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Intergenerational Persistence in Income and Social Class: The Impact of Within-Group Inequality

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Abstract
Family income is found to be more closely related to sons' earnings for a cohort born in 1970 compared to one born in 1958. This result is in stark contrast to the finding on the basis of social class; intergenerational mobility for this outcome is found to be unchanged. Our aim here is to explore the reason for this divergence. We derive a formal framework which relates mobility in measured family income/earnings to mobility in social class. Building on this framework we then test a number of alternative hypotheses to explain the difference between the trends, finding evidence of an increase in the intergenerational persistence of the permanent component of income that is unrelated to social class. We reject the hypothesis that the observed decline in income mobility is a consequence of the poor measurement of permanent family income in the 1958 cohort.

Keywords: Intergenerational income mobility, social class fluidity, income inequality
JEL Classifications: J13, J31, Z13

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1. Introduction

Both economists and sociologists measure the intergenerational persistence of socio-economic status, with the first group of researchers tending to use income or earnings as the measure of status (Solon, 1999, Black and Devereux, 2010) while the second use fathers' social class (Erikson and Goldthorpe, 1992) or an index of occupational status (Blau and Duncan, 1967). To ascertain whether the measured extent of mobility is high or low, both literatures have asked i) how does mobility compare across nations; ii) has mobility increased or decreased across time. For both of these comparisons the findings of economists and sociologists are sharply contrasting for the UK.

International comparisons of income mobility place the UK as a country with low mobility (Corak, 2006) whereas sociologists tend to rank it closer to the middle (Erikson and Goldthorpe 1992, Breen, 2004). Cross-country rankings across the two approaches are barely correlated with each other (Blanden, 2011) Likewise on trends, Blanden, Goodman, Gregg and Machin (2004) find that intergenerational mobility decreases for a cohort born in 1970 (British Cohort Study) compared to a cohort born in 1958 (National Child Development Study) while Goldthorpe and Jackson (2007) find no change in social class mobility for the same datasets. Our aim in this research is to analyse the factors responsible for the difference in the measured trends in mobility. Our interest in trends is driven, in part, by wide acceptance of the finding of falling mobility among politicians and commentators and its contribution to the sense that Britain has a 'mobility problem' (Goldthorpe and Jackson, 2007, Blanden, 2010 and Saunders, 2010). It is therefore crucial to examine the robustness of this result.

In addition, we aim to draw out the conceptual links between mobility as measured by economists and sociologists and therefore offer a fresh perspective on both literatures. The divergent results may simply reflect underlying conceptual differences. Economists are aiming to measure economic resources whereas class reflects workplace autonomy and broader social capita (Goldthorpe, 2000). However, the view we adopt here is that both approaches are trying to assess long-term or permanent socio-economic status but measure this in different ways.

In principle there are advantages and disadvantages of both measurement approaches. Erikson and Goldthorpe use a seven category class schema, and might therefore only capture a limited amount of the potential variation in permanent economic status between families (see critiques by Grusky and Weeden 2001 and McIntosh and Munk 2009). In addition, mobility measures based on fathers' social class will ignore the contribution of mothers. However, social class measures are sometimes argued to be better at measuring the most important aspects of the permanent status of the family (see Goldthorpe and McKnight, 2006). A particular difficulty with the income data that we use from the cohorts is that it is measured based on a single interview where families are asked about their current income. Erikson and Goldthorpe (2010) and Saunders (2010) suggest that social class is a more reliable measure than current income and that the differing results between the two approaches are explicable by the poor measurement of family income in the 1958 cohort.

We begin our analysis by formulating a framework to examine the relationship between permanent income, social class and current income. This framework is then explored empirically using the British Household Panel Survey (BHPS). We find that there is a substantial portion of permanent income which is unrelated to social class. Conceptually, this component can account for the divergent results.

Section 3 of the paper outlines the main results concerning the trend in mobility over the British cohorts using both economic and sociological methodologies and addresses the main issues concerning data and measurement. We focus on a number of specific measurement issues in the National Child Development Study (NCDS) which might explain our result that income mobility is greater in the earlier cohort compared with the later British Cohort Study (BCS). We find no evidence to support the hypothesis that data quality or differential measurement is generating the decline in mobility observed.

In Section 4 we detail other potential mechanisms that could generate different trends in measured income and social class mobility. To do this we show that current income can be decomposed into a number of different components. As mentioned above, the permanent component can be split into the part associated with social class, and the residual part, which we refer to as within-class permanent income. In addition current measured income will include transitory error (the difference between current and permanent income) and finally any pure mismeasurement.

We then establish four alternative testable hypotheses that could account for the diverging trends in mobility. In brief they are: first, that the link between father's social class and family income within generations has changed, perhaps due to the increasing role of women in accounting for family socio-economic position; second, that the divergence is due to differential measurement error across the cohorts; third, within-class permanent income has become more important in determining children's outcomes; and fourth, that differences can be explained by a decline in the transitory component of parental income.

We find no evidence that a change in the mapping from father's social class to income affects our results, instead we find that a substantial part of the increased persistence across generations can be predicted by observable short and long-run income proxies. Indeed, it is possible to plausibly account for the full rise in income persistence through the increased persistence of within-class permanent income. This is fully consistent with the data examination which finds no evidence that the differential results could be explained by measurement problems.

2. Measuring permanent income

2.1 The components of income

Here we set out a framework which demonstrates the relationships between permanent family income, income at a point in time and fathers' social class. This provides clear foundations for our examination of the reasons behind the divergent results for income and social class.

For economists, the intergenerational relationship of interest is the relationship between parents' *permanent* income (y, for income, subscript p for parental) and the child's *permanent* income (y_s^*). This is subscripted s here, as it refers to sons only in our application. As is common we shall denote permanent variables by * and logs by lower case variables. Intergenerational mobility can be summarised by $\hat{\beta}$, the estimate of the coefficient β from the following regression:

$$y_{si}^* = \alpha + \beta y_{pi}^* + u_i \qquad (1)$$

The focus on sons here simplifies the analysis so that we are focusing on male social class in both generations and to reduce the issues resulting from endogenous labour market participation. Note that we are considering an asymmetric relationship, relating combined parental income to the sons' own earnings. We take care to reflect this asymmetry in the rest of the paper and we explicitly consider the role of mother's earnings in Section 4 below.

The intergenerational correlation, *r*, is also of interest in cross-cohort studies as this adjusts β for any changes in variance that occur across cohorts. $\hat{r}$ is calculated by adjusting $\hat{\beta}$ by the sample standard deviations of parental income and child's income. Björklund and Jäntti (2009) urge the more widespread use of this statistic when making international comparisons of mobility and the same arguments apply when considering trends over time.

$$\hat{r} = \hat{\beta}\frac{(\hat{\sigma}^{y_p^*})}{(\hat{\sigma}^{y_s^*})} \tag{2}$$

Following Björklund and Jäntti (2000), permanent parental income can be decomposed into the part that is associated with father's social class (in our exposition social class is denoted by a continuous variable, but categorical variables are used in our analysis, the subscript f represents father) and v_p. This is permanent income that is uncorrelated to fathers' social class (SC_{fi}).

$$y_{pi}^* = \delta_p SC_{fi} + v_{pi} \tag{3}$$

δ_p will reflect the relationship with father's social class of all the different components which make up total income; fathers' and mothers' earnings and unearned income. This is a point we shall return to later. The child's permanent income can also be split into similar components; the part that is related to the child's own class and the part that is independent of this.

$$y_{si}^* = \delta_s SC_{si} + v_{si} \tag{4}$$

Unfortunately, permanent income is generally not available for intergenerational research (see Solon, 1992 for the first discussion of the biases that result) and the British cohort studies suffer from this limitation. Measured current parental income is permanent income plus the deviation between current measured income and permanent income (e_{pi}). Later in the analysis we will explore the components that make up this term, but for now we consider it to be anything which leads to a difference between measured and permanent income.

$$y_{pi} = \delta_p SC_{fi} + v_{pi} + e_{pi} \tag{5}$$

$$y_{si} = \delta_s SC_{si} + v_{si} + e_{si} \tag{6}$$

Under classical measurement error assumptions, that the level of measured y_i is uncorrelated with the size of the total error and that errors are uncorrelated across generations, it is straightforward to show that any error in measuring parental permanent income will lead to a downward bias in the OLS estimate of β and that this bias will be contingent on the amount of variance in the error components.

$$p\lim \hat{\beta} = \beta \frac{\sigma^2_{y^*_p}}{\sigma^2_{y^*_p} + \sigma^2_{e_p}} \quad (7)$$

Under these assumptions, errors in the dependent variable will have no impact on estimates of β.

In recent years the intergenerational mobility literature has began to address sources of systematic bias, in particular lifecycle bias (Haider and Solon, 2006). Lifecycle bias is a consequence of the age at which incomes are measured. For example, if sons' earnings are measured before their career is established the largest error will be found for those with the highest permanent income level leading to a correlation between the error and permanent income. In this particular case, the estimated beta will be downward biased. It seems that this is more likely to occur in the BCS than the NCDS as earnings are measured in the BCS at age 30, compared to age 33 in the earlier cohort. It is therefore hard to explain our results using lifecycle bias.

Turning to other sources of non-classical measurement error, Gottschalk and Huynh (2010) have recently explored the consequences of reporting bias for lifetime earnings mobility. As found by Bound et. al. (2001) mean reversion is a common consequence of reporting bias, with those with high incomes under-reporting and those with low incomes having positive errors. In the lifetime mobility context, where this type of error appears on both sides of the equation, a consequence of this mean reversion is that mobility is understated due to the correlation in errors over time within individuals. However Gottschalk and Huynh find that this tends to be offset by the attenuation bias generated by classical error. In the intergenerational context, we would imagine that errors are more weakly correlated across generations as the incomes are reported many years apart and by different agents. As a consequence we believe that classical measurement error is the dominant concern in this context.

Notice that with classical measurement error the partial correlation, $\hat{r}$, is affected in a different way from $\hat{\beta}$ (see equation 2), because $\hat{r}$ is $\hat{\beta}$ multiplied by the ratio of the standard deviations of parents' to sons' income. As classical measurement error will tend to increase the estimated variance of the variable that it effects, any error in sons' earnings will downward bias $\hat{r}$ (it has no effect on $\hat{\beta}$) while any error in parental income will have less of an impact on this measure relative to $\hat{\beta}$. We shall take up these points again in section 3.4. It is also notable that $\hat{r}$ will be sensitive to measurement error in the dependent variable as a good estimate of the standard deviation of sons' earnings is required (Black and Devereaux, 2010). In this paper we concentrate our efforts on exploring the impact of measurement error in the independent variable, as the divergence between the results for class and income applies to both the measured $\hat{\beta}$ and $\hat{r}$ and therefore cannot be driven by error in sons' earnings.

2.2 Applying the framework to the BHPS

The cohort data only has information on current parental income at age 16 meaning that we cannot directly measure permanent parental income in this data. We can, however, estimate permanent income in the BHPS. This can be used to understand more about how current measured income and fathers' social class might be related to permanent income as described in equations (3) and (5).

The British Household Panel Study (BHPS) began in 1991 and now provides a long enough series of income data to allow us to approximate permanent income in childhood for the youngest sample members. We choose to use the derived net household income data as it provides the best comparison with the current income data in the cohort studies (Levy and Jenkins, 2008). The current income components are measured over the month prior to the annual interview or the most recent relevant period, except for employment earnings which are 'usual earnings'. We select 1206 two-parent families (to be comparable to our main cohort sample) with children under 16 who have more than 7 income reports available. 17 per cent of these have reported income in the full 15 years of the study while 65 per cent have income reports for 10 years or more. A 'permanent' childhood income measure is created by averaging across all observed current incomes. This can be compared with current income measured when the child is aged 16 or in the latest sweep available.

Alongside income, the BHPS includes information on father's social class and so we are able to predict $\hat{\delta}_p SC_f$ from both (3) and (5) using our two measures of income. We also have information on other household characteristics that will be related to permanent income and using these we can split v_{pi} into the part that can be predicted ($\hat{\gamma}_p X_p$), with the remainder forming a permanent unmeasured residual capturing any variance in permanent income not related to social class or our observable household characteristics, we denote this element as $\hat{\varepsilon}_{pi}$.

$$y^*_{pi} = \hat{\delta}_p SC_{fi} + \hat{\gamma}_p X_{pi} + \hat{\varepsilon}_{pi} \qquad (8)$$

Note that this two step approach allows fathers' class its maximum explanatory power. The characteristics X_p in the BHPS are parental education, father and mother's employment status, age, housing tenure, region and self-reported financial difficulties, all measured in the most recent sweep at the same time as current income. These are chosen to capture as much of the remaining variation in permanent income as possible, free from measurement error. The same approach can also be used to decompose current income.

$$y_{pi} = \hat{\lambda} SC_{fi} + \hat{\phi}_p X_{pi} + \hat{\varepsilon}_{pi} + \hat{e}_{pi} \qquad (9)$$

Notice that the extra term over equation (8) is the difference between current measured income and permanent income. Later we explore different components of this residual. The components associated with social class and other income proxies will differ from those estimated in equation (8), as they are based on current rather than permanent income. Our aim is to see if these current income components are good proxies for permanent income and its components. If successful this approach can be used to identify permanent income variation in the cohort studies.

