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Working Paper No. 15-03
March 2015

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Nonlinear Estimation of Lifetime Intergenerational Economic Mobility and the Role of Education

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Abstract

Previous studies of intergenerational income mobility have typically focused at on estimating persistence across generations at the mean of the distribution of sons' earnings. Here, we use the relatively new unconditional quantile regression (UQR) technique to consider how the association between parental income in childhood and sons' adult earnings vary across the distribution of sons' earnings. We find a J-shaped relationship between parental income and sons' earnings, with parental income a particularly strong predictor of labour market success for those at the bottom, and to a greater extent, the top of the earnings distribution. We explore the potential role of early skills, education and early labour market attachment in this process. Worryingly, we find that education is not as meritocratic as we might hope, with the role of parental income dominating that of education at the top of the distribution of earnings. Early unemployment experience has long-lasting impacts on sorting those at the bottom, alongside parental income.

JEL codes: I20, J62, J24

Keywords: Intergenerational mobility, education, nonlinear

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Acknowledgements: This research has been funded under ESRC Grant RC-SP1069.

1. Introduction

Intergenerational economic mobility, the association between the socio-economic status (SES) of parents and children, has re-emerged as a topic of considerable attention in academia, policy circles and in the public domain in recent years. In the UK, the government has claimed to have made social mobility its key objective of social policy (Cabinet Office, 2011) establishing a statutory commission on Social Mobility and Child Poverty.[3] This has been driven, in part, by research that showed that Britain has a poor record on intergenerational mobility, both in terms of a decline in income mobility in the UK for a cohort born in 1970 compared to one born in 1958 (Blanden et. al, 2004) and that Britain has low mobility by international standards (Corak, 2013). While early studies focused on estimating the association between father's and son's earnings, there has been a recent shift in focus to studying the relationship between parental income in childhood and adult lifetime labour market earnings (Gregg et. al., 2014). Recent estimates of mobility therefore represent the extent to which adult outcomes mirror childhood circumstances and are an indicator of the persistence of inequality across generations.

The measure of persistence in incomes across generations most commonly estimated is the intergenerational elasticity (IGE), which provides an assessment of this relationship evaluated at the mean of the distribution of sons' earnings. Much of the recent literature has been concerned with estimating this relationship taking account of biases that arise from using point in time approximations of these lifetime concepts (see Black and Devereux, 2011, for an extensive discussion and Deaden et al 1997 and Gregg et al. 2014 for UK studies). While these studies describe the extent of intergenerational persistence on average for a given country at a given point in time, they tend not to address differences in the extent of intergenerational persistence across the distribution of income or earnings in either generation. There have been a small number of studies that have considered whether intergenerational mobility differs at different parts of the distribution of parental income (Bratsberg et al, 2007, Corak and Heisz, 1999), seeking to understand whether the association between family background and life chances are greater for those from the poorest or richest families. There has also been a small literature to date exploring nonlinearity in

[3] https://www.gov.uk/government/organisations/social-mobility-and-child-poverty-commission accessed 2.44pm, 8/12/14.

intergenerational persistence across earnings in the second generation using quantile regression (Eide and Showalter, 1999, Grawe, 2004 and Bratsberg et al. 2005).

There is a raft of evidence that the labour market in the UK, and many other countries, is producing a polarisation of employment opportunities, with employment growth focused on the highest and lowest paid occupations with a shrinking middle (Goos and Manning, 2007), combined with rising earnings inequality between jobs at the top and bottom of the earnings ladder (Machin, 2011). In a closely related vein, a number of studies have focused on a particular portion of the distribution of adult outcomes, exploring intergenerational poverty (Blanden and Gibbons, 2006) or who gets into the top professions (Macmillan, 2009, Macmillan, Tyler and Vignoles, 2014). Given this, our first objective here is to look at the IGE across the earnings distribution, considering whether parental income is a more powerful predictor of opportunities at the top and bottom of the earnings ladder compared to those in the middle in the UK.

We employ the relatively new unconditional quantile regression (UQR) technique (see Firpo et al., 2009) to explore the IGE across the earnings distribution in the offspring's generation. We use a measure of (near) lifetime earnings for the second generation to explore both how this evolves over the lifecycle, and the impact of the inclusion of periods out of work on this picture. While many of the existing studies find that the association with childhood circumstance is decreasing across the distribution of earnings in the US, Norway and Canada (Eide and Showalter, 1999, and Bratsberg et al. 2005, or broadly flat in the US in Grawe, 2004), we find that the returns to family background are increasing across the earnings distribution in the UK. So the economic return to coming from a more affluent family is greatest at the top of the earnings distribution. Family background becomes an increasing predictor of success, the more successful you are in the UK. This is in line with recent research into access to the top professions (Macmillan, 2009, Macmillan, Tyler and Vignoles, 2014). We also find a strong association between parental income and lifetime earnings for the lowest paid, resulting in a 'J' shape across the earnings distribution. The stronger association between family background and earnings at the bottom of the distribution is shown to derive from periods of youth unemployment, which is rare among those from affluent families, even when they have low educational attainment. This 'J' shape association is particularly concerning for policy makers when combined with polarised labour markets and large wage inequalities.

Given this positive and increasing association between parental income and earnings across the distribution of sons' earnings, a sensible place to explore possible explanations for this trend comes from the returns to education literature. A number of studies have explored nonlinearities in returns to schooling in the US and Europe (Angrist and Pishke, 2009, Martins and Periera, 2004 and Brunello et al. 2009) and find that these are increasing in the earnings distribution – an extra year of education produces a higher return among the highest paid jobs. Therefore we assess whether the relationship between parental income and sons' earnings varies across the distribution of sons' earnings, conditional on their IQ, early skills, educational attainment and early labour market experiences. Here we ask: is education, in this narrow sense, meritocratic or is it the case that even with the same levels of educational achievement, those from more affluent families achieve privileged access to top jobs and avoid downward mobility into the lowest paid job opportunities? Exploring intergenerational persistence in this way may have important implications for policy as it shines new light on where the core problem of low mobility lies and the effectiveness of education in having the potential to create a meritocratic society (Gregg et. al., 2013). We find that even conditional on a range of measures of IQ, early skills, educational attainment and early labour market experience, parental income still has a strong association with later labour market earnings at the top and bottom of the distribution of sons' earnings. These results suggest that reducing educational inequalities, a key policy objective for governmental policy on improving social mobility, can only be a partial solution and we must look beyond the more standard approaches to reduce stickiness in the tails of the distributions.

An additional benefit of considering nonlinearities in the association between education and later earnings is that it also allows us to directly explore patterns in the labour market returns to ability, early skills, years of schooling and youth unemployment across the earnings distribution in the UK. The UQR technique allows us to assess whether the labour market returns to ability (IQ test score) and education are greater among high or low earners, assessing this in the unconditional earnings distribution. The existing UK research on the nonlinearity of the returns to education has used the conditional quantile regression (CQR) technique (Koenker and Basset, 1978), which becomes hard to interpret with multiple regressors included as it is based on position in the distribution of regression residuals. Hence in addition to the main focus on intergenerational mobility we also consider the association between early skills, education and early labour market attachment and sons' earnings using this relatively new approach.

Focusing on the role of ability, early skills and education, ability is broadly linear in its association with earnings and therefore does not drive the differential effect of family background across the earnings distribution. Indeed, the inclusion of early tests scores eradicates entirely the role of IQ test scores as found in previous literature (Blanden et. al., 2007). Early maths test scores have a 'U' shaped pattern with a stronger return to these tests at the bottom and the top of the distribution of earnings. Consistent with previous literature from the US and Europe, the returns to schooling increase across the earnings distribution. Introducing measures of qualifications such as GCSEs and degree attainment, including university attended and subject studied, explains the rising returns to year of schooling across the earnings distribution. Youth unemployment is a powerful driver of earnings at the bottom of the earnings distribution and explains a large part of the family background effect in the lower tail.

The following section reviews the literature on intergenerational mobility and nonlinear estimates of intergenerational mobility and the returns to education. Section 3 presents our methodology while section 4 outlines the data used in this analysis. Our main results are presented in section 5 and we end with some discussion and brief conclusions in section 6.

2. Related Literature

The majority of the existing research on intergenerational mobility has investigated the transmission of incomes or earnings across generations at the mean of the distribution. International comparisons mainly using data from Europe and North America have revealed some stylized facts: the Nordic countries stand out as those with the highest levels of mobility (lowest persistence) while the US followed by the UK are characterized by the highest intergenerational persistence (lowest mobility) among developed economies (see for instance Corak, 2013 for a review of the existing literature). A great deal of recent research has focused on measurement issues: observing a person's entire childhood and adult working life is very data demanding and proxy measures are regularly utilised. Lifecycle bias and attenuation bias have been shown to have significant impacts on the estimation of intergenerational persistence when using point in time proxy measures (see for instance Solon, 1992, Zimmerman, 1992, Mazumder, 2005 and Dearden et al. 1997). Gregg et. al. (2014) offer new estimates of intergenerational mobility in the UK using the mature birth cohort studies with repeated measures across the life course, which take into account lifecycle bias and attenuation bias along with a bias driven by spells out of work.

One of the limitations with focusing on the average IGE is that this summary measure may conceal potentially important details about the pattern of intergenerational mobility at different points of the distribution of parental and child's incomes. There is no a-priori reason to believe that the intergenerational transmission of economic resources is the same in all parts of these distributions (Black and Devereaux, 2011). The same point has also been made when considering the returns to education (see Angrist and Pishke, 2009) and here we address these two issues together. In particular, we consider whether higher returns to educational attainment at the top of the earnings distribution, the common finding, lies behind a similar greater importance of family background at the top of the earnings distribution or whether there is a less meritocratic process behind family background in top jobs. Hence our paper seeks to make a significant advancement to the intergenerational literature as well as the literature on returns to education for the UK.

