend. Thus, I amend a commonly-used methodology overcoming this problem via predicting parental earnings.

Utilising the proposed method allows me to make two contributions to the literature. Firstly, using data from the Labour Force Survey, I explore the long-term trend in earnings mobility in the UK with robust estimates for the first time for the cohorts born between 1958 and 1997. While earnings mobility has deteriorated for the cohort born immediately after the baby boomers, it has remained stable for the cohorts born since the early 1970s.

Secondly, I estimate intergenerational mobility on the regional level in the UK, given that there are good reasons to expect that intergenerational mobility is not homogeneous across the country, e.g., London has largely been seen as 'pulling away' from the rest of the UK in terms of economic opportunities. My result suggest that the Intergenerational Rank Association (the most robust measure of intergenerational mobility) is found to vary from 0.10 in Northern Ireland to 0.37 in London. Since lower value of this measure indicate high social mobility, my estimates suggest that

Northern Ireland have the highest intergenerational mobility in the UK.[1]

Beyond estimating regional mobility, I use the regional intergenerational mobility estimates to investigate their relationship with the results of the 2016 EU Referendum. One popular explanations for UK's decision suggests that deteriorating local labour market conditions caused many people to feel 'left-behind' and so support Brexit (Colonatone and Stanig, 2018). Local characteristics such as housing prices (Ansell and Adler, 2019) and austerity measures (Fetzer, 2018) have been used as proxies for local economic conditions. I go beyond these indicators by adopting a broader long-term measure of economic opportunities, namely intergenerational mobility. I test the hypothesis that areas with low mobility are more likely to support Brexit. Overall, the evidence for such a claim is inconclusive.

My rest of this paper is divided into six sections. In Section II, I review the key issues in estimating intergenerational mobility and its connection to the referendum results. Section III discusses the main dataset whereas Section IV lays out my methodology. Section V reports my results for the historic evolution of national mobility and my estimates of regional mobility. Next, Section VI explores if they are related to the Referendum results and Section VII concludes with some suggestions for further research. Appendix A and B contain some supplementary materials such as the variables selected and further robustness checks.

2 Literature Review

2.a *National* Mobility Rates

In the last 15 years, there has been a fierce academic debate about whether intergenerational mobility has deteriorated in the UK over the late 20^{th} century (Goldthorpe, 2013; Blanden et al., 2013). Being traditionally a quantity of interest in sociology, numerous sociological studies found stable intergenerational *class* mobility (Bukodi et al., 2015; Goldthorpe and Jackson, 2007). In contrast, a few studies by economists have found deteriorating *earnings* mobility (Blanden et al., 2004; Gregg et al., 2017). Economists' findings have been very influential in policy-making despite the fact that the sociological tradition has been much richer in terms of exploring different channels

[1] When I started writing this paper, there were no other estimates of regional earnings mobility in the UK. However, one month before my submission Bell et al. (2019) also calculated regional intergenerational transmission in term of education, occupation and home ownership (but not earnings).

of intergenerational transmission of advantages (Goldthorpe, 2013). If *class* mobility and *earnings* mobility study the same underlying concept, how can this divergence be explained?

While estimates of class mobility are more robust, e.g. transitory shocks do not affect classes as much as earnings, classes are also found not to capture various transmission mechanisms of intergenerational advantage such as education (Torche, 2015). Moreover, the divergent results between economists and sociologists can be explained by an increase in *within*-class earnings inequality (Blanden et al., 2013). For this reason, I focus on *earnings* mobility while also reporting class measures as they are less complex to estimate.

Ideally, intergenerational *earnings* mobility would be measured with the simple linear model (Solon, 1992):

$$\log ChildrenEarnings_i^* = \alpha + \beta_1 \log ParentEarnings_i^* + \varepsilon_i \tag{1}$$

where $ChildrenEarnings_i^*$ and $ParentEarnings_i^*$ refer to the *true* income of parents and children. The parameter measuring intergenerational mobility is β_1 interpreted as the Intergenerational Earnings Elasticity (IGE). Earnings are logged because their distribution is often positively skewed. To understand IGE's interpretation, assume father A earns twice as much as father B. If IGE is 0.2, father B's child will earn 20% *less* than father A's child (Blanden, 2015). Higher values of IGE indicate greater dependence on parental earnings, suggesting that *higher* IGE is associated with *lower* mobility. Nevertheless, due to measurement error, capturing true income is quite complex, so usually a proxy is used by averaging earnings over several years (Torche, 2015).

Applying model (1) to two cohorts studies in the UK, economists have found a decrease in intergenerational *earnings* mobility for the 1970 cohort relative to the 1958 cohort (Friedman et al., 2017). The original estimates suggested that IGE has increased from 0.205 to 0.291 (Blanden et al., 2004). Using another dataset, Nicolleti and Ermish (2007) claim to have refuted this finding, as they found no significant differences in IGE for the same cohorts. However, their point estimates suggest that IGE increased from approximately 0.160 to 0.410 and the lack of statistical significance can perhaps be attributed to their small samples.

2.b Data Requirements

Estimating IGE with earnings imposes heavy data requirements. A dataset should have both children and parents' earnings. For many countries, including France and Italy, appropriate datasets contain only parental *characteristics* such as class (Corak, 2013). To tackle this pervasive issue, the Two-Sample Two-Stage Least Squares (TSTSLS) procedure was developed (Björklund and Jäntti, 1997). It allows estimating IGE when the *main* dataset contains only parental characteristics and not earnings. Intuitively, TSTSLS uses parental characteristics to predict parental earnings which are then used to estimate (1).

TSTSLS proceeds in three stages employing an additional *auxiliary* dataset with both parental earnings and parental characteristics. Firstly, the auxiliary dataset is used to estimate:

$$\log ParentEarnings_i = \alpha + \beta_1 Educ_i + \beta_2 Occ_i + \beta_3 OtherCharacteristics_i + \varepsilon_i \tag{2}$$

where the right-hand side contains all parental characteristics in the *main* dataset. Secondly, the coefficients from (2) that best fit the *auxiliary* dataset are applied to the *main* dataset to make a prediction of parental earnings. Lastly, mobility is estimated in the main dataset via:

$$\log ChildrenEarnings_i = \alpha + \beta_1 \log \widehat{ParentEarnings}_i + \varepsilon_i \tag{3}$$

where $\log \widehat{ParentEarnings}_i$ refers to predicted parental earnings from the second stage. Studying TSTSLS's consistency, Jerrim et al. (2016) find that IGE based on *predicted* earnings from TSTSLS are 13% higher than IGE based on *actual* earnings suggesting that TSTSLS' estimates are not perfect.

2.c Biases in estimating IGE

Moreover, even if the main dataset contains parents' and children's earnings, estimates may still be inaccurate due to three biases (Torche, 2015) Firstly, the ***lifecycle bias*** emerges when measuring children's earnings too early (Grawe, 2006). For instance, earnings from early 20s do *not* approximate true earnings due to wage growth later in their career. Secondly, the ***attenuation bias*** stems from measuring earnings for parents and children at a single point in time (Mazumder, 2005). Such measures of earnings suffer from measurement error given transitory shocks such as tax rebates. Thirdly, the ***worklessness bias*** follows from excluding inactive and unemployed people from estimates, as we do not observe any earnings for them. This exclusion renders IGE estimates unrepresentative for the whole population (Gregg et al., 2017).