Table 1A decomposes the variances of permanent and current income into the components described in the equations above. The first aspect to notice is that the social class component captures less of the variance of average (permanent) childhood income (15.7 per cent) than that part that is accounted for by the alternative income proxies (23.4 per cent). This is in spite of the fact that the alternative income proxies are only picking up variation in income within social class. The majority of the variance in average (permanent) childhood income is unexplained; $\hat{\varepsilon}_{pi}$ accounts for the remaining 61 per cent. The weak predictive power of social class and large permanent residual component is also found for current income.

Table 1B shows the correlations between the different components of current and permanent income. This once again emphasises the importance of residual permanent income ($\hat{\varepsilon}_{pi}$) as this component of current income has the strongest correlation with our measure of permanent income. What is also apparent is that the correlation between current income and permanent income is stronger than the association between permanent income and current income as predicted by fathers' social class (0.74 compared to 0.40). In addition there is a very strong correlation (0.83) between permanent income as correlated with the Xs and the current income correlated with Xs, indicating that we can legitimately make use of predictions based on long-term income proxies in our examination of the cohort data.

Our results suggest that the relationship between current income and permanent income is strong, and that current income is a better proxy for permanent income than fathers' social class is. Other income proxies capture a large share of the variance of permanent income, certainly larger than social class, but there still remains a large residual permanent component of income which forms a substantial part of residual current income (that is, income that is orthogonal to social class and our other explanatory variables). The implication of this is that it is not correct to assume that all current income which is unrelated to social class or other income proxies is simply error.

3. Mobility in the cohort studies

3.1 Data

For the headline results on intergenerational mobility, both sociologists and economists have utilised the two publicly accessible mature British cohort studies, the British Cohort Study (BCS) of those born in 1970 and the National Child Development Study (NCDS) of those born in 1958. Both cohorts began with around 9000 baby boys included, although as we shall see the samples used are considerably smaller than this. The NCDS contains all children born in the UK in a week in 1958 and obtains detailed data at birth and ages 7, 11, 16, 23, 33, 42, 46 and most recently at 50. The BCS included all those born in Great Britain in a week in 1970 and was followed-up at ages 5, 10, 16, 30, 34 and 38.

Information on parental income is taken from the age 16 survey for both cohorts. In the NCDS parents were asked to place father's earnings, mother's earnings and other income into a category. Family income is obtained by taking the adjusted midpoints (see Appendix B) of the three measures within their category and summing. In the BCS parents are only asked about their total family income, and are asked to choose one of eleven categories. In addition to the difference between the 'single-question' income measure asked in the BCS and the components used to generate the NCDS income data, there are other differences in the types of income asked about in the two surveys. We provide a Data Appendix B to give details of the precise questions asked and adjustments made to move from the raw data to the variables used in our analysis.

As already noted, the validity of the comparisons we make depends crucially on the extent of measurement error being similar in the two datasets. As detailed in the Appendix, there is no evidence that the results are sensitive to the approach taken to ensuring comparability between the income measures. An additional concern is the fact that the NCDS parental income was, for about 30 per cent of our sample, obtained during the period of the 1974 Three-Day week when working hours in many occupations were restricted due to a coal shortage. We will return to this issue shortly when we evaluate measurement issues in the income measures. Information on father's social class is obtained from the aged 11 survey in the NCDS and the aged 10 survey in the BCS, in line with those used to provide the headline results in sociology (Erikson and Goldthorpe, 2010). The schema used is a 7-category variable which is derived from the information on Socio-Economic Group available in the datasets.

Adult earnings and destination social class information is obtained at age 33 (NCDS) and 30 (BCS), where individuals are asked to provide information on their usual pay. This is then deflated using the relevant GDP deflator for the month of the interview. Although more recent earnings are available for both cohorts, we continue with the measures used in the original papers to keep the analysis consistent. Evidence suggests that the patterns would not change if we used other earnings variables (Gregg and Macmillan, 2013). A limitation of the data is that information on self-employment income is poor. Consequently, self-employed cohort members are dropped from our analysis. Destination social class in the NCDS is measured at 33 and is already available as a Goldthorpe schema. In the BCS there is no measure of the Goldthorpe schema at aged 30 so the individuals' SOC90 occupational codes and employment status are recoded to the same schema used in the NCDS. We follow Goldthorpe and Jackson (2007) in the way we do this.

For the second stage of this paper, additional parental background variables are obtained at various points during the cohort member's childhood; this enables us to generate a matrix of X_p variables as used in section 2.2, and similarly the adult surveys provide variables X_s to predict sons' income. We use these to address the issue of measurement error directly. Our decomposition analysis provides a full discussion of the selection process for X_p and X_s.

3.2 Measures of Intergenerational Mobility using Income and Class

Table 2 provides the 'headline results' from the examination of intergenerational income mobility using the regression approach. These differ very slightly from those reported in Blanden, Gregg and Macmillan (2007) as age controls are not included (these are added later as one of the Xs used to predict permanent differences in parental income through childhood). In the second panel we exclude families headed by single-parents. We argue that this further selection is appropriate for our analysis in this research given the focus on father's social class. Combined, these alterations do little to the change in $\hat{\beta}$, from 0.067 to 0.070, and the change in $\hat{r}$ from 0.107 to 0.114. The key finding remains extremely clear: intergenerational income mobility has fallen across the two birth cohort studies.

For both income based measures of persistence, $\hat{\beta}$ and $\hat{r}$, the association of parental income at age 16 and sons' earnings in his early 30s has increased substantially and statistically significantly (at the 95% confidence level). The strengthened intergenerational association can also be demonstrated by using the transition matrix approach. We group incomes in each generation into equal-sized categories (in this case quintiles) and document the proportion of the total sample of families who make each possible move. In a world of perfect mobility each cell would contain 4 per cent of the sample. Table 3 reveals the change in the extent of income persistence across generations using this approach. A larger proportion of cases are clustered near to the diagonal and there is less evidence of long-range movement. The difference in total mobility across the two birth cohorts is significantly different at the 1% level (see note to Table). These results form the basis for the conclusion that intergenerational mobility fell between cohorts of children leaving school in the mid-1970s and late 1980s, when measured using income and earnings.

The results for absolute social class mobility can also be summarised by transition matrices, and these are reported for the two cohorts in Table 4. The scales have been reversed from the usual reading of social class; one is now the bottom social class and seven the top social class. This is for ease of comparison with income and earnings measures. As with Goldthorpe and Jackson's (2007) results, there is no evidence of a change in absolute mobility across the cohorts at the 5% level. In the NCDS some 28 per cent of fathers were in the top two social classes and 42 per cent of their sons and in BCS this is the case for 34 per cent of fathers and 46 per cent of sons.

The unadjusted proportions provide information on absolute mobility, but as the size of social classes changes across generations and cohorts it is also important to look at 'relative fluidity' (see Erikson and Goldthorpe 1992). Table 5 compares relative mobility for the income and social class measures showing the relative odds of staying put compared to large movements. The results for income mobility reinforce the pattern shown in Table 3; there is a substantial fall in mobility. The results for social class show that for both cohorts just over 30 per cent of children born into the two lowest social classes migrate to the top two as adults and likewise a constant 65 per cent of those born with fathers in the top two social classes remain in these classes as adults. A near constant 2:1 ratio of chances of entering the top two classes is revealed indicates no change in relative mobility.

Notice that the results presented here do not allow for a direct comparison of the strength of the association in social class and income. We concentrate on trends only. In Erikson and Goldthorpe (2010) much is made of the stronger association across generations in social class compared to income. Their method for a direct comparison between the two is based on comparing income quintiles to a collapsed 5 rather than 7 social class schema. However, this still does not provide the relevant comparison. By aggregating income into 5 quintiles much of the important variation which is used in calculating the betas and partial correlations has been lost. In the social class context, much less variation has been lost when the categories are collapsed slightly from 7 to 5; therefore we do not regard this as an informative comparison.

This preliminary exploration of income and class mobility suggests that simple cross-tabulations reveal a growth in the association of income across the two cohorts while the strength of links in social class between generations remains quantitatively similar. This confirms the findings of Blanden, Goodman, Gregg and Machin (2004), Goldthorpe and Jackson (2007) and Erikson and Goldthorpe (2010).

3.3 Samples

Before digging deeper we must first check if differences in samples can explain the divergent results. The cross-tabulations for income and social class we have seen so far are not based on the same sample, and this alone could generate differences in the estimated trends. The last two columns of Table 5 repeat the results for relative social class for the income sample. There is some evidence of more long-range mobility from the bottom two into the top two social classes and less mobility from the top into the bottom. There is no evidence, however, that restricting the sample has affected the trend in intergenerational mobility by social class.

As has already been mentioned in section 3.1, the samples available for both analyses are substantially smaller than the initial samples of around 9,000 male cohort members. Even though we have shown that the *difference* in samples is not responsible for the different trends in mobility, attrition and item non-response could nonetheless be leading to a misleading perception of the change in mobility. In the Data Appendix B we spend some time documenting the impact of attrition on the samples in the NCDS and BCS and comment on the implications of this for the estimated change in mobility. While it is doubtless the case that these problems are substantial and do affect the representativeness of the samples used, as far as we can tell there is no evidence that these are responsible for the finding that UK income mobility fell between these cohorts.

3.4 Data quality

As shown above in Section 2.1 classical measurement error in parental income will lead to attenuation in our parameters of interest. If the share of non-permanent variance in parental income is larger in the first cohort than the second, this could explain the differences in the results obtained by income and social class. Here we directly confront this possibility by collecting together a number of pieces of evidence to enable us to evaluate the relative quality of the parental income data in the two cohorts.

The structure of the parental income questions is different between the cohorts; this could be a source of differential error. The parents of the NCDS cohort members provide banded information on three sources of income, fathers' earnings, mothers' earnings and other income; the mid points are then summed together to create total parental income. In the BCS just one total band is provided. The precise wording of the questions and the distribution of the raw data are recorded in Appendix B. We might think that the difference in the structure of the questions would lead to more accurate income information in the NCDS (Micklewright and Schnef, 2010) or alternatively a single banded total income measure may reduce the measured variance of income by more than one derived from three component sources of income. We have modelled the implications of both banding approaches in the continuous BHPS data in our Data Appendix B. We find that neither has an appreciable impact on total variance or the decomposition of current income into the different permanent income components shown in equation 8.

Banded data must be transformed in some way for use in regression and the nature of the questions means this is done differently in each cohort. In the NCDS we assign midpoints for each category based on comparisons with information on similar families in the FES, this provides a fairly continuous measure when the three income sources are added together. For the BCS, when there are only 11 categories to choose from we adopt an alternative approach to assigning a midpoint for each category (and most importantly to closing the top band). To take account of the usual skewed distribution of income we fit a Singh-Madalla (or Burr) distribution across the data to assign the best estimates of income within each category. In this regard, there seem to be more issues with the transformation of the BCS data. We examine the implications of our choice of method compared to others in Appendix B and find that it makes very little difference to the results and is not driving the increase in persistence across time.

An alternative approach to checking for measurement issues within the cohort data is to compare the income reports from the cohorts with incomes given in a nationally representative survey. Table 6 reports descriptive statistics for parental income in the cohorts alongside comparable income measures for families with children aged 10-16 in the Family Expenditure Survey (FES) in the same years. Both cohort studies appear to be underestimating family income for most of the income distribution with the exception of the lowest band in the BCS. This understatement is not surprising as questioning in the FES is more thorough so is likely to uncover more income sources.

As has already been mentioned, the parental income question in the NCDS was asked, in part, during the period of the three-day working week which occurred at the start of 1974 as a result of industrial action in the coal industry. It is possible that the reported income is that of the three-day week rather than usual weekly income. If this is the case it could lead to unusually high measurement error in the first cohort and bias results towards finding a fall in mobility. In Appendix B we estimate the intergenerational coefficient and partial correlation for those families only interviewed in January and February 1974 (definitely within the three-day-week period). We find that, if anything, persistence is greater for those families for whom we would expect attenuation bias to be strongest. This is in line with Grawe's (2004) study who finds no evidence of income misreporting in the NCDS due to the reduced working week.

Erikson and Goldthorpe (2010) raise concerns about the parental income data in the NCDS because of the weaker link between social class and parental income in the NCDS compared with the BCS. Social class explains 9% of the variance of parental income in the NCDS and 23% in the BCS. They infer from this that the extent of measurement error is higher in the NCDS. However, this need not be the case; the share of income not predicted by social class may have genuinely increased. We check this in the General Household Survey (which contains income and social class information) in Table 7 and find that fathers' social class explains more of the variance in family income in the second period in the GHS, mirroring the pattern found in the cohorts. This finding is not sensitive to selecting the sample based on the employment status of parents.