The majority of the existing nonlinear intergenerational literature focuses solely on nonlinearities in parental income or father's earnings, by either including higher order polynomials of father's log income or earnings or using nonparametric regression techniques. Bratsberg et al. (2007) present the most comprehensive study of the nonlinearity of the relationship between family income across a range of countries, Denmark, Finland, Norway, the UK and the US, and reveal some important differences. While in the US and the UK the relationship turns out to be rather linear, the Nordic countries show a convex pattern, where the relationship starts out flat and is increasingly positive in the middle and upper segments of the distribution of incomes. This suggests that sons growing up in the poorest families have similar life chances to those born in moderately poor families, while coming from a well off family increases the chances of keeping the same economic advantage in the future. Estimating IGEs with a linear model therefore understates the degree of persistence in the central and upper parts of the parental earnings distribution where the IGEs are steeper.[4] Likewise in Canada, Corak and Heisz (1999) find that the intergenerational elasticity is almost equal to zero in lower parts of the distribution of father's earnings and increases along the father's earnings distribution up to 0.4, using a non-parametric method.

[4] As the authors point out, the convexity in the Nordic countries might be related to the strong existing public education systems.

A separate, smaller, strand of the literature has also explored nonlinearities along the distribution of son's earnings, changing the focus to the outcome of the intergenerational mobility process rather than the origin. This literature has mainly relied upon quantile regression estimates. Quantile regression, also known as conditional quantile regression (hereafter, CQR), was proposed by Koenker and Bassett (1978) and in the intergenerational setting allows one to capture differences in the persistence of fathers earnings (parental income) across the conditional distribution of sons' earnings. Findings based on CQR for the US, Norway and Canada all show that intergenerational persistence is higher at the lower end of the offspring's earnings distribution than at the upper end. This suggests that where you come from sorts people more for those who end up at the bottom of the earnings distribution among top jobs, where it is more equitable in these countries.

In the US, Eide and Showalter (1999) show that the estimated IGE at the mean of the distribution is 0.45, while the CQR estimates reveal a greater IGE at the bottom of the son's conditional distribution rather than the top (0.67 for the 10^{th} percentile against 0.26 for the 90^{th} percentile). Bratsberg et al. (2005) and Grawe (2004) demonstrate similar findings for Norway and Canada. Results are robust when looking at sons and daughters in Norway (Bratsberg et al., 2005) and when using either parental income or father's earnings as the measure of first generation resources in the US (Eide and Showalter, 1999).[5] By contrast, a recent paper by Schnitzlein (2014) finds more intergenerational persistence at the top of the offspring's distribution in Germany as well as the US using both standard CQR and unconditional quantile regression (UQR) techniques.

Other recent studies have investigated the presence of nonlinearities in the offspring's distribution by using parental occupation or parental education to measure family background. Raitano and Vona (2014) find that parental occupation is a stronger predictor of earnings for those that end up at the top of the earnings distribution rather than at the bottom. This result is consistent across some European countries with the exception for Spain and particularly strong for the UK.[6] Jerrim (2014) finds an increasing relationship between parental education and sons' earnings for France, Germany and Switzerland but a stable or slightly declining relationship across the distribution of sons' earnings for the UK.

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[5] Using father's earnings rather than parental income yields lower degree of persistence but the same general pattern. The IGE is 0.34, whereas estimates at the 10^{th} and 90^{th} percentiles respectively are 0.47 and 0.17. More persistence at the bottom of the offspring's distribution is found when conditioning on years of schooling also.
[6] Estimates are obtained using CQR also controlling for personal and job characteristics.

A key driver of intergenerational mobility is education. Models by Blau and Duncan (1967) and Becker and Tomes (1986) place education, or human capital, as the central mechanism through which advantage (or disadvantage) is passed from one generation to the next. Empirical studies on the role of education in intergenerational mobility date back to the early 1980s (Atkinson, 1980; Atkinson and Jenkins, 1984) and over the past ten years a number of studies have analysed the role played by education and also cognitive and non-cognitive skills in the intergenerational mobility process (Blanden, Gregg and Macmillan, 2007; Mood, Jonsson and Bihagen, 2012). These studies find that the dominant transmission effect is through educational attainment and that early cognitive and non-cognitive skills play an independent role in transmitting incomes across generations. Only one study to date has investigated the role of education in the transmission of intergenerational persistence in a nonlinear manner. Corak and Heisz (1999) find a uniform drop in the IGEs (around one third) across all quintiles and higher returns to schooling at the bottom of the earnings distribution rather than at the top for Canada, using CQR.[7]

The parallel literature on returns to education has considered heterogeneity in the returns to schooling across the distribution of wages based on CQR The empirical evidence for Europe and the US has almost consistently found that education is more valuable at the top of the wage distribution. A comprehensive study for Europe by Martins and Pereira (2004) analyses male workers from 16 countries for the mid-1990s and finds that returns to schooling are higher for the high earners, conditional on their observable characteristics.[8] Evidence of stronger returns to education at higher points of the conditional distribution are also documented in the pioneering work of Buchinsky (1994) for the US, and more recently using the Census micro datasets by Angrist et al. (2006). In the UK, Harmon et al. (2003) find that returns to schooling are higher for those at the very top of the wage distribution compared to those at the very bottom during the period 1980-1995.

The general finding of greater returns to schooling among higher earners is somewhat at odds with the smaller literature which suggests that family background matters most in

[7] As discussed by Eide and Showalter (1999) these results could possibly be driven by the fact that quantile regressions compares quantile distributions conditional on specific values of X. This means that higher values of beta at the bottom entail more differences between the bottom quintiles of the university graduates and the high school graduates in their earnings so that college turns out to be more valuable at the bottom of the conditional quantile distribution.

[8] For instance in Sweden the average return to education is 4%, at the first decile is no greater than 2% and the return at the ninth decile reaches 6%. In Portugal returns to education are strongly heterogeneous: the average return of education of 13% masks a return of only 6% at the first decile and more than 15% at the last decile.

sorting people in the lower parts of the earnings distribution, as schooling is strongly related to family background. As this is especially true for the UK (see Jerrim and Macmillan, 2014 for example) we might not expect to find that family background matters more among lower earners, at least for that part of the IGE that is associated with schooling.

2. Methodology

Using standard linear regression models to measure intergenerational mobility consists of estimating an ordinary least squares (OLS) regression of log son's income or earnings (y_i^{son}) on log parental income in childhood (y_i^{parent}).[9]

$$y_i^{son} = \alpha_1 + \beta y_i^{parent} + \varepsilon_i \qquad (1)$$

The estimated parameter, $\hat{\beta}$, captures the intergenerational elasticity or the persistence in income gaps between more and less affluent families across generations. Mobility, or the extent to which incomes are *not* associated across generations, is measured as $1 - \hat{\beta}$. With standard OLS assumptions, this regression gives a consistent estimate of the average association between parental income and sons' income or earning.

One limitation of this approach is that $\hat{\beta}$ could hide important differences in the extent to which parental income matters at different parts of the distribution of sons' earnings. When the underlying question of economic and policy interest concerns aspects of the distribution of the dependent variable that go beyond the mean, for instance are the economic returns to coming from a more affluent family background associated with higher paid positions or avoidance of the lowest paid employment, we need to use other estimation methods.

An obvious way of characterizing the distribution of sons' earnings is to compute its quantiles. The early literature in this regard used conditional quantile regression (CQR) estimates (Konker and Basset, 1978) which allow us to explore the nonlinearities in the dependent variable by capturing the impact of an explanatory variable on the conditional distribution of the dependent variable at a given point in the distribution. In the

[9] All regressions control for a quadratic function of the age of the parents to control for lifecycle bias in the first generation.

intergenerational setting, as discussed in the previous section, there are a number of studies employing this technique. However, this approach has some important drawbacks, as argued in the seminal paper of Firpo et al. (2009). Contrary to OLS estimates, CQR estimates do not allow us to retrieve the marginal impact of a specific variable on the unconditional quantile of the dependent variable but on the quantile of the residuals of the fitted model.

In a standard OLS regression, $\hat{\beta}$ can both be interpreted as the association between an explanatory variable on the conditional mean of the dependent variable (conditional mean interpretation) as well as the effect of increasing the mean value of an explanatory variable on the unconditional mean value of the dependent variable (unconditional mean interpretation)[10]. By contrast, when using CQR models for the τ_{th} conditional quantile, only the conditional quantile interpretation can be applied: the effect of an explanatory variable on the conditional quantile τ_{th} of Y given X: $Q_t(x) = X\beta_t$. This is because the law of iterated expectation does not apply in the case of quantiles. [11] In other words, β_t cannot be interpreted as the effect of increasing the mean value of X on the unconditional outcome variable at quantile Q_t . Rather it reflects the quantile of the residuals from the regression once other factors are included in the regression, which has no easily interpretable meaning. Therefore estimates based on conditional quantile regressions may lead to confusing results and need to be interpreted with caution (see Fournier and Koske, 2012 for a discussion). For example, this technique cannot be used to consider the simple association between an extra year of education and median earnings (Firpo et al. 2007). To do this we need to rely upon a recent advancement made by Firpo et al. (2009): unconditional quantile regressions.

Unconditional quantile regressions (hereafter, UQR) allows us to estimate the association between an explanatory variables and quantiles Q_t (or other distributional parameters) of the unconditional (marginal) distribution of the outcome variable using a Re-centred Influence Function (RIF) regression technique. This method builds upon the concept of the influence function which is a tool used to obtain robust estimates of statistical and econometric models, measuring the influence of an individual observation on a distributional statistic of interest (Monti, 1991). This RIF-regression is similar to a standard regression except that the dependent variable is replaced by the RIF of the statistic of interest, v,

[10] Under the conditional mean interpretation $E(y/x) = x\beta$ and using the law of iterated expectations we also have that $E(y) = E_x[E\,(y/x)] = E(x)\beta$.
[11] $Q_t \neq E_x[Q_t(x)] = E(x)\beta_t$.

$RIF(y;v)$.[12] In its simplest form the conditional expectation of the RIF can be modelled as a linear function of the explanatory variables and the parameters can simply be estimated using standard OLS regressions.[13] If the statistic of interest is the quantile ($v = q_{\tau}$), Firpo et. al. (2009) refer to this RIF-regression also as an *unconditional quantile regression* (UQR).

