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Intergenerational income mobility: access to top jobs, the low-pay no-pay cycle and the role of education in a common framework

Paul Gregg[1] · Lindsey Macmillan[2] · Claudia Vittori[3]

Abstract
Studies of intergenerational mobility have typically focused on estimating the average persistence across generations. Here, we use the relatively new unconditional quantile regression technique to consider how intergenerational persistence varies across the distribution of sons' earnings. We find a J-shaped relationship between parental income and sons' earnings, with parental income a strong predictor of labour market success for those at the bottom, and to an even greater extent, the top of the earnings distribution. We explore the role early skills, education and early labour market attachment in shaping this pattern for the first time. Worryingly, we find that the association with childhood parental income dominating that of a high level of education at the top of the distribution of earnings. In this sense, education is not as meritocratic as we might hope, as those with the same detailed educational attainment still see a strong association between their earnings and their parental income. Early labour market spells out of work have lasting effects on those at the bottom, alongside parental income.

Keywords Intergenerational mobility · Children · Education · Nonlinear estimation · Quantile regression

JEL codes J13 · J62 · I24

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✉ Paul Gregg
     p.gregg@bath.ac.uk

[1] Department of Social and Policy Sciences and Centre for the Analysis of Social Policy, University of Bath, Bath, UK

[2] Department of Social Science, UCL Institute of Education, University College London, London, UK

[3] National Institute for the Analysis of Public Policy (INAPP), Rome, Italy

1 Introduction

Intergenerational mobility, the independence between the socio-economic status (SES) of parents and children, has been a topic of considerable attention in academia, policy circles and in the public domain in recent years. There has been a wealth of new research on this in the USA (Chetty et al. 2014a, b; Mitnik et al. 2015) with the US government finally taking note of the issue of social mobility (The White House 2013). In the UK, the topic has been the main focus of social policy for the past decade with successive governments attempting to address Britain's poor record on intergenerational mobility by commissioning policy reviews, developing indicators to measure progress and establishing a statutory commission, the Social Mobility Commission (SMC).[1] These all had the aim to provide evidence on the nature of the problem, make policy proposals and, above all, hold government to account on the issue. This emergence in policy attention has been driven by research that showed that Britain and the USA has low levels of mobility by international standards (Corak 2013; Jerrim and Macmillan 2015) and mobility declined over time in Britain (Blanden et al. 2004; Gregg et al. 2017b).

Yet, while these studies have been influential in establishing intergenerational mobility as a priority, they have been lacking in being able to speak to specific policy priorities, due to their focus on mean-based measures of mobility such as the intergenerational elasticity (IGE). Instead, the focus of UK policy makers has been on three issues that reflect different parts of the distribution of incomes: (a) access to elite jobs (SMC 2014a, b, 2017b; HM Government 2015), (b) those who are stuck on low pay (SMC 2017a; HM Government 2015; D'Arcy and Hurrell 2014) and (c) the role of educational attainment in improving the life chances of poor children (HM Government 2011; HM Government 2015; SMC 2017c). While each of these areas have been assessed separately,[2] it is important to understand their relative contribution as different dimensions of the social mobility issue to the overall policy problem. This requires using a common framework where comparisons across the distribution of parent and child incomes are possible and informative. Here, our first contribution is to present estimates of intergenerational income persistence across the distribution of sons' lifetime adult earnings for the first time in Britain, providing a framework for exploring the persistence between family background and outcomes, such as elite jobs and low lifetime earnings, together. In doing so, we present evidence of the strength of the associations between parental income in childhood and adult earnings for those who are at the top of the earnings ladder compared to those at the middle or the bottom. Our second contribution is to consider the role of cognition, educational attainment and the labour market in accounting for these associations across the distribution.

This work contributes to the small existing literature focusing on intergenerational transmissions across the distribution of adult outcomes (Eide and Showalter 1999; Grawe 2004; Bratsberg et al. 2005; Palomino et al. 2018) and to the literature exploring nonlinearities in returns to schooling in the USA and Europe (Angrist and Pischke

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[1] https://www.gov.uk/government/organisations/social-mobility-commission

[2] A number of studies have focused on a particular point in the distribution of adult outcomes, exploring intergenerational poverty (Blanden and Gibbons 2006) or access to and progression within the top professions (Macmillan 2009; Macmillan et al. 2015; Laurison and Friedman 2016) and top earnings/incomes (Björklund et al. 2012).

2009; Martins and Pereira 2004; Brunello et al. 2009). More broadly, this work also speaks to the much larger literature on wage inequality and polarisation in the labour market. Recent evidence suggests that employment growth is 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). Here, we add to this literature by assessing the childhood circumstances of those who achieve high-end rewards or get stuck at the lower parts of the earnings distributions.