If we return to equation (7) the effect of classical measurement error on the intergenerational elasticity is that it will increase the variance in the parental income variable. In fact, the pattern in the cohorts is the reverse of what we would anticipate if there was more classical measurement error in the first cohort. The total variance of log income in the NCDS (measured in 1974) is .138 compared with .225 in the BCS (measured in 1986). The shift in variance appears large but is consistent with widely documented rise in income inequality over this period, and with our investigation of the FES included in the Appendix.

Another feature of measurement error is its impact on the two measures of intergenerational persistence $\hat{\beta}$ and $\hat{r}$. With classical measurement error in the explanatory variable $\hat{\beta}$ will be a downward biased estimate of the true parameter β. However, as $\hat{r}$ is estimated as $\hat{\beta}$ scaled by the relative variance of parental to sons' income, a larger variance in parental income will lead to a larger estimate of $\hat{r}$ relative to $\hat{\beta}$. In this case differential measurement error would manifest itself in a smaller rise in $\hat{r}$ across the cohorts compared to the rise in $\hat{\beta}$. Our results in Table 2 show a clear rise in both measures, with the partial correlation increasing slightly more than the elasticity.

Our evidence so far has rejected explanations of the divergence between the income and social class mobility results which are based on measurement approaches, samples and data quality. In section 2.2 we used the BHPS to demonstrate that it is incorrect to assume that all residual income (i.e. measured income uncorrelated with social class) is measurement error; this provides scope for alternative explanations. We now turn our attention to expanding our framework to formulate and evaluate a wider set of hypotheses to explore why the income and class-based results differ, including a more formal approach to capturing the impact of measurement error.

4. Alternative hypotheses

4.1 Expanding the framework: A decomposition approach

Returning to our relationship of interest, the link between permanent incomes across generations, we can rewrite our parital correlation $\hat{r}$ in terms of variances and covariances.

$$\hat{r} = \frac{Cov(y^*_{p_i}, y^*_{s_i})}{\sqrt{Var(y^*_{p_i})}\sqrt{Var(y^*_{s_i})}} \qquad (10)$$

The numerator can be decomposed into the elements described above in equations (3) and (4).

$$Cov(y^*_{pi}, y^*_{si}) = Cov(\delta_p SC_{pi}, \delta_s SC_{si}) + Cov(v_{pi}, \delta_s SC_{si}) + Cov(v_{si}, \delta_p SC_{pi}) + Cov(v_{pi}, v_{si}) \qquad (11)$$

One reason why results based on social class and income might vary is because the covariance between those parts of income associated with social class differs from the direct association in social class across generations. A possible reason why this might occur is due to the changing role of mothers' earnings.

To see this, think of permanent parental income as having three components, the permanent elements of each of fathers' earnings, mothers' earnings and other income.

$$y^*_{pi} = y^*_{fi} + y^*_{mi} + y^*_{oi} \qquad (12)$$

Each of these three elements can be decomposed into the part which is associated with father's social class and a permanent component which is uncorrelated with this. The overall $\delta_p SC_{pi}$ will be a weighted average of these components with the weights dependent on the component's share in total income.

$$\delta_p SC_{pi} = S_f \delta_f SC_{pi} + S_m \delta_m SC_{pi} + (1 - S_f - S_m)\delta_o SC_{pi} \qquad (13)$$

where S_f (S_m) is the share of fathers' (mothers') permanent earnings in permanent parental income.

The overall $Cov(\delta_p SC_{pi}, \delta_s SC_{si})$ will be influenced by changes in any of the following aspects; the shares, the δ s on the components and the intergenerational relationship between the parts associated with social class. If these factors are to explain the divergence in income and social class results it must be the case that there is an increase in $Cov(\delta_p SC_{pi}, \delta_s SC_{si})$ that is not present for $Cov(SC_{pi}, SC_{si})$.

We can use the NCDS data on income sources to explore the three aspects mentioned above. First, considering the intergenerational relationship between the parts of income associated with social class, the correlation between sons' earnings as predicted by his social class and the part of father's earnings predicted by fathers' social class is .288. For mothers' earnings this correlation is .253 and for other income it is -.265. Secondly, considering the δ s on the components, the association with father's social class is weaker for mothers' earnings than for father's own earnings (the r-squared for the mothers' earnings regression is just 0.01 compared with 0.16 for fathers). Given this evidence, only a fall in the share of income contributed by mothers rather than fathers can lead to a decline in $Cov(\delta_p SC_{pi}, \delta_s SC_{si})$. Evidence from the General Household Survey demonstrates that the proportion contributed by mothers rose slightly in the relevant period. Nevertheless, we need to investigate the role of $Cov(\delta_p SC_{pi}, \delta_s SC_{si})$ empirically as it could rise for other reasons, such as a strengthened relationship between mother's earnings and sons' earnings or an increased link between father's social class and mother's earnings.

As with the BHPS data, we can regress current income on social class in each birth cohort and for each generation j to identify $\hat{\lambda}_j SC_{ji}$. The residual from the regression of income on social class is the sum of the estimated v_{ji} and e_{ji}. That is the sum of residual permanent income and the difference between current measured income and permanent income. By expanding the co-variances as suggested in equation (11) and scaling them by the denominator of equation (10) we can formulate a 2x2 matrix for each cohort of the components of $\hat{r}$.

	$\hat{\lambda}_s SC_{si}$	$\hat{v}_{si} + \hat{e}_{si}$	
$\hat{\lambda}_p SC_{fi}$	$\frac{Cov(\hat{\lambda}_p SC_{pi}, \hat{\lambda}_s SC_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\lambda}_p SC_{pi}, \hat{v}_{si} + \hat{e}_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	(14)
$\hat{v}_{pi} + \hat{e}_{pi}$	$\frac{Cov(\hat{v}_{pi} + \hat{e}_{pi}, \hat{\lambda}_s SC_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{v}_{pi} + \hat{e}_{pi}, \hat{v}_{si} + \hat{e}_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	

We start by exploring the element in the top-left hand corner of matrix (14). As discussed above, if this part shows a different pattern across cohorts from the trend in social class mobility then the social class predictions of income have changed their role across the cohorts. The upper right quadrant shows the contribution of the relationship between fathers' social class variation in income and within-class variation in sons' earnings. The lower half shows the relationships between within-class measured family income and sons' outcomes.

At this stage within-class income will contain both within-class permanent income and any deviation between current and permanent income. This latter term will include both measurement error and also any genuine transitory fluctuations in income. In order to begin to distinguish the role of measurement error we again follow the BHPS analysis and estimate $\hat{\phi}_j X_{ji}$ by regressing the residual from the regression of income on social class, $\hat{\upsilon}_{ji}$, on a set of Xs.

$$\hat{\upsilon}_{ji} = \hat{\phi}_j X_{ji} + \hat{\varepsilon}_{ji} + \hat{e}_{ji} \tag{15}$$

Expanding the covariance matrix gives

	$\hat{\lambda}_s SC_{si}$	$\hat{\phi}_s X_{si}$	$\hat{\varepsilon}_{si} + \hat{e}_{si}$
$\hat{\lambda}_p SC_{fi}$	$\frac{Cov(\hat{\lambda}_p SC_{pi}, \hat{\lambda}_s SC_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\lambda}_p SC_{pi}, \hat{\phi}_s X_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\lambda}_p SC_{pi}, \hat{\varepsilon}_{si} + \hat{e}_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$
$\hat{\phi}_p X_{pi}$	$\frac{Cov(\hat{\phi}_p X_{pi}, \hat{\lambda}_s SC_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\phi}_p X_{pi}, \hat{\phi}_s X_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\phi}_p X_{pi}, \hat{\varepsilon}_{si} + \hat{e}_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$
$\hat{\varepsilon}_{pi} + \hat{e}_{pi}$	$\frac{Cov(\hat{\varepsilon}_{pi} + \hat{e}_{pi}, \hat{\lambda}_s SC_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\varepsilon}_{pi} + \hat{e}_{pi}, \hat{\phi}_s X_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\varepsilon}_{pi} + \hat{e}_{pi}, \hat{\varepsilon}_{si} + \hat{e}_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$

(16)

The within class income predicted by a set of observable income proxies will capture a portion of both within class permanent income and within class transitory income (we attempt to distinguish the two below). What is clear is that it will be uncorrelated with random error. Table 1B demonstrated that in the BHPS the prediction of permanent income using income proxies and the prediction for current income are strongly correlated. The intergenerational persistence of income can therefore be decomposed into the relationships between the $\hat{\lambda}_j SC_{ji}$, the $\hat{\phi}_j X_{ji}$ and the residual component $\hat{\varepsilon}_{ji} + \hat{e}_{ji}$. Hence the three by three matrix above will indicate whether within-class income is becoming more persistent across the cohorts and contributing to the divergent results. If the elements in the middle row of equation (16) are higher in the BCS this suggests that the divergence is not driven by pure measurement error, as this is uncorrelated with $\hat{\phi}_p X_{pi}$. However we must remember that $\hat{\phi}_j X_{ji}$ is not equivalent to v_{ji}, so a substantial element of permanent income variation will remain in the estimated residual.

Finally, we expand our framework to consider the role of transitory income, which has been highlighted by Erikson and Goldthorpe (2010) as a potential source of bias. The argument is that even if NCDS family income is measured just as accurately as it is in the BCS, the NCDS results might still be unreliable if the parental income measure is more transitory, and is therefore a poorer indicator of permanent family background. To test this hypothesis, we can expand our residual income term further to incorporate the transitory element of income. Note that there remains a pure 'error' component (η) which means that measured income deviates from true income even at a point in time.

$$y_{pi} = \delta_p SC_{fi} + v_{pi} + u_{pi} + \eta_{pi} \tag{17}$$

$$y_{si} = \delta_s SC_{si} + v_{si} + u_{si} + \eta_{si} \tag{18}$$

With this expansion, is possible to enhance the decompositions to further distinguish permanent income from transitory income and evaluate its impact. We estimate this transitory component by dividing the characteristics, X_{pi} into those considered more permanent characteristics X_{pi}^{P} and those considered transitory X_{pi}^{T}. Note that permanent and transitory income which is orthogonal to the Xs, ($\hat{\varepsilon}_{pi}$, and $\hat{\varphi}_{pi}$) will remain in the error term.

	$\hat{\lambda}_s SC_{si}$	$\hat{\phi}_s X_{si}$	$\hat{\varepsilon}_{si} + \hat{e}_{si}$
$\hat{\lambda}_p SC_{fi}$	$\frac{Cov(\hat{\lambda}_p SC_{pi}, \hat{\lambda}_s SC_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\lambda}_p SC_{pi}, \hat{\phi}_s X_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\lambda}_p SC_{pi}, \hat{\varepsilon}_{si} + \hat{e}_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$
$\hat{\vartheta}_p X_{pi}^{P}$	$\frac{Cov(\hat{\phi}_p X_{pi}^{P}, \hat{\lambda}_s SC_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\phi}_p X_{pi}^{P}, \hat{\phi}_s X_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\phi}_p X_{pi}^{P}, \hat{\varepsilon}_{si} + \hat{e}_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$
$\hat{\vartheta}_p X_{pi}^{T}$	$\frac{Cov(\hat{\vartheta}_p X_{pi}^{T}, \hat{\lambda}_s SC_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\vartheta}_p X_{pi}^{T}, \hat{\phi}_s X_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\vartheta}_p X_{pi}^{T}, \hat{\varepsilon}_{si} + \hat{e}_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$
$\hat{\varepsilon}_{pi} + \hat{\varphi}_{pi} + \hat{\eta}_{pi}$	$\frac{Cov(\hat{\varepsilon}_{pi} + \hat{\varphi}_{pi} + \hat{\eta}_{pi}, \hat{\lambda}_s SC_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\varepsilon}_{pi} + \hat{\varphi}_{pi} + \hat{\eta}_{pi}, \hat{\phi}_s X_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$	$\frac{Cov(\hat{\varepsilon}_{pi} + \hat{\varphi}_{pi} + \hat{\eta}_{pi}, \hat{\varepsilon}_{si} + \hat{e}_{si})}{\sqrt{Var(y_{pi})}\sqrt{Var(y_{si})}}$

(19)

To summarise; the differences in the reported results for trends in income and social class mobility could be generated in the following ways:

1. The mapping from social class to income/earnings changed between the cohorts. This might occur as a consequence of changes in mothers' earnings.
2. There is a greater degree of measurement error in the first cohort, the NCDS, which leads to larger attenuation bias understating intergenerational persistence in the cohort. This results in a misleading picture of rising persistence across the cohorts.
3. The permanent income of parents that is unrelated to social class has a larger influence on sons' income in the second cohort (the BCS) compared with the first (the NCDS). This can be captured through a set of proxies for long-term income ($\hat{\phi}_p X_{pi}$). This stronger permanent income transmission may also come through the parental residual permanent income ($\hat{\varepsilon}_{pi}$), although this is not directly observable.