In this work we explore how the IGE differs across percentiles of the unconditional distribution of the sons' earnings (10^{th} 30^{th}, 50^{th}, 70^{th}, 90^{th}) by estimating equation (1) using unconditional quantile regression (2), so replacing the dependent variable (sons' earnings) by the RIF of the quantiles q_{τ} where τ =0.1,0.3,0.5,0,7,0.9. This approach enables us to assess how $\hat{\beta}$ varies at different parts of the distribution of earnings of the second generation. In other words this allows us to understand if family income in childhood has a stronger association with later earnings for those who end up being rich compared to those who end up being poor.

$$RIF(y_i^{son}; q_{\tau}) = \alpha^{\tau} + \beta^{\tau} y_i^{parent} + u_i \tag{2}$$

Following Blanden et. al. (2007) we explore the association between early skills, education and early labour market experiences and later sons' earnings, conditional on parental income, by including a vector X of measures ($X = \rho^{\tau} early\_skills_i^{son} + \delta^{\tau} educ_i^{son} + \gamma^{\tau} lm_i^{son}$) in model (2). We therefore estimate

$$RIF(y_i^{son}; q_{\tau}) = \alpha^{\tau} + \beta'^{\tau} y_i^{parent} + X^{'} \theta^{\tau} + \varepsilon_i \tag{3}$$

using a RIF regression at different quantiles q_{τ} where τ = 0.1,0.3,0.5,0,7,0.9 (10^{th} 30^{th}, 50^{th}, 70^{th}, 90^{th}). This approach has two advantages: first, we can explore the direct relationship between family income and sons' earnings across the distribution of sons' earnings (β'^{τ}), conditional on early skills, education and early labour market attachment to assess how meritocratic education is at different points of the distribution. Second, we can also explore

[12] The RIF is obtained by adding the distributional parameter concerned to the influence function, $IF(y;v)$.

[13] The expected value of the RIF is equivalent to its statistic of interest (i.e quantile) and by applying the law of iterated expecations, it is possible to write

$$q_{\tau} = E[RIF(y;q_{\tau})] = E_x\{E[RIF(y;q_{\tau})|X]\} = X'\gamma_{\tau}$$

This exercise can be applied to other distributional parameters such as for instance the Gini index or the variance and the parameters γ can be estimated with OLS.

the heterogeneous returns to early skills and ability (ρ^{τ}), education (δ^{τ}) and labour market experience (γ^{τ}) across the distribution of the sons' earnings.

We build our model in stages, focusing first on the role of early ability and skills before considering the importance of years of schooling, educational qualifications achieved and early labour market attachment. This allows us to assess both the direct association between these measures and later labour market earnings across the distribution and to assess how early measures of skills and ability are working through later measures of educational attainment and early labour market experiences.

4. Data

We use data from the British Cohort Study (BCS), a birth cohort of all individuals born in one week in April 1970 within Great Britain. This longitudinal data followed the cohort members from birth, through childhood at ages 5, 10 and 16, asking questions to both the parents and the cohort member themselves as they aged. The cohort members were then followed into adulthood with interviews at age 26, 30, 34, 38 and 42. As is standard practice in analysis of intergenerational income mobility, we focus on male cohort members given difficulties with modelling participation decisions of female cohort members in adulthood.

Information on the incomes of the cohort members in childhood were collected when the son was aged 10 and 16 (1980 and 1986). This information was collected from the respondent's parents, where they were asked to place their gross family income into a given band of data. This banded data was adjusted as in previous studies of intergenerational income mobility in the UK (Blanden et. al., 2004, Blanden et. al., 2007, Blanden et. al., 2013, Gregg et. al., 2014) allocating individuals within bands using a Singh-Maddala (SM) distribution and maximum likelihood estimation (Singh and Maddala, 1976), converting the gross incomes into net measures using the family expenditure survey (FES) from 1980 and 1986 and adjusting for child benefit payments based on the number of children observed in the household. A number of robustness checks have been carried out on these income measures to ensure that they are comparable with external data sources (see data appendix from Blanden et. al., 2013 for full details). To minimise transitory variation and measurement error in the data, an average was taken across the two observed income measures at 10 and 16 with values imputed where income was missing in one period, based on changes in employment status, housing tenure and family structure (see Gregg et. al., 2014 for further details). The log of the average was then taken.

Sons' earnings are observed in the cohort studies at all ages in adulthood, allowing us to observe earnings across two-thirds of the cohort member's adult working life (26-42). This information is reported in a standard way at each wave with sons reporting their usual gross pay and their usual gross pay period. A gross monthly earnings measure is created at each point in time based on this information which is deflated to 2001 prices and logged. We also combine all information available across the cohort member's adult life to create a lifetime earnings measure, extrapolating information between observed periods of earnings to create an average lifetime earning measure. If earnings are missing in any given period, they are imputed based on the cohort members' observed earnings in other periods and their observed age-earnings profile, to allow for variation in earnings growth by education levels (see Gregg et. al., 2014 for further details). Finally, we consider a measure of average lifetime earnings that includes periods spent out of work. Ignoring workless spells can lead to substantial biases in estimating IGEs (Gregg et. al., 2014). Information from cohort members' monthly work histories are combined with their extrapolated monthly earnings observations to assign an earnings replacement value for months where cohort members are workless. This earnings replacement value is based on observed out-of-work benefit rates (Job Seekers and Income Support), deflated to 2001 prices (see Gregg et. al., 2014 for further details). For both lifetime earnings measures, an average is taken across the observed period and a log of the average is used for our analysis.

Early skills are measured based on childhood tests at age 10 including an early measure of ability or IQ (British Ability Scale test), reading and maths, and a number of teacher and mother reported behaviours which are combined to create non-cognitive measures at age 10 including application, hyperactivity, clumsiness, extroversion and anxiety (see Blanden. et. al., 2007 for full details of how these scales were constructed). These measures have been shown to be significant predictors of educational and later life outcomes and strongly related to parental circumstance in childhood (Blanden. et. al., 2007, Macmillan, 2013). Education measures combine information on years of schooling, standard in the literature on returns to education across the distribution of earnings, with more finely-graded measures of qualifications obtained including the number of GCSEs grade A*-C, number of

A levels, degree attainment, degree subject studied[14] and higher education institution attended.[15] The information on GCSE qualifications and A levels is taken from reports at age 16 where available and age 30 and 26 where necessary. The information on degree attainment, subject and institution attended uses new questions from the BCS survey at age 42. This wealth of information helps us compare the IGE for individuals with very similar educational experiences. Finally, the early labour market attachment of the cohort member, the proportion of the total time that is spent in employment, is calculated based on the monthly work history of the cohort member from leaving full time education until age 23.

Our sample is restricted to cohort members with at last one parental income observation and over 5 years of monthly work history available from 26-42. Table 1 presents means and standard deviations of our measures of early skills, education and early labour market attachment across the distribution of lifetime average earnings. Our measures of early skills are standardised to mean 0, standard deviation 1 at the population level, indicating that those in our sample perform slightly better on average in terms of IQ and maths test scores. They are also more likely to be hyperactive and clumsy and slightly less likely to apply themselves less in class. Across the distribution of earnings, as expected those who end up earnings lower wages score lower on maths, reading and IQ tests, are more introverted, clumsy, hyperactive and anxious and less likely to apply themselves. Similarly education increases as expected across the wage distribution with the mean years of education increasing from 11.8 to 14 and the proportion obtaining a degree increasing from 9% to 49% from the 10th to the 90th percentile. There is interestingly little variation in the proportion of time spent in employment above the 10th percentile of earnings, indicating that this measure is likely to kick most strongly at the bottom of the distribution of earnings where individuals spend 85% of their time in employment compared to 96% at the 30th percentile upwards.

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[14] There are 49 possible degree subjects including Medicine, Dentistry, Sports Science, Economics, Accountancy and a category for ‘other’. These are included as separate dummies in the models against a baseline of ‘no university subject’.

[15] There are 165 institutions including a category for ‘other’. These are included as separate dummies in the models against a baseline of ‘no institution’.

5. Results

We begin by focusing on the IGE using childhood parental income[16] and earnings at different point in time across sons' adulthood to show the pattern of the importance of family background across the wage distribution and to consider the changing patterns of any nonlinearities across the lifecycle. Table 2 shows the estimated IGEs across the lifecycle for sons at the mean of the distribution of earnings at various ages. As is commonly found in the literature, the estimated IGEs increase as sons' age, with an IGE of 0.23 at age 26 increasing to 0.50 by age 42.[17] Figure 1 shows how the age at which adult earnings is assessed changes the distributional picture of the returns to coming from a more affluent family. This figure plots the estimated IGE from UQR at each age in Table 2 but assessing the relationship at the 10th, 30th, 50th (median), 70th and 90th percentiles of sons' earnings rather than at the mean of the distribution. There is a clear increase in the steepness of the IGE across the wage distribution as individuals' age. At age 26 for example, the IGE at the 10th percentile is 0.15 and at the 90th percentile is 0.31 whereas at age 34, this has increased to 0.27 and 0.62 respectively. At later ages, there is a clear kick up at the top of earnings distribution with an IGE of 0.79 and 0.93 at age 38 and 42 respectively at the 90th percentile of the distribution. At the 10th percentile the IGE remains around 0.27-0.30.

This pattern implies that when in the lifecycle sons' earnings are observed clearly matters for observing patterns of nonlinearity in the returns to childhood circumstance across the distribution of earnings. Already, it is clear that in the UK the relationship between childhood affluence and adult earnings increases as we move up the earnings distribution: parental childhood income has a stronger association with earnings among those at the top of the earnings distribution. This is in contrast to what has been found in previous studies of other countries using standard conditional quantile regression (Bratsberg, et al. 2005 for Norway, Eide and Showalter, 1999, for the US and Grawe, 2004 for Canada). Our findings are robust to using an alternative measure of family background, namely parental education. Appendix Table A1 illustrates the intergenerational association between having a highly educated parent compared to a low educated parent and later sons' earnings using three

[16] Averaged at 10 and 16 to reduce attenuation bias. Note that using a point in time measure of parental income does not change the pattern of the estimated IGE across the earnings distribution. The estimates increase at a consistent rate across the entire distribution as attenuation bias is reduced.

[17] Age 36 to 38 is typically seen as ideal point in time to proxy lifetime earnings as here the correlation between current and annual average lifetime earnings approaches unity (see Bohlmark and Lindquist, 2006).

alternative UK data sources, the British Household Panel Survey (BHPS), the National Child Development Study (NCDS) and the BCS. Figure A1 shows that this relationship is increasing in sons' earnings, as with parental income.

