Intergenerational earnings mobility: Changes across cohorts in Britain

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ABSTRACT

The aim of this paper is to analyse intergenerational earnings mobility in Britain for cohorts of sons born between 1950 and 1972.

Since there are no British surveys with information on both sons and their fathers' earnings covering the above period, we consider two separate samples from the British Household Panel Survey: a first sample containing information on sons' earnings and a set of occupational and education characteristics of their fathers and a second one with data on the same set of fathers' characteristics and their earnings. We combine information from the two samples by using the two-sample two-stage least square estimator described by Arellano and Meghir (1992) and Ridder and Moffit (2005).

1. Introduction

At present, there is not information about intergenerational earnings mobility in Britain for sons belonging to very distant birth cohorts. In this paper we remedy this and provide an analysis of the trend in intergenerational earnings mobility across the cohort period 1950-1972.

The absence of previous findings is due to the lack of British surveys with information on both sons and their fathers' earnings covering a long period. Using the British Household Panel Survey (BHPS) we are, however, able to observe sons' earnings and a set of occupational characteristics of their fathers. All BHPS respondents aged 16 or more are asked to report the education, the age and the occupation of their parents when they were aged 14. This gives us a set of instrumental variables, such as education dummies, age, occupational prestige scores, socio-economic groups and social classes, which can be used to predict the fathers' missing earnings. It is then possible to estimate consistently intergenerational earnings mobility by using the two-sample instrumental variables estimator described in Angrist and Krueger (1992), Arellano and Meghir (1992) and Ridder and Moffit (2005). More precisely we use a computationally easier variant of that estimator, the two-sample two-stage least square estimator, which is asymptotically equivalent and therefore consistent but can produce different estimates in small samples as emphasized by Inoue and Solon (2005). Using this estimator it is possible to combine information from two separate samples; a sample of sons with observations on their earnings and their fathers' education, age and occupational characteristics, and a sample of potential fathers with observations on earnings, education, age and occupational characteristics. The latter sample is used to estimate an earnings equation for fathers using their age, education and occupational characteristics as explanatory variables, while the former is used to estimate an intergenerational earnings equation by replacing the missing fathers' earnings with its best linear prediction.

The two-sample two-stage least square estimation has been already applied to study intergenerational mobility by Björklund and Jäntti (1997) in Sweden, Fortin and Lefebvre (1998) in Canada, by Grawe (2004) in Ecuador, Nepal, Pakistan and Peru, and Lefranc and Trannoy (2005) in France. In all those studies, but the last one, the choice of the instrumental variables is dictated by the few variables available. We use a larger set of instrumental variables, which gives us a greater degree of freedom in choosing the instrumental variables to predict the missing fathers' earnings.

Moreover, we try to control for the potential life cycle bias affecting intergenerational mobility estimation. Theoretically we would like to measure intergenerational earnings mobility by considering long run permanent earnings, but we observe instead current earnings at a specific age. Since the earnings profile across age is probably neither constant nor a deterministic function of age, measuring earnings when sons (fathers) are too young or too old can cause an estimation bias, as emphasized by Jenkins (1987), Haider and Solon (2005) and Grawe (2005). To take account of this potential life cycle bias we adopt two methods. The first method consists in restricting the age for sons and fathers to a range in which current earnings are likely to be more close to long run earnings or in other words excluding people too young and too old. As second solution we follow the suggestion of Lee and Solon (2005) to estimate the intergenerational mobility equation by allowing the intergenerational mobility elasticity to change by son's age and by son's cohort.

The rest of the paper is organized as follow. In Section 2 we describe the data requirement and issues in estimating intergenerational earnings mobility with special emphasis on sample selection and measurement error problems. In Section 3 we briefly review the previous finding on trends in intergenerational mobility in Britain. In Section 4 we describe the two-sample two-stage least squares estimator and its potential inconsistency when the instrumental variables are endogenous, and we explain how to choose the instrumental variables to impute missing father's earnings. In Section 5 we describe the data source, the samples and the variables used in the empirical analysis. Section 6 reports the results of different estimation methods of the intergenerational earnings mobility trend. Finally, Section 7 draws some conclusions.

2. Intergenerational mobility: data requirement and issues

Intergenerational mobility studies estimate the correlation between socioeconomic status of parents and their offspring. A high correlation would imply that people born in disadvantaged families have a smaller chance to occupy the highest socio-economic positions than people born in privileged families. A zero correlation would imply instead a high degree of mobility and more equal opportunities.

Different measures of intergenerational mobility have been used in previous studies. Economists usually consider intergenerational elasticity in continuous monetary variables, typically income or earnings, while sociologists use association measures between ordered categorical variables such as social and economic class positions.[1] Following the economic approach, we focus in this article on intergenerational immobility measured by the intergenerational elasticity of sons' earnings with respect to fathers' earnings. More precisely, we consider the following intergenerational mobility equation:

$$y = \alpha + \beta x + A\gamma + u \tag{1}$$

where y is the son's log earnings; x is the father's log earnings; A is a vector of other control variables, specifically the sons' and fathers' age and age square; α is the intercept term representing the average change in the sons' log earnings, β and γ are coefficients; and u is a random error identically and independently distributed (i.i.d.) with zero mean and homoskedastic. The coefficient β is the intergenerational elasticity of son's earnings with respect to their father's earnings, and it is our parameter of interest.

Notice that β can be alternatively computed by considering the following equation:

$$\tilde{y} = a + \beta\tilde{x} + \varepsilon \tag{2}$$

where $\tilde{k}$ is the residual of the regression of k on A, $\tilde{k} = \tilde{y}$ or $\tilde{x}$, a is a new intercept and ε is a new error term still *i.i.d.* with zero mean and homoskedastic. Let ρ be the correlation between $\tilde{y}$ and $\tilde{x}$; then β is related to ρ by the following equation:

$$\beta = \rho \frac{\sigma_{\tilde{x}}}{\sigma_{\tilde{y}}}, \tag{3}$$

where $\sigma^2_{\tilde{k}}$ is the variance of $\tilde{k}$, $\tilde{k} = \tilde{y}$ or $\tilde{x}$. In other words, the coefficient β is related to the correlation between sons' and fathers' log earnings net of sons' age. Moreover, β is exactly equal to ρ when $\sigma^2_{\tilde{y}} = \sigma^2_{\tilde{x}}$.

[1] We refer to Solon (1999), Björklund and Jäntti (2000), Bowles and Gintis (2002), Erikson and Goldthorpe (2002) for a review.

A coefficient β equal to zero indicates a situation where all sons have "equal opportunities". When $\beta=0$ all sons have an average log earnings equal to α plus an additional deterministic component function of their age. When β is instead different from zero, sons' average log earnings depend also on their fathers' earnings.

In an attempt to investigate whether β has increased across generations in Britain, we would like to estimate a separate β for sons born in different years from 1950 to 1972. This implies very stringent data requirements because we need to observe for a representative sample of individuals born during this period their own earnings and their fathers' earnings. Blanden et al (2002) try to estimate intergenerational earnings mobility using two British cohort studies, the 1958 and the 1970 cohorts, but because of data limitations they consider parental income instead of fathers' earnings.

The absence of any other previous finding on trends in intergenerational earnings mobility in Britain is due to the lack of British surveys with information on both sons' and their fathers' earnings covering a long period. Considering the British Household Panel Survey, which henceforth we refer to as the BHPS, we can easily observe earnings for a sample of men born over the period 1950-1972. We can instead observe their fathers' earnings only if they have been living together with their fathers in at least one wave of the panel. Obviously the probability of being observed living together with their fathers decreases with age. We observe both sons' and their fathers' earnings for about 12% of cases. It is evident that analyses based on the restricted sample of sons coresident with fathers would imply a sample selection problem.

Francesconi and Nicoletti (2005) analyse intergenerational mobility using an occupational prestige score, considering sons born between 1966 and 1985 in the BHPS. They find that the β coefficient is underestimated when considering the subsample of sons coresident with their fathers. Since all BHPS respondents aged 16 or more are asked to report the occupation of their parents when they were aged 14, Francesconi and Nicoletti (2005) are able to observe an occupational prestige score for both sons and their fathers. This allows them to measure the extent of the selection bias and to assess different sample selection correction methods. They conclude that most of the methods seem to be unable to correct the negative bias except the propensity score weighting.

The occupational prestige score used by Francesconi and Nicoletti (2005), the Hope-Goldthorpe score, is strongly related to earnings (see Phelps Brown (1977) and Nickell (1982)).

Nevertheless, the β coefficient using earnings is usually higher then the β coefficient using the occupational prestige scores (see for example Ermisch et al (2005)). Moreover, it is not clear whether the positive trend in intergenerational mobility found in Ermisch and Francesconi (2004) using the Hope–Goldthorpe score in the BHPS, would be confirmed by an analysis of intergenerational earnings mobility.

A method to estimate intergenerational earnings mobility taking into account the missing fathers' earnings problem could be by adopting the propensity score weighting estimation suggested by Francesconi and Nicoletti (2005). While this method can be useful for the sample of sons born between 1966 and 1980, its usefulness is doubtful for the sample of sons born between 1950 and 1972 where fathers' earnings are missing in more than 88% of cases.