4. Parental transitory income is larger in the first cohort compared with the second. This can be captured by the estimated portion of this, $\hat{\vartheta}_p X_{pi}^T$ but may also come about because there is more residual transitory income in the within class income not captured by income proxies. This will generate attenuation bias if transitory income changes have zero or very small correlations with sons' outcomes.

4.2 Decomposing persistence by the components of income

The first explanation for the differences in results for trends in social class and income mobility is that the association between $\delta_p SC_{fi}$ and $\delta_s SC_{si}$ increased across the cohorts even though the relationship between social class is constant. In our conceptual discussion we pointed to the role of mothers' earnings as one possible source of any discrepancy. To test for this we use our decomposition approach to assess the relationships between $\hat{\lambda}_p SC_{fi}$ and $\hat{\lambda}_s SC_{si}$ in each cohort.

Table 8 estimates matrix (14) for the two cohorts and decomposes $\hat{r}$ into four parts, the correlation across individuals of permanent income/earnings predicted by social class, the correlation of residual income (residual permanent and transitory income plus measurement error) and their cross-correlations. The cells sum to the total partial correlation. There is very little change in the correlation of incomes/earnings associated with social class as shown in the top left-hand corner of the matrix for each cohort. Indeed this element of persistence has reduced slightly. We therefore reject hypothesis 1.

Table 8 also allows us to explore the relationship between fathers' income associated with social class and sons' residual earnings. This element of persistence has increased from 0.01 to 0.04 suggesting that there is a contribution to the difference in mobility from an increased relationship between income associated with fathers' social class and the sons' earnings, but that this does not come through sons' social class. Combined, the results show that the larger part of the difference in the results between income and social class must be generated by the relationship between sons' earnings and the other elements of parental income.

Following equation (16) we further decompose measured income/earnings, picking out the part of income that is associated with characteristics other than social class in each generation. The Xs used to predict parental income are those shown to have a strong correlation with income in the BHPS as shown in Section 2. Additional information available in the cohorts is also added including information on lone parenthood at birth, five and 16 (our sample is restricted to couples only for the last observed measure in the BHPS and therefore lone parenthood is not available in this study) and free school meal receipt at age 10 (FSM status is not available in the BHPS).

Table 9 summarises the relationship between current income and the available *X*s in the BHPS and in the cohorts. The full regression results for the cohorts are reported in Appendix A (Table A1). The R-squareds for residual income on these characteristics are around 0.3 in both the NCDS and the BCS (this contrasts with the difference in these for the regression of parental income on social class, as we have seen). This contradicts the hypothesis of differential data quality. Note also that the low contribution of social class explaining the variance in parental income, highlighted by Erikson and Goldthorpe (2010) as an indicator of measurement error in the NCDS, is also seen in the BHPS.

The *X*s used to predict sons' earnings include detailed education measures, information on early labour market attachment and variables on housing tenure, car ownership and pension contribution. As the sons' variables are concerned with individual earnings rather than family income, it is no surprise to find a stronger relationship with social class and a rather weaker relationship with the other income predictors (shown in Appendix A, Table A2). In general, we are less concerned about the selection of the sons' Xs as our primary concern is with discovering the impact of measurement problems in the independent variable.

Table 10 reports the results from using predicted income from these regressions to expand the decomposition. The results show that all of the elements of sons' income are more strongly correlated with $\hat{\phi}_p X_{pi}$ in the second cohort compared with the first, we can be confident that this component is not generated by differential measurement error. Overall the increase in the partial correlation associated with this predicted part of permanent income provides 0.052 points or 46 per cent of the total rise.

In total, 0.067 points or 59 per cent of the change in income persistence can be accounted for as due to income associated with father's social class (0.015 point increase) or other parental characteristics (0.052 points increase). We can think of this as a lower bound estimate of the true change in persistence, as it assumes that the change in persistence associated with the residual permanent income $\hat{\varepsilon}_{pi}$ and unmeasured transitory income is zero. We relax this assumption below.

4.3 The role of transitory income

Blanden et al (2004) use the New Earnings Survey (NES) to calculate the proportion of variance in earnings over a five year period that could be regarded as 'permanent' for men in the years around the age 16 income measures. In that paper we find that in the years around 1986 men's transitory fluctuations account for 21 per cent of the variance in any year, around 1974 this was 32 per cent. It appears that there is some evidence to point towards greater transitory income in the time period of first cohort, a view supported by Dickens (2000). Erikson and Goldthorpe (2010) note that if allowance were made for this problem, the fall in mobility would 'no longer appear as dramatic as it does when the data are taken at face value'. Applying the same figures to parental income, transitory error of this magnitude would imply a true β of .321 in the NCDS and .366 in the BCS, reducing the change in beta to 0.045, compared to the 0.07 found in Table 2.

There are three points that need to be made about this evidence. First, that this reduced figure is still a statistically significant rise and, at about 60% of the observed figure, is broadly in line with the lower bound estimate given at the end of the previous subsection. Secondly, the NES calculations are for individual earnings, whereas we need to know about transitory error in family income, including the impact of mothers' earnings and other income. Third, this assumes that income shocks have no effect on children's' outcomes and are thus the same as measurement error. There is a large body of evidence to suggest that this is not the case. Mayer (1998), Blanden and Gregg (2004) and Tominey (2010) (looking at income changes) and Oreopolous et al. (2008) and Gregg et al. (2012) (focusing on father's job loss) show that shocks to parental income do influence children's outcomes, although not to the same extent as differences in permanent income. Transitory income should not be thought of as simply another form of measurement error. However, given our focus on permanent income, we try to uncover the implications of excluding the influence of transitory income from our mobility estimates.

To provide some direct evidence on the importance of transitory income we return to the decomposition framework. So far, our decomposition analysis has shown that the relationship between predicted parental income and sons' earnings increased between the cohorts. However, this will be predicting some elements of transitory income alongside permanent income. In this case we cannot safely rule out the hypothesis that the results are being generated by a larger amount of predictable transitory income in the first cohort, if this has a weak relationship with sons' outcomes.

To assess this, we divide our predicting characteristics into two groups. To assist with the classification Table 11 shows the correlations between income predicted by the various Xs and the permanent (average) and transitory (current less average) income in the BHPS. We select as permanent Xs those factors which are clearly more strongly correlated with permanent income, such as education. We also include in the permanent group those time-varying factors which are measured in the cohorts prior to age 16, as their predictive power must come from their correlation with long-term differences in living standards. An example of such a characteristic is the housing tenure of the parents five (six) years before income is measured in the NCDS (BCS) (when the child is aged 11/10). We use as transitory predictors housing tenure, lone parent status, region and employment status measured at the time the income variable is obtained; when conditioned on earlier measures of the same variable these will provide a good indicator of transitory income shocks. For example, father not working at 16 given their employment status at 10 will predict income associated with changes in employment status.

Table 12 repeats the decomposition, separating out the influence of predicted transitory income as described by equation (19). The results from this exercise indicate that transitory income is unlikely to be driving the difference in results, although as expected the transitory component is correlated with sons' earnings, and this association increases slightly across the cohorts. The increase in the partial correlation in the permanent predicted part is 0.048, just a slight reduction on the 0.052 increase observed in Table 10. Taking the predicted rise in income persistence from social class and the observable permanent characteristics gives a combined increase in persistence of 0.063 out of the total 0.114 rise observed overall, or 55 per cent of the total. Once again this is a lower bound, assuming no change in the relationship between permanent residual parental income and sons' earnings.

An alternative approach allows us to put an upper bound on this quantity by applying some of our knowledge about residual permanent income in the BHPS to the cohorts. We know that the magnitudes of the different components of the final column of the decompositions will be dependent on the share of the variance of income accounted for by each. Table 9 compared the shares of the variance in current parental income that are attributable to social class, other characteristics and the residual. Broadly, the cohorts seem quite similar to the BHPS. Based on these results we can make the assumption that in the cohorts, as in the BHPS, the variance of the permanent residual component is twice the magnitude of the $\hat{\phi}_p X_{pi}$ part. Using an Oaxaca-style decomposition, where $S_{\varepsilon c}$ is the share of permanent income accounted for by ε in cohort c and R_c is the ratio which transforms the beta into the partial correlation (see Table 2) we can show that:

$$\frac{Cov(\varepsilon_{pi}, y_{si})_{70}}{Var(\varepsilon_{pi})_{70}} S_{\varepsilon 70} R_{70} - \frac{Cov(\varepsilon_{pi}, y_{si})_{58}}{Var(\varepsilon_{pi})_{58}} S_{\varepsilon 58} R_{58} = \left(\frac{Cov(\varepsilon_{pi}, y_{si})_{70}}{Var(\varepsilon_{pi})_{70}} - \frac{Cov(\varepsilon_{pi}, y_{si})_{58}}{Var(\varepsilon_{pi})_{58}}\right) S_{\varepsilon 58} R_{58} + \frac{Cov(\varepsilon_{pi}, y_{si})_{70}}{Var(\varepsilon_{pi})_{70}} (S_{\varepsilon 70} R_{70} - S_{\varepsilon 58} R_{58}) \tag{20}$$

We assume that the shares of permanent income from ε_{pi} ($S_{\varepsilon 70}$ and $S_{\varepsilon 58}$) do not change and are set to the level in the BHPS, and that the multiplying ratios are constant across the cohorts so the second term drops out. (In fact $R_{70} > R_{58}$ so the second term will likely also add a small amount to the upper bound.) Setting the change in the persistence of ε_{pi} across the cohorts equal to that of $\hat{\phi}_p X_{pi}$ means that the 0.048 change is doubled to make 0.096 (because the share of permanent income associated with ε_{pi} is twice that associated with $\hat{\phi}_p X_{pi}$). If this is added to our lower bound of 0.063 the expected change is 0.159. This is actually larger than the real change and suggests that in reality either the share of residual permanent income in the 1958 cohort may be lower than in the BHPS, and/or persistence in this component has risen less strongly than persistence in predicted permanent income. However, this thought experiment shows that it is easy to explain the changes we do find using this approach. The upper and lower bound estimates based on assessments of permanent income straddle the observed rise in intergenerational persistence and clearly indicate that permanent income mobility declined across the cohorts.

5. Discussion and Conclusion

This paper extends a framework first set out by Björklund and Jäntti (2000) to model the link between social class and income measures of intergenerational mobility. We take as our baseline model the relationship between the permanent income of parents and the permanent income of sons. Using a framework that relates permanent income to social class and current income we are able to offer four possible explanations for the divergence between trends in intergenerational mobility in income and social class in the UK. Here we will briefly review the evidence for each hypothesis in turn, drawing out the broader implications of our results for the study of mobility.

First we produce a number of pieces of evidence which counter the claim that poorer quality parental income data in the first cohort is the primary explanation for the apparent increase in income mobility. This is confirmed in our later analysis with clear evidence of a rise in intergenerational mobility in income predicted by observable characteristics, which are free from the influence of measurement error. Hence the hypothesis of differential measurement error is rejected.

Using a framework relating current and permanent income to social class and other measured characteristics enables us to explore alternative explanations for the divergent results. It is possible that the relationship between fathers' social class and family income has changed, perhaps owing to changes in the importance of mother's earnings for family income. This could lead to a divergence between the intergenerational correlations in social class and intergenerational persistence in income associated with social class. This turns out not to be important over this period, perhaps because this data predates the large rise in mothers employment and lone parenthood which occurred from the mid-1980s to the late 1990s. However, our framework has drawn attention to the potential importance of this issue for more recent cohorts of children, for whom the male breadwinner premise is less and less appropriate. This section of the analysis also found that differences in income associated with social class are having a greater influence on sons' earnings in the second cohort, this accounts for 13 per cent of the observed rise in intergenerational income persistence.

The third hypothesis which would explain the divergence is that the trend in the persistence in permanent income *within* fathers' social class groups differs from the trend in persistence in income that is predicted by father's social class. This is plausible given that analysis of BHPS data reveals social class is a rather poor predictor of permanent childhood income. This hypothesis can be explored by looking at income predicted by other proxies, such as parental education, lone-parenthood and housing tenure. Our investigations find that around 46 per cent of the headline rise in intergenerational income mobility is accounted for by income predicted by other characteristics. It appears that this component of permanent income has an increasing impact on the outcomes of the next generation. Taken together with the increased importance of fathers' social class in predicting sons' earnings above, 59 per cent of the total rise is explained.

A further possibility is that the magnitude of the transitory component of income is greater in the first cohort. Erikson and Goldthorpe (2010) focus on transitory variations in income as the most likely source of bias in the income mobility results and imply that social class is a more stable measure. We seek to capture transitory income variation by predicting income based on characteristics at age 16 that have changed since age 10. Our investigations show that measurable transitory income is responsible for only a small fraction of the observed changes in persistence.