The use of point in time (at a single age) measure of earnings is common in the intergenerational literature as a proxy for lifetime earnings (see Black and Devereux, 2011) but when assessing mobility across the distribution, the upper tail in the UK at least, is going to be incredibly sensitive to the choice of age used. Given this sensitivity we move towards a lifetime estimate of IGE, considering average earnings across the observed portion of the lifecycle from ages 26 to 42. This also allows us to assess the role that the exclusion of periods of worklessness plays in affecting estimates of the IGE across the distribution of lifetime earnings, as we can introduce periods spent out of work and recorded in the work history files, as discussed in the data section above. Table 3 and Figure 2 show the returns to average parental income across the distribution of lifetime adult earnings first excluding and then including spells out of work from our measure of lifetime earnings (see Gregg et. al., 2014 for further discussion of this important bias at the mean of the distribution when using point in time measures of earnings that exclude those not currently in work). Focusing first on lifetime earnings excluding workless spells, there is a clear increasing pattern in the IGE as we move up the earnings distribution: at the 10th percentile, the association between parental income and lifetime earnings is 0.240, increasing to 0.620 at the 90th percentile. This mimics the pattern seen in Figure 1 at around age 34, illustrating that where you come from matters more the higher up the distribution of earnings you climb.

When spells out of work are included in our lifetime earnings measure and we give people the value of benefits that replace earnings, as recorded in the data and cross checked with published rates applying to benefits at the relevant period, the return to parental childhood income shows a marked increase at the lower end of the distribution of earnings. There is now a 'J' shape relationship in the returns to coming from a more affluent family across the earnings distribution when this important dimension of lifetime earnings is taken into account, illustrating that family background matters most at the very bottom (the IGE is 0.414 at the 10th percentile) and then to a larger extent at the very top of the earnings distribution (0.652 at the 90th percentile).

The data appendix reports sensitivity analysis for the bottom and top tail of the distribution to assess if there are signs of instability in the tails. As shown in Appendix Table A2, the bottom tail is not very sensitive to the treatment of worklessness. If we exclude from the sample the small number (just over 1% of the sample) of people who have been workless for the entire period (so not reporting a wage at each age 26, 30, 34, 38, 42) the UQR of our lifetime earnings measure including worklessness at the 10^{th} percentile falls a fraction from 0.41 to 0.37. In addition the use of zero earnings instead of benefit replacement makes little difference at the 10^{th} percentile (0.44 compared to 0.41). Hence including periods of worklessness in the data is important to the assessment of the role of family background on earnings in the lower tail but this stems from intermittent worklessness for those with observed earnings in some periods rather than the small group with (near) permanent worklessness.

Coming from a more affluent family has its greatest reward among those who get into top earning jobs and coming from a deprived family also hits earnings hard at the lower end of the lifetime earnings distribution when worklessness is included. The first point has parallels to the studies looking at access to the top professions in the UK. Macmillan (2009) and Macmillan, Tyler and Vignoles, (2014) show that family background is a significant predictor of working in top jobs, even after controlling for IQ and educational attainment. Table A3 in data appendix reports UQR results for the top percentiles when the always workless are included in the sample. The results are very robust in the upper tail if the 85^{th} or 95^{th} percentiles are used instead of the 90^{th} . Table 4 introduces measures of ability, early skills, years of schooling, educational qualifications achieved and early labour market attachment in an additive sequence. The UQR estimates illustrate the returns to ability, education and early labour market experiences conditional on parental childhood income. These estimates therefore address two distinct literatures. First, they show how the intergenerational association is mediated by educational attainment (Blanden et al. 2007, Björklund et al. 2012) across the distribution of sons' earnings. Second, they give estimates of the returns to early skills, education and early labour market attachment across the distribution of sons' earnings.

Panel A of Table 4 shows the OLS and UQR estimates of the returns to IQ test scores across the distribution of sons' lifetime earnings (including spells out of work), conditional on parental childhood income. Throughout this analysis the IGE conditional on early skills, education and early labour market attachment, the top row of each panel, can be contrasted to the unconditional IGE shown in the second row of Table 3, as illustrated in Figure 3. This indicates whether the 'J' shaped pattern observed in the unconditional IGE can be accounted for by any of these measures of ability, educational attainment and early labour market attachment or whether an intergenerational association remains after controlling for differences in these key characteristics. The IGE diminishes slightly with the inclusion of IQ at age 10 (around 5 percentage points across the distribution) with the returns to IQ also exhibiting a slight 'U' shape of stronger returns in the lower and upper parts of the distribution but the differences are not statistically significant. The contribution of IQ to the IGE is therefore modest, in line with Blanden et al. (2007) and broadly uniform in its effects across the earnings distribution. There is no evidence that there are larger returns to IQ at the top of the earnings distribution.

In Panel B, early maths and literacy test scores (measured at age 10) are introduced to the model and a number of non-cognitive traits available in the cohort study measured at the same age are also introduced. These early skills have been found to be important drivers of intergenerational persistence in the UK (see Blanden et. al, 2007). The addition of these early skills diminishes the IGE by around 3 to 5 percentage points, again uniformly across the distribution of sons' earnings. As illustrated in Figure 3, the total contribution of early skills reduces the IGE but does not change the shape across the distribution of sons' earnings, with a strong 'J' shape remaining after conditioning on these measures.

These attributes dominate the role of the returns to IQ, which is now insignificant. The returns to maths scores at age 10 are strongly 'U' shaped across the distribution of lifetime earnings, with higher maths ability gaining stronger wage returns at both the bottom and top of the wage distribution. Reading, by contrast, grows steadily in importance across the distribution making little difference to earnings in the lower tail of the earnings distribution. A number of the personality characteristics are valued differently across the distribution: the measure of application which reflects the child's ability to concentrate is valued slightly more in the upper parts of the earnings distribution. Physical co-ordination, in contrast, matters only in the lower half of the earnings distribution where work may have a stronger physical component. Extroversion attracts positive returns across the distribution, again with a slight 'U' shape.

In line with standard estimates of nonlinearities in the returns to education, Panel C includes the total years of schooling. The inclusion of years of schooling reduces the estimated IGE at the top of the distribution (by 12 percentage points) but has no impact on the IGE at the bottom of the distribution of earnings. Part of the strong association between parental income and sons' later lifetime earnings for those who make it to the top of the earnings distribution is therefore accounted for by the extended schooling and higher returns to those extra years of schooling among those from richer compared to poorer families.

The returns to an additional year of schooling is estimated at 4% per year in the average OLS estimation, conditional on family background and early ability and literacy and Maths test scores.[18] The returns to an extra year of schooling are markedly larger in the upper portion of the wage distribution, consistent with previous findings in this area (Angrist et al., 2006). At the 10th percentile there is no significant return to an additional year of school, increasing to 4% at the median and twice this at the 90th percentile. This indicates that additional education matters to a greater degree amongst higher earning jobs. The inclusion of this common indicator of education also reduces the impact of earlier test scores on later lifetime earnings across the distribution, as would be expected. The additional returns to reading test scores over and above years of schooling become insignificant, although the returns to early maths test scores remain strong, particularly at the bottom of the earnings distribution. This suggests that improving maths skills may make a difference in reducing low pay over and above extending years of education. Extroversion and co-ordination (clumsiness) also still appear to matter among lower paid jobs.

A key feature of the UK education system is the extensive examination of attainment at age 16, in the form of GCSEs, which are important milestones for pursuing continued education. Panel D, therefore includes the number of GCSEs passed (with grades A-C)[19]. Panel E extends this to include measures of post-compulsory qualifications (A levels and degree attainment) and Panel F adds finer-grade measures of higher educational attainment including the subject studied at university and the institution attended. By Panel F we are considering the IGE across the distribution of sons' earnings for individuals with very similar levels of early skills and later educational attainment. The inclusion of these detailed measures of education diminishes the association between parental childhood income and lifetime earnings at the 90th percentile but has little impact at the bottom of the earnings distribution (top row, Panel F).

The returns to coming from a more affluent family are now markedly U shaped: strongest at the 10th and 90th percentiles and more modest in the middle of the distribution of

[18] The unconditional estimates are around 7% which is slightly below that found for males (0.09) by Harmon et. al. (2003) without attempting to correct for ability bias. The returns to an extra years of schooling, conditional on family background and IQ test scores only, is 4% at the mean, ranging from 0% at the 10th percentile of the earnings distribution to 9% at the 90th percentile (3% at 30th, 4% at 50th, 6% at 70th).

[19] GCSEs in English and Maths are particularly important for continued study but the subject specific data is often incomplete in the data.

earnings as illustrated in Figure 3. Interestingly, even when comparing individuals with very similar early skills and similar years of schooling who attained the same level of GCSEs and A levels and studied the same subject at the same institution, parental income is still a very strong predictor of later labour market earnings, particularly at the top and bottom of the distribution. This suggests that education is not enough to level the playing field for those in the tails of the distribution of earnings and in particular among top jobs. So comparing two people who achieve the same levels of educational achievement where one comes from a family with twice the income levels of the other (say for example at the median and twice the median) then the one from the more affluent family receives 20% higher wages among jobs in the middle of the distribution rising to 35% among top jobs.

The pattern of returns to GCSEs attained mirrors that of years of schooling, in that there is little return in the lower part of the earnings distribution and large returns at the top (Panel D). The returns to an extra year of education conditional on GCSE attainment falls markedly as these are strong predictors of continued study. Extending measures of education to include measures of post-compulsory schooling, A levels and degree attainment (Panel E), remove the impact of years of schooling as these are the major sources of extra years of education in this period. As with years of schooling and GCSE, these measures of continued study have no return (or a negative return in the case of A levels) at the bottom of the earnings distribution but large returns at the top.[20] Adding in finer-graded measures of degree attainment including the subject studied and the institution attended (Panel F) completely wipes out the higher payoff to degree attainment at the 90th percentile of the lifetime earnings distribution. This suggests that for those who make it to the highest paid jobs, it is the subject studied at university (accounting for around 40 percent of the degree association) and the institution attended (accounting for the remaining 60 percent of the degree association) that matters rather than the signal of the degree qualification itself. This is not true further down the distribution of sons' lifetime earnings.