For this reason we attempt to overcome the coresidence sample selection problem in a different way. We use the two sample two-stage least squares estimator, denoted by the abbreviation TS2SLS estimator,[2] to combine two separate samples from the BHPS: a first sample containing information on sons' earnings and a set of education and occupational characteristics of their fathers (which are collected through retrospective questions about the fathers asked to all respondents) and a second one with data on earnings and the same set of education and occupational characteristics.

Another well known problem potentially biasing intergenerational mobility studies is the measurement error in earnings. Theoretically, we would like to consider the intergenerational elasticity in long run permanent earnings but earnings can be observed only in a single or few specific years. The most common approach is then to assume the following classical measurement error model:

$$w_{it} = w_i + \varepsilon_{it} \tag{4}$$

where w_{it} is the log earnings for the i-th individual (son or father) at age (time, year) t, w_i is the long run permanent log earnings and ε_{it} is a transitory component or random error *i.i.d.* across the life cycle and across individuals and independent of w_i. Under those assumptions it is easy to prove (see Solon (1992) and Zimmerman (1992)) that the measurement error in fathers' earnings causes an attenuation bias for the intergenerational elasticity, whereas the measurement error in sons' earnings does not cause any bias. This attenuation bias can be reduced by averaging the

[2] We refer to Angrist and Krueger (1992), Arellano and Meghir (1992), Ridder and Moffit (2005) and Inoue and Solon (2005) for a detailed description of the properties of the TS2SLS estimator.

fathers' earnings over several years. Nevertheless, this correction procedure does not take account for potential biases due to the life cycle growth of earnings.

If the earnings growth across the life cycle is a deterministic function of age and homogenous across individuals, then controlling for father's and son's age should reduce the potential life cycle bias. More precisely if we assume the following new measurement error model

$$w_{it} = w_i + m_1 t + m_2 t^2 + ... + m_p t^p + \varepsilon_{it} , \tag{5}$$

where the log earnings depends on a polynomial function of order p in age, t, then it is possible to correct for the life cycle bias by considering a polynomial in age for sons and fathers as in the equation (1) where we consider specifically a second order polynomial.

If, instead, the earnings growth is heterogeneous across individuals, because for example of a different investment in human capital as suggested by Haider and Solon (2005), then the life cycle bias does not cancel. More generally, life cycle biases do not cancel when they are due to changes in the variance of the permanent earnings and/or of the transitory earnings along the life cycle as suggested by Jenkins (1987), Haider and Solon (2005) and Grawe (2005). Those authors suggest the following relationship between current and long run permanent earnings, w_i,

$$w_{it} = \gamma_t w_i + \varepsilon_{it} , \tag{6}$$

where the permanent component has mean and variance changing in t and the transitory earnings component ε_{it} may have a variance changing in t or may be autocorrelated. Notice that if γ_t is equal to one for all t and ε_{it} is *i.i.d.* across i and t, then the model (6) turns into the classical measurement error model (4).

Under the model (6) the ordinary least squares estimator, $\widehat{\beta}$, of the intergenerational elasticity using y_{it} and x_{is} instead of y_i and x_i, is inconsistent. In particular, Haider and Solon (2005) consider the model (6) for sons,

$$y_{it} = \gamma_t y_i + \varepsilon_{it} , \tag{7}$$

and fathers,

$$x_{is} = \gamma_s x_i + \upsilon_{is} , \tag{8}$$

where the error terms are *i.i.d.* and show that

$$plim\ \hat{\beta} = \gamma_t \theta_s \beta , \tag{9}$$

where *plim* denotes the probability limit and $\theta_s = \gamma_s \Big/ \left(\gamma_s^2 + \dfrac{Var(\upsilon_{is})}{Var(x_i)} \right)$. Notice that θ_s is affected by two types of measurement errors: the attenuation bias caused by the transitory earnings component and the life cycle bias caused by a changing permanent earnings component. The life cycle bias cancels when $\gamma_t=1$ for all t, whereas the attenuation bias cancels when $Var(\upsilon_{is}) = 0$.

It is easy to prove that the estimation of the correlation, $\hat{\rho}$, by using y_{it} and x_{is} instead of y_i and x_i, is also inconsistent. As proved in Hertz (2005), the estimator $\hat{\rho}$ converges in probability to ($\rho\sqrt{\gamma_t\theta_t\gamma_s\theta_s}$), which can be rewritten as

$$plim\ \hat{\rho} = \rho \sqrt{\frac{V(y_i)}{V(y_i) + \dfrac{V(\varepsilon_{it})}{\gamma_t}} \frac{V(x_i)}{V(x_i) + \dfrac{V(\upsilon_{is})}{\gamma_s}}}. \tag{10}$$

If $\gamma_t=1$ for all t, then $\hat{\rho}$ is affected by an attenuation bias due to transitory components ε_{it} and υ_{it}. When γ_t varies with t, then the attenuation bias due to measurement errors in y_i (x_i) is magnified if γ_t (γ_s) is lower than one and attenuated if it is higher than one.

It seems reasonable to assume that γ_t is increasing in t along the life cycle, while θ_s could be either increasing or decreasing in t. In absence of the transitory component bias $\theta_s = \gamma_s^{-1}$ and θ_s would be decreasing in t. In absence of the life cycle bias $\theta_s = \dfrac{Var(x_i)}{Var(x_i) + Var(\upsilon_{is})}$ and it would be constantly lower than one.

Haider and Solon (2005) estimate γ_t and θ_t for the USA by considering men respondent to the Health and Retirement Study born between 1931 and 1933 and their Social Security earnings histories for 1951-1991. Assuming that the life cycle earnings profile does not change across generations, fathers and sons should have identical γ_t and θ_t when observed at the same age t.

They find that γ_t is lower than one until the age of 42 and higher afterwards and it varies between 0.3 at age 19 and 1.4 at age 48. It seems therefore that measuring sons' earning at too young age (old age) may cause an underestimation (overestimation) of the intergenerational elasticity. They find instead a θ_t always lower than one and varying between 0.1 at age 19 and 0.4-0.5 between 33 and 56. This implies an underestimation bias for the intergenerational elasticity which is especially evident at very young ages and stabilises at lower level between 33 and 56.

The question is then: which is the age at which the current earnings should be observed to provide a proper measure of permanent earnings? Looking at the results in Haider and Solon (2005) and assuming that similar results hold for other countries, it seems reasonable to choose sons around age 40 and fathers with an age between 31 and 55. In our empirical application we follow this suggestion and we choose fathers with an age between 31 and 55 and sons with an age between 31 and 45. We choose a quite large range for the sons' age to avoid a drastic sample size reduction. Anyway, we also use a second method to correct for the potential life cycle bias due to observing sons at different ages. This second method, suggested in Lee and Solon (2005), consists in estimating intergenerational mobility equation by allowing β to change by sons' age and cohort, see Section 6 for further details.

3. Trends in intergenerational mobility: previous findings

Empirical studies find mixed results about the trend in intergenerational mobility. In particular in the USA and in Britain a set of contradictory findings coexist. Those conflicting results may be due to at least three main reasons: differences in the measure of the socio economic status of sons and fathers, in the cohort periods compared, and in the age when sons and fathers are observed. Mayer and Lopoo (2005) reconcile contradictory empirical results found for the USA by using those types of explanation. In particular, they find that changing the cohort periods compared it is possible to find a positive, negative or flat trend. This is because the trend in the USA seems to be non linear. It is decreasing for sons born between 1949 and 1953 and then increasing for sons born between 1954 and 1965. In a similar attempt to reconcile contradictory findings we review the empirical papers on trends in intergenerational mobility between sons and fathers in Britain.

Using the British Household Panel Survey, Ermisch and Francesconi (2004) estimate the intergenerational elasticity between children's and their fathers' occupational score, measured by the Hope-Goldthorpe score, separately for sons born before 1941, 1941-1945, 1946-1950 and on until 1966-70 and after 1970. They find a downward trend in the intergenerational elasticity.

Prandy et al (2002) consider instead all surveys containing information on occupation for both sons and their parents in Britain and Ireland (Political change in Britain; Oxford Mobility Study; Irish, Northern Ireland and Scottish Mobility Studies; Social Status in Great Britain;

Social Class in Modern Britain; General Household Survey; Welsh and Scottish Election Studies; British Household Panel Survey) and pooling those surveys together they are able to cover individuals born from 18th to the 20th century. They compute the correlation between children's and their fathers' occupational score, measured by the CASMIS (Cambridge Social Interaction and Stratification scale), separately for cohorts born before 1770, 1770-1779, 1780-1789 and son on until 1970-79. They find a strong negative trend over time in the correlation between sons' and fathers' occupational score.

Using the British cohort studies, Blanden et al (2002) find instead that the intergenerational earnings elasticity increases for the 1970 cohort compared with the 1958 cohort.

The conflicting results in Blanden et al (2004), who find a negative trend in mobility, and Prandy et al (2002) and Ermisch and Francesconi (2004), who find instead a positive trend in mobility, could be due to differences in the cohort period considered, in the age when sons are observed and in measure of the economic status.