We employ the relatively new unconditional quantile regression (UQR) technique to explore the association between parental income and sons' lifetime earnings across the distribution of earnings. We use a measure of sons' (near) lifetime earnings to also explore how the intergenerational association evolves over the lifecycle. While many existing studies find that the association with childhood circumstance is declining across the distribution of earnings in the USA, Norway and Canada (Eide and Showalter 1999; Bratsberg et al. 2005; or broadly flat in the USA in Grawe (2004)), Björklund et al. (2012) find a much larger intergenerational association for top earnings and incomes compared to the mean IGE in Sweden. Recent studies for Germany and the USA also suggest higher intergenerational persistence at the top of the earnings distribution compared to the middle (Schnitzlein 2016; Palomino et al. 2018). Our findings are more in line with these recent studies with the association between earnings and childhood parental income strongest for the highest earning sons: family background becomes an increasing predictor of success, the more successful you are in the UK. This is also in line with recent research into access to and progression within the top professions (Macmillan 2009; Macmillan et al. 2015; Laurison and Friedman 2016). We also find a stronger association between childhood parental income and lifetime earnings for the lowest paid compared to those in the middle, resulting in a 'J'-shaped pattern of associations across the earnings distribution.

Given this positive and increasing association between parental income and earnings across the majority of the distribution of sons' earnings, a natural place to explore possible explanations for this trend comes from the returns to education literature. We assess whether the relationship between parental income and sons' earnings varies across the distribution of sons' earnings, conditional on a wide range of measures of cognitive ability, 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 higher wages and avoid the lowest paid opportunities? Exploring intergenerational persistence in this way has important implications for policy as it both shines new light on where in the distribution the core problem of low mobility lies, and highlights the effectiveness of education in having the potential to create a meritocratic society (Gregg et al. 2017a). 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. The extremely strong association between earnings and family background for those in top jobs, conditional on cognition, early skills, educational attainment, university attended and degree studied is particularly concerning for policy makers as it suggests that elite jobs in Britain are not meritocratically accessed via education.

Finally, our approach also allows us to directly explore patterns in the labour market returns to ability, early skills, years of schooling and months of 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 in the unconditional earnings distribution. This makes an advancement on existing research on the nonlinearity of the returns to education (see Harmon et al. 2003) using the conditional quantile regression (CQR) technique, which becomes hard to interpret with multiple independent variables included. We find that an early measure of ability has a linear association with earnings and therefore does not account for the differential persistence of family background across the earnings distribution. However, 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 USA and Europe, increased schooling has a progressively larger effect on earnings as you move up the earnings distribution. Measures of attained qualifications such as GCSEs and degree attainment, including university attended and subject studied, explain this pattern while youth unemployment has a strong association with earnings at the bottom of the earnings distribution, accounting for a large part of the persistence in family background 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

Much of the existing research on intergenerational mobility has investigated the persistence of incomes across generations at the mean of the distribution. 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 (Nybom and Stuhler 2017; Chetty et al. 2014a, b; Mitnik et al. 2015; Gregg et al. 2017b). 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 while the USA and the UK are characterised by the lowest mobility among developed economies (Corak 2013). A focus of recent literature has been estimating this relationship taking account of biases that arise from using point in time approximations of lifetime incomes (see Black and Devereux (2011) and Jäntti and Jenkins (2015) for an extensive discussion). Recent estimates of mobility therefore represent the extent to which adult outcomes mirror family's economic resources in childhood and are an indicator of the persistence of inequality across generations.

One of the limitations of focusing on the average IGE is that this summary measure may conceal potentially important differences in the pattern of intergenerational mobility. There are a number of domains over which such variation may occur, see for example Chetty et al. (2014b) who explore geographical variation in the USA. An obvious dimension to explore variation is at different points of the distribution of

parental and children's adult 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 Devereux 2011). Indeed, a recent theoretical contribution by Becker et al. (2018) predicts that intergenerational mobility will not be constant across the distribution, due to both credit constraints and wealthier parents making better investment decisions regarding their children's human capital (due to higher returns to those investments; Heckman and Mosso 2014). This will lead to higher intergenerational persistence at the top and the bottom of the parental income distribution. By investigating variations in intergenerational persistence across domains, we can highlight particular areas where policy should focus.