The final panel (Panel G) includes a measure of early labour market attachment; exposure to periods out of work and education before the age of 23. People who spend more time out of employment and education during this early period of adult life are commonly called NEETs (Not in Employment, Education or Training). This measure alone is as important as qualifications and years of schooling in the intergenerational transmission among those at the

[20] Maths test scores remain important in the lower portion of the wage distribution.

bottom of the distribution of sons' lifetime earnings, reducing the association between parental childhood income and lifetime earnings at the 10th percentile by over 10 percentage points (see Figure 3). The IGE, after conditioning on early skills, education and early labour market attachment is linear then across the distribution of sons' lifetime earnings until we reach the 90th percentile, where the IGE is 13 percentage points higher. The proportion of time spent employed from leaving full time education to age 23 has a very high return in the bottom tail of the distribution of lifetime earnings and more modestly so elsewhere. Again this is not very sensitive to the exclusion of the small sample with no reported earnings at any age (see Appendix Table A4). Youth unemployment has regularly been found to have long term scars on wages and future employment (Gregg, 2001 and Gregg and Tominey, 2005) and is strongly focused on those from poorer families (Macmillan, 2014). That this reduces the family background effect at the very bottom quite markedly suggests that if more affluent parents cannot achieve higher educational attainment for their offspring then at least they are successful at getting them into work soon after leaving school.

6. Conclusions

Research has established that there is a strong association between parental income in childhood and later labour market earnings, which becomes increasingly stark as sons' age (see for example Gregg et al. 2014). When assessed across the earnings distribution instead of at mean earnings there is little difference in the IGE at age 26 but by age 42 childhood parental income is a much stronger predictor of earnings among higher paying jobs that in the middle of the distribution. Using measures of lifetime earnings to allow us to also account for spells spent out of work in adulthood, there is a distinct 'J' shape in the relationship between parental childhood income and lifetime earnings. Coming from a more affluent family matters more at the bottom and even more starkly at the top of the distribution of lifetime earnings. These findings are in contrast to studies from the US, Norway and Canada that find a decreasing intergenerational relationship as they move up the earnings distribution. They are however consistent with the emerging literature in the UK about the strong role of family background in access to top jobs (Macmillan, 2009, Macmillan et. al., 2014).

Importantly when we include measures of early ability and test scores, education and early labour market attachment to assess their role in accounting for this relationship between family background and lifetime earnings we find that even comparing individuals with very similar early skills, years of schooling, GCSE, A level and degree attainment, who attended the same institution and studied the same subject, and similar early labour market attachment, childhood parental income is still an important predictor of sons' lifetime earnings. This is particularly marked at the top of the distribution of earnings until we condition on degree subject and institution the degree was studied at. This strongly suggests that the strong returns to family background here bite by getting to elite universities which top employers recruit heavily from and in studying subjects with high returns such as medicine, law and economics. Education, in terms of level attained, alone is not enough to level the playing field and for those entering the top positions in society is not as meritocratic as we might hope. Policy makers may need to look at how young people choose subjects to study at university and to both widen participation in elite universities and to push employers to seek talent from a wider pool than currently. There is a clear need to move beyond educational achievement to tackle the dominance at the top of our society by those from affluent families.

When we consider patterns in returns to these characteristics in their own right we find little return to continued educational participation or exam performance in the bottom half of the earnings distribution. Here the key returns are to maths test scores, coming from a more affluent family and, in particular, avoiding youth unemployment. Although the estimated effects are not strictly causal they are conditional on parental income, ability as measured by an IQ test score and education, which is a fairly strong test. The findings related to the importance of early labour market attachment would imply large returns to policy development to tackle youth unemployment in terms of addressing low wages and intergenerational persistence of inequality in who ends up with the lowest lifetime earnings. The results also suggest that improvements in maths skills, even without leading to extended schooling, are likely to be very valuable.

By contrast the returns to education are stronger in the middle and especially the upper parts of the wage distribution. Here, continued education and exam performance are powerful discriminators of lifetime earnings differences and drive part of the returns to coming from an affluent family. In particular for those at the top of the distribution who attend higher education, it is the subject studied and the institution attended rather than the degree attainment itself which drives the strong returns to higher education in top jobs. This suggests that students looking to stay on in higher education and make it to the top of the earnings distribution should consider not just attending university but carefully consider their degree course and institution.

Frank and Cook (1995) in their book 'The Winner-Take-All Society' argue that top salaries have been growing sharply due to technological forces that greatly amplify small increments in job performance and increased competition for the services of top performers. They argue that this has become so important that a small difference in talent or effort often giving rise to large differences in labour market rewards. This study supports the notion that returns to education and ability are higher among top salaries but it also highlights that these high rewards reflect family background as much as ability and education. This is more indicative of the ability of rich families to manoeuvre their offspring into professions with high rewards rather than the genuine rewarding of scarce talent. Bingley et al. (2012) show that the labour market returns for those from affluent families who are employed in the same firm as their father at some point are high. Macmillan, Tyler and Vignoles (2014) show that access to leading professions is higher among graduates who attended private schools even compared to a state school student who got the same A level grades, attended the same university on the same degree programme and with the same degree class. This research and these other studies thus present a compelling picture of affluence being linked to careers by far more than education and ability, with high returns to coming from an affluent family at the top of the earnings distribution being associated with elite universities and subjects studied.

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Figure 1 Unconditional quantile regression estimates of the intergenerational income elasticity in the BCS

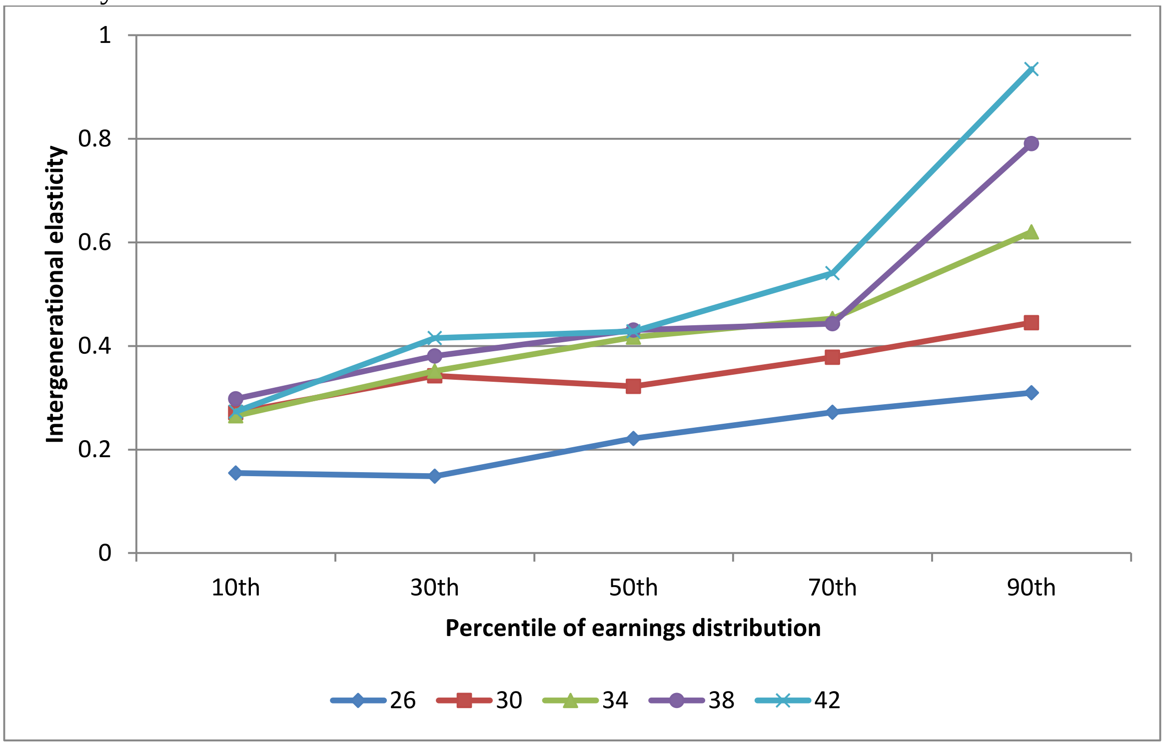


Figure 2 Unconditional quantile regression estimates of the intergenerational income elasticity in the BCS for lifetime earnings with and without workless spells (26-42)

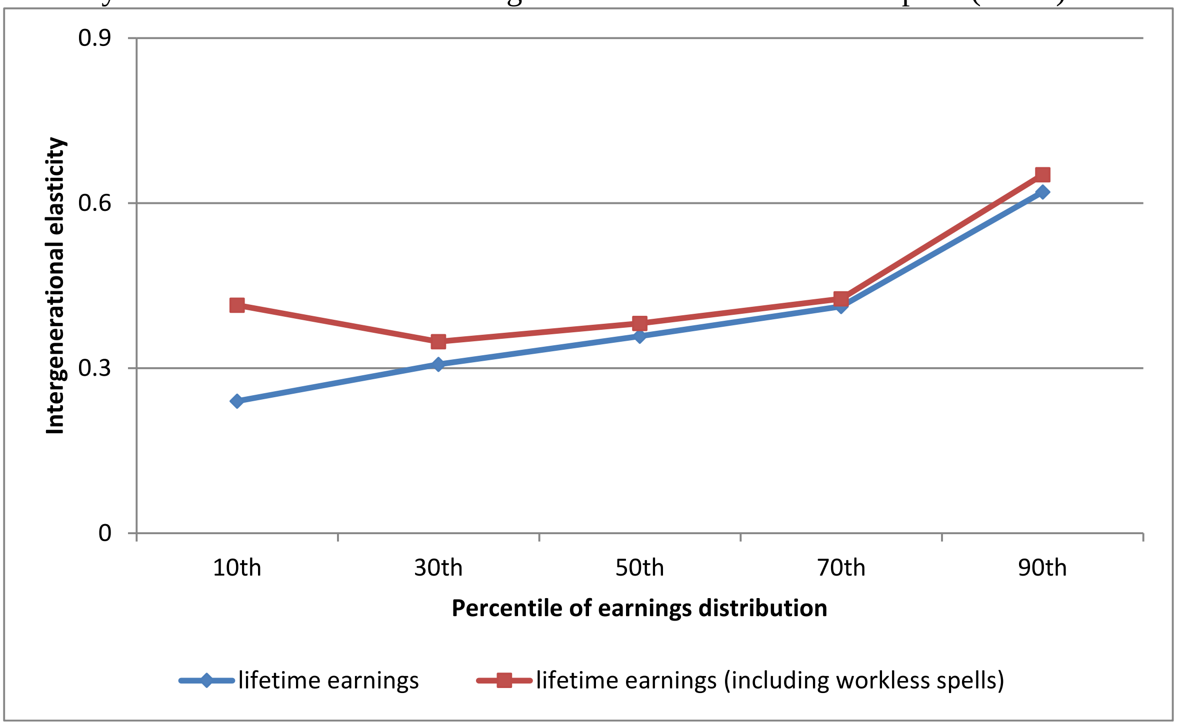


Figure 3 Unconditional quantile regressions of the association between average parental childhood income on lifetime earnings (including workless spells) (26-42), conditional on early skills, education and early labour market experience