Blanden et al (2004) compare two relatively close cohorts, 1958 and 1970; moreover, because of data limitations, they consider parents' combined income instead of father's earnings in the intergenerational equation. Considering the lower labour participation of women in the past, there is a higher percentage of women with zero labour income among mothers of sons born in 1958 compared with mothers of sons born in 1970. Therefore, it is likely that the correlation between sons' and mothers' earnings has increased for the 1970 cohort with respect to the 1958 one. Blanden et al (2002) try to check this by estimating intergenerational mobility considering the subsample of sons in families where only the father works and they find a smaller decrease in intergenerational mobility.

On the other side, Prandy et al (2002) and Ermisch and Francesconi (2004) consider a wider cohort period; but they consider also a very large range for sons' age, respectively 25-75 and 20-60, whereas Blanden et al (2004) consider sons at 30 and at 33. The average sons' age is likely to change a lot across the cohort groups considered by Prandy et al (2002) and Ermisch and Francesconi (2004) so that the sons belonging to the most recent cohorts are supposedly observed at much younger age than the sons belonging to the older cohorts. Under the measurement error model (6) and the assumption that γ_t increases in t, i.e. an improving occupational position along the life cycle, both the elasticity and the correlation coefficients are affected by a life cycle bias which depends on the son's age, see Section 2. In particular the intergenerational elasticity is underestimated for young sons and overestimated for old sons, whereas the correlation coefficient is always underestimated and the bias is decreasing in son's age. This implies that the negative trend observed in the intergenerational elasticity in Ermisch and Francesconi (2004) and in the correlation in Prandy et al (2002) could be spurious because of a life cycle bias. In a previous version of this paper, where we did not limit the range for sons' age, we found a negative trend which disappears when restricting the sons' age range.

In all three above studies the fathers' socio–economic position is measured when the sons are 14 or 16, therefore the comparability of the results should not be affected by the potential life cycle bias due to observing fathers at a specific age.

By using again the British Household Panel Survey and cohorts from 1910 to 1960, but considering a transition matrix between three occupational classes (salariat, intermediate and working class), Gershuny (2002b) finds that "… a modest but clear increase in equality of opportunity from the 1940's cohort onward". Using three categories given by the bottom quintile, intermediate quintiles and top quintile of a continuous measure of the human capital, he finds instead different results. He concludes that "[m]obility into the salariat as a whole, whose size is growing, may be easing, but entry into a fixed proportion of the most privileged members of the society from less privileged origins nevertheless becomes increasingly difficult, or at least gets no easier to achieve." In another paper Gershuny (2002c) uses a new measure of intergenerational immobility, which is a Gini index taking account of both transition probabilities between socioeconomic positions of parents and their offspring and inequality in the expected rewards for offspring in each possible socioeconomic position. Using this new measure with the British Household Panel Survey, Gershuny (2002c) finds that intergenerational immobility between sons and fathers does not change much across the sons' cohort 1925-1964.

It is evident that the measures adopted by Gershuny are very different and not directly comparable with the ones considered in the three previous studies. This may explain in part some of the contradictory results. Nevertheless, we think that the main reason for contradictory results found in Ermisch and Francesconi (2004) and Gershuny (2002b, c), who use the same survey, is due to observing sons at different ages. Gershuny observe the son's socio-economic status at age 34, 35 or 36 for all sons' cohorts, whereas Ermisch and Francesconi (2004) observe sons at different ages for different cohorts. For this reason Gershuny's analysis of mobility across sons' cohorts should not be affected by life cycle bias. Nevertheless, Gershuny uses retrospective data for both sons and fathers which can be affected by recall error or ex-post rationalisation problems.

Erikson and Goldthorpe (1992) use the Oxford Mobility Study, which provides data for sons in 1972 and on their fathers when their sons were 14 years old. They analyse the trends in occupational class mobility by using a log linear model and considering sons' cohort from 1905 to 1945. They find that the distribution of classes changes across cohorts but the association between father's and son's class does not change significantly across cohorts. A problem which may affect Erikson and Golthorpe study is the fact that all sons are observed in 1972 irrespective of to their birth cohort. This implies, for example, that sons born in 1905 are observed when 67 while sons born in 1945 are observed when 27. This may bias the association measure between origin and destination class in a way similar to the intergenerational earnings elasticity or correlation, as explained in Section 2.

Extensions of the Oxford Mobility Study results to more recent years have been produced by using the British General Election Surveys (BGES), see for example Heath and Payne (2000), and using the General Household Surveys (GHS), see Goldthorpe and Mills (2005). Both data sources are affected by problems such as the quality of the occupational classification (GHS) and of the sampling frame (BGES and GHS), and a relative high percentage of missing data for some years (BGES). Heath and Payne (2000) find a positive trend in the intergenerational occupational class mobility for sons' birth cohorts from 1900 to 1959. This as the authors emphasize could be due to the fact that sons born in old cohorts are observed at older ages then sons born in more recent cohorts. Using the General Household Survey to observe sons in 1973 and in 1992, Goldthorpe and Mills (2005) find change in the intergenerational occupational class mobility after controlling for changes in the class distribution.

Using the British Cohort Studies 1958 and 1970, Breene and Goldthorpe (2001) study class mobility and find little change across the two generations. This result contradicts the negative trend in mobility found in Blanden et al (2004) using the same cohort studies. There can be at least two reasons for those contradictory results: (i) the difference in the socio-economic measure; (ii) the difference in the age when children and fathers are observed. Breene and Goldthorpe (2001) observe sons at age 23 and 26 and fathers when their children are 11 and 10, whereas Blanden et al (2004) observed sons at age 33 and 30 and fathers when their children are 16.

Finally, there are some historical studies of intergenerational mobility in the eighteenth and nineteenth centuries whose results are difficult to compare with studies covering the twentieth century because of data comparability problems. Among those there are the studies of Miles (1993), by Prandy and Bottero (2000) and Long and Ferrie (2005).

Miles (1993) uses marriage registry data for couples married between 1839 and 1914. For those couples they can observe their own occupations and their respective fathers' occupations. Unfortunately the data source has some limitations. In particular, only weddings in Anglican churches are recorded and the occupational classification in not very fine. Anyway, the results seem to give evidence for a positive trend in the mobility over the period.

Prandy and Bottero (2000) consider intergenerational occupational mobility in Britain and Ireland and the cohort period 1790-1909. Prandy and Bottero (2000) use the family histories drawn from the members of the family history societies in Britain and Ireland. This dataset allows them to observe occupational characteristics for 5 generations back following both parents and parents in law at different points over their life cycle. As the authors admit, this sample may suffer from selection problems. In particular, it is likely that families geographically more stable are overrepresented. Moreover, people, belonging to the middle class and with higher education, are more likely to be able to trace back their ancestors. Nevertheless, the authors find encouraging results by comparing this dataset with census data and with the Oxford Social Mobility study. Using these data from the family history societies, they study the intergenerational mobility for 12 cohorts of men, 1790-1799, 1800-1809 and so on until 1900-1909. They find an increasing intergenerational mobility from 1850 onward and especially for the last three cohorts.

Long and Ferrie (2005) consider intergenerational mobility in the nineteenth century by using matched data from 1851 and 1881 censuses and considering the occupational class in 1881 for sons and in 1851 for fathers. They also analyse occupational intergenerational mobility in the twentieth century by using the Oxford Mobility Study and observing sons in 1972 and fathers when their sons were 14 years old. Nevertheless, they do not analyse the possible presence of a trend in intergenerational mobility because of data comparability issues.

In conclusion, we would emphasize that most of the previous contradictory results on intergenerational mobility in Britain depend on sons' age, cohort period and socio-economic measure considered. In our empirical analysis we use different sons' age ranges and the cohort periods to be able to compare our results with previous ones, in particular with Blanden et al (2004) and Ermisch and Francesconi (2004). But we focus attention only on occupational intergenerational mobility measured by the elasticity, β, and the correlation, ρ, between sons' and fathers' earnings.

4. Estimation method

As noted in Section 2, we estimate the intergenerational mobility equation

$$y = \alpha + \beta x + A\gamma + u \tag{11}$$

by using the TS2SLS (two-sample two-stage least squares) estimator, which is asymptotically equivalent to the 2SIV (two-sample instrumental variable) estimator described by Angrist and Krueger (1992), Arellano and Meghir (1992) and Ridder and Moffit (2005). Both estimators are consistent under the assumptions described in Angrist and Krueger (1992). In particular, both estimators are not consistent if the two samples used are not two independent random samples. Moreover, the instrumental variables common to both samples have to be identically and independently distributed in the two samples.

Let Z be a set of proper instrumental variables for x, then we can estimate equation (11) by using a generalized method of moments estimator (or generalized instrumental variable estimator) based on the following conditions:

$$E\big((y - \alpha - \beta x - A\gamma)A\big) = 0\,, \tag{12}$$

$$E\big((y - \alpha - \beta x - A\gamma)Z\big) = 0\,. \tag{13}$$

Since the instrumental variable estimator is numerically identical to the two-stage least squares,[3] we can replace x with its best linear predictor in Z, say $\hat{x} = Z(Z'Z)^{-1}Z'x$, and rewrite the population moment conditions as:

$$E\big((y - \alpha - \beta\hat{x} - A\gamma)A\big) = 0\,, \tag{14}$$

[3] The two types of estimator produce mathematically the same estimated coefficients when using a single sample, their equivalence holds instead only asymptotically when combining two separate samples. In our estimation procedure we use the TS2SLS to estimate the intergenerational mobility equation, but we consider standard error properly estimated to take account of the replacement of x with its prediction, see Arellano and Meghir (1992).

$$E\big((y-\alpha-\beta\hat{x}-A\gamma)\hat{x}\big)=0\,. \tag{15}$$

When combining two independent samples the instrumental variable and the least square estimators become respectively the 2SIV and TS2SLS estimators.