The majority of existing intergenerational literature looking across distributions focuses on nonlinearities in the *first generation* measures of parental incomes or father's earnings, using a range of techniques such as higher order polynomials or non-parametric regressions, with mixed results across countries. Bratsberg et al. (2007) present a comparative study of nonlinearity in the IGE across family incomes for Denmark, Finland, Norway, the UK and the USA. While in the USA and the UK, they find a linear relationship, the Nordic countries show a more convex pattern. More recently, Björklund et al. (2012) find a similar stronger association at the top of parental earnings/income distribution for Sweden. Interestingly, when using administrative tax records rather than survey data in the USA, Chetty et al. (2014b) find a concave relationship across the distribution of parental income with an estimated IGE of 0.452 if estimated between the 10th and 90th percentiles compared to 0.344 when estimated across the entire distribution. 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.

A smaller strand of literature has explored nonlinearities along the distribution of the second-generation measures, where we make our contribution. This literature has generally used the well-known conditional quantile regression (CQR) technique proposed by Koenker and Bassett (1978). In the intergenerational setting, this estimates differences in the association between parent and child incomes across the *conditional* distribution of sons' adult earnings. Studies using CQR for the USA, Norway and Canada, all show that intergenerational persistence is strongest among the lowest paid. In the USA, Eide and Showalter (1999) found that the estimated IGE at the mean of the distribution is 0.45, while the CQR estimates are 0.67 for the 10th percentile and 0.26 for the 90th percentile. Bratsberg et al. (2005) and Grawe (2004) demonstrate similar findings for Norway and Canada. Recent papers by Palomino et al. (2018) and Schnitzlein (2016) use both conditional and unconditional quantile regression techniques for the USA and Germany and have findings more in line with ours. Palomino et al. (2018) find a U-shaped relationship for the importance of family background across the distribution of sons' earnings while Schnitzlein (2016) finds more intergenerational persistence at the 75th percentile of the offspring's distribution in Germany and the USA (although does not explore further into the tails).

Another key literature that this paper contributes to is that which places human capital as a key driver of intergenerational mobility. Models by Blau and Duncan (1967) and Becker and Tomes (1986) emphasise the role of human capital as the central mechanism through which advantage (or disadvantage) is passed from one generation

to the next. More recent theoretical models have developed to focus on both the timing of skill formation, emphasising particularly critical (early) time periods for investments, and the contribution of different capabilities and skills (cognitive, non-cognitive, and health) to later outcomes (Heckman and Mosso 2014). Mirroring these theoretical developments, while empirical studies on the role of education in intergenerational mobility date back to the early 1980s (Atkinson 1980; Atkinson and Jenkins 1984), over the past 10 years, a number of studies have considered the wider role of cognitive and non-cognitive skills, and health, along with education in the intergenerational mobility process (Blanden et al. 2007; Mood et al. 2012; Rothstein 2018; Björklund et al. 2017). These studies broadly find that the dominant transmission effect is through educational attainment with early skills feeding in to later attainment, leaving a small independent role for skills in accounting for income persistence across generations. So far, only Corak and Heisz (1999) have investigated the role of education in the transmission of intergenerational persistence in a nonlinear manner. They 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 for Canada, using CQR.[3]

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 USA has consistently found that education is more valuable at the top of the wage distribution (Martins and Pereira 2004; Buchinsky 1994; Angrist et al. 2006; Harmon et al. 2003) This general finding of greater returns to schooling among higher earners is somewhat at odds with the smaller literature which suggests that intergenerational associations are stronger 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 (2015) for example), we might not expect stronger intergenerational associations for low and middle earners, at least for that part of the IGE that is associated with schooling. There is less literature on whether returns to education differ by family background. A number of studies show that among graduates those from more affluent families earn more (Chetty et al. 2017; Crawford et al. 2016). However, Nybom (2017) suggests that for Sweden at least, the prima facie evidence of higher returns for those from more affluent families is driven by rising returns to cognitive and non-cognitive abilities.

3 Methodology

The intergenerational elasticity (IGE) is estimated using 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}).[4]

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[3] As discussed by Eide and Showalter (1999), these results could possibly be driven by the fact that quantile regressions compare 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.

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

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

The estimated parameter, $\hat{\beta}$, captures the IGE or the persistence in income 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' adult income or earnings.

As discussed, a limitation of this approach is that $\hat{\beta}$ is likely to hide important variations in the strength of the association at different parts of the distribution of sons' earnings. The mean IGE can therefore conceal areas or groups that may benefit more from policy interventions. An obvious way of characterising the distribution of sons' earnings is to compute its quantiles. The early literature generally used conditional quantile regression (CQR) (Koenker and Bassett 1978) to explore nonlinearities in sons' earnings by measuring the association between parental income and sons' earnings at a given point in *the conditional distribution* of sons' earnings. However, this approach has some important drawbacks. For example, the pre-regression rank order of sons' earnings is not the same as that for the post-regression residuals making the interpretation of the coefficients unclear. Further, adding covariates means that the *conditional* quantiles will vary across specifications. As Cooke (2014) notes, the association for someone at the 10th percentile of the wage distribution of university graduates may not be the same as the association for someone at the 10th percentile of the wage distribution of all workers. Therefore, unlike 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).[5] By contrast, when using CQR models, only the conditional interpretation can be applied.[6] 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).