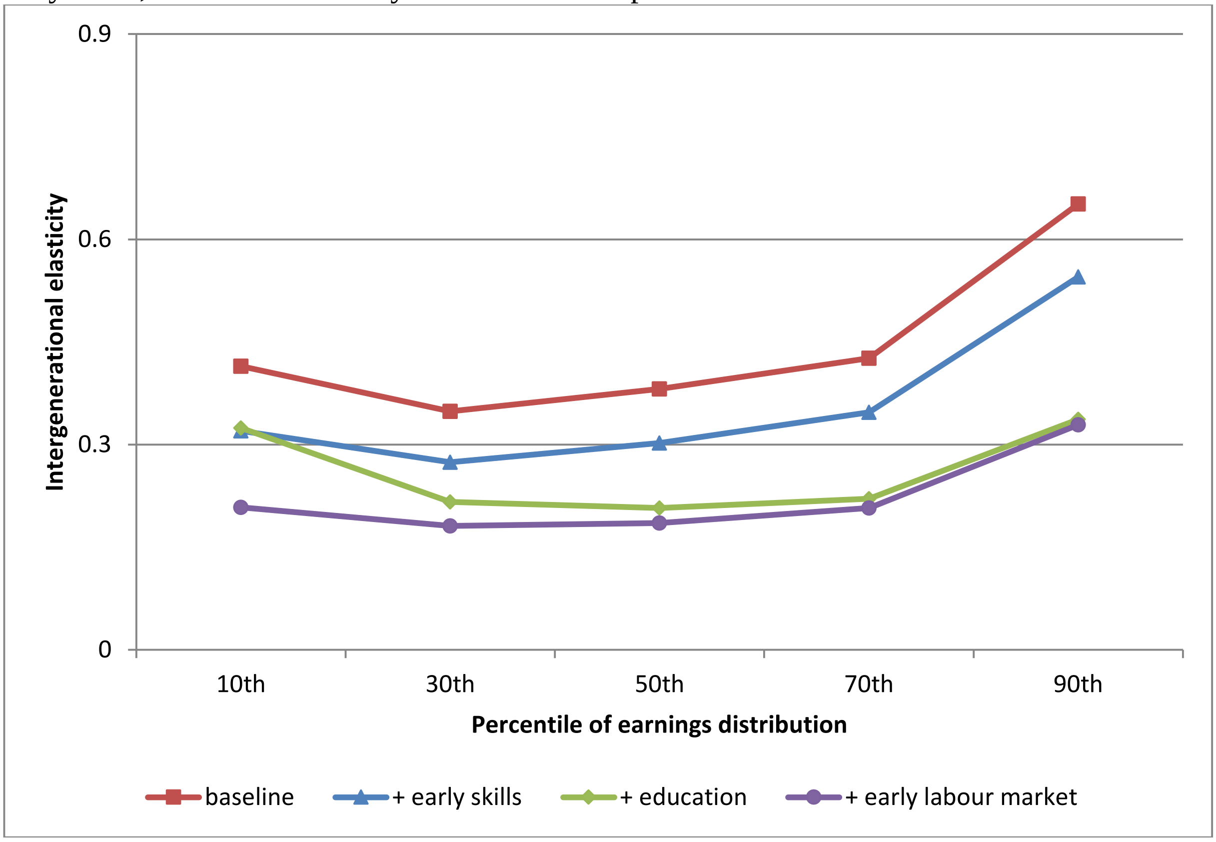


Table 1 Mean and standard deviation of average parental childhood income, early skills, education and early labour market attachment across the distribution of lifetime earnings

Percentile of earns dist.	Mean	10th	30th	50th	70th	90th
Average parental income	1360.90	1146.53	1249.76	1329.47	1418.49	1660.54
(2001 £s monthly)	(569.21)	(419.22)	(465.54)	(519.85)	(550.22)	(709.67)
IQ at 10	0.11	-0.21	-0.05	0.12	0.23	0.46
	(0.88)	(0.83)	(0.88)	(0.82)	(0.83)	(0.87)
Maths at 10	0.15	-0.23	-0.02	0.15	0.27	0.55
	(0.88)	(0.90)	(0.88)	(0.81)	(0.83)	(0.80)
Reading at 10	0.05	-0.29	-0.11	0.05	0.19	0.43
	(0.88)	(0.86)	(0.88)	(0.83)	(0.83)	(0.79)
Application at 10	-0.05	-0.36	-0.22	-0.06	0.10	0.28
	(0.86)	(0.89)	(0.87)	(0.83)	(0.81)	(0.74)
Hyperactive at 10	0.13	0.29	0.22	0.13	0.03	-0.03
	(0.98)	(1.05)	(1.02)	(0.98)	(0.93)	(0.90)
Clumsy at 10	0.06	0.28	0.19	0.02	-0.09	-0.11
	(0.88)	(0.98)	(0.95)	(0.83)	(0.79)	(0.78)
Extrovert at 10	0.00	-0.20	-0.04	0.02	0.08	0.14
	(0.89)	(0.90)	(0.92)	(0.88)	(0.86)	(0.88)
Anxious at 10	-0.05	0.11	0.05	-0.07	-0.14	-0.20
	(0.90)	(0.91)	(0.94)	(0.89)	(0.90)	(0.84)
Years of Education	12.56	11.80	11.94	12.31	12.81	13.96
	(2.29)	(1.60)	(1.63)	(2.09)	(2.42)	(2.80)
Number of GCSEs	4.01	2.69	2.95	3.68	4.61	6.12
	(3.13)	(2.24)	(2.44)	(2.87)	(3.20)	(3.43)
Number of A-levels	0.88	0.66	0.58	0.74	0.92	1.47
	(1.10)	(0.71)	(0.72)	(0.95)	(1.14)	(1.52)
Degree	0.22	0.09	0.10	0.16	0.28	0.49
	(0.40)	(0.26)	(0.28)	(0.35)	(0.44)	(0.49)
Proportion time employed	0.94	0.85	0.96	0.96	0.96	0.95
	(0.15)	(0.27)	(0.12)	(0.09)	(0.07)	(0.07)

Standard deviation in parentheses. N= 4312

Table 2 Lifecycle bias in estimates of the intergenerational income elasticity (IGE) in the UK

Age of earnings	26	30	34	38	42
IGE (β)	0.227 (.022)***	0.366 (.022)***	0.420 (.031)***	0.468 (.031)***	0.497 (.032)***
N	*2364*	*3340*	*2806*	*2080*	*2685*

Standard errors in parentheses, * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Dummy variables included where income is imputed.

Table 3 Unconditional quantile regressions (UQR) of the IGE between average parental childhood income and lifetime earnings, excluding and including workless spells (26-42)

Percentile of earns dist.	OLS (β)	10th	30th	50th	70th	90th
Excluding workless spells	0.383 (.020)***	0.240 (0.03)***	0.307 (0.02)***	0.358 (0.02)***	0.412 (0.03)***	0.620 (0.05)***
Including workless spells	0.430 (0.02)***	0.414 (0.05)***	0.348 (0.02)***	0.381 (0.02)***	0.426 (0.03)***	0.652 (0.05)***

N= 4170, 4312. Standard errors in parentheses, * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Dummy variables included where income and earnings are imputed.

Table 4 Unconditional quantile regressions of the impact of average childhood parental income, cognition, non-cognitive skills, education and early labour market experience on lifetime earnings (including workless spells) (26-42)

Percentile of earns dist.	OLS	10th	30th	50th	70th	90th
Panel A – Ability at 10						
Average parental income	0.380	0.355	0.301	0.335	0.379	0.592
	(0.02)***	(0.05)***	(0.02)***	(0.02)***	(0.03)***	(0.06)***
IQ at 10	0.115	0.137	0.109	0.107	0.107	0.135
	(0.01)***	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***
Panel B – + Age 10 skills						
Average parental income	0.348	0.320	0.274	0.302	0.347	0.545
	(0.02)***	(0.05)***	(0.02)***	(0.02)***	(0.03)***	(0.06)***
IQ at 10	0.032	0.044	0.041	0.021	0.024	0.009
	(0.01)**	(0.03)	(0.01)***	(0.01)	(0.01)*	(0.03)
Maths at 10	0.063	0.116	0.038	0.050	0.048	0.080
	(0.01)***	(0.04)***	(0.02)**	(0.02)***	(0.02)***	(0.03)***
Reading at 10	0.023	-0.021	0.035	0.037	0.038	0.068
	(0.01)*	(0.03)	(0.02)**	(0.02)**	(0.02)**	(0.03)**
Application at 10	0.054	0.044	0.038	0.055	0.059	0.071
	(0.01)***	(0.03)	(0.02)**	(0.01)***	(0.01)***	(0.02)***
Hyperactive at 10	-0.012	-0.033	0.011	-0.007	-0.012	-0.015
	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)
Clumsy at 10	-0.022	-0.046	-0.039	-0.036	-0.012	-0.003
	(0.01)**	(0.03)*	(0.01)***	(0.01)***	(0.01)	(0.02)
Extrovert at 10	0.057	0.091	0.065	0.047	0.043	0.063
	(0.01)***	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***
Anxious at 10	0.007	0.036	0.004	0.005	-0.009	0.006
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Panel C – + Years of Education						
Average parental income	0.297	0.313	0.240	0.251	0.276	0.435
	(0.02)***	(0.05)***	(0.03)***	(0.02)***	(0.03)***	(0.06)***
IQ at 10	0.027	0.047	0.038	0.016	0.016	-0.002
	(0.01)**	(0.03)	(0.01)**	(0.01)	(0.01)	(0.03)
Maths at 10	0.051	0.113	0.030	0.038	0.031	0.055
	(0.01)***	(0.04)***	(0.02)*	(0.02)**	(0.02)**	(0.03)**
Reading at 10	0.011	-0.022	0.027	0.025	0.020	0.041
	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
Application at 10	0.044	0.040	0.031	0.045	0.046	0.050
	(0.01)***	(0.03)	(0.02)**	(0.01)***	(0.01)***	(0.02)**
Hyperactive at 10	-0.010	-0.032	0.013	-0.005	-0.009	-0.010
	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)
Clumsy at 10	-0.024	-0.046	-0.041	-0.039	-0.016	-0.009
	(0.01)**	(0.03)*	(0.01)***	(0.01)***	(0.01)	(0.02)
Extrovert at 10	0.059	0.088	0.067	0.050	0.048	0.070
	(0.01)***	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***
Anxious at 10	0.005	0.035	0.002	0.003	-0.013	-0.000
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Years of education	0.038	0.001	0.026	0.039	0.055	0.083