Let us consider two independent samples: the first one has data on fathers' log earnings, *x*, and their age, education and occupational characteristics, *Z*, which we call the supplemental sample; and the second sample has data on sons' log earnings, *y*, sons' and fathers' age and age square, *A*, and characteristics of their fathers, *Z*, which we call the main sample. Then the 2SIV estimator will be still based on the conditions (12) and (13) which can be rewritten as

$$E\big((y-\alpha-A\gamma)A\big)-E\big(\beta xA\big)=0$$

and

$$E\big((y-\alpha-\beta x-A\gamma)Z\big)-E(-\beta xZ)=0\,,$$

where the first addends in the left hand sides can be estimated using the main sample and the second addends can be computed using the supplemental sample.

In the empirical application we combine the supplemental and the main sample by using the TS2SLS estimator. In the first step we use the supplemental sample to estimate a log earnings equation for fathers using as explanatory variables their characteristics, Z, that is

$$x=Z\delta+\nu\,. \tag{16}$$

In the second step we estimate the intergenerational mobility equation (11) by using the main sample and replacing the unobserved *x* by its predictor, $\hat{x}=Z\hat{\delta}$, where $\hat{\delta}$ are the coefficient estimated in the first step while *Z* are the variables observed in the main sample. This method can be viewed as a cold-deck linear regression imputation. Cold-deck refers to the fact that an external data source (the supplemental sample) is employed to estimate the coefficients used to impute the missing *x* in the main sample. This method was first proposed by Klevmarken (1982).

The 2SIV estimator can be alternatively defined as the generalized method of moment estimator which minimizes the following quadratic form:

$$m_N(\vartheta)'W_N m_N(\vartheta), \tag{17}$$

where $m_N(\vartheta)$ are the sample equivalent of the population moments in (12)-(13), ϑ is the vector of parameters (α,β,γ') and W_N is the optimal weighting matrix given by the inverse of the variance of $m_N(\vartheta)$, see Angrist and Krueger (1992).

Since we have a number of instrumental variables greater then the number of parameters to be estimated it is possible to test whether the instruments satisfy the moment condition (12)-(13); see Angrist and Krueger (1992) and Ridder and Moffit (2005). The test is simply the goodness of fit test given by the quadratic form (17) where parameters and weighting matrix are replaced by estimates. The test is distributed as a Chi square with number of degrees of freedom equal to the number of instrumental variables used in the first step less the number of variables used in the second step.[4]

The choice of the instrumental variables in the three previous papers that estimate intergenerational mobility combining two different datasets was dictated by the few variables available. Björklund and Jäntti (1997) use father's education and occupation, Grawe (2004) uses only the education levels, while Fortin and Lefebvre (1998) use only 16 occupational groups, which, as the authors admit, can affect the quality of the imputation of earnings for fathers. The only exception is Lefranc and Trannoy (2004) who use instead 8 different levels of education, 7 occupational groups and age. In our case the possible set of candidates as instrumental variables is also quite large and we try different combinations of the instrumental variables available.

As emphasized by Bound, Jaeger and Baker (1995), when the instrumental variables are weakly correlated with the variable to be instrumented, "[…] then even a weak correlation between the instruments and the error in the original equation can lead to a large inconsistency in the IV estimates." This suggests choosing instruments such that the R^2 of the imputation regression be as higher as possible.

Nevertheless, in our case, in contrast to Bound, Jaeger and Baker (1995), the variable to be instrumented, the fathers' log earnings x, is exogenous or at least assumed so. In other words x is independent of u and u is independent of v. Under this assumption, the ordinary least squares (OLS) estimation of the intergenerational mobility equation produces consistent estimates. The reason why we use the TS2SLS estimator is to combine two separate samples to solve the problem of missing x. The consistency of the TS2SLS (2SIV) estimator requires that $\hat{x}$ be exogenous. In the following we compute the asymptotic potential bias of the TS2SLS (2SIV) estimator for the coefficient β when $\hat{x}$ and u are not independent. Since we are considering an asymptotic result, we can replace $\hat{x}$ with its limit in probability $Z(Z'Z)^{-1}Z'x = P_Z x$.

[4] Notice that we cannot compute tests of the independence between instrumental variables and errors based on the residuals of the two-sample instrumental variable estimator. This is because with two separate samples we cannot compute the residuals.

Let us suppose that the instruments are endogenous because the sons' log earnings is given by

$$y = \lambda_1 x + \lambda_2 P_Z x + u \quad (18)$$

instead of

$$y = \beta x + u \quad (19)$$

We are interested in the estimation of β, and we show in the following that the TS2SLS (2SIV) estimator is asymptotically upward (downward) biased if $\lambda_2>0$ ($\lambda_2<0$).

To simplify the notation we do not consider additional variables, A, or a constant in the main equation of interest. This does not affect the proof as long as we substitute for x and y the residuals from their regression on the omitted exogenous variables.

Notice that λ_1 and λ_2 can be alternatively estimated by considering the following regression:

$$y = \lambda_1 M_Z x + (\lambda_1 + \lambda_2) P_Z x + \omega, \quad (20)$$

where $M_Z=I-P_Z$, where I is the identity matrix and P_Z is projection matrix on the space generated by the instrumental variables Z. Notice that M_Z and P_Z are orthogonal and $x=P_Z x+ M_Z x$. In equation (20) the sons' log earnings still depend on fathers' log earnings, x, but the intergenerational transmission differs between the part of the fathers' log earnings linked to their age, education and occupational characteristics, $P_Z x$, and the residual orthogonal part, $M_Z x$, linked to unobserved further father's characteristics relevant for explaining his earnings, such as ability.

Assuming that x is exogenous, the OLS estimation of β in (19) is consistent and therefore asymptotically convergent in probability to:

$$\beta = \frac{\sigma_{y,x}}{\sigma_y^2}, \quad (21)$$

where $\sigma_{k,s}$ is the covariance between k and s and σ_k^2 is the variance of k.

Following Solon (1992) and Björklund and Jäntti (1997), it is possible to prove that the TS2SLS (2SIV) estimator of β converges in probability to:

$$\lambda_1 + \lambda_2 \frac{\sigma_{\hat{x}}}{\eta\sigma_x} = \beta + \lambda_2 \sigma_{\hat{x}} \frac{1-\eta^2}{\eta\sigma_x}, \quad (22)$$

where $\eta = \dfrac{\sigma_{\hat{x},x}}{\sigma_{\hat{x}}\sigma_x}$. Therefore the TS2SLS (2SIV) estimator is inconsistent and overestimated if $\lambda_2>0$. Notice that, given our assumptions, η is equal to the square root of the R^2 for the regression of x on the instruments, which is

$$\eta = \frac{\sigma_{\hat{x},x}}{\sigma_{\hat{x}}\sigma_x} = \frac{\sigma_{\hat{x}}^2}{\sigma_{\hat{x}}\sigma_x} = \frac{\sigma_{\hat{x}}}{\sigma_x} = R\,. \tag{23}$$

Therefore the TS2SLS (2SIV) estimator of β converges in probability to

$$\lambda_1 + \lambda_2 = \beta + \lambda_2(1-R^2)\,. \tag{24}$$

and it is consistent when either λ_2 is zero or when R^2 is one.

If the residual fathers' log earnings, $M_Z x$, linked to unobserved fathers' characteristics are transmitted in the same way as the part of the fathers' log earnings explained by observed age, education and occupational characteristics, $P_Z x$, then λ_2=0 and the OLS and TS2SLS (2SIV) estimators are asymptotically equivalent. If instead the residual fathers' log earnings, $M_Z x$, are not transmitted across generations, then the OLS estimator of β converges in probability to $(\lambda_2 R^2)$, while the TS2SLS (2SIV) estimator converges in probability to λ_2. In this case OLS and 2SIV estimators give asymptotically equivalent results only if R^2 is one.

In conclusion the well-known rule for the choice of the instruments still applies. Instruments should be independent of u, that is such that λ_2=0, and with maximum multiple correlation with x, that is such that R^2 be maximum.

5. Description of the data

The data we use are from the first thirteen waves of the British Household Panel Survey (BHPS)[5] collected over the period 1991-2003. Since Autumn 1991 the BHPS has annually interviewed a representative sample of about 5,500 households covering more than 10,000 individuals. All adults and children in the first wave are designated as original sample members. On-going representativeness of the non-immigrant population has been maintained by using a "following rule" typical of household panel surveys: at the second and subsequent waves, all original sample members are followed (even if they moved house or if their households split up).

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[5] See Taylor (2003) for a full description of the dataset. Detailed information on the BHPS can also be obtained at <http://www.iser.essex.ac.uk/bhps/doc>.