To evaluate these biases for the UK, Gregg et al. (2017) use a dataset for 1970 cohort that can overcome all biases. However, they work with a constrained version of the dataset allowing the effects of individual biases in order to evaluate how much each bias affects their best estimates. Lifecycle, attenuation and worklessness bias underestimate IGE by respectively 32%, 20% and 11% (Figure 1).

Fortunately, recent research has started estimating mobility not only in terms of earnings, but also income ranks, i.e. the percentile rank in the national earnings distribution that varies from 0 to 1 (Dahl and DeLeire, 2008). Since the relationship between parents' and children's ranks is nearly linear, estimates of intergenerational mobility with ranks are not affected by the biases as strongly as log earnings (Chetty et al., 2014, p.2). Using Gregg et al.'s results (2017), Figure 1 shows that rank mobility is nearly immune to attenuation and worklessness bias but suffers from lifecycle bias.

If ranks are used, intergenerational mobility is estimated by:

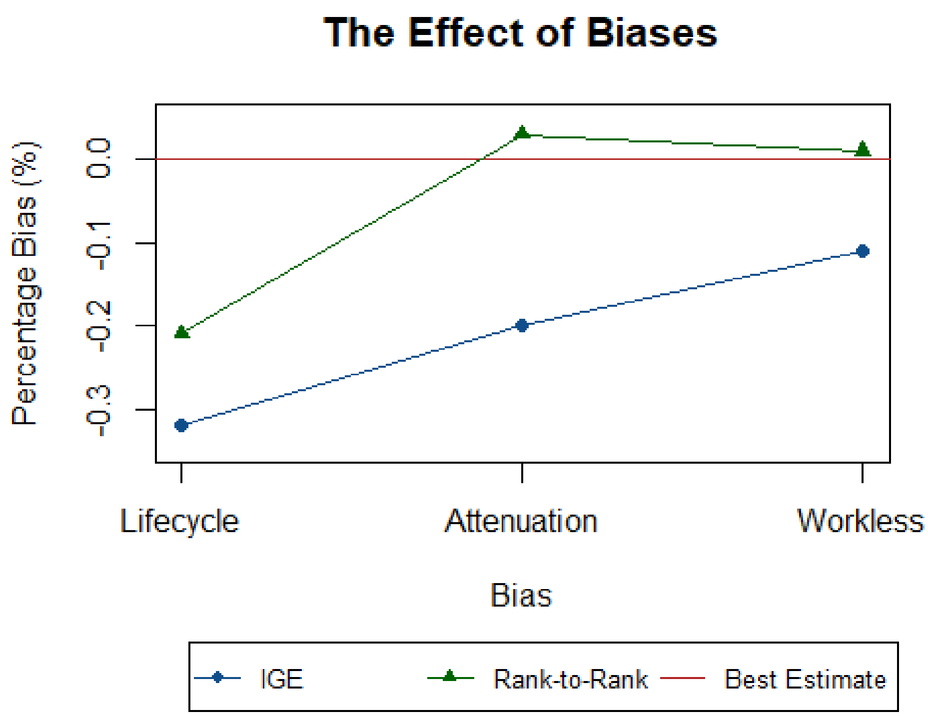
$$ChildrenRank_i = \alpha + \beta_1 ParentRank_i + \varepsilon_i \tag{4}$$

Where β_1 measures intergenerational mobility and can be interpreted as Intergenerational Rank Association (IRA).[2] IRA may be better equipped to tackle the biases when estimated with *observed* parental earnings but does it provides robust results when combined with *predicted* earnings via TSTSLS? Unfortunately, no study has yet explored this question, so this is a fruitful area for further research.[3] Thus, the major first contribution of this dissertation is to amend TSTSLS, so that it can work with income ranks.

[2]Formally, β_1 gives both the *slope* and the *association coefficient* due to the definition of income percentile ranks. See Chetty et al. (2014).

[3]A related study by Jerrim et al. (2016) compares TSTSLS when applied to earnings but not to income ranks

Figure 1: The effect of the biases on IGE relative to the non-biased estimate for 1970 cohort. *Source:* Gregg et al. (2017, Table 6)



2.d *Regional* Mobility Rates

Taking account of all known biases, the best estimates for the UK suggest an IGE of 0.430 and IRA of 0.297 for 1970 cohort (Gregg et al., 2017). While estimates for 1958 cohort are still subject to attenuation bias as parental earnings are observed at one point in time, the best estimates for IGE and IRA are respectively 0.251 and 0.196, confirming that intergenerational mobility has fallen for 1970 cohort. However, these estimates beg the question whether they resemble the actual experience of social mobility across the UK.

Given the significant regional inequalities in the UK (Overman, 2017), intergenerational mobility is perhaps not homogeneous across the country. For example, the Social Mobility Commission (2016) has produced the so-called Social Mobility Index on Local Authority level in England.[4] The index has been very influential for policy-making as it forms the basis for selecting areas with few economic opportunities in which the government invest significant funds (Perera, 2017). The index suggests that London is 'pulling away' from the rest of the UK by offering much greater economic opportunities (Commission, 2016). However, it has been criticised for failing to identify the most disadvantaged areas across the UK (Andrews et al., 2017). Furthermore, the index does not directly include an intergenerational aspect and so ignores potentially important changes in opportunities over time (Bell et al., 2019). Despite these limitations, it can be described as a measure of *intra*-generational mobility because it calculates mobility via indicators such as the share of children on free school meals only for one particular year. Moreover, its relation to actual measures of *inter*-generational mobility is also worth exploring in order to test if they both captures the same latent concept of social mobility.

The only two studies that explicitly considers regional intergenerational mobility contradict the index by finding that on many measures London has the lowest mobility in the UK (Friedman et al., 2017; Bell et al., 2019). However, these studies have several weaknesses. Firstly, they estimate mobility on a regional or country level rather than lower geographical level. Secondly, mobility is calculated in terms of class or education, ignoring within-class earnings inequality (Blanden et al., 2013). Nevertheless, their results suggest that intergenerational mobility is not homogeneous across the UK.

[4]The index is not estimated for Scotland, Wales and Northern Ireland for data constraints

Measuring regional mobility imposes the additional data requirement of geographic identifiers for children. Datawise, the most sophisticated research on regional intergenerational mobility up-to-date employs administrative tax records. Estimating mobility in the US with such data, regional IRA varies from 0.235 in the most mobile decile of small administrative units to 0.402 in the least mobile decile (Chetty et al., 2014). Unfortunately, such a dataset is unavailable (yet) in Britain.