	(0.00)***	(0.01)	(0.00)***	(0.00)***	(0.00)***	(0.01)***
Panel D – + GCSEs at 16						
Average parental income	0.248 (0.02)***	0.301 (0.05)***	0.200 (0.03)***	0.197 (0.02)***	0.214 (0.03)***	0.361 (0.06)***
Years of education	0.018 (0.00)***	-0.003 (0.01)	0.010 (0.00)**	0.018 (0.00)***	0.031 (0.01)***	0.053 (0.01)***
Number of GCSEs	0.034 (0.00)***	0.001 (0.01)	0.027 (0.00)***	0.038 (0.00)***	0.045 (0.00)***	0.058 (0.01)***
Early skills measures	x	x	x	x	x	x
Panel E – + Post-16 education qualifications						
Average parental income	0.249 (0.02)***	0.305 (0.05)***	0.202 (0.03)***	0.199 (0.02)***	0.214 (0.03)***	0.357 (0.06)***
Years of Education	-0.001 (0.01)	-0.002 (0.01)	0.003 (0.01)	-0.002 (0.01)	0.003 (0.01)	0.001 (0.01)
Number of GCSEs	0.029 (0.00)***	0.006 (0.01)	0.027 (0.00)***	0.034 (0.00)***	0.036 (0.00)***	0.037 (0.01)***
Number of A-levels	0.001 (0.01)	-0.062 (0.02)***	-0.024 (0.01)***	-0.011 (0.01)	0.013 (0.01)	0.110 (0.03)***
Degree	0.188 (0.03)***	0.103 (0.05)**	0.107 (0.03)***	0.224 (0.03)***	0.245 (0.04)***	0.307 (0.07)***
Early skills measures	x	x	x	x	x	x
Panel F – + Institution Fixed Effects and subject studied at uni						
Average parental income	0.255 (0.02)***	0.324 (0.05)***	0.216 (0.03)***	0.207 (0.02)***	0.221 (0.03)***	0.337 (0.05)***
Years of Education	-0.004 (0.01)	-0.002 (0.01)	0.005 (0.01)	-0.003 (0.01)	0.002 (0.01)	-0.009 (0.01)
Number of GCSEs	0.027 (0.00)***	0.007 (0.01)	0.027 (0.00)***	0.033 (0.00)***	0.034 (0.00)***	0.030 (0.01)***
Number of A-levels	-0.012 (0.01)	-0.071 (0.02)***	-0.027 (0.01)***	-0.014 (0.01)	0.006 (0.01)	0.074 (0.03)***
Degree	0.168 (0.05)***	0.132 (0.09)	0.097 (0.05)*	0.235 (0.06)***	0.276 (0.07)***	0.085 (0.12)
Early skills measures	x	x	x	x	x	X
Institution Fixed Effects	x	x	x	x	x	X
Subject studied	x	x	x	x	x	X
Panel G – + Early labour market experience (from leaving FT education until age 23)						
Average parental income	0.212 (0.02)***	0.208 (0.05)***	0.181 (0.03)***	0.185 (0.02)***	0.207 (0.03)***	0.329 (0.05)***
Proportion time employed	0.915 (0.05)***	2.450 (0.19)***	0.750 (0.06)***	0.463 (0.04)***	0.279 (0.04)***	0.161 (0.06)***
Constant	5.839 (0.34)***	4.326 (0.80)***	5.439 (0.43)***	6.269 (0.38)***	6.796 (0.39)***	6.480 (0.69)***
Early skills measures	x	x	x	x	x	X
Education measures	x	x	x	x	x	X
Institution Fixed Effects	x	x	x	x	x	X
Subject studied	x	x	x	x	x	X
R^2	0.39	0.27	0.23	0.25	0.27	0.26
N	4,312	4,312	4,312	4,312	4,312	4,312

Standard errors in parentheses, * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Dummy variables included where income and earnings are imputed.

Appendix:

Alternative measures of family background

In this section we investigate if our findings are robust to using an alternative measure of family background, namely parental education. We estimate the intergenerational elasticity at different quantiles of the unconditional distribution of lifetime earnings on parental education using three different data sources: the British Household Panel (BHPS) which refers to the period 1991-2008 and the two major British cohort studies: the British Cohort Study (BCS) and the National Child Development Study (NCDS). We use a measure of sons' lifetime earnings, obtained as the average of earnings at ages 30-45 in the BHPS and at ages 26-42 in the BCS and NCDS. The log of the average is taken. Parental education is classified as the highest level of education of either the mother or the father and split into three categories: low, medium and high.

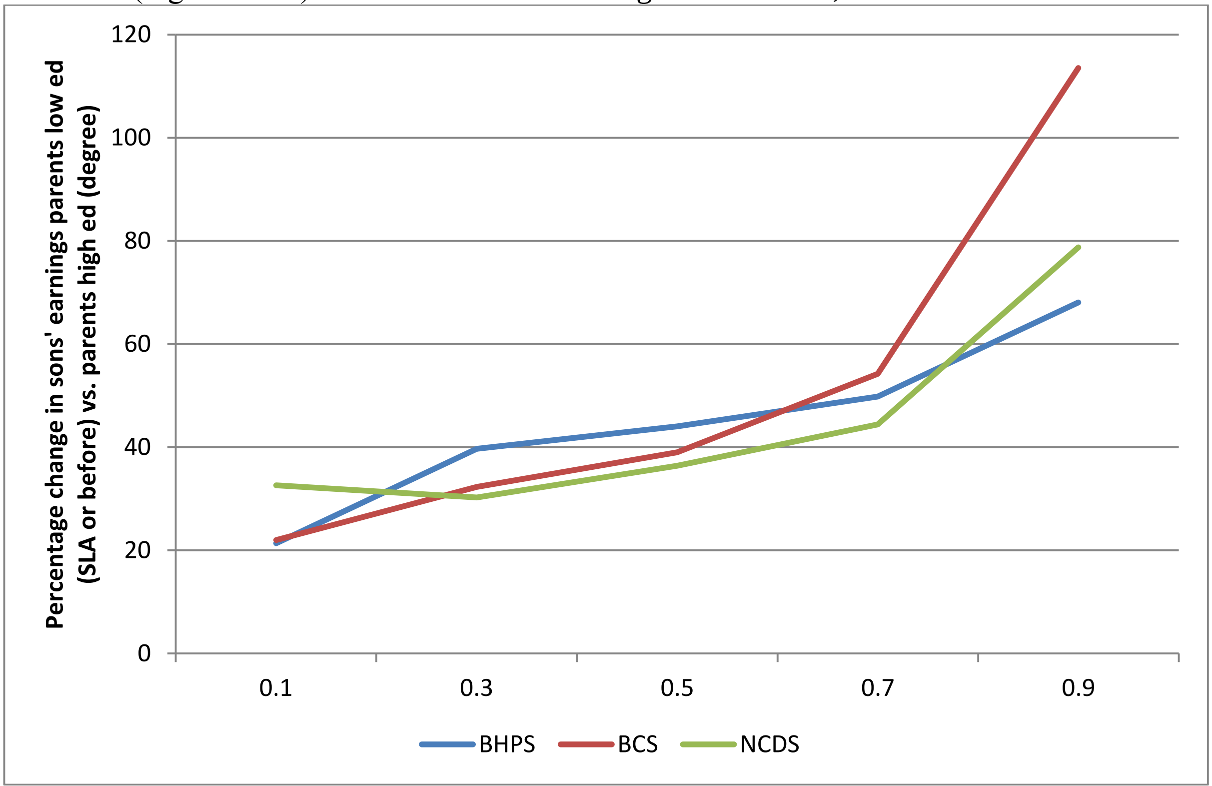
Table A1 presents the average associations between parental education and sons' earnings using standard OLS regression. We find similar associations to those found by Jerrim (2014) for the UK, using EU-SILC, ESS and PIACC data: sons with higher educated parents earn 42-48% more on average than sons with low educated parents. Figure A1 plots UQR estimates of high versus low parental education across the three data sources and confirms the presence of higher persistence between parental education and sons' earnings at the top of the unconditional distribution of sons' wages across the three data sources, consistent with our findings for parental income in childhood. This is in contrast to the findings of Jerrim (2014) who finds a flat relationship across the distribution of sons' earnings for the UK, using EU-SILC, ESS and PIACC data.