Our decomposition approach to account for transitory income variation indicates that around 43 per cent of the increased rise in intergenerational persistence is associated with within class permanent income and 9 per cent with the increased importance in transitory parental income on sons' outcomes. This still leaves a large element unexplained, but enables us to provide an upper and lower bound on how much of the change in intergenerational persistence is genuine. The lower bound treats the entire unexplained rise as measurement error and says that the true rise is a statistically significant 6.6 points rather than the observed 11.4. This, however, ignores that in the BHPS these predictors account for only about 40 per cent of permanent family income differences. If the rest of permanent family income variation behaved in the same way as the observed permanent income then the headline rise in persistence across generations would be exceeded, leading to the conclusion that the observed pattern is highly plausible.

Income inequality rose strongly through the 1980s (see Brewer et al. 2008, for a recent summary), and in a companion paper, Blanden (2011) finds a strong association between intergenerational income persistence and cross-sectional income inequality based on international comparisons. It seems plausible that the divergence in trends in intergenerational mobility for income and social class in the UK is related to the growth in within-class income inequality over the same period. It should be noted, however, that evidence from the US is very unclear as to whether increasing income inequality there has occurred primarily between social class groups or within them (Weeden et al, 2007, and Kim and Sakamoto, 2008). There is no comparable evidence for the UK and is an area that requires future research.

Intergenerational income and social class mobility capture different things. Social class reflects job autonomy and wider social capital while income and earnings reflect economic opportunities. In this study we find limited common ground between the two approaches. We show that social class is a poor proxy for permanent income, and that there are good reasons why the trends for economic and social mobility differ for those growing up in 1970s and 80s Britain, as inequality grew.

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Table 1A: Components of Permanent Childhood and Current Income in the BHPS

	% share of variance
Permanent childhood income, components associated with:	
Fathers' social class ($\hat{\delta}_p SC_{fi}$)	15.67
Other income predictors ($\hat{\gamma}_p X_{pi}$)	23.38
Residual permanent income ($\hat{\varepsilon}_{pi}$)	60.96
Current childhood income, components associated with:	
Fathers' social class ($\hat{\lambda}_p SC_{fi}$)	7.53
Other income predictors ($\hat{\phi}_p X_{pi}$)	18.48
Residual permanent income ($\hat{\varepsilon}_{pi}$)	39.76
Error ($\hat{e}_{pi}$)	34.22

Note: This methodology has been replicated using the father's modal social class instead: measured social class changes and and cannot be thought of as permanent. As expected this measure accounts for a larger percentage share of the variation in permanent income (25 per cent as opposed to 16 per cent) suggesting that class measured at a single point in time has limitations as a measure of 'permanent class'.

Table 1B: Correlation matrix between components of income in BHPS

	Permanent income components			
Current income components	Total permanent income	Fathers' social class ($\hat{\delta}_p SC_{fi}$)	Other income predictors ($\hat{\gamma}_p X_{pi}$)	Residual permanent income ($\hat{\varepsilon}_{pi}$)
Total current income	0.735	0.294	0.446	0.539
Fathers' social class ($\hat{\lambda}_p SC_{fi}$)	0.398	0.951	0.347	-0.152
Other income predictors ($\hat{\phi}_p X_{pi}$)	0.525	0.338	0.832	0.000
Residual permanent income ($\hat{\varepsilon}_{pi}$)	0.707	-0.160	0.000	1.000
Error ($\hat{e}_{pi}$)	-0.007	-0.001	0.000	-0.009

Notes:
1. N=1206
2. Other income characteristics; parental education, parental age, parental employment, housing tenure, self reported financial difficulties and region all from the last observed period
3. Fathers' Social class is from last recorded period
4. Permanent income measured as an average of all income observations across time; min obs=7 max obs=16, 30% 14 obs or more, 65% 10 obs or more.
5. Current income is from the last data point available for the family.

Table 2: Changes in Intergenerational Mobility using Family Income at age 16 and Sons' Earnings (at age 33 NCDS and 30 BCS): Elasticities and Partial Correlations

	NCDS	**BCS**	**Difference**
$\hat{\beta}$	0.211 (.026)	0.278 (.021)	0.067 (.034)
Partial correlation ($\hat{r}$)	0.172 (.021)	0.280 (.022)	0.107 (.030)
N	2163	1976	
Cohort members living with both parents	**NCDS**	**BCS**	**Difference**
$\hat{\beta}$	0.219 (.027)	0.289 (.022)	0.070 (.034)
Partial correlation ($\hat{r}$)	0.176 (.021)	0.290 (.022)	0.114 (.031)
N	2109	1932	

Notes:

1. These figures differ very slightly from those Blanden, Gregg and Macmillan (2007) table 4 because parental age controls are not included.
2. Standard errors are in parentheses.

Table 3: Changes in Income Mobility:
Transition Matrices of Quintiles of Family Income and Sons' Earnings

NCDS						**BCS**					
	Destination (earnings at 33)						**Destination (earnings at 30)**				
Origin (inc at 16)	**1**	**2**	**3**	**4**	**5**	**Origin (inc at 16)**	**1**	**2**	**3**	**4**	**5**
1	5.5	4.8	3.4	3.9	2.5	**1**	7.1	4.9	3.2	3.6	2.4
2	4.7	4.4	4.2	3.5	3.2	**2**	5.0	4.5	3.9	3.1	2.9
3	4.3	4.2	4.7	3.8	3.8	**3**	3.9	4.6	4.5	4.8	3.1
4	3.2	3.6	3.8	4.4	4.5	**4**	2.5	3.4	4.1	4.6	4.4
5	2.3	3.1	3.9	4.6	5.9	**5**	1.7	2.7	4.1	3.9	7.2

Notes:

1. Sample sizes 2109 in the NCDS and N=1932 in the BCS
2. Cells indicate the proportions of each origin quintile in each destination earning quintile
3. If society was perfectly mobile, every cell would contain 4%
4. Total mobility is significantly different at the 1% level across the cohorts using a log linear model to test the difference. Cells on the diagonal and one cell either side are considered immobile. All others are mobile.

Table 4: Changes in Fathers' and Sons Social Class Mobility: Distribution of Origin and Destination Social Classes

NCDS								
	Destination							
Origin	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Σ**
1	6.0	4.9	1.7	0.9	0.9	1.9	2.6	**19.0**
2	7.0	7.3	1.9	1.8	2.1	4.4	6.3	**30.8**
3	1.4	1.4	0.4	0.5	0.3	1.0	1.2	**6.3**
4	1.3	1.0	0.3	1.5	0.2	0.6	1.1	**5.8**
5	1.3	1.4	0.6	0.5	1.1	2.1	2.7	**9.7**
6	1.6	2.3	1.0	0.8	1.4	3.6	6.1	**16.7**
7	1.0	1.0	0.3	0.4	0.8	2.4	5.7	**11.7**
Σ	**19.5**	**19.3**	**6.2**	**6.4**	**6.9**	**16.1**	**25.6**	**100**

BCS								
	Destination							
Origin	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Σ**
1	3.6	1.5	2.0	1.1	0.8	2.5	1.2	**12.7**
2	5.6	3.8	4.3	1.6	1.6	5.0	3.6	**25.4**
3	1.9	1.4	1.7	0.9	0.7	2.3	1.6	**10.4**
4	1.9	1.3	1.2	1.6	0.5	2.7	1.8	**11.1**
5	0.7	0.6	0.7	0.2	0.7	1.8	1.5	**6.1**
6	1.6	1.5	1.8	1.1	1.3	5.9	5.5	**18.7**
7	0.9	0.7	1.1	0.6	1.3	4.4	6.6	**15.6**
Σ	**16.3**	**10.7**	**12.8**	**7.1**	**6.9**	**24.5**	**21.8**	**100**

Notes:

1. Sample sizes 3,858 in the NCDS and 3,810 in the BCS
2. Cells indicate the proportions of each origin social class in each destination social class
3. Social class 1, Non-skilled manual; Social class 2, Skilled manual; Social class 3, Lower grade technicians; Social class 4, Self employed; Social class 5, Routine non-manual; Social class 6, Lower grade managers; Social class 7, Professionals.
4. The last column and bottom row give the sum of all other columns and rows.

Table 5: Summary statistics of changes in relative class mobility across cohorts and samples

Income measures			Social class measures				
	Income sample (Cohort members living with both parents)			Social class sample		Income sample (Cohort members living with both parents)	
	NCDS	BCS		NCDS	BCS	NCDS	BCS
Proportion of those in top income quintile remaining there	30%	37%	Proportion of those in top two origin social classes remaining there	63%	65%	68%	67%
Proportion of those in bottom income quintile moving to the top	13%	11%	Proportion of those in bottom two origin social classes moving to the top two	31%	32%	35%	35%
Relative odds	2.39	3.19	Relative odds	2.04	2.02	1.95	1.94
Proportion of those in bottom income quintile remaining there	27%	34%	Proportion of those in bottom two origin social classes remaining there	51%	38%	48%	40%
Proportion of those in top income quintile moving to the bottom	12%	8%	Proportion of those in top two origin social classes moving to the bottom two	21%	13%	16%	13%
Relative odds	2.32	3.97	Relative odds	2.45	2.78	3.02	2.95

Notes:

1. Sample sizes for income measures; 2109 in the NCDS and N=1932 in the BCS for income sample
2. Sample sizes for social class measures; 3,858 in the NCDS and 3,810 in the BCS for the social class sample.
3. Sample sizes for social class measures; 1,729 in the NCDS and 1,646 in the BCS for income sample with no lone parents. (Note this differs from 1 as fathers' social class is missing for some families where income is reported).
4. The restriction to no lone parents makes almost no difference to these statistics as only very few of those we define as lone parents have information on social class.

Table 6: Comparisons of age 16 income data from the cohorts with comparable FES data

	5th percentile	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile	95th percentile
NCDS income data at age 16	£22.50	£27.50	£35.40	£47.45	£59.54	£74.31	£83.60
FES in 1974	£26.97	£34.15	£44.94	£58.06	£75.15	£96.84	£111.65
Gap	20%	24%	28%	22%	26%	30%	34%
BCS income data at age 16	£84.43	£91.43	£125.54	£165.91	£225.37	£325.71	£368.03
FES in 1986	£73.78	£92.56	£142.19	£202.38	£267.18	£357.26	£424.98
Gap	13%	1%	13%	22%	19%	10%	16%

Notes:

1. Incomes reported are in current prices.
2. The figures for the cohorts refer to all observations with age 16 income reports.
3. Figures for the FES in the relevant years are based on households which include at least one child aged between 10 and 16. The samples obtained are 4247 for 1974 and 3781 for 1986.
4. Family income for the 1974 FES comparison is total net household income, for the 1986 comparison it is net parental income plus non-means tested benefits. The difference is because the BCS parents are asked to exclude the incomes of other household members.

Table 7: R-Squared for Father's Social Class Predicting Income for Alternative Samples

	GHS 74/75	NCDS	GHS 86/87	BCS
Income – full sample	0.143 [4271]	0.079 [2109]	0.238 [2623]	0.196 [1932]
Combined income – dad employed	0.144 [3944]	0.092 [1917]	0.279 [2238]	0.200 [1163]
Combined income – either employed	0.147 [4091]	0.079 [2020]	0.251 [2378]	0.196 [1237]
Percentage of dads employed	92.3	90.9	85.2	86.2

Notes:
1. Sample sizes are given in square brackets.