Personal interviews are collected, at approximately one-year intervals, for all adult members of all households containing either an original sample member, or an individual born to an original sample member. Individuals are defined as “adult” (and are therefore interviewed) from their sixteenth birthday onwards. The sample therefore remains broadly representative of the population of Britain as it changes over time. The households from the European Community Household Panel subsample (followed since the seventh wave in 1997), those from the Scotland and Wales booster subsamples (added to the BHPS in the ninth wave) and those from the Northern Ireland booster subsample (which started in wave 11) are excluded from our analysis.

From the BHPS, we select three different samples and employ various measures of the earnings for sons and fathers, with the aim of attenuating the measurement error problem inherent in all intergenerational studies. We now turn to describe samples and variables.

5.1 Sample definitions

As explained in Section 4 we combine two separate samples from the BHPS to estimate the intergenerational mobility equation, the main sample and the supplemental sample.

We consider a main sample given by all men, sons, born between 1950 and 1972, self-employed or in paid employment, who report a labour income in last month greater than zero in at least one wave of the panel when aged between age 31 and 45, with fathers born between 1918 and 1949 and aged between 31 and 55 when they(the sons) were 14 years old. For those men we observe their labour income (earnings), their age, their father’s occupational characteristics, age and education, which are reported retrospectively by the sons. This main sample is used throughout our empirical application except in two cases: (1) when we estimate the intergenerational mobility equation suggested by Lee and Solon (2005), (2) when we try to assess the bias caused by estimating an intergenerational mobility equation without restricting the sons’ age. Theoretically the Lee and Solon equation takes account of the potential life cycle bias due to observing sons at different ages; therefore we estimate it by considering sons at any age. The unrestricted age range is 19-53.

The supplemental sample is given instead by all men born between 1923 and 1946, who should be a representative sample for the fathers born between 1918 and 1949 in the main sample. We observe those men at the youngest age possible by selecting the first wave when they are respondent and we observe their earnings, occupational characteristics, age and education.

5.2 Variable definitions

We consider two alternative measures of earnings for sons and one for fathers. Assuming exogenous selection into the labour market, the first measure used for sons is given by the average log earnings over all waves in the main sample after excluding the cases with missing information because the son does not work. The second measure for sons is given by the log earnings observed in all available wave between 1991 and 2003. We measure the earnings for father by considering the log earnings observed in the first wave available in the supplemental sample.

In our analysis we use then a set of instrumental variables given by the following characteristics:

1. the Hope-Goldthorpe score, say *HG*, which is an score of occupational prestige computed according to the technique proposed by Goldthorpe and Hope (1974);
2. dummies for managerial duties (manger0 for self-employed, maneger1 for manager, manager2 for foreman/supervisor, manager3 for not foreman/supervisor)
3. education level dummies (education0 for no qualification or some qualification, education1 for further education qualification, education2 for first degree or higher)
4. age and age square.

Those instrumental variables have been selected from a larger set of possible candidates which includes:

- the Cambridge scale, which is another score of occupational prestige, see for a definition Prandy (1992);
- dummies for the following socio-economic groups; large employers, large managers, small employers, small managers, professional self-employed, professional employees, intermediate non-manual workers, intermediate non-manual foreman, junior non-manual, personal service workers, foreman manual, skilled manual workers, semi-skilled manual workers, unskilled manual workers, own account workers, farmers employers or managers, farmers – own account, agricultural workers, members of armed force.
- dummies to distinguish occupations in professional, managerial and technical, skilled non-manual, skilled manual and unskilled.

In table 1 we report some descriptive statistics of the variables used for the main sample and the supplemental sample.

6. Intergenerational mobility estimation results

In this section we present the empirical results on intergenerational mobility estimation. As explained in Section 4 we use a two-sample two-stage least squares estimation which first step consists in the estimation of the log earnings equation (16) using the supplemental sample. The results of this estimation are then used to impute fathers' earnings in the main sample to estimate the intergenerational mobility equation (11).

In Table 2 we report the estimation results for two specifications of the log earnings equation (16) with explanatory variables given by: three cohort dummies 3 cohort groups (reference cohort for 1923-1930, cohortf2 for 1931-1938 and cohortf3 for 1939-1946), the log Hope-Goldthorpe score, say HG, interacted with the 3 cohort dummies say respectively HGc1, HGc2 and HGc3,[6] 4 dummies for managerial duties (self-employed is the reference category, manager1 is for manager, manager2 is for foreman/supervisor, and manager3 if for not foreman/supervisor) interacted with the 3 cohort dummies, education level dummies (no qualification or some qualification is the reference category, education1 indicates further education qualification and education2 indicates instead first degree or higher), age and age square. Looking at the first specification in Table 2, the relationship between the occupational prestige score and the log earnings seems to change across cohorts. Most recent cohorts seem to have lower earnings returns to their occupational prestige. A similar change across cohorts is observed also for the relationship between managerial duties dummies and log earnings. Strangely instead returns to education do not seem to be significant at all. This may be due to the fact the occupational prestige and education level are correlated. For this reason we try a different specification for the log earnings equation, see Table 2 model specification 2, where we drop the occupational prestige and consider instead the dummies for education level interacted with the cohort group dummies. The education level dummies become relevant and there are some changes in the returns to education. Nevertheless, the occupational prestige seems to explain better the log earnings, therefore we choose the first model specification. The estimated coefficients of this model are then used to impute the log earning for fathers in the main sample for the estimation of all intergenerational elasticities and correlations.

[6] We add to the name of the variable the suffix *c1*, *c2* or *c3* when we consider the interaction with the cohort dummies: *c1* for 1923-1930, *c2* for 1931-1938 and *c3* for 1939-1946.

In the following section we report the results on intergenerational mobility changes across cohorts by using different types of specifications for the trend. In section 6.1 we consider a non-linear trend, while in Section 6.2 we impose a linear trend to compare our results with previous studies, in particular Blanden et al (2004). Finally in section 6.3, following Lee and Solon (2005), we allow the intergenerational elasticity to change across cohorts (linearly or non-linearly) and across sons' age.

6.1 Non-linear trend estimation

By estimating the intergenerational elasticity separately for a set of consecutive cohort groups, it is possible to observe its profile across cohorts without imposing any specific trend shape. We consider cohort groups of 6 years beginning with 1950-1955 and going on by adding an additional year, 1951-1956, 1952-1957, … , until 1967-1972. As in Mayer and Lopoo (2005) we plot the estimated intergenerational elasticities for those rolling groups in the Figure 1. We also plot the upper and lower bands, see dotted lines, of the confidence interval computed considering a 0.05 level of significance. Finally, we compute the correlation between sons and fathers log earnings for each rolling group which we plot as a dashed line in the Figure 1. All results in Figure 1 are computed by regressing the repeated annual measures of sons' log earnings on the imputed fathers' log earnings.[7]

The intergenerational elasticity does not seem to change significantly across cohorts and if any trend exists it does not seem to be linear. When considering the correlation there seems to be a slight positive trend from 1950-1955 to 1958-1964 and a slight negative trend from 1958-64 to 1967-1972, but the changes are not significant.

The reason for the more irregular profile observed for the intergenerational elasticity with respect to the correlation is due to changes in the log earnings variance across cohorts for sons and fathers. If we are interested in a measure of intergenerational mobility that is not affected by changes in the log earnings variance across cohorts then the correlation is a better measure then elasticity.

In Figure 2 we report again the profile by rolling cohort groups of the intergenerational elasticity and correlation, but we use averaged log earnings instead then repeated annual log

[7] The standard errors are corrected to take account for the possible correlation between errors referring to the same individuals.

earnings for sons. Averaging the log earning across waves should reduce the transitory error component. Considering again the model (6) for the sons' log earnings,

$$w_{it} = \gamma_t w_i + \varepsilon_{it}, \tag{25}$$

and averaging the variables on both sides, we obtain

$$\overline{w}_i = \overline{\gamma}_{t,t+d} w_i + \overline{\varepsilon}_i, \tag{26}$$

where the overline indicates the average and $\overline{\gamma}_{t,t+d}$ is the average of γ_t from t to $t+d$, and $(d+1)$ is the number of waves during which the *i-th* son is observed. Assuming that the transitory error component in (25) is *i.i.d.* across individuals and waves and that the model (8) applies for the fathers' log earnings, it is easy to show that (9) and (10) become

$$plim\ \hat{\beta} = \overline{\gamma}_{t,t+d}\theta_s\beta \tag{27}$$

and

$$plim\ \hat{\rho} = \rho\sqrt{\frac{V(y_i)}{V(y_i)+\dfrac{V(\overline{\varepsilon}_i)}{\overline{\gamma}_{t,t+d}}}\frac{V(x_i)}{V(x_i)+\dfrac{V(\upsilon_{is})}{\gamma_s}}}\,. \tag{28}$$

If γ_t does not change much within the sub-period when an individual is observed, then we should not observe relevant differences when estimating the elasticities using average log earnings instead of yearly log earnings for sons. This seems to be true for all cohorts groups until 1961-1967, afterwards there seems to be instead a more evident positive trend in Figure 2 than in Figure 1. This change in the results may be due to a less precise estimation because of a reduced sample size when using averages instead of yearly observations. The confidence intervals in Figure 2 are indeed quite large for the most recent cohort groups. The change may be also due to a more rapid change across age in γ_t for sons born in most recent cohorts and observed to a relative younger age (beginning of their thirties). Under this assumption, using average log earnings instead of yearly log earnings helps in reducing the possible life cycle underestimation bias for sons belonging to the most recent cohorts.