2.e Mobility and Referendum Results

While estimating intergenerational mobility per Region is interesting in itself as an alternative to the Social Mobility Index, it is important to explore the political ramifications of regional differences in mobility. One widely discussed implication of different opportunities across regions is the increase in support for extremest parties in regions that are falling behind economically (Lee et al., 2018). This idea raises the question whether fewer economic opportunities on a local level are correlated with the results of the 2016 EU Referendum.

There are two main explanations for the referendum's outcome. Firstly, the decision is seen as following from excessive immigration (Hobolt, 2016). There is mixed support for this claim. On Local Authority level, the opposite holds: areas with *more* immigrants are *less* likely to support Brexit (Goodwin and Heath, 2016). In contrast, Becker and Fetzer (2017) find that not all types of immigration are causally associated with support for Brexit. Rather, it is specifically immigration from Eastern Europe that matters. So, the link between immigration and Brexit is more complicated than previously thought.

Secondly, higher support for Brexit in certain locations is hypothesised to have resulted from decreasing economic opportunities there (Colonatone and Stanig, 2018; Becker et al., 2019). Regarding the economic causes of Brexit, a further distinction should be drawn between explanations in terms of *domestic* factors and *global* factors as leading to this decrease in opportunities. Regarding the latter, some UK regions are found to have been hit harder by imports from China in the last 30 years leading to the displacement of manufacturing away from the UK and so to fewer job opportunities in local labour markets (Colonatone and Stanig, 2018). These regions were affected negatively by globalisation creating a feeling for being 'left-behind' which translated into supporting Brexit. Turning to *domestic* factors, increasing inequality in housing prices (Ansell and Adler, 2019) and different exposure to austerity since 2010 (Fetzer, 2018) have been found to be causally related to the results.

Given that economic factors are more strongly supported than immigration-related reasons, they seem more likely to be the main cause of Brexit. However, so far most studies have focused on lower economic opportunities stemming from either domestic or global factors rather than a single measure of economic opportunities that captures both factors. Intergenerational mobility is one candidate for such an indicator. For example, it would be higher in locations with lower house prices because obtaining a mortgage would be less costly. It will be lower in places hit harder by globalisation because there will be fewer opportunities for upwards mobility there (Zimmerman, 2008). Moreover, most economic factors discussed in the literature only capture short-term factors such as austerity measures rather than a long-term measure. However, there is some evidence that many people voted for Brexit due to long-term dissatisfaction with economic conditions (Thompson, 2017), pointing to the importance of long-term decline in opportunities.

Thus, the last main contribution of this paper is to explore the relationship between the Brexit Vote and a long-term measure of economic opportunities combining both domestic and global channels. So far, only one study directly explores the association between mobility and the Referendum results (Sensier and Devine, 2017). However, it employs the Social Mobility Index which presents a snapshot of mobility in one particular year and ignores intergenerational dynamics. I build on this approach by adopting a long-term mobility measure.

3 Main Data

Conventionally, intergenerational mobility in the UK has been estimated with cohort studies that follow a single cohort of individuals through their lifetime (Gregg et al., 2017). However, after imposing the necessary constraints, their sample sizes become too small for meaningful regional estimates. Other researchers have used longitudinal datasets that follow a sample of British households for a longer period (Nicolleti and Ermish, 2007). While these studies provide bigger samples, they lack enough data for respondents in separate cohorts because they contain respondents of various age groups. Thus, changes in intergenerational mobility in time cannot be precisely calculated.

Given these problems with traditional datasets, I employ the Labour Force Survey (LFS) which is big enough to allow both estimating regional mobility rates and accommodate changes in mobility over time. The LFS is a quarterly cross-sectional study of UK's labour force that contains detailed data on demographic and job characteristics, including earnings. Respondents are interviewed for five consecutive waves. Each quarter a fifth leaves the survey and another fifth replaces them. In the terminology so far, respondents are equivalent to the children, i.e. the second generation, so I use children and respondents interchangeably in this section.

The key variables necessary for estimating regional mobility are parents' earnings, children's earnings and geographic identifiers:

1. ***Parents' Earnings.*** Unfortunately, parental earnings are unavailable. However, children are asked various questions about the main earner in their family when they were 14. These parental characteristics can be utilised to predict ranks via TSTSLS. Specifically, respondents are asked about the main earners' occupation in addition to gender, ethnicity, class and geographic location.[5] These questions relating to social mobility only started being asked after 2014. Moreover, only children in the July-September wave are asked them. So, my main dataset contains only the five July-September waves in period 2014-2018.

2. ***Children's Ranks.*** The LFS asks children about their weekly pay, from which it is possible to derive their yearly earnings and so income ranks. Given the sensitivity of the question, respondents are only asked about earnings in their first and last wave. So, I further constrain my dataset to respondents who were asked the question about earnings. While workless children are not asked about earnings, both employed and workless children are asked about the various benefits they receive. So, a proxy for yearly earnings can be calculated for workless children based on the average yearly value of the benefit which they receive.[6] Even if benefits are considered, around 23% of children have missing earnings. Since earnings are unlikely to be missing-completely-at-random, I employ more than 30 predictors for multiple imputation with chained equation from R package **mice**.

3. ***Geographic Identifiers*** The *publicly* available version of LFS only contains identifiers on the level of the 12 UK regions rather than lower geographic units such as Local Authorities. However, a *secure* version contains such identifiers. To gain access to this dataset, I obtained a

[5] See Appendix A for details

[6] In this way, I tackle the worklessness bias.

Provisional Research Accreditation from Office for National Statistics (ONS). After completing a day-long training at ONS Titchfield in January 2019, I became an Accredited Researcher which was supposed to give me access to the secure data. However, even though I additionally completed various documents including a very detailed project description, I was unable to receive the data on time. Thus, I can only provide regional estimates in this paper.

4 Methodology

My methodology proceeds in three steps. Firstly, several different approaches for predicting parental ranks via TSTSLS are evaluated. Secondly, parental earnings are predicted in the main dataset and utlised to estimate national and regional intergenerational mobility. Thirdly, the correlation between the Brexit vote and regional mobility is explored. For brevity, Table 1 shows which dataset is used for which model, as it summarises this section.

Table 1: Models and Data.

Model	Type Model	Purpose	Data
5	Complete Pooling	Get Parents' Rank	2001-2002 LFS
6	Multilevel with Random Effects	Get Parents' Rank	Individual level: 2001-2 LFS Group level: 2001 Small Area Micro
7	Multilevel with Random Effects	Estimate mobility	Individual level: 2014-8 LFS Group level: 2001 Small Area Micro
8	Linear Regression	Brexit causes	Mobility from Model 7 Brexit vote from BBC

4.a Predicting Parents' Ranks

In the literature, parents' *earnings* rather than ranks are usually modelled in TSTSLS. However, I use both measures in my estimates and study if TSTSLS performs better under ranks. My discussion is focused on ranks due to its advantages over earnings, as discussed in the previous section.

Applying TSTSLS requires an additional *auxiliary* dataset containing both ranks and the parental characteristics available in the main dataset. This auxiliary dataset should allow accurately estimating parental ranks for the period when children were being brought up. As explained below, my *main* dataset contains children aged 29-34 in 2018. Usually in the literature parental rank is evaluated at 14 (Chetty et al., 2014). In my case children were around 14 in late 90s and early 00s. So, I need an auxiliary dataset that will accurately predict people's rank at this time. To that aim, I pool all waves of 2001 and 2002 LFS to create the auxiliary dataset.