Table 8: Decomposition of Income Mobility Changes – Social class only

NCDS	$\hat{\lambda}_s SC_{si}$	$\hat{v}_{si} + \hat{e}_{si}$	**Total**
$\hat{\lambda}_p SC_{fi}$	0.068	0.010	**0.078**
$\hat{v}_{pi} + \hat{e}_{pi}$	-0.006	0.103	**0.097**
Total	**0.062**	**0.114**	**0.176**
BCS	$\hat{\lambda}_s SC_{si}$	$\hat{v}_{si} + \hat{e}_{si}$	**Total**
$\hat{\lambda}_p SC_{fi}$	0.054	0.039	**0.093**
$\hat{v}_{pi} + \hat{e}_{pi}$	0.066	0.130	**0.197**
Total	**0.120**	**0.170**	**0.290**

Notes:
1. Sample sizes 2,109 and 1,932
2. Notation refers to notation in text
3. Each cell represents a covariance scaled by the total variance as illustrated in equation (14)

Table 9: Decomposition of Parental Income Variance: NCDS, BCS and BHPS cohorts

NCDS current income	y_p	$\hat{\lambda}_p SC_{fi}$	$\hat{\phi}_p X_{pi}$	$\hat{\varepsilon}_{pi} + \hat{e}_{pi}$
Variance	0.1381	0.0115	0.0435	0.0830
Percentage of total variance		8.36	31.53	60.11
BCS current income	y_p	$\hat{\lambda}_p SC_{fi}$	$\hat{\phi}_p X_{pi}$	$\hat{\varepsilon}_{pi} + \hat{e}_{pi}$
Variance	0.2248	0.0463	0.0590	0.1195
Percentage of total variance		20.60	26.24	53.16
BHPS current income	y_p	$\hat{\lambda}_p SC_{fi}$	$\hat{\phi}_p X_{pi}$	$\hat{\varepsilon}_{pi} + \hat{e}_{pi}$
Variance	0.2715	0.0204	0.0502	0.2009
Percentage of total variance		7.53	18.48	73.99

Notes:

1. X_{pi} for the BHPS is detailed in the notes to Table 1B.
2. X_{pi} for the cohorts is parental education, parental age, maternal employment at birth, 7/5, 11/10 and 16, fathers' employment at 11/10 and 16, region at 11/10 and 16, housing tenure at 11/10 and 16, free school meals status at 11/10, lone parent at birth, 7/5and 16 and self reported financial difficulties at 16.
3. Samples: NCDS, 2109, BCS, 1932, BHPS 1206
4. Notation refers to notation in text
5. Table 9 is based on banded income data for the cohorts but continuous income information in the BHPS. We have explored converting the BHPS into comparable bands and find that this does not influence the broad conclusion that the BHPS and cohort data are similar on the explored dimensions. See Appendix Table B4

Table 10: Decomposition of Income Mobility Changes – Social class and other permanent income predictors

NCDS	$\hat{\lambda}_s SC_{si}$	$\hat{\phi}_s X_{si}$	$\hat{\varepsilon}_{si} + \hat{e}_{si}$	Total
$\hat{\lambda}_p SC_{fi}$	0.068	0.027	-0.016	**0.078**
$\hat{\phi}_p X_{pi}$	0.014	0.030	0.030	**0.074**
$\hat{\varepsilon}_{pi} + \hat{e}_{pi}$	-0.020	-0.002	0.045	**0.023**
Total	**0.062**	**0.054**	**0.059**	**0.176**
BCS	$\hat{\lambda}_s SC_{si}$	$\hat{\phi}_s X_{si}$	$\hat{\varepsilon}_{si} + \hat{e}_{si}$	**Total**
$\hat{\lambda}_p SC_{fi}$	0.054	0.033	0.006	**0.093**
$\hat{\phi}_p X_{pi}$	0.053	0.036	0.037	**0.126**
$\hat{\varepsilon}_{pi} + \hat{e}_{pi}$	0.014	0.018	0.039	**0.071**
Total	**0.120**	**0.087**	**0.082**	**0.290**

Notes:
1. Sample sizes 2,109 and 1,932
2. Notation refers to notation in text
3. Each cell represents a covariance scaled by the total variance as illustrated in equation (16)
4. X_{pi} for the cohorts is as for Table 9.
5. $X_{si}$is the number of GCSEs at grades A-C, number of A-levels, staying on decisions at 16 and 18, degree attainment, proportion of time spent as a NEET 16-24, housing tenure at 33/30, car ownership at 33/30, pension contributor at 33/30

Table 11: Correlations of current income associated with our Xs with permanent and transitory income in the BHPS

	Permanent income (average)	Transitory income (current-average)
Variables used to predict permanent income		
Mum's education	0.4337	-0.0966
Dad's education	0.4101	-0.1015
Social housing	-0.3260	0.0867
Rented accommodation	-0.0449	0.0811
Financial difficulties	-0.3170	-0.1452
Age	0.1475	-0.1161
Variables used to predict transitory income		
Dad employed	0.1284	0.0807
Mum employed	0.0984	0.0961
Region	0.0798	-0.0166

Notes:
1. All characteristics in the BHPS measured in the last observed period
2. Our sample restriction of couples only prevents us from measuring lone parent status
3. Transitory income is calculated as the deviation of current income in the last observed period from average income across all observed periods.
4. The correlations are between current income associated with each of the Xs and permanent and transitory income

Table 12: Decomposition of Income Mobility Changes –
Social class, other permanent income predictors and transitory income predictors

NCDS	$\hat{\lambda}_s SC_{si}$	$\hat{\phi}_s X_{si}$	$\hat{\varepsilon}_{si} + \hat{e}_{si}$	**Total**
$\hat{\lambda}_p SC_{fi}$	0.068	0.027	-0.016	**0.078**
$\hat{\theta}_p X_{pi}^{P}$	0.017	0.026	0.026	**0.068**
$\hat{\vartheta}_p X_{pi}^{T}$	0.010	0.010	0.002	**0.022**
$\hat{\varepsilon}_{pi} + \hat{\varphi}_{pi} + \hat{\eta}_{pi}$	-0.033	-0.008	0.048	**0.007**
Total	**0.062**	**0.054**	**0.059**	**0.176**
BCS	$\hat{\lambda}_s SC_{si}$	$\hat{\phi}_s X_{si}$	$\hat{\varepsilon}_{si} + \hat{e}_{si}$	**Total**
$\hat{\lambda}_p SC_{fi}$	0.054	0.033	0.006	**0.093**
$\hat{\theta}_p X_{pi}^{P}$	0.050	0.032	0.033	**0.116**
$\hat{\vartheta}_p X_{pi}^{T}$	0.013	0.011	0.008	**0.032**
$\hat{\varepsilon}_{pi} + \hat{\varphi}_{pi} + \hat{\eta}_{pi}$	0.003	0.011	0.036	**0.049**
Total	**0.120**	**0.087**	**0.082**	**0.290**

Notes:

1. Sample sizes 2,109 and 1,932
2. Notation refers to notation in text
3. Each cell represents a covariance scaled by the total variance as illustrated in equation (19)
4. X_{pi}^{P} : parental education, parental age, maternal employment at birth, 7/5 and 11/10, fathers' employment at 11/10, region at 11/10, housing tenure at 11/10, free school meals status at 11/10, lone parent at birth and 7/5 and self reported financial difficulties at 16
5. X_{pi}^{T} maternal employment 16, fathers' employment at 16, region at 16, housing tenure at 16 and lone parent at 16.
6. X_{si} as for Table 10.

Appendix A: Additional Tables

Table A1: Background regressions for fathers' social class and Xs

	NCDS	BCS
$y_{pi} = \hat{\lambda}_p SC_{fi} + \hat{\upsilon}_{pi}$		
Social class 2 – Skilled manual	0.112 (.024)	0.098 (.036)
Social class 3 – Lower grade technicians	0.130 (.038)	0.173 (.044)
Social class 4 – Self employed	0.054 (.053)	0.223 (.047)
Social class 5 – Routine non-manual	0.150 (.033)	0.251 (.047)
Social class 6 – Lower grade managers	0.289 (.029)	0.450 (.038)
Social class 7 – Professionals	0.351 (.032)	0.666 (.040)
Constant	7.045 (.019)	6.947 (.029)
R-squared	0.079	0.196
$\hat{\upsilon}_{pi} = \hat{\phi}_p X_{pi} + \hat{\varepsilon}_{pi} + \hat{e}_{pi}$		
Dad left education before school leaving age	0.007 (.020)	0.027 (.028)
Dad left education 16-18	0.055 (.021)	-0.053 (.036)
Dad higher education	0.109 (.029)	0.002 (.038)
Mum left education before school leaving age	0.014 (.018)	0.089 (.026)
Mum left education 16-18	0.033 (.021)	0.120 (.031)
Mum higher education	0.065 (.034)	0.252 (.043)
Mum employed at birth of son	-0.050 (.015)	-0.020 (.045)
Mum employed at 5	0.021 (.016)	0.009 (.019)
Dad employed at 10	0.091 (.048)	-0.000 (.049)
Mum employed at 10	-0.069 (.018)	0.037 (.020)
Dad employed at 16	0.270 (.031)	0.162 (.035)
Mum employed at 16	0.201 (.016)	0.099 (.025)
Social housing at 10	0.076 (.024)	0.039 (.026)
Renting at 10	0.055 (.035)	0.044 (.064)
Social housing at 16	-0.076 (.023)	-0.226 (.028)
Renting at 16	-0.098 (.035)	-0.218 (.077)
Lone parent at birth	-0.083 (.047)	0.078 (.046)
Lone parent at 5	0.054 (.084)	-0.045 (.064)
Lone parent at 16	0.246 (.176)	-0.338 (.049)
Free school meals at 11/10	0.094 (.033)	-0.056 (.040)
Financial difficulties at 11/10	-0.101 (.027)	-0.204 (.027)
Region at 10 – North	-0.056 (.083)	-0.009 (.089)
Region at 10 – Yorkshire	0.070 (.068)	-0.039 (.075)
Region at 10 – North West	0.077 (.065)	-0.112 (.074)
Region at 10 – Midlands	-0.002 (.056)	-0.078 (.054)
Region at 10 – East	-0.036 (.061)	-0.083 (.077)
Region at 10 – South West	-0.089 (.067)	-0.197 (.063)
Region at 10 – Wales	0.028 (.103)	-0.071 (.080)
Region at 10 - Scotland	-0.032 (.085)	-0.075 (.084)
Region at 16 – North	0.034 (.081)	-0.161 (.083)
Region at 16 – Yorkshire	-0.118 (.066)	-0.105 (.071)
Region at 16 – North West	-0.091 (.063)	-0.063 (.069)
Region at 16 – Midlands	-0.025 (.055)	-0.051 (.051)
Region at 16 – East	0.003 (.059)	-0.011 (.067)

Region at 16 – South West	-0.049 (.065)	0.027 (.054)
Region at 16 – Wales	-0.057 (.101)	-0.129 (.073)
Region at 16 - Scotland	0.020 (.084)	0.016 (.080)
Constant	-0.669 (.312)	-0.432 (.353)
R-squared	0.339	0.323

Notes:
1. Omitted class in social class regressions is ‘unskilled manual’.
2. Omitted parents’ education level ‘School leaving age’, Omitted housing tenure ‘Owned’. Omitted region ‘South East’
3. NCDS Sample size: 2109, BCS Sample size: 1932.

Table A2: Background regressions for sons’ social class and Xs

	NCDS	BCS
$y_{si} = \hat{\lambda}_s SC_{si} + \hat{\upsilon}_{si}$		
Social class 2 – Skilled manual	0.120 (.034)	0.218 (.038)
Social class 3 – Lower grade technicians	0.185 (.045)	0.277 (.034)
Social class 4 – Self employed	0.074 (.110)	0.358 (.190)
Social class 5 – Routine non-manual	0.180 (.042)	0.170 (.042)
Social class 6 – Lower grade managers	0.316 (.034)	0.392 (.031)
Social class 7 – Professionals	0.553 (.031)	0.645 (.031)
Constant	7.165 (.024)	7.103 (.024)
R-squared	.160	.209
$\hat{\upsilon}_{si} = \hat{\phi}_s X_{si} + \hat{\varepsilon}_{si} + \hat{e}_{si}$		
O level/GCSE	0.005 (.004)	0.011 (.004)
Stay on at 16	0.034 (.027)	-0.018 (.025)
A levels	0.044 (.013)	0.021 (.010)
Stay on at 18	-0.017 (.034)	0.035 (.032)
Degree	0.094 (.034)	0.024 (.030)
Proportion of time NEET	-0.495 (.076)	-0.421 (.062)
Pension contributer at 33/30	-0.012 (.022)	0.062 (.020)
Owns home at 33/30	0.335 (.085)	0.178 (.031)
Rents home at 33/30	0.166 (.089)	0.096 (.034)
No car	-0.050 (.027)	-0.010 (.031)
Constant	-0.277 (.086)	-0.188 (.033)
R-squared	.134	.089

Notes:
1. Omitted class in social class regressions is ‘unskilled manual’.
2. Omitted housing tenure ‘Social housing’.
3. NCDS Sample size: 2109, BCS Sample size: 1932.

Appendix B: Data

The Income Variables

There are clear limitations in the gathering of income data in both the NCDS and BCS. As noted throughout the paper, the most important issue is whether the NCDS parental income data is measured more poorly than the BCS data. In order to help readers assess this issue we provide more detailed information on the precise nature of the questions posed, responses given and the manipulations made to the data prior to estimation.

The income question in the NCDS at age 16 is:

'Ask the informant(s) to indicate the range in which the members of the household's usual net income falls (i.e. after all deductions at source viz. income-tax, health contributions, pensions etc. Include bonuses, commissions, overtime pay, etc if this is usually received). Please show the informant(s) the following section and ask them to indicate the approximate range in which the net income of members of the household falls. Either (i) the weekly or (ii) the monthly income is required whichever the informant(s) finds it most convenient to give.'

The question is asked for three components 'father's net pay', 'mother's net pay' and 'net income from all other sources' (note that this last includes the earnings of other members of the household and benefits received from the state).

For all three components the respondents are asked to indicate one of 12 bands either in weekly or monthly amounts, where the weekly and monthly bands are designed to correspond to the same annual income.

The BCS parental income data at age 16 is not reported by component. Instead, parents are asked to indicate which band (from 11) their gross total weekly income falls into.

More precisely; 'Please show the following table of incomes to the respondent and ask her to mark the income band which is appropriate. The figures refer to the COMBINED GROSS INCOME OF THE CHILD'S MOTHER AND FATHER (Do not include Child Benefit but include all other earned and unearned income before deductions for tax, national insurance etc.)

The raw data obtained is presented in Tables B1 and B2 below, and in both surveys the parental income reports appear to be reasonably well spread across the categories.