Since $V(\overline{\varepsilon}_i) = V(\varepsilon_{i,t})/(d+1)$ in (28), the attenuation bias affecting the correlation should reduce when using average log earnings instead of yearly log earnings for sons. We find indeed an increase in correlations plotted in Figure 2. This type of attenuation bias does not seem to affect instead the intergenerational elasticity estimation in line with the theoretical results, see (9) and (27). The correlation in Figure 2 seems to be still increasing until the cohort 1958-1964 and then decreasing.

Summarizing, we do not find evidence for a very strong trend in intergenerational mobility; if any, this trend is negative especially for the most recent cohorts. The confidence intervals for our estimates are quite large, so that the significance of this trend is not very high, but we will come back to this problem in next section where we test the presence of a linear trend.

6.2 Linear trend estimation.

In this section we report the results of the estimation of a linear trend by considering 4 different specifications for the intergenerational equation (1).

The first model is specified as is

$$y = \alpha + \beta x + x\, cohort\, \delta + u, \tag{29}$$

where *cohort* is a variable taking value 0 for sons born in 1950, 1 for sons born in 1951 and so on until 22 for sons born in 1972, and δ is the estimated linear trend coefficient. We estimate equation (29) without considering any control for sons' and fathers' ages and without restricting the sons' age range but allowing it to vary between 19 and 53. This leads to a negative and significant trend see Table 3. This negative trend is likely to be spurious because due to an underestimation bias for sons observed at too young ages and to an overestimation bias for sons observed at too old ages. A similar type of comment applies to the analysis carried by Ermisch and Francesoni (2004) who find a negative trend in the intergenerational occupational prestige (*HG*) elasticity considering sons born around 1940-1970 and observed at any age between 20 and 60 during the first 9 waves of the BHPS (1991-1999).

The second model estimated is given by:

$$y = \alpha + \beta x + x\, cohort\, \delta + age\, \gamma_1 + age^2\, \gamma_2 + agef\, \gamma_3 + agef^2 \gamma_4 + cohort_1\, \gamma_5 + cohort_2\, \gamma_5 + u, \tag{30}$$

where *age* is the son's age, *agef* is his father's age, *cohort1* is a dummy indicating sons born between 1950 and 1957, *cohort2* is a dummy indicating sons born between 1958 and 1965 and *cohort3*, the reference category, is for sons born in 1966-72. We estimate the model (30) by considering our main sample which includes only sons aged between 31 and 45. The estimated trend coefficient, see Table 3, is positive and significant at 5% level but insignificant at 1% level. This change in the direction of the trend with respect to equation (29) is likely to be due to a strong life cycle bias affecting the estimation of equation (29).

The third model estimated is given by:

$$y = \alpha + \beta x + x\ cohort\ \delta + age\ \gamma_1 + age^2\ \gamma_2 + agef\ \gamma_3 + agef^2 \gamma_4 \\ + cohort1\ \gamma_5 + cohort2\ \gamma_5 + cohortf_1\ \gamma_6 + cohortf_2\ \gamma_7 + u, \tag{31}$$

where $cohortf_1$ is the dummy indicating fathers born between 1918 and 1930, $cohortf_2$ is the dummy for fathers born between 1931 and 1938 and, $cohortf_3$ is the reference category of fathers born between 1939 and 1949. We again use the main sample and we find an insignificant trend at both 5 and 10% levels, see Table 3.

In all the above estimation we use repeated observations on yearly log earnings for sons and we correct the standard errors estimates to take account of the possible correlation in the errors for the same individuals. When we estimate equations (30) and (31) by using average log earnings instead of yearly log earnings for sons, we do not find any significant trend and this may be due to a reduced sample size.

In an attempt to analyse better the possible presence of a positive trend in intergenerational elasticity for the most recent cohorts of sons, we estimated again equation (31) by restricting the cohort period to 1957-1972 and to 1961-1972. This further empirical analysis should help in reconciling the positive trend observed from 1961-1967 cohort group onward in Figure 2 and in Blanden et al (2004) by comparing sons born in 1958 and in 1970 using two British Cohort Studies. In both cases we find a positive trend but the trend seems to be steeper and more significant for the period 1961-1972 than for the period 1957-1972, see Table 4. Therefore, our results do not contradict the ones found in Blanden et al (2004). Nevertheless, the presence of a positive linear trend is not confirmed for the larger cohort period 1950-1972.

6.3 Elasticity changing across sons' age and cohorts

In this section we do not restrict the main sample to sons aged between 31and 45. We consider instead all sons born between 1950 and 1972 and observed at least once during the first 13 waves of the BHPS, 1991-2003. Therefore those sons can be observed at any age between 19 and 53. To control for the life cycle bias due to measuring sons at different ages we allow the intergenerational elasticity to change across sons' cohorts and age as suggested by Lee and Solon (2005). More precisely, we estimate the following two equations:

$$y_{it} = \sum_{j=1}^{6} \alpha_j d_j + \sum_{j=1}^{6} x_i d_j \beta_j + x_i (t-40)\mu_1 + x_i (t-40)^2 \mu_2 \\ + (t-40)\gamma_1 + (t-40)^2 \gamma_2 + agef\ \gamma_3 + agef^2 \gamma_4 + u_{it}, \tag{32}$$

$$
\begin{aligned}
y_{it} = \sum_{j=1}^{6} \alpha_j d_j + x_i \beta + x_i \, cohort\, \delta + x_i (t-40)\mu_1 + x_i (t-40)^2 \mu_2 \\
+ (t-40)\gamma_1 + (t-40)^2 \gamma_2 + agef\, \gamma_3 + agef^2 \gamma_4 + u_{it},
\end{aligned} \tag{33}
$$

where (*t-40*) is the son's age expressed as deviation from the mean, say *age*, *agef* is the fathers' age, the subscript *i* indicates the *i-th* pair father-son, d_j, j=1,…,6, are the sons' cohort dummies d_1 for 1950-53, d_2 for 1954-57, d_3 for 1958-61, d_4 for 1962-65, d_5 for 1966-69 and d_6 for 1970-72, δ is again the coefficient for a linear trend as in previous section, β_j is the intergenerational elasticity for sons belonging to the cohort group *j* and 40 years old, and $(\beta_j + (t-40)\mu_1 + (t-40)^2\mu_2)$ is the intergenerational elasticity for sons belonging to the cohort group *j* and *t* years old.

In tables 5 and 6 we report the results for the two equations (32) and (33). μ_1 and μ_2 are not significantly different form zero, therefore the intergenerational elasticity does not seem to change much across son's age. We find instead that the intergenerational elasticity increases across cohorts but not very significantly both when imposing a linear trend or when allowing the β coefficient to change across 6 cohort groups, see Tables 5 and 6. The increase in the intergenerational elasticity for any additional cohort year, given by the δ coefficient, is very modest. It is equal to 0.001 with a p-value of 0.787 when considering different intercepts for the above 6 sons' cohort groups, whereas it is equal to 0.002 with a p-value of 0.001 when excluding the cohort dummies.

Since changes of β across cohorts could reflect changes in the variance of the fathers' log earnings, we consider again equation (32) where both sons log earnings and fathers log earnings have been standardized dividing them by their corresponding standard deviation computed separately for 6 sons' cohort groups. This is equivalent to consider correlation instead of elasticity. The correlation coefficient does not change significantly across cohorts, see Table 6 last two columns. This suggests that the slight positive trend observed in intergenerational elasticity can be due to changes in the log earnings variance across cohorts.

8. Conclusions

In this paper we provide for the first time an analysis of the trend in intergenerational earnings mobility for sons born between 1950 and 1972 in Britain. Since it is impossible to observe earnings for both sons and their fathers covering the above period, we use the TS2SLS estimation to combine two different samples extracted from the BHPS.

Our estimation results seem to suggest that intergenerational mobility does not change much over the cohort period 1950-1972. The trend in the intergenerational elasticity does not seem to be linear except for the most recent cohorts, say 1961-1972 where the trend is positive. When imposing a linear trend for the larger cohort period 1950-1972, we find a slight positive trend and generally not very significant. Without controlling for sons' and fathers' age and without restricting the sons' age range we find instead a significant negative trend, which should caution applied researchers about potential life cycle biases causing spurious negative trends. Moreover when considering intergenerational correlation instead of elasticity, the changes across cohorts are even more insignificant.

In conclusion we would suggest there are no strong changes in intergenerational mobility across cohorts from 1950 to 1972. However, some extensions improving our understanding of the trend in intergenerational mobility should be considered for future research. In particular, it is possible that the absence of a trend be due at least partially to changes in the education system and to a general increase in the level of education observed for younger cohorts. An analysis that controls for the effect of changes in the education system could therefore be useful. Moreover, if the intergenerational transmission differs at different points of the earnings distribution, it could be interesting to estimate different quantile regressions instead of the mean regression.