Studies in the UK employing TSTSLS usually fit a linear regression to predict ranks (e.g. Nicolleti and Ermish, 2007). For my auxiliary dataset, the model will be:

$$Rank_i = \alpha + \beta_1 Occ_i + +\beta_2 NSSEC_i + \beta_3 MainEarner_i + \beta_4 Ethnicity_i + \varepsilon_i \tag{5}$$

where the right-hand side includes all parental characteristics[7] from the main dataset.[8]

However, such a model ignores potentially important differences of predictors' effect in various regions (Laurison and Friedman, 2016). Moreover, since TSTSLS was first introduced, various new techniques allowing better prediction have gained prominence in the literature, e.g. Multilevel Regression and Post-stratification (Lax and Phillips, 2009) and Artificial Neural Network (Chakraborty and Joseph, 2017). So, I estimate two additional models that may be better at predicting ranks.

Firstly, model (5) is estimated by including group fixed effects in order to capture unobserved heterogeneity across regions. Secondly, a more sophisticated multilevel model with random effects is included (Gelman and Hill, 2006). Essentially, this technique works by balancing between complete pooling and zero pooling, i.e., estimating a separate regression in each region. Furthermore, multilevel modelling with random effects allows including regional level predictors such as regional unemployment that may be important for determining rank. In my model, I allow the intercept to vary between different regions:

$$\begin{gathered} Rank_i = \alpha_{j[i]} + \beta_1 Occ_i + +\beta_2 NSSEC_i + \beta_3 MainEarner_i + \beta_4 Ethnicity_i + \varepsilon_i \\ \alpha_j \sim N(\gamma_1 + \gamma_2 Demographic_j + \gamma_3 Economic_j + \gamma_4 Social_j, \sigma^2) \end{gathered} \tag{6}$$

Where j refers to parent i's region. While the first row is nearly identical to (5), the intercept α here is modeled in the second row as a random coefficient that is a function of various LA-level characteristics which can broadly be categorised into Demographic, Economic, and Social. In (6), the less observations there are per region, the more the intercept is pooled to the national intercept.

[7]See Appendix A for details

[8]NSSEC stands for National Statistics Socioeconomic Classification which is a common measure of social class related to but different from occupation.

The group-level predictors were obtained from Census 2001: Small Area Microdata which is a sample of individuals across all regions.[9]

After estimating the three models, they are compared based on model fit and the optimal one selected. Thus, I make a dual methodological contribution to the literature. I explore if TSTSLS performs better with ranks than earnings and also if a more sophisticated model than complete pooling can better predict parental ranks.

4.b Intergenerational Mobility

The optimal predictive model is then applied to the main dataset in order to predict parental rank. Estimating intergenerational mobility now becomes possible. Firstly, I obtain various national estimates of mobility in terms of ranks, earnings and class and study the trend in mobility over a long-term period. By comparing my estimates with the results in the literature, I evaluate if using TSTSLS with ranks provides robust estimates of mobility. If that is the case, I would be able to contribute to the on-going debate between sociologists and economists on whether intergenerational mobility has deteriorated in late 20^{th} century. To that aim, I fit a simple linear regression of children's status on parents' status such as model (4) for eight different cohorts.

Secondly, regional intergenerational mobility is estimated to test if it varies across regions. A multilevel model with random effects is utilised because it allows group-level predictors and also compensates for small samples in certain regions:

$$\begin{aligned} ChildrenRank_i &= \alpha_{j[i]} + \beta_{j[i]} ParentRank_i + \varepsilon_i \\ \alpha_j &\sim N(\gamma_1 + \gamma_2 Demographic_j + \gamma_3 Economic_j + \gamma_4 Social_j, \sigma^2) \\ \beta_j &\sim N(\mu_1 + \mu_2 Demographic_j + \mu_3 Economic_j + \mu_4 Social_j, \sigma^2) \end{aligned} \tag{7}$$

Where j refers to children's region of birth. The first row is similar to (4) but here both the intercept and the slope of earnings vary as functions of regional predictors which as above can again broadly be categorised into Demographic, Economic and Social predictors. For model (7), they are also derived from Census 2001: Small Area Microdata since I am interested in the LA conditions when respondents were brought up, i.e., early 2000s. The measure of intergenerational mobility in (7) is

[9] See Table 4 in Appendix A for details.

β_j which gives IRA in each region.

4.c Relation to the Brexit Vote

These estimates are then utilised to study the relationship with the Brexit vote. I work with data on regional level where the results from the 2016 UK Referendum were obtained from BBC's website. I run the simple linear regression:

$$PerLeave_k = \alpha_k + \beta_1 IRA_k + \varepsilon_k \tag{8}$$

where k refers to the Region and $PerLeave$ is the percentage of people supporting a Leave vote. Originally, I planned to include various other variables potentially correlated with Brexit such as the share of immigrants and observe the change in the significance of IRA. However, at the time I was working under the assumption that I will gain access to secure LFS allowing estimates of IRA per Local Authority. Since this is not the case, I only end up with a sample of 12 regions suggesting that it is not sensible to further include regional predictors especially in light of my initial results (see Section 6.a).

One alternative measure of regional mobility is the Social Mobility Index discussed in Section II.d. Since this index is only available for England for Local Authorities, I aggregate it on regional level and further constrain my dataset only to English regions. While the index does not consider intergenerational mobility directly, I explore whether my estimates and the index capture the same underlying latent variable of social mobility. Since lower values of IRA indicate greater social mobility, I expect that Social Mobility Index is negatively related to my mobility estimates. I further test the relation between social mobility and the Brexit vote with the Social Mobility Index on both regional and Local Authority level. Note that in studying this relation I do *not* make any claim about low mobility *causing* greater support for Brexit. Testing such a mechanism via linear regression would require further very strong assumptions in (8) such as strict exogeneiety that are unlikely to hold.

5 Mobility Results

5.a Parental Rank Prediction

Before estimating mobility, I employ cross-validation where I divide my *auxiliary* data into a training and testing dataset. Firstly, I train my model in the former and then see how it performs in the testing dataset by studying R^2 and AIC allowing me to avoid overfitting. In that way, I can make an educated guess about how well the model will perform when exported to the *main* dataset.