However, the different forms of the questions present issues in ensuring comparability. In the NCDS, There is some ambiguity in terms of what missing reports for each component mean: does it mean that families have no income from this source or simply that the information is missing? If it is the case that a component is missing then there is an argument for dropping the observation. This issue is considered in some detail in a data note by Micklewright (1986) and we have followed his advice in excluding families where a parent's earnings are missing but they are reported to be working in another part of the questionnaire. We also exclude the 2,555 families who indicated that they did not answer one of the income components because they 'did not know' 'would not give an answer' or did not answer for unknown reasons.

There may be some concern about the nature of the banded data in each cohort given that one measure is the combined sum of three separate banded components and the other is a single banded measure of total family income. On the one hand we may expect that combining three sources of income produces a more detailed estimate of family income in the NCDS. Alternatively it may be thought that reporting one's total income within a band is likely to be measured with less error.

In a recent work Micklewright and Schnef (2010) discuss the reliability of 'single income questions' such as the one used in the British Cohort Study. They have a number of findings that are relevant here. Comparing income distributions from the ONS omnibus survey and the British Social Attitudes Survey (single questions) with the Family Resources Survey (income information comes from detailed questioning) they find that single questions are particularly poor at capturing income when one individual is asked to report income for the household; individuals do better in reporting individual incomes. In addition they find that women do markedly worse when reporting income through a single question. Unfortunately, in both cohorts roughly 90% of respondents is the mother alone. These observations doubtless indicate another source of unreliability which applies to the cohort studies. However, it is worth noting that the exploration of three components may lead to more accurate income reports in the NCDS.

In order to use banded data as an explanatory variable in the usual intergenerational model it must be converted it into a continuous form. One possibility is to use the midpoint of the band in which the observation lays. But this does not take account of the underlying distribution of data. This is resolved in two ways. For the NCDS we assign each component a single value which is the median for this component for families in this band in the Family Expenditure Survey (FES) in the years around 1974, the extent to which this shifts the final values is shown in Table B3.[1] Family income is generated by summing these variables. Combining information on three components means that the final income distribution has 77 different values.

For the BCS, where there is only one banded variable, we use maximum likelihood estimation to model a Singh-Maddala or Burr distribution for the data. This provides an expected value within each band which is applied to all families. It also enables an appropriate value to be applied to the upper band. The fitted values drawn from the distribution are described in column 2 of table B2. This method is chosen rather than an interval regression technique as the underlying distribution is more appropriate for income than the normal distribution that the interval regression technique draws from. As discussed later and shown in table B5, this choice makes little difference to our findings. In principle, it

[1] It is possible to choose many different ways of doing this, changing the selection of the families, the years and the income measure used. As we show later the approach taken to this does not make any difference so we do not focus on these details here.

should also be possible to estimate the distribution based on the 77 unique categories in the NCDS, but the fact that the upper and lower bounds for the categories are not exclusive means that this is computationally impractical.

The methods of data collection indicate some clear problems with the comparability of the parental income data across the cohorts. First, there are clearly many more unique values possible for the NCDS than the BCS. To examine the consequences of the different question structures we replicate the banding procedures used in the cohorts in the BHPS using continuous fathers' earnings, mothers' earnings, other income, and total measured and permanent income measures. By applying the same proportions in each band in the cohort studies to the three separate components of father's earnings, mother's earnings and other income in the BHPS and summing the midpoints we can recreate the structure of the NCDS variable. Similarly by banding the total measured income variable in the BHPS by the proportions in each band in the BCS we can recreate the structure of the BCS variable. We replicate Table 1A from our main analysis using these banded measures (see Table B4) and find negligible differences in the total variances predicted.

The second problem faced is that the NCDS income components are reported as net of tax while the BCS asks for gross income. To account for this, we refer across to the FES data for the appropriate year (in this case 1986) where incomes are reported both net and gross. We can then calculate the proportion paid in tax by families in each band and subtract the median of this from the expected value obtained in the Singh-Maddala distribution for the BCS.[2] The proportion subtracted in tax is zero for the first two income bands (up to £100 a week in 1986 prices) and rises up to 26% in the top income band (those with incomes of £500 or more). Note that we do not attempt to adjust for other deductions, such as pension contributions. The final difficulty is that the NCDS income question clearly asks parents to

[2] Singh and Madalla (1976). Many thanks to Christopher Crowe for providing his stata program smint.ado which fits Singh-Maddala distributions to interval data.

include child benefit, whereas the BCS data asks that it be excluded. We therefore impute a value for child benefit based on the number of children in the household (and lone parent status for the BCS). The estimates reported use data where this amount is added to the BCS income, but we have also experimented with subtracting it from the NCDS instead. Child benefit rates for 1974 and 1986 were obtained from the Institute for Fiscal Studies web site http://www.ifs.org.uk/taxsystem/contentsben.shtml.

Despite our best efforts, the resulting variables are still not completely comparable. The NCDS income variable is capturing something close to net household income, but the BCS variable is capturing net parental income. It is impossible to estimate the income of other household members which is explicitly excluded in the BCS but included in the NCDS. Both of the resulting concepts can be captured in the FES and Figures A1 and A2 shows the evolution of their medians and variances over several years. As we might anticipate the NCDS equivalent measure is slightly higher in all years, but what is more important for us is that there is very little difference in the variances.

Both the NCDS and BCS data are manipulated from their raw form, and some of the approaches used in the original analysis might be considered rather arbitrary. For example, it would be possible to base the adjusted midpoints on a different selection of FES families and years, or to use Stata intreg function rather than the Singh-Madalla distribution. We have conducted a number of robustness checks on these issues, presented in Table B5. As can be seen from the table, the choice of method used does not affect the results. We have also experimented with changing the approach taken to ensuring the comparability of the income variables through adding child benefit and removing tax from parental income in the BCS. Investigations reveals that these manipulations influence the variances of the income variables but have a minimal affect on the ranking of incomes across families. As a consequence they influence the estimates of beta but have very little effect on the estimated partial correlations ($\hat{r}$) which we focus on here. To take an extreme example, if no adjustment is made in the BCS for tax, child benefit or the midpoints (and the midpoint for the upper category is set to £625) $r = .275$.

There is one final concern with the parental income data, which relates to the NCDS only. In 1974, when the age 16 data was being collected for this cohort, Britain was in the midst of a three-day working week brought about by unrest in the coal industry. There may be some concern that the people who reported their incomes during this period were reporting their reduced income rather than their usual weekly or monthly income, despite the use of the word ‘usual’ in the question. If there is misreporting in the NCDS due to this, there may be greater measurement error in the first cohort biasing down the mobility coefficient and exaggerating any measured change. One way to test for this is to restrict our sample to those who report specifically during the two months of 1974 that were affected by the three-day week strikes, January and February. If there was reporting bias leading to measurement error during this period we would expect the mobility coefficient and partial correlation to both be considerably smaller if we restrict the sample to just there individuals. As can be seen from table B6, this sample restriction does very little to the mobility coefficient and actually increases the strength of the partial correlation contrary to what we would expect to find in the presence of attenuation bias.

The Social Class Variables

Father’s social class is measured at various ages in childhood but for consistency we follow Goldthorpe and Jackson (2007) in using Heath and McDonald’s (1987) coding from Socio-Economic Group to seven-category social class at age 11/10. The classifications are given in Goldthorpe and Jackson’s Table 1 and are replicated here are Table B7. The main concession that is made in coding these variables is that self-employed workers with less than 25 employees (class IVa) are combined with lower grade professionals and managers in class II.

Aside from this minor point the coding of origin social class appears fairly straight-forward. However, it is important to note that parents were asked to give details of the fathers ‘job’ and secondly their ‘trade, industry or profession’ it is from this information that Socio-Economic Group is coded. Although it is hard to know the extent of any coding problems that occurred it seems likely that a number of judgements were made in this process.

Attrition and Non-Response in the Cohort Studies

Table 2 in the main paper reports information on intergenerational income elasticities and correlations for around 2000 sons in each cohort. This is a much reduced sample compared to the numbers selected to be included in the original cohorts. As noted in the main body of the paper, differences in the samples for the income and social class are unable to explain the differences in trends that are found. Nonetheless it seems important to give some information about the attrition and non-response patterns in the cohorts. For even more detail see Plewis et al (2004).

Table B8 shows how the sample sizes evolve across the sweeps of the surveys for both cohorts. The top line includes all individuals, including those who eventually die or emigrate and those who enter the sample in later childhood as immigrants (for more detail on this see Plewis et al, 2004). Both cohorts experienced a steady drop in the number of individuals as they move towards adulthood. This Table also demonstrates the impact of the survey methodology, as individuals remain in the sample frame even if they miss a sweep, it is possible for the sample size to increase as well as decrease between surveys. It is clear that this occurs between the age 16 and age 23 sweeps in the NCDS

In the bottom panel of Table B8 similar figures are displayed for the BCS sweeps. By the time we obtain earnings at 33 and 30 the proportion of men who are still participating is almost identical in the two cohorts (57 and 56 per cent). Unfortunately the age 16 data appears to be more problematic in the BCS, in this sweep only around half of the parents of the sample cohorts were interviewed. It is not clear what is behind the difficulties in the BCS cohorts at age 16.

Table B9 gives the response rates for some variables of interest. This is calculated as a proportion of cohort members who were included in the relevant survey. We might expect that questions about money might be particularly likely to suffer from item non-response, and this proves to be the case. In the age 16 data we have information on parental income for about three quarters of the cohort members included in that sweep. There is usable adult income information for more than two thirds of the adults in the relevant sweeps, but much of the loss here is accounted for by the unemployed and self-employed. Comparing the proportion of those in the surveys who have earnings variables with the proportion employed reveals that the earnings information is there for about 6 or 8 percentage points less of the sample than it should be.

Effects of Attrition and Non-response on Sample Size

The evidence presented so far points to several points of concern about the quality of the data used when analysing intergenerational income mobility in the cohorts. We rely on parental income age 16 and not only is there substantial attrition by this point, but only around 75% of families included in the sweep provide an answer to this question.

Table B10 presents the combined implications of non-response and attrition. It is clear that limiting the samples to those who have parental income data at age 16 has a huge effect on the samples. Just under half of the NCDS sample and less than 40 per cent of the BCS sample meet this restriction.

To be included in the intergenerational samples information is required on adult earnings; therefore the final sample is influenced by both the attrition into adulthood and any non-response to the earnings questions. When these are combined the impacts are very similar in the two cohorts, with around 20 per cent of the original sample used in the main income estimations. It is somewhat reassuring that the same final proportion of survey members remain in both samples, but we have seen that the points where the losses occur differ and the key issue is whether *the same* selection mechanisms are underlying this process in the two cohorts, and what the consequences are for the estimates of changing intergenerational mobility are over time.

The appendix to Blanden (2005) undertakes a fairly extensive analysis of both these points, which will only be summarised here. The first exercise undertaken is to explore the impacts of attrition and non-response on the socio-economic composition of the two samples.

The evidence obtained from this exercise suggest attrition patterns mean that the final samples for both cohorts have higher parental status and child outcomes than if non-response and attrition did not affect the surveys and there is also some evidence that this problem is more acute in the BCS than the NCDS. To illustrate: the average social class index of the NCDS is 3.76 for all male cohort members compared with 3.73 for the intergenerational sample; in the BCS the difference is 3.55 compared with 3.40, where 1 indicates managerial/professional fathers.

While the descriptive patterns are interesting they are not very informative about the consequences of sample selection for mobility. As we have shown one of the main concerns is the effect of limiting the samples to those who have parental income data at age 16 in the

BCS. However the BCS also contains information about parental income at age 10. By comparing the intergenerational estimates based on age 10 data ($\hat{\beta}_{10}$ and $\hat{r}_{10}$) for those who have age 16 income and those who do not we can evaluate how intergenerational relationships compare for those with age 16 income missing and for those who are included in the final sample. The evidence from this exercise is quite encouraging, $\hat{\beta}_{10}$ and $\hat{r}_{10}$ do not vary significantly by missing data at age 16. Using the raw data from age 10 as the independent variable (i.e. without attempting to ensure comparability with the NCDS data) the estimates for families with income at 16 (used in the lower panel of Table 2) are .237 (.024) for the elasticity and .235 (.024) for the partial and .249 (.017) for the elasticity (N=1667) and .247 (.017) for the partial for a wider group of children (N=3106) who live with both parents and have information on income at age 10. This suggests that the stronger intergenerational persistence observed in the BCS compared with the NCDS is not a consequence of missing data at 16.