References

Angrist J.D., Krueger A.B. (1992), The effect of age at school entry on educational attainment: an application of instrumental variables with moments from two samples, *Journal of the American Statistical Association*, 87, 328-336.

Arellano M., Meghir C. (1992), Female labour supply and on-the-job search: an empirical model estimated using complementary data sets, *The Review of Economic Studies*, 59, 537-559.

Björklund A., Jäntti M. (1997), Intergenerational Income Mobility in Sweden Compared to the United States, *American Economic Review*, 87, 1009--1018.

Björklund A., Jäntti M. (2000), Intergenerational mobility of socioeconomic status in comparative prospective, *Nordic Journal of Political Economy*, 26,1, 3-32.

Blanden J., Goodman A., Gregg P., Machin S. (2004), Changes in generational mobility in Britain, in M. Corak (ed.), *Generational Income Mobility in North America and Europe*, Cambridge University Press, Cambridge.

Bound J., Jaeger D.A., Baker R.M. (1995), Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak, *Journal of the American Statistical Association*, 90, 430, 443-450.

Bowles S., Gintis H. (2002), The Inheritance of Inequality, *Journal of Economic Perspectives*, 16, 3-30.

Breen R, Goldthorpe J.H. (2001), Class mobility and merit. The experience of two British birth cohorts, *European Sociological Review*, 17, 81-101.

Erikson R., Goldthorpe J.H. (1992), The constant flux. A study of class mobility in industrial societies, Clarendon Press, Oxford.

Erikson R., Godthorpe J.H. (2002), Intergenerational Inequality: A Sociological Perspective, *Journal of Economic Perspectives*, 16, 31-44.

Ermisch J., Francesconi M. (2004), Intergenerational Mobility in Britain: New Evidence, in M. Corak (ed.), *Generational Income Mobility in North America and Europe,* Cambridge University Press, Cambridge.

Ermisch J., Francesconi M., Siedler T. (2005), Intergenerational Mobility and Marital Sorting, *Economic Journal*, forthcoming.

Fortin N., Lefebvre S. (1998), Intergenerational income mobility in Canada, in M. Corak (ed.), *Labour Market, Social Institutions and the Future of Canada's Children*, Statistics of

Canada, Ottawa.

Francesconi M, Nicoletti C. (2005), Intergenerational mobility and sample selection in short panels, *Journal of Applied Econometrics*, forthcoming.

Gershuny J. (2002a), A new measure of social position: social mobility and human capital in Britain, *Working papers of the Institute for Social and Economic Research*, Paper 2002-2, University of Essex, Colchester.

Gershuny J. (2002b), Beating the odds (1): intergenerational social mobility form a human capital perspective, *Working papers of the Institute for Social and Economic Research*, Paper 2002-17, University of Essex, Colchester.

Gershuny J. (2002c), Beating the odds (2): a new index of intergenerational social mobility, *Working papers of the Institute for Social and Economic Research*, Paper 2002-18, University of Essex, Colchester.

Goldthorpe J.H., Hope K. (1974), *The Social Grading of Occupations*, Oxford: Clarendon Press.

Goldthorpe J.H., Mills C. (2005), Trends in intergenerational class mobility in Britain in the late twentieth century, in Breen R. (ed.), *Social mobility in Europe*, Oxford University Press, Oxford.

Grawe, N.D. (2003), Life-cycle bias in the estimation of intergenerational income persistence, Statistics of Canada, Analytical Studies Branch Research Paper Series, 207.

Grawe N.D. (2004), Intergenerational mobility for whom? The experience of high- and low-earning sons in international perspective, in M. Corak (ed.), *Generational Income Mobility in North America and Europe,* Cambridge University Press, Cambridge.

Haider S., Solon G. (2005), Life-cycle variation in the association between current and lifetime earnings, unpublished working paper.

Heath A., Payne C. (2000), Social mobility, in Halsey A.H. and Webb J. (eds.), *Twentieth century British social trends*, Macmillan Press Ltd, London.

Hertz T. (2005), Attrition- and age-bias-corrected estimates of the trend in the intergenerational persistence of family income, unpublished working paper.

Inoue A., Solon G. (2005), Two-sample instrumental variables estimators, *National Bureau of Economic Research,* Technical working paper 311.

Jenkins, S.P. (1987), Snapshots versus movies: ‘lifecycle bias' and the estimation of intergenerational earnings inheritance, *European Economic Review*, 31, 1149-58.

Lee C.-I., Solon G. (2005), Trends in interrogational income mobility, unpublished working paper.

Lefranc A, Trannoy A. (2005), Intergenerational earnings mobility in France: Is France more mobile than US?, *Annales d'Economie et de Statistique*, forthcoming.

Long J., Ferrie J. (2005), A tale of two labor markets: intergenerational occupational mobility in Britain and the U.S. since 1850, *National Bureau of Economic Research,* Working paper no. 11253.

Klevmarken W.A. (1982), Missing variables and two-stage least-squares estimation from more than one data set, *Proceeding of the American Statistical Association 1981*, Business and Economic Statistics Section, 156-161.

Mayer S. E., Lopoo L.M. (2005), Had the intergenerational transmission of economic status changes?, *The Journal of Human Resources*, 40, 169-185.

Miles A. (1993), How open was nineteenth century British society? Social mobility and equality of opportunity, 1839-1914, in Miles A. and Vincent D. (eds.), *Building European society; occupational change and social mobility in Europe, 1840-1940*, Manchester University Press, Manchester.

Nickell, S. (1982), The determinants of the occupational success in Britain, *Review of Economic Studies*, 49, 45-53.

Phelps Brown H. (1977), *The inequality of pay*, Oxford University Press, Amsterdam.

Prandy K. (1992), Cambridge scale scores for CASOC groupings, *Working Papers Sociological Research Group,* University of Cambridge, 11.

Prandy K., Bottero W. (2000), Social reproduction and mobility in Britain and Ireland in the nineteenth and early twentieth centuries, *Sociology*, 34, 265-281.

Prandy K., Lambert P., Bottero W. (2002), By slow degrees: two centuries of social reproduction and mobility in Britain, *International Sociological Association Research Committee 28 On Stratification and Mobility*, Integrating Theory and Research, Nuffield College, Oxford.

Ridder G., Moffit R. (2005), The econometrics of data combination, in Heckman J.J. and Leamer (Eds.), Handbook of Econometrics, vol. 6, Elsevier Science, North Holland, Amsterdam, forthcoming.

Solon G. (1992), Intergenerational Income Mobility in the United States, *American Economic*

Review, 82, 393-408.

Solon G. (1999), Intergenerational Mobility in the Labor Market, in O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics*, Volume 3, Chapter 29, 1761-1800, Amsterdam: Elsevier.

Zimmerman D.J. (1992), Regression toward Mediocrity in Economic Stature. *American Economic Review*, 82, 409-29.

Table 1 Descriptive statistics

Variable	Main sample No. of obs.	Main sample Mean	Main sample SD	Supplemental sample No. of obs.	Supplemental sample Mean	Supplemental sample SD
Son's characteristics						
Age	8832	37.370	4.084			
Year birth	8832	1960.347	4.896			
Earnings	7974	1851.297	1186.116			
Father's characteristics						
Age	8832	42.978	5.317	1104	53.178	5.913
Year birth	8832	1931.370	7.173	1104	1938.181	5.919
HG	8832	42.978	5.317	1092	48.589	15.676
educaution1	8286	0.269		1063	0.466	
educaution2	8286	0.083		1063	0.086	
manager1	7442	0.220		1100	0.207	
manager2	7442	0.185		1100	0.139	
manager3	7442	0.420		1100	0.414	