This procedure is applied separately for earnings and ranks and Table 2 reports my results. Firstly, it suggests that predicting parental rank rather than earnings leads to a better fit. Secondly, using fixed effects seems better than random effects or complete pooling. Including random effects is not useful here because the big sample size allows robust estimates of separate intercept in each region. Complete pooling is also suboptimal since the AIC score is higher than with fixed effects indicating worse fit. Anova test in Table 5 from Appendix B suggests that the fixed effects model fits the data significantly better than complete pooling.[10]

Table 2: R^2 and AIC in models for TSTSLS

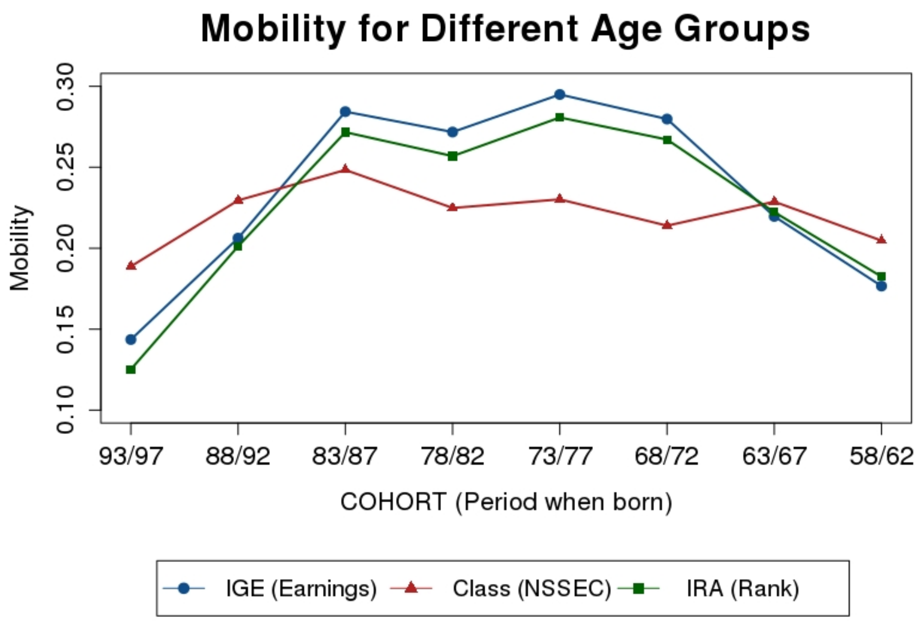
Data	Complete pooling	Fixed Effects	Random Effects
R^2			
Earnings, Training	0.350	0.353	0.353
Earnings, Testing	0.367	0.370	0.347
Ranks, Training	0.428	0.431	0.431
Ranks, Testing	0.428	0.430	0.430
AIC			
Ranks, Training	−18268	−19034	−18536

5.b National Mobility Rates

Next, I estimate national intergenerational mobility separately for class, earnings (IGE) and ranks (IRA) for eight cohorts (Figure 2). Class mobility is relatively stable over time at around 0.220. While class mobility is less affected by lifecycle bias, i.e., measuring children earnings too early, both IRA and IGE are lower for the youngest two cohorts due to this bias. Thus, if lifecycle biases

[10] Appendix B further reports results for predicting Ranks via an Artificial Neural Network which does *not* outperform fixed effects model.

Figure 2: Comparing Different Methodologies for Estimating Mobility



is to be tackled, mobility should be estimated after age 30 where the bias seems to disappear.

Interestingly, IRA's trend follows very closely IGE. While for both cases I dealt with workless bias by imputing earnings from benefits to workless individuals, the IGE estimates are probably underestimated due to attenuation bias, i.e., measuring children earnings only once. In contrast, IRA is not affected by attenuation bias to the same extent (Figure 1).

How do these results compare against other national estimates? The most robust estimates are calculated for the cohorts born in 1958 and 1970 (Gregg et al., 2017). They are comparable to my estimates for 1958-1962 and 1968-1972 cohorts. Table 7 in Appendix B compares directly my estimates to Gregg et al. (2017). Their best estimates of IRA for 1958 and 1970 cohorts are respectively 0.196 and 0.297 which are very close to my own estimates of 0.182 and 0.267. In contrast, my IGE's estimates are similar to Gregg et al.'s *biased* estimates but underestimated by 30% relative to their *unbiased* estimates (see Table 7 in Appendix B).

These results point to the robustness of using IRA for comparing mobility over time. Moreover, a key difference between Gregg et al.'s estimates and mine is that they have data on parental earnings whereas I had to use TSTSLS to predict parental earnings. Despite this inconveniences, applying TSTSLS to IRA renders robust estimates of intergenerational mobility confirming that fusing TSTSLS with ranks can overcome the problem of unavailable parental income.

More generally, assuming that this result generalises to other cohorts, Figure 2 allows us to study the long-term trend in earnings mobility with robust estimates for the first time. Both sociologists' results for stable *class* mobility (Bukodi et al., 2015) and, arguably, economists' findings about decreasing *earnings* mobility (Gregg et al., 2018) in late 20^{th} century are confirmed. Figure 5 in Appendix B finds significant differences between earnings mobility in 1958-1962 cohort relative to 1968-1972 cohort. However, while earnings mobility was higher for 1958-1962 cohort, it remained stable at least until cohorts born in 1980s (Figure 2). Recent cohorts have not have experienced the fall in intergenerational mobility which previous research has claimed. Moreover, mobility for 1958-1962 cohort might be overestimated because, as people approach retirement, they work less hours causing a downward bias in IRA (Gregg et al., 2017) and here I only observe their earnings when aged nearly 60.

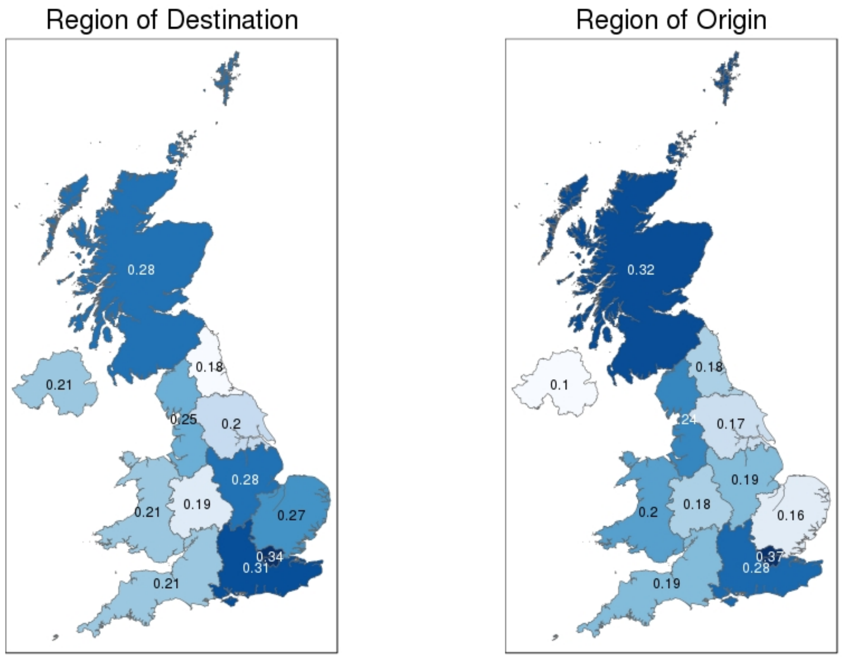
5.c Regional Mobility Rates

Before presenting my results, I consider the distinction between region of *origin* and region of current *residence* since it is crucial for estimating IRA. Ideally, IRA will be estimated using respondents' region of *origin*, i.e., the region in which they were raised (Friedman et al., 2017). For privacy reasons often datasets do not contain data on region of origin but only region of *residence*, i.e., the region where they live currently. However, in the UK many people migrate in search of better opportunities such as university education, so region of residence is frequently different from region of origin (Greenwood, 1997).