Table B1: Raw parental income data from NCDS income questions

Weekly	Monthly	Fathers' earnings %	Mothers' earnings %	Other income %
£0-£4	£0-£17	0.17	9.10	55.15
£5-£9	£18-£40	0.38	20.98	14.77
£10-£14	£41-£60	0.92	28.32	8.79
£15-£19	£61-£80	2.44	19.76	7.13
£20-£24	£81-£105	11.03	12.95	5.76
£25-£29	£106-£125	19.77	4.99	2.94
£30-£34	£126-£145	21.33	2.26	1.97
£35-£39	£146-£170	14.71	0.87	1.35
£40-£44	£171-£190	10.41	0.30	0.84
£45-£49	£191-£210	5.91	0.18	0.46
£50-£59	£211-£255	5.55	0.16	0.30
£60+	£256+	7.38	0.12	0.52
	N	8,366	6,755	8,051

Table B2: Raw parental income data from the BCS

Weekly	Yearly	% of responses	S-M assigned values within band
Less than £50	Less than £2600	2.54	37.65
£50-£99	£2600-£5199	14.32	77.69
£100-149	£5200-£7799	14.04	122.89
£150-£199	£7800-£10399	14.52	171.44
£200-£249	£10400-£1299	11.60	221.41
£250-£299	£13000-£15599	9.16	271.74
£300-£349	£16000-£18199	5.93	322.10
£350-£399	£18200-£20799	3.58	372.45
£400-£449	£20800-£23399	3.23	422.69
£450-£499	£24000-£25999	1.49	472.91
£500 and over	£26000 and over	3.67	675.42
REFUSE TO ANSWER		5.92	.
UNCERTAIN		10.01	.
N		8,549.	7185

Table B3: Applied Adjusted Weekly Midpoints for the NCDS

Weekly	Monthly	Fathers' earnings	Mothers' earnings	Other income
£0-£4	£0-£17	2.98	3.27	2.5
£5-£9	£18-£40	7.42	7.79	7.5
£10-£14	£41-£60	13.26	12.38	12.5
£15-£19	£61-£80	18.48	17.34	17.5
£20-£24	£81-£105	22.79	22.17	22.5
£25-£29	£106-£125	27.61	27.10	27.5
£30-£34	£126-£145	32.42	32.33	32.5
£35-£39	£146-£170	37.42	36.99	37.5
£40-£44	£171-£190	42.20	41.50	42.5
£45-£49	£191-£210	47.58	47.42	47.5
£50-£59	£211-£255	54.00	55.64	55
£60+	£256+	72.11	62.00	65

Table B4: Components of Permanent Childhood and Current Income in the BHPS

	% share of variance	% share of variance	% share of variance
	Continuous BHPS	NCDS style banding	BCS style banding
Current childhood income, components associated with:			
Fathers' social class ($\hat{\lambda}_p SC_p$)	7.53	7.08	7.38
Other income predictors ($\hat{\phi}_p X_p$)	18.48	23.26	19.97
Residual permanent income ($\hat{\varepsilon}_p$)	39.76	36.59	37.69
Error	34.22	33.08	34.96

Notes:

1. The first column replicates table 1A in the main paper
2. The second column aggregates mothers' earnings, fathers' earnings and other income sources in the BHPS into proportions within each band in the NCDS, takes mid-points and sums to create a total income measure. Our variance analysis is then repeated.
3. The third column aggregates the continuous total family income measure in the BHPS into the proportions within each band within the BCS and takes midpoints. Our variance analysis is then repeated. As can be seen from table A5, this procedure is identical to the Singh-Madalla procedure in terms of our final results. We therefore use the simple method here for clarity

Table B5: Changes in Intergenerational Mobility using different approaches to the banding problem

	NCDS			BCS			
	Adjusted mid-points	**Interval regression**	**Unadjusted mid-points**	**Singh-Maddala**	**Adjusted mid-points**	**Interval regression**	**Unadjusted mid-points**
β	0.211 (.026)	0.207 (.026)	0.208 (.026)	0.278 (.021)	0.286 (.026)	0.272 (.026)	0.264 (.025)
Partial correlation (r)	0.172 (.021)	0.167 (.021)	0.173 (.021)	0.280 (.022)	0.279 (.025)	0.271 (.026)	0.271 (.026)
N	2163	2163	2163	1976	1976	1976	1976
				BCS			
Couples only	**Adjusted Mid points**	**Interval regression**	**Unadjusted Midpoints**	**Singh-Maddala**	**Adjusted mid-points**	**Interval regression**	**Unadjusted mid-points**
β	0.219 (.027)	0.215 (.028)	0.215 (.027)	0.289 (.022)	0.298 (.025)	0.285 (.026)	0.276 (.025)
Partial correlation (r)	0.176 (.021)	0.170 (.022)	0.176 (.022)	0.290 (.022)	0.290 (.025)	0.281 (.026)	0.281 (.026)
N	2109	2109	2109	1932	1932	1932	1932

Notes:

1. The results shown in the main body of the paper are based on the data in the first columns reported here.
2. Adjusted midpoints are determined by comparing the data with similar families in the FES as reported in the text. Most importantly the information on these families enables the closing of the open top band.
3. Unadjusted midpoints are the simple mid-points of each band, with the mid-point for the top band selected as $1/6^{th}$ higher than the lower band in each case.

Table B6: Estimates for the sample recorded during the Three-day week

Full sample	**NCDS**	**NCDS - three-day week**
β	0.211 (.026)	0.204 (.041)
Partial correlation (r)	0.172 (.021)	0.178 (.036)
N	2163	666
Couples only	**NCDS**	**NCDS – three-day week**
β	0.219 (.027)	0.219 (.044)
Partial correlation (r)	0.176 (.021)	0.185 (.037)
N	2109	649

Notes:

1. The three-day week sample is restricted to only those responding in January or February 1974 at the height of the three-day week

Table B7: Goldthorpe and Jackson's Social Class Schema: The Assignment of Socio-Economic Groups into a seven-class version of the Goldthorpe Scheme

	Coding of SEGS into Classes	
Class	NCDS	BCS
I: Professional administrators and managers, higher-grade	1, 3, 4	11, 12, 30, 40
II+Iva: Professional, administrators and managers, lower-grade, small employers, higher grade technicians.	2, 5	21, 22, 51, 52
III: Routine non-manual employees	6, 7	60, 70
IVb+c: Self-employed workers (including farmers)	12, 13, 14	120, 130, 140
V: Lower-grade technicians	8	80
VI: Skilled manual workers	9	90
VII: Non-skilled manual workers	10, 11, 15	10, 110, 150

Table B8: Attrition in the Cohorts

	National Child Development Study
Male cohort members	9593
In at age 7	7569 (.789)
In at age 11	7118 (.741)
In at age 16	5995 (.625)
In at age 23	6267 (.653)
In at age 33	5443 (.567)
	British Cohort Study
Male cohort members	9644
In at age 5	6787 (.704)
In at age 10	7711 (.800)
In at age 16	4738 (.491)
In at age 30	5405 (.560)

Notes:
1. The proportion of the total sample is in parentheses.
2. For the childhood sample responses are calculated on the basis of the presence of parent-reported variables, as these contain the data relevant for our analysis. In some cases the school questionnaire was returned when the parental questionnaire was not completed.

Table B9: Item non-response rates

	National Child Development Study Proportion of males in the relevant sweep with a valid observation
Income at 16	.764
Staying On observed at 23	.996
Education Information at 23	.999
Employment Status at 33	.999
(Employed at 33)	.745
Usable Earnings at 33	.684
	British Cohort Study Proportion of males in the relevant sweep with a valid observation
Income at 10	.840
Income at 16	.753
Staying On observed at 16	.613
Education Information at 30	.994
Employment Status at 30	.991
(Employed at 30)	.785
Usable Earnings at 30	.727

Table B10: The Combined Effect of Attrition and Non-Response

Variables	**National Child Development Study** Proportion of all male cohort members
Income at 16	.478
Income at 16 and Employed at 33	.276
Income at 16 and Earnings at 33	.226
	British Cohort Study Proportion of all male cohort members
Income at 16	.370
Income at 16 and Employed at 30	.229
Income at 16 and Earnings at 30	.205

Figure B1: Median FES parental income over time: NCDS and BCS equivalent measures

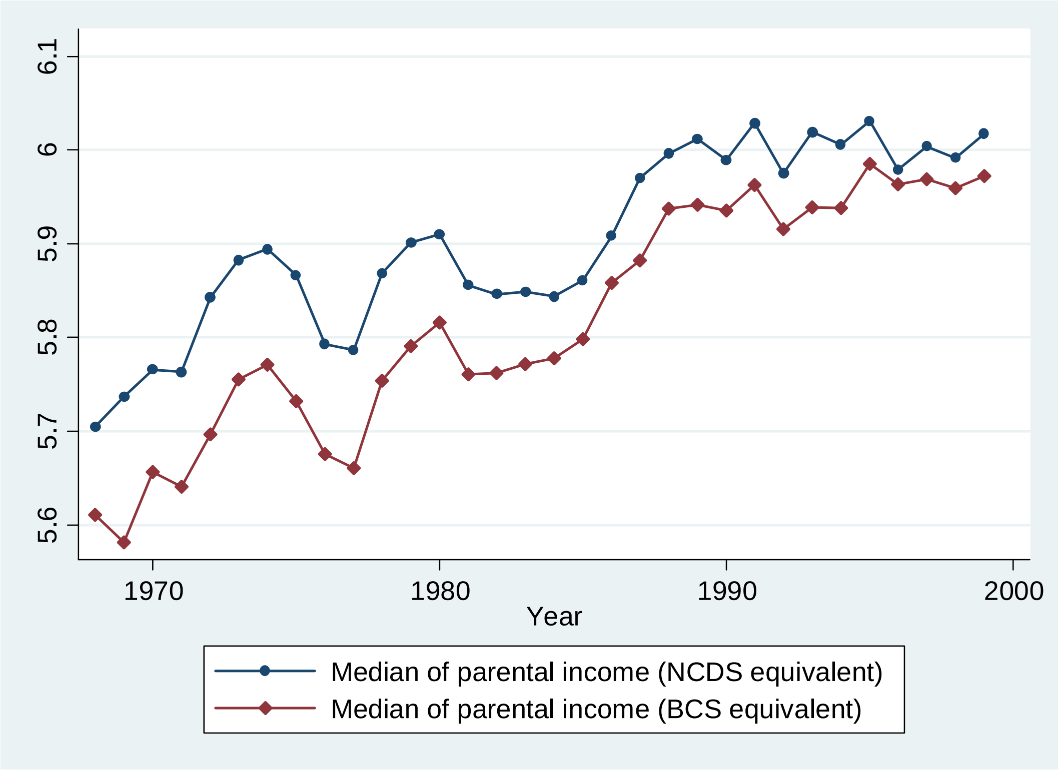
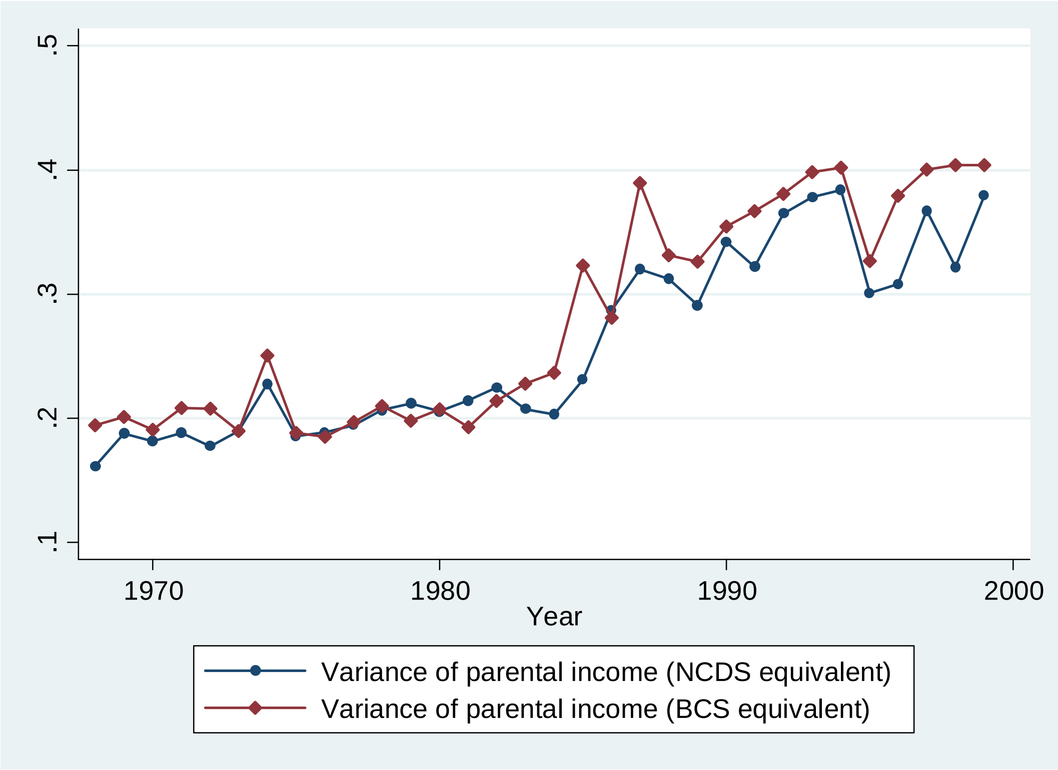


Figure B2: Variance in FES parental income over time: NCDS and BCS equivalent measures



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