The two-step procedure developed by Firpo et al. (2009), unconditional quantile regressions (UQR), offers a way forward in this setting. 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

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

[6] Indeed, the law of iterated expectations does not apply in the case of conditional quantile regressions.

statistic of interest, v, $\text{RIF}(y; v)$.[7] 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.[8] If the statistic of interest is the quantile ($v = q_\tau$), Firpo et al. (2009) refer to this RIF-regression as an UQR.

In this work, we explore how the association between parental income and sons' earnings varies across the percentiles of the unconditional distribution of sons' earnings (10th 30th, 50th, 70th, 90th) by estimating Eq. (1) using UQR replacing the dependent variable with the RIF of the quantiles q_τ where τ=0.1, 0.3, 0.5, 0, 7, 0.9 (in Eq. (2)). 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 parental childhood income has a stronger association with sons' earnings for those who end up being rich compared to those who end up being poor.

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

The interpretation of the coefficients $\hat{\beta}^\tau$ from using this UQR technique differs in some cases from the standard OLS interpretation, depending on the type of explanatory variable of interest. This is because UQR gives a population estimate of a unit change in the explanatory variable at that specific point in the distribution of the dependent variable. Under assumptions of rank invariance, or at least similarity (Dong and Shen 2017), unit changes in this setting can be interpreted as individual-level effects. For continuous variables, such as parental income (and indeed test scores used below), this assumption is likely to hold for small incremental changes and therefore $\hat{\beta}$ can then be interpreted as the estimated effect of the marginal change in parental income on sons' earnings at the quantile of interest (a similar interpretation to the IGE at a given point in the distribution). However, for binary variables such as degree attainment, this assumption is more problematic. In this setting, the coefficients should be interpreted at a population level: in the case of degree attainment as an example, this would reflect the association between having a degree and labour market earnings at a given point in the distribution, for a marginal change in the proportion of people with a degree at that point in the earnings distribution.[9]

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 ($X = \rho^\tau \text{early\_skills}_i^{\text{son}} + \delta^\tau \text{educ}_i^{\text{son}} + \gamma^\tau lm_i^{\text{son}}$) in model (3). We therefore estimate

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[7] The RIF is obtained by adding the distributional parameter concerned to the influence function, $\text{IF}(y; v)$.
[8] The expected value of the RIF is equivalent to its statistic of interest (i.e. quantile) and by applying the law of iterated expectations, it is possible to write

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

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.
[9] Note that a rank-rank model using UQR is problematic, as the interpretation of the effect of a marginal change in the rank family income on the distribution of the rank of sons' earnings has no meaning as the distribution of a rank measure cannot change. Further, an assumption of rank invariance from a marginal change must be violated in rank-rank regression as the models are predicting the degree of rank re-ordering. Hence, we do not undertake rank-based analysis here.

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

using UQR at different quantiles q_τ where $\tau = 0.1, 0.3, 0.5, 0, 7, 0.9$ (10th, 30th, 50th, 70th, 90th). This approach has two advantages: first, we can explore the direct association between family income and sons' earnings across the distribution of sons' earnings ($\hat{\beta}^{c\tau}$), conditional on early skills, education and early labour market attachment to assess how meritocratic education is at different points of the distribution. Here, the interpretation on the coefficient $\hat{\beta}^{c\tau}$ is similar to the standard IGE, estimating the effect of a marginal change in family income on sons' earnings at the quantile of interest, given other conditioning variables. Second, we can also explore the heterogeneous returns to early skills and ability ($\hat{\rho}^\tau$), education ($\hat{\delta}^\tau$) and early labour market experience ($\hat{\gamma}^\tau$) across the distribution of the sons' earnings, subject to the interpretation discussed above for discreet measures.

Motivated by theoretical advancements, we build our model in stages across childhood, focusing first on the role of early ability and skills before considering the importance of later measures of attainment such as 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 1 week in April 1970 within Great Britain. This longitudinal survey 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, 2007, 2013; Gregg et al. 2017b) allocating individuals within bands using a Singh-Maddala (Singh and Maddala 1976) distribution and maximum likelihood estimation, 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 is taken across the two observed income measures at 10 and 16 with values imputed where income was missing in one period, based on the income observed in the non-missing period plus