To see why this distinction matters, consider the case of Rajesh who is born in a very poor family in Yorkshire. Assume that Rajesh attends a Russell Group university and strikes a highly paid job in the City where he works and live. If IRA is estimated based on region of *origin*, Rajesh's IRA (the correlation with his parents' earnings rank) will be low signifying high mobility in Yorkshire. In contrast, if IRA is estimated based on region of *residence*, Rajesh's IRA will still be low but indicate high mobility in London rather than Yorkshire. Given high levels of internal migration across the UK (Lee et al., 2018), using region of residence can bias our result.

While the LFS only asks about region of residence, it also questions respondents about the length of time spent at their current address. One of the suggested answers is '10 years or longer'.

Figure 3: Regional IRA in the UK for Region of *Origin* and Region of *Destination*



Combining information from this key question with region of residence, I can only obtain a proxy for some people's region of origin. Using this proxy, I assume that people who do not migrate are representative of people who do (Lee et al., 2018). This assumption may be problematic as discussed in Section 5.d.

Thus, I estimate IRA separately for region of residence and region of origin. My estimates are obtained for the cohort aged 29-34 in 2018 for two reasons. Firstly, only in that case I obtain a reasonable proxy for region of origin since many people changed location after finishing university which is on average at 22 (ONS, 2016). Secondly, I avoid the lifecycle bias.

My results are presented in Figure 3 which provides the first regional estimates of intergenerational earnings mobility in the UK. Darker shades of blue indicate *higher* IRA and so *lower* mobility. For all regions but NI, Eastern England and East Midlands, results in the two maps are similar. For example, both maps reject the so-called 'London effect', i.e., the idea that London is pulling away from the rest of the country in terms of social mobility (Friedman and Macmillan, 2016). One leading explanation for the effect points to within-London inequality in mobility which is low in *Inner* London has but exceptionally high in *Outer* London (Bell et al., 2019).

Despite these similarities between the maps, the choice for which approach is more accurate depends on which approach captures mobility better in Northern Ireland, East Midlands and Eastern England. My literature review of regional *class* mobility in England suggests that East Midlands is relatively mobile whereas results for Eastern England are much more mixed.[11] Moreover, *educational* mobility is found to be higher in Northern Ireland than the rest of UK (Hertz et al., 2007). So, region of origin captures better intergenerational earnings mobility.

Thus, my best estimates suggest that IRA is lowest in Northern Ireland[12] (0.10) and East Midlands (0.16) and highest in London (0.37) and Scotland (0.32). Given that there is no clear spatial pattern in these results, intergenerational mobility varies significantly across different regions.

Regarding how my results compare against the literature, several points should be noted. While I estimate earnings mobility, other papers (Friedman and Macmillan, 2016; Bell et al., 2019) look at other indicators of social status such as class or education. Moreover, these different indicators show radically different results. London, for instance, is found to have the *highest* class mobility but the *lowest* educational mobility (Bell et al., 2019). Besides, Friedman and Macmillan (2016) use a different designation of regions which makes direct comparison challenging. It is thus not so unexpected that my results differ from the literature, although there are some important similarities with (Bell et al., 2019) (Table 8 in Appendix B).

One may still question my estimates' robustness given these differences and the difficulties in estimating earnings mobility. However, since I obtain very good estimates on the national level, my regional estimates should also be close to the real rates.

5.d Limitations

My study has two key limitations. Firstly, my proxy for region of *origin* may be inadequate. To see this point, consider the distinction between *Localist Somewheres* who spent most of their life at one location and *Internationalist Anywheres* who move to a different location often in search of better opportunities (Goodhart, 2016). My proxy excludes Anywheres by definition since their birth place is unavailable. However, on average Anywheres are found to be different from Somewhereas, e.g., they are more liberal, cosmopolitan and educated (Lee et al., 2018, 147). Since they are excluded from my analysis, perhaps my estimates do not capture the actual social mobility especially in areas

[11] See Table 8 in Appendix B which compares my results against the literature.

[12] To the best of my knowledge, this the first estimate of earnings mobility in Northern Ireland

with many Anywheres which can explain my surprising findings about low mobility in London. In other words, selection bias might be a big problem for my estimates. Moreover, being an Anywhere is related to the probability of voting Brexit which may affect my analysis in the next part (Lee et al., 2018).

Secondly, since I did not receive access to the secure LFS, I estimated IRA only per region. However, there is perhaps *within*-regional inequality in intergenerational mobility. Inequality in class and educational mobility exists, for example, between Inner and Outer London (Bell et al., 2019). Unfortunately, with the current data such dynamics are hidden.

6 Brexit Results

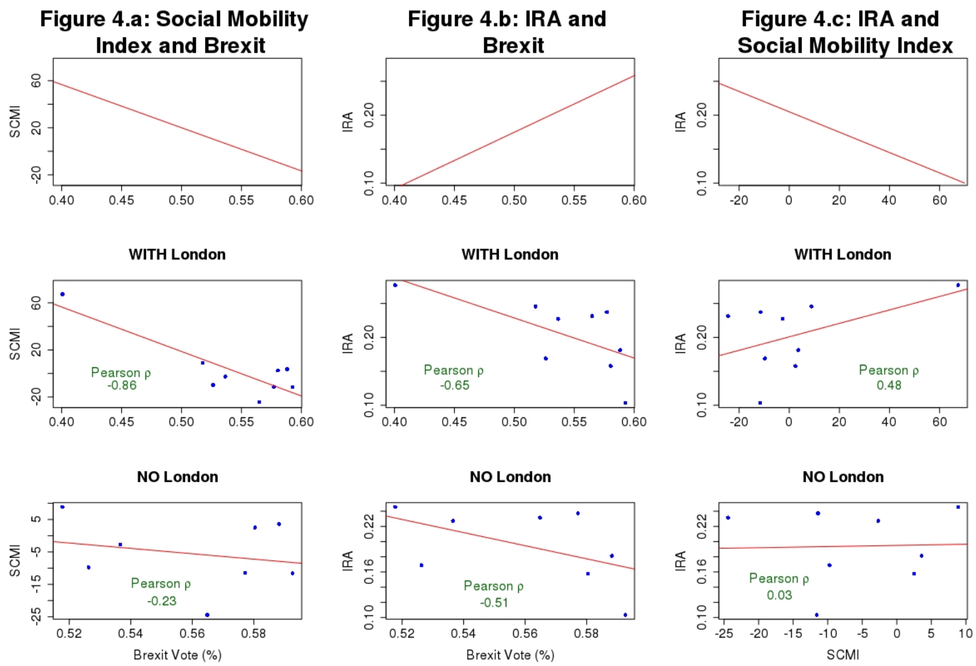
6.a Testing the relation between social mobility and the Brexit vote

To examine if areas with high mobility are less likely to support Brexit, as suggested by my literature review, I run a simple linear regression with the Percent of Leave voters as outcome and my IRA or Social Mobility Index as predictor. I further examine the relationship between IRA and the Social Mobility Index.