Table A1 OLS regression estimates of the association between parental education (high vs. low) and sons' lifetime earnings in the BHPS, BCS and NCDS

Average Earnings (age)	Coefficient on high parental education (baseline SLA or less)	Percentage change {(exp(b)-1)*100}
BHPS (30-45)	0.348 (0.037)***	41.6
BCS (26-42)	0.389 (0.028)***	47.5
NCDS (26-42)	0.353 (0.032)***	42.3

N= 3134, 4312, 3453. Standard errors in parentheses, * p<0.1; ** p<0.05; *** p<0.01

Figure A1 Unconditional quantile regressions (UQR) of the association between parental education (high vs. low) and sons' lifetime earnings in the BHPS, BCS and NCDS



UQR sensitivity analysis to the tails and to the inclusion of the always workless

In this section we provide some robustness checks of the UQR estimates for the tails of the income distribution of our imputed benefit lifetime earnings measure (26-42).
The bottom row of Table 3 reported the UQR estimates computed at the 10th, 30th 50th, 70th and 90th percentiles. In Table A2 (first row of Panel A) and in Table A3 we respectively show the same estimates also computed at low percentiles (5th-20th) and top percentiles (80th-95th)
Table A2 also reports a sensitivity analysis to the inclusion of the always workless, those who have experienced workless spells at each given age (26, 30, 34, 38, 42). These are included in our lifetime imputed benefit measure (26-42).
The second row of panel A replicates the UQR estimates of our lifetime imputed benefit measure excluding these people from the sample (only 1.2 percent of the sample are workless at each given age) . Panel B replicates the estimates on the same sample using the zero

earnings instead of benefit replacement.

As discussed in the results section, the bottom tail (10th percentile) is not very sensitive to the treatment of worklessness if we either use the benefit measure or the zero earnings replacement. Differences arise when UQR are computed at the 5th percentile, suggesting that the strong association between parental income and childs resources for those ending up very poor is further amplified by unemployment spells.
UQR estimates are robust to the top tails, as shown in Table A3.
Finally Table A4 replicates results of Table 4 when the always workless are excluded from the sample.

Table A2 Unconditional quantile regressions (UQR) of the IGE between average parental childhood income and lifetime earnings (26-42) including and excluding the always workless

Percentile of earns dist.	5th	10th	15th	20th
PANEL A: Lifetime earnings imputed benefit when not earning				
Including the always workless	1.020 (0.21)***	0.414 (0.05)***	0.323 (0.03)***	0.352 (0.03)***
excluding the always workless	0.741 (0.17)***	0.371 (0.05)***	0.297 (0.03)***	0.336 (0.03)***
PANEL B: Lifetime measure with zeros when not earning				
Including the always workless	2.369 (0.49)***	0.441 (0.05)***	0.344 (0.03)***	0.360 (0.03)***

N=4312, 4258. Standard errors in parentheses, * $p<0.1$; ** $p<0.05$; *** $p<0.01$.
Dummy variables included where income and earnings are imputed.

Table A3 Unconditional quantile regressions (UQR) of the IGE between average parental childhood income and lifetime earnings (26-42)

Percentile of earns dist.	80th	85th	90th	95th
Lifetime imputed benefit measure				
Including the always workless	0.479 (0.32)***	0.587 (0.04)***	0.652 (0.05)***	0.644 (0.07)***

N=4312. Standard errors in parentheses, * $p<0.1$; ** $p<0.05$; *** $p<0.01$.
Dummy variables included where income and earnings are imputed.

Table A4 Unconditional quantile regressions of the impact of average childhood parental income, cognition, non-cognitive skills, education and early labour market experience on lifetime earnings (including workless spells) (26-42) but excluding the always workless

Percentile of earns dist.	OLS	10th	30th	50th	70th	90th
Panel A – Ability at 10						
Average parental income	0.380	0.273	0.293	0.328	0.379	0.575
	(0.02)***	(0.04)***	(0.02)***	(0.02)***	(0.03)***	(0.06)***
IQ at 10	0.115	0.130	0.111	0.105	0.108	0.132
	(0.01)***	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***
Panel B – + Age 10 skills						
Average parental income	0.348	0.243	0.265	0.296	0.348	0.528
	(0.02)***	(0.04)***	(0.02)***	(0.02)***	(0.03)***	(0.06)***
IQ at 10	0.032	0.048	0.040	0.021	0.026	0.009
	(0.01)**	(0.02)*	(0.01)***	(0.01)	(0.01)*	(0.03)
Maths at 10	0.063	0.093	0.039	0.049	0.049	0.080
	(0.01)***	(0.03)***	(0.02)**	(0.02)***	(0.02)***	(0.03)***
Reading at 10	0.023	-0.005	0.039	0.036	0.035	0.065
	(0.01)*	(0.03)	(0.02)**	(0.02)**	(0.02)**	(0.03)**
Application at 10	0.054	0.035	0.038	0.055	0.058	0.071
	(0.01)***	(0.03)	(0.02)**	(0.01)***	(0.01)***	(0.02)***
Hyperactive at 10	-0.012	-0.024	0.012	-0.007	-0.011	-0.014
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Clumsy at 10	-0.022	-0.051	-0.042	-0.034	-0.012	-0.002
	(0.01)**	(0.02)**	(0.01)***	(0.01)***	(0.01)	(0.02)
Extrovert at 10	0.057	0.071	0.060	0.048	0.043	0.062
	(0.01)***	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***
Anxious at 10	0.007	0.039	0.006	0.003	-0.008	0.006
	(0.01)	(0.02)*	(0.01)	(0.01)	(0.01)	(0.02)
Panel C – + Years of Education						
Average parental income	0.297	0.238	0.231	0.245	0.278	0.422
	(0.02)***	(0.04)***	(0.01)***	(0.02)***	(0.03)***	(0.06)***
IQ at 10	0.027	0.049	0.036	0.016	0.019	-0.002
	(0.01)**	(0.02)**	(0.01)**	(0.01)	(0.01)	(0.03)
Maths at 10	0.051	0.091	0.030	0.037	0.033	0.055
	(0.01)***	(0.03)***	(0.02)*	(0.02)**	(0.02)**	(0.03)**
Reading at 10	0.011	-0.006	0.030	0.023	0.018	0.039
	(0.01)	(0.03)	(0.02)*	(0.02)	(0.02)	(0.03)
Application at 10	0.044	0.033	0.031	0.045	0.044	0.050
	(0.01)***	(0.03)	(0.02)**	(0.01)***	(0.01)***	(0.02)**
Hyperactive at 10	-0.010	-0.024	0.014	-0.005	-0.008	-0.010
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Clumsy at 10	-0.024	-0.051	-0.041	-0.037	-0.016	-0.008

	(0.01)**	(0.02)**	(0.01)***	(0.01)***	(0.01)	(0.02)
Extrovert at 10	0.059	0.070	0.062	0.052	0.048	0.068
	(0.01)***	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***
Anxious at 10	0.005	0.038	0.004	0.001	-0.012	-0.000
	(0.01)	(0.02)*	(0.01)	(0.01)	(0.01)	(0.02)
Years of education	0.038	0.002	0.026	0.039	0.054	0.081
	(0.00)***	(0.01)	(0.00)***	(0.00)***	(0.00)***	(0.01)***
Panel D – + GCSEs at 16						
Average parental income	0.248	0.223	0.190	0.191	0.218	0.350
	(0.02)***	(0.04)***	(0.02)***	(0.02)***	(0.03)***	(0.06)***
Years of education	0.018	-0.003	0.011	0.018	0.031	0.052
	(0.00)***	(0.01)	(0.00)**	(0.00)***	(0.01)***	(0.01)***
Number of GCSEs	0.034	0.006	0.027	0.038	0.043	0.056
	(0.00)***	(0.01)	(0.00)***	(0.00)***	(0.00)***	(0.01)***
Early skills measures	x	x	x	x	X	x
Panel E – + Post-16 education qualifications						
Average parental income	0.249	0.227	0.192	0.193	0.218	0.346
	(0.02)***	(0.04)***	(0.02)***	(0.02)***	(0.03)***	(0.06)***
Years of Education	-0.001	-0.004	0.003	-0.002	0.003	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of GCSEs	0.029	0.008	0.027	0.033	0.035	0.036
	(0.00)***	(0.01)	(0.00)***	(0.00)***	(0.00)***	(0.01)***
Number of A-levels	0.001	-0.043	-0.020	-0.009	0.012	0.106
	(0.01)	(0.01)***	(0.01)**	(0.01)	(0.01)	(0.03)***
Degree	0.188	0.091	0.110	0.216	0.247	0.304
	(0.03)***	(0.04)**	(0.03)***	(0.03)***	(0.04)***	(0.07)***
Early skills measures	x	x	x	x	X	x
Panel F – + Institution Fixed Effects and subject studied at uni						
Average parental income	0.255	0.241	0.204	0.201	0.225	0.331
	(0.02)***	(0.04)***	(0.03)***	(0.02)***	(0.03)***	(0.05)***
Years of Education	-0.004	-0.005	0.004	-0.002	0.002	-0.008
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of GCSEs	0.027	0.009	0.027	0.033	0.033	0.029
	(0.00)***	(0.01)	(0.00)***	(0.00)***	(0.00)***	(0.01)***
Number of A-levels	-0.012	-0.050	-0.022	-0.011	0.006	0.071
	(0.01)	(0.02)***	(0.01)***	(0.01)	(0.01)	(0.03)***
Degree	0.168	0.145	0.124	0.239	0.275	0.092
	(0.05)***	(0.08)*	(0.05)**	(0.06)***	(0.07)***	(0.12)
Early skills measures	x	x	X	x	X	X
Institution Fixed Effects	x	x	X	x	X	X
Subject studied	x	x	X	x	X	X
Panel G – + Early labour market experience (from leaving FT education until age 23)						
Average parental income	0.212	0.171	0.177	0.184	0.214	0.324
	(0.02)***	(0.04)***	(0.03)***	(0.02)***	(0.03)***	(0.05)***
Proportion time employed	0.915	1.891	0.734	0.474	0.279	0.179
	(0.05)***	(0.18)***	(0.06)***	(0.04)***	(0.04)***	(0.06)***
Constant	5.839	5.122	5.538	6.275	6.854	6.493
	(0.34)***	(0.18)***	(0.43)***	(0.38)***	(0.40)***	(0.70)***

Early skills measures	x	x	X	X	X	X
Education measures	x	x	X	x	X	X
Institution Fixed Effects	x	x	X	x	X	X
Subject studied	x	x	X	x	X	X
R^2	0.39	0.21	0.21	0.24	0.26	0.26
N	4,258	4,258	4,258	4,258	4,258	4,258

Standard errors in parentheses, * p<0.1; ** p<0.05; *** p<0.01. Dummy variables included where income and earnings are imputed.