Figure 1 Elasticities and correlations for single year earnings

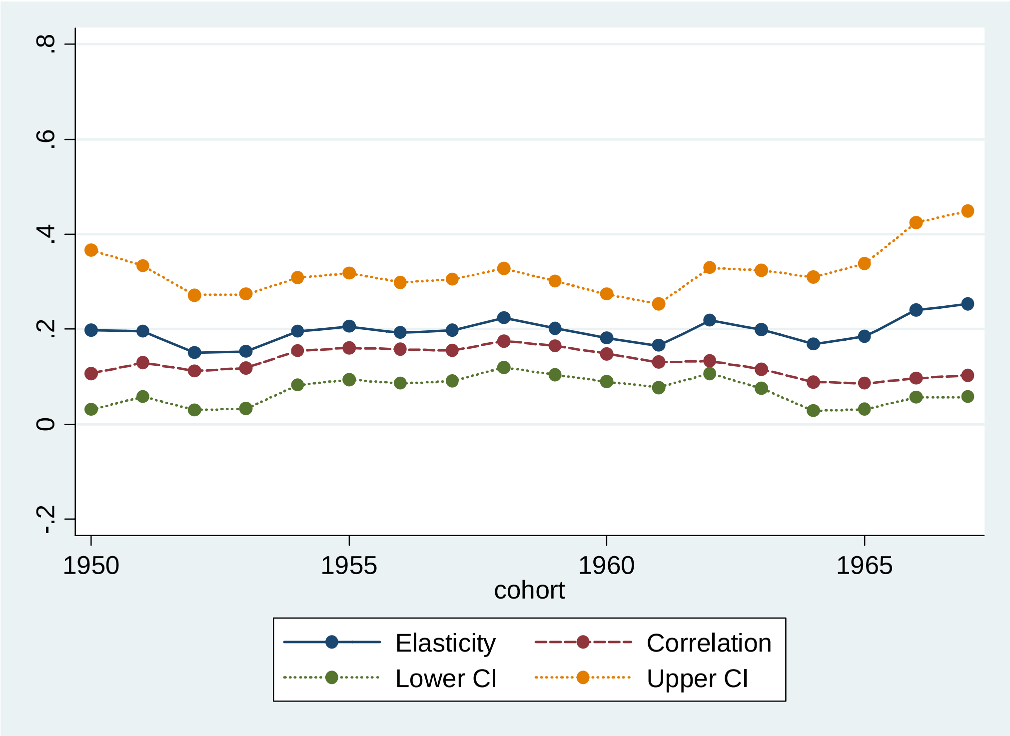

Figure 2 Elasticities and correlations for average earnings

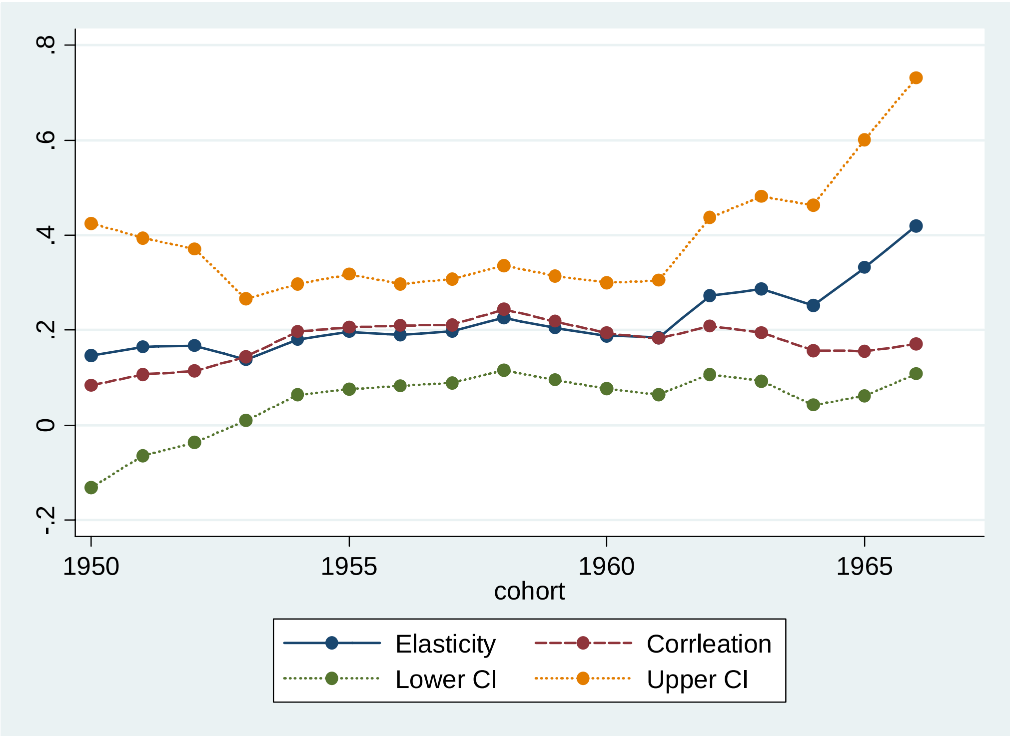

Table 2 Log earnings equation using supplemental sample

	Model specification 1			Model specification 2	
Variable	Coefficient	S.E.	Variable	Coefficient	S.E.
cohortf2	1.447	0.951	cohortf2	-0.157	0.193
cohortf3	2.022	0.914	cohortf3	0.129	0.217
age	0.374	0.090	age	0.399	0.091
age^2	-0.004	0.001	age^2	-0.004	0.001
HGc1	0.928	0.203	education1c1	0.129	0.134
HGc2	0.570	0.137	education1c2	0.199	0.083
HGc3	0.492	0.112	education1c3	0.182	0.064
education1	0.067	0.049	education2c1	-0.800	0.265
education2	0.133	0.089	education2c2	0.598	0.163
manager1y1	1.026	0.203	education2c3	0.432	0.106
manager1c2	0.745	0.124	manager1y1	1.060	0.206
manager1c3	0.324	0.092	manager1c2	0.851	0.122
manager2c1	0.692	0.264	manager1c3	0.409	0.090
manager2c2	0.414	0.129	manager2c1	0.711	0.269
manager2c3	0.077	0.095	manager2c2	0.441	0.131
manager3c1	0.699	0.153	manager2c3	0.108	0.096
manager3c2	0.468	0.105	manager3c1	0.280	0.142
manager3c3	0.120	0.083	manager3c2	0.332	0.099
constant	-6.074	2.381	manager3c3	0.007	0.080
			Constant	-3.002	2.372
Number of obs	1033		Number of obs	1033	
R^2	0.309		R-squared	0.289	
Adjusted R^2	0.297		Adj R-squared	0.276	

Table 3 Intergenerational mobility equations with linear trend for sons' cohorts 1950-72

Variable	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
x	0.217	0.034	0.245	0.053	0.266	0.054
x cohort/10	-0.016	0.004	0.032	0.012	0.020	0.014
Ages			0.122	0.053	0.119	0.052
$Ages^2$			-0.001	0.001	-0.001	0.001
Agef			-0.129	0.054	-0.128	0.056
$Agef^2$			0.001	0.001	0.001	0.001
$cohort_1$			0.156	0.144	0.139	0.140
$Cohort_2$			0.152	0.088	0.134	0.085
$Cohortf_1$					-0.126	0.125
$Cohortf_2$					0.005	0.077
Constant	5.889	0.243	5.580	1.327	5.465	1.387
Sons' age range	19-53		30-45		30-45	
No of obs	9673		6413		6413	
R^2	0.024		0.030		0.032	

Table 4 Intergenerational mobility equations with linear trend for sons' cohorts 1961-72 and 1956-72

Variable	Coeff.	S.E.	Coeff.	S.E.
x	0.206	0.089	0.290	0.061
x cohort/10	0.064	0.028	0.020	0.012
Ages	0.093	0.120	0.104	0.071
$Ages^2$	-0.001	0.002	-0.001	0.001
Agef	-0.142	0.092	-0.154	0.066
$Agef^2$	0.002	0.001	0.002	0.001
$Cohort_2$	0.260	0.116	0.102	0.048
$Cohortf_1$	-0.051	0.163	-0.134	0.135
$Cohortf_2$	0.093	0.107	0.024	0.085
Constant	6.088	2.703	6.127	1.680
Sons' cohorts	1961-72		1956-72	
Sons' age range	30-45		30-45	
No of obs	2956		5292	
R^2	0.0362		0.0398	

Table 5 Intergenerational mobility equations with linear trend for sons' cohorts 1950-72 and sons' age 19-53

Variable	Coeff.	S.E.	Coeff.	S.E.
x	0.252	0.054	0.265	0.058
x cohort/10	0.021	0.006	0.006	0.023
Age x	-0.006	0.008	-0.007	0.007
Age^2 x	-0.001	0.001	-0.001	0.001
Age	0.055	0.054	0.065	0.052
Age^2	0.002	0.008	0.003	0.008
Agef	-0.134	0.053	-0.132	0.054
$Agef^2$	0.001	0.001	0.001	0.001
d1	8.559	1.068	-0.147	0.360
d2			-0.090	0.295
d3			-0.044	0.239
d4			0.086	0.191
d5			-0.021	0.163
Constant	8.559	1.068	8.550	1.108
No of obs	6413		6413	
R^2	0.028		0.031	

Table 6 Intergenerational mobility equations sons' cohorts 1950-72 and sons' age 19-53

	y and *x* are not standardized		*y* and *x* are standardized	
Variable	Coeff.	S.E.	Coeff.	S.E.
x d1	0.227	0.127	0.121	0.066
x d2	0.268	0.074	0.206	0.057
x d3	0.304	0.080	0.226	0.060
x d4	0.306	0.074	0.244	0.060
x d5	0.475	0.142	0.231	0.064
x d6	0.590	0.146	0.243	0.059
Age x	0.008	0.005	0.009	0.006
Age^2 x	-0.001	0.000	-0.001	0.000
Age	-0.033	0.034	-0.040	0.043
Age^2	0.003	0.003	0.004	0.003
Agef	-0.131	0.052	-0.143	0.065
$Agef^2$	0.001	0.001	0.002	0.001
d1	2.276	1.343	1.645	1.524
d2	2.085	1.119	3.732	1.382
d3	1.889	1.069	3.018	1.293
d4	2.038	0.972	5.180	1.206
d5	0.755	1.115	-0.190	1.216
constant	6.376	1.457	7.129	1.823
No of obs	9673		9673	
R^2	0.055		0.760	

Note: y and x are standardized dividing them by their standard deviation computed separately for 6 difference cohort groups.