My results are presented in Figure 4 which contains three panels depending on the relationship studied: a) Social Mobility Index and Brexit vote, b) IRA and Brexit vote, and c) IRA and Social Mobility Index. The first row in Figure 4 represents the hypothesised associations based on the literature. For example, since higher values of IRA mean lower mobility, I would expect a positive correlation between IRA and the Brexit vote, thus the first row in Figure 4.b.

The second and third row represent my results with and without London. While Figure 4.a. confirms that Social Mobility Index is negative associated with the Brexit vote *with* London, the evidence grows weaker when London is excluded as shown by the change in the correlation coefficient in Figure 4.b. Moreover, there is no evidence about the negative association when IRA is employed independently of whether London is included or not. Strikingly, the relationship is in the *opposite* direction from expectation: areas with higher mobility are *more* likely to support Brexit. Lastly, Figure 4.c shows *no* association between IRA and Social Mobility Index in *not* the expected direction, thus failing to find evidence that the two measures are negative correlated.

Figure 4: Results for the relationships between social mobility and the Brexit vote



6.b Discussion and Limitations

These results are quite puzzling. They should, however, be taken with a pinch of salt given the sample size of nine regions. Perhaps there are important *within-regional* differences which my current analysis ignores. So, I study the relationship between the Brexit vote and Social Mobility Index for Local Authorities (Figure 6 in Appendix B). The association holds even if London is excluded, confirming that regions with lower social mobility were associated with higher support for Brexit. Thus, my results for regional IRA and the Brexit vote may be different once IRA is estimated on Local Authority level.

Depending on whether the lack of a correlation between IRA and the Brexit vote is accepted, two widely different implications follow. Firstly, if I accept the results employing IRA, one of the main explanations for the Referendum Results will be strongly discredited.[13] How can then the significant association between the Social Mobility Index and the Brexit vote be interpreted? It might be suggesting that the Social Mobility Index is not capturing social mobility but something else such as local economic opportunities. Such an interpretation has significant policy implications. Policy-makers should either select another measure of social mobility as selecting deprived areas in

[13]Even though my IRA estimates should *not* be interpreted causally.

which to invest or acknowledge that the Social Mobility Index is not measuring social mobility *per se*.

Secondly, assume I do not accept the result on IRA, given the strong evidence on a negative correlation between the Social Mobility Index and the Brexit vote. Thus, measuring mobility through IRA may be an inadequate way to capture actual social mobility. This could be fruitful area for fruther research.

7 Conclusion

Given the aforementioned, this paper makes four contributions to the literature. Firstly, I proposed a slightly amended version of the TSTSLS procedure that allows robust estimates of mobility even when parents' income rank is unavailable. My novel procedure works by re-framing the first-stage problem into a prediction problem. Importantly, this methodological contribution opens the door to obtaining robust estimates in countries such as France where parental and children earnings are unavailable in one dataset.

Secondly, I examined the evolution of intergenerational earnings mobility over time in the 20^{th} century. Despite not observing parental income, my estimates were very similar to comparable estimates from the literature that do not suffer from such data limitations. The results suggested that there is some evidence for economists' claim that intergenerational mobility has fallen for the cohort born in 1972 relative to 1958, albeit it has remained stable for cohorts born after the early 70s.

Thirdly, I provided the first estimates of regional intergenerational earnings mobility. My results showed significant differences in mobility across the UK. Lastly, this paper directly explores if long-term local economic opportunities are associated with the 2016 EU Referendum results. Unfortunately, I did not find a significant effect probably because my dataset only allowed estimating mobility on regional level.

Further research should firstly obtain such results on a Local Authority level using secure LFS data and then employ a more sophisticated causal inference technique to explore if there is a causal effect of social mobility on referendum results. One tempting possibility is using an instrumental variable. In this case a suitable instrument would randomly be encouraging some areas to have greater intergenerational mobility without being related to the Referendum results. While finding such a valid and informative instrument may seem challenging at first, I calculated intergenerational mobility for cohorts which were around 14 in the late 1990s and early 2000s. From a political perspective, this was the time of the new Blair government which introduced various reforms to local labour markets aimed at decreasing labour insecurity and de-commodifying workers (Shaw, 2003). So, perhaps a suitable instrument can be found among these policies.

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Appendix A. Variables used from each survey

Table 3: Variables from LFS 2014-2018 used for predicting parental earnings

Variable Code	Description
ETHCEN15	Ethnicity of Parent. Derived from the Ethnicity of Respondent
HOHID	Whether the main earner was father, mother or somebody else
NSECMMJ	The NSSEC, i.e. class, categorisation of parent. See Wikipedia (2019)
SC2KMMN	2-Digit Occupation Index of Parent
GOVTOF	Region of current residence

Table 4: Variables from SAM 2001 used in TSTSLS' random effects model (model (6)) and in multilevel modelling of intergenerational mobility (model (7)). Table Created with **stargazer** (Hlavac, 2018)

Variable Code	Description
id	cross-country unique identifier
lacode	local authority (GB) or parliamentary constituency (NI)
agea	Age of Respondents
cobirta	Country of Birth
distwrka	Distance to Work (Including Study in Scotland)
econach	Economic Activity (last week)
ethewa	Ethnic Group for England and Wales
ethn	Ethnic Group for Northern Ireland
ethsa	Ethnic Group for Scotland
everwork	Ever Worked
health	General Heath Over the Last Twelve Months
lastwrka	Year Last Worked
llti	Limiting Long Term Illnes
marstata	Marital Status
migorgn	region of origin
qualvewn	Level of Highest Qualifications
relgew	Religion (England and Wales)
relgn	Religion (Northern Ireland)
relgs1	Religion Belongs to (Scotland)
sex	Sex
student	Schoolchild or Student in Full-Time Education
supervsr	Supervisor/Foreman
workforc	Size of Work Force
nssec8	NS-SEC 8 Classes

Appendix B. Additional Figures & Tables

Table 5: Chi-squared test in **anova** that compares the fit of the Fixed Effects model with the Complete Pooling model.

Res.Df	RSS	Df	Sum of Sq	F-statistic	Pr(>F)
$142,212$	$7,320.460$				
$142,201$	$7,280.048$	11	40.412	71.761	$< 2.2e - 16$

Note: The test is statistically significant which means that the Fixed Effects model fits the data better.

Table 6: The results from fitting an Artificial Neural Network (ANN) to the dataset.

Approach	Testing dataset	Training dataset
Logged Income	0.336	0.368
Income Ranks	0.441	0.416

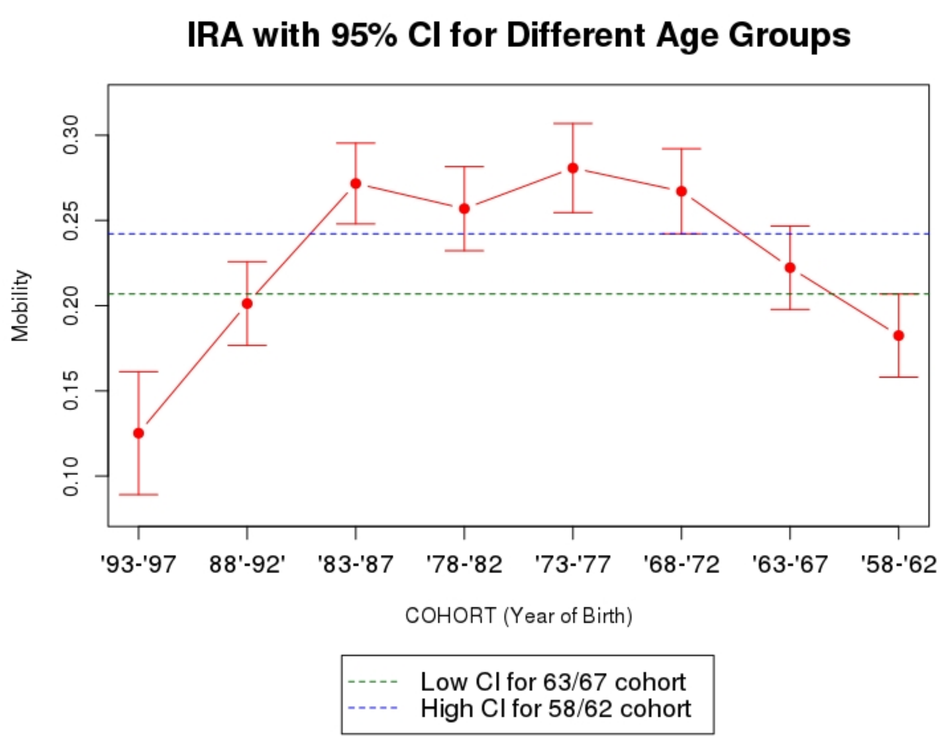
Note: I was unable to use occupations directly as a factor variable given that ANN cannot handle categorical variables. So, each occupation was replaced with the mean wage for this occupation in 2001. Other categorical variables were simply recoded as dummy variables. In reality, finding the best possible ANN to fit the data can take months (Garson, 1998). However, even a basic ANN fitted the training dataset quite well. This result is to be expected given the growing literature finding that ANN are better at predicting various typical economic variables such as inflation (Chakraborty and Joseph, 2017) and housing prices (Feng and Jones, 2015) than traditional econometric approaches.

Table 7: Comparison of National Estimates. The figure compares

Source	Estimate	Cohort	Estimate	Cohort
IRA				
My estimate	0.182	1958-1962	0.267	1968-1972
Gregg et al. (2017)	0.175	1958	0.306	1970
Gregg et al. (2017) unbiased	0.194	1958	0.298	1970
IGE				
My estimate	0.176	1958-1963	0.279	1968-1972
Gregg et al. (2017)	0.205	1958	0.291	1970
Gregg et al. (2017) unbiased	0.251	1958	0.430	1970

Note: The figure compares my IRA and IGE estimates for the 58/62 cohort and 68/72 cohorts with the estimates obtained by Gregg et al. (2017) who provides the most up-to-date estimates for the UK. By *unbiased*, I mean that the results have further been adjusted for attenuation bias, i.e. measuring earnings at a single point in time for parents and children. All the other estimates have been adjusted for workless and lifecycle bias but not for attenuation bias.

Figure 5: The 95% CI for IRA in different cohorts.



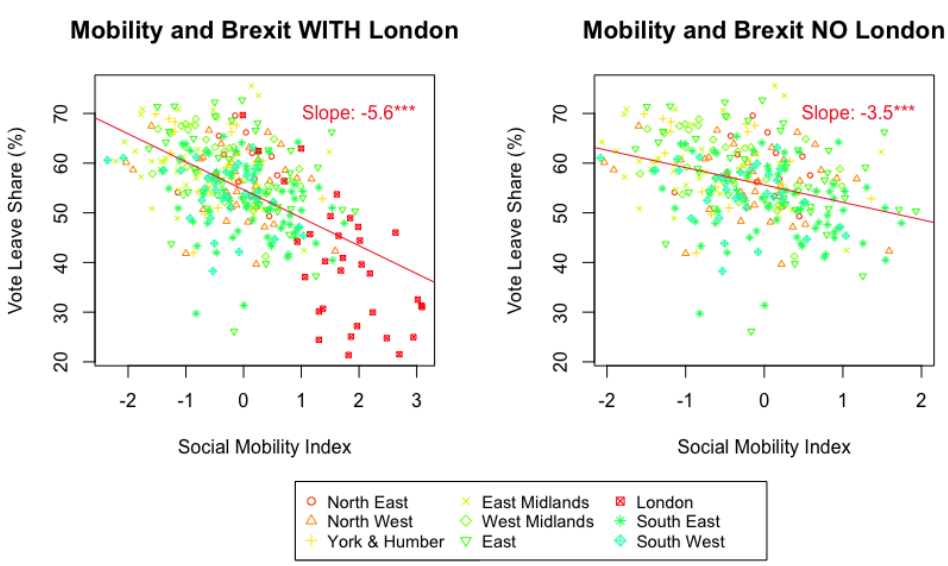
Note: Since the blue and green line do not cross, there is a statistically significant differences in mobility rates for the 68/72 and 58/62 cohorts.

Table 8: Ranking Regions by Mobility Based on Different Sources

Region	Figure 3 IRA		Bell et al. (2019)			FM (2016)	
	Dest	Orig	Class	House	Educ	Dest	Orig
East Midlands	9	7	8	2	3	5	4
East of England	8	2	7	5	7	8	8
London	12	12	1	10	9	11	1
North East	1	4	2	3	10	3	3
North West	7	9	9	8	5	1	6
Northern Ireland	4	1	*NA*	*NA*	*NA*	*NA*	*NA*
Scotland	10	11	*NA*	*NA*	*NA*	6	7
South East	11	10	3	6	1	7	11
South West	5	6	6	4	4	9	10
Wales	6	8	4	1	8	10	9
West Midlands	2	5	5	7	6	2	2
Yorkshire	3	3	10	9	2	4	5

Note: *Dest* refers to estimation based on Region of Destination whereas *Orig* refers to estimation based on Region of Origin. FM (2016) refers to the estimates of Friedman and Macmillan (2016). For each measure of intergenerational mobility, I compile a ranking from 1 to n where n is the number of regions available. In the case of Friedman and Macmillan (2016), estimates were not compiled on the regional level but on a lower geographical level, so I pulled their estimates to obtain a single estimate for each region by taking the average in each region. Housing mobility is estimated as the association between parental and children ownership of houses.

Figure 6: Relationship between Brexit voters and Social Mobility Index in Local Authorities



Note: The differences between the left and right scatterplots are that the left includes London whereas the right one excludes London. In the left plot, London Local Authorities are painted in red for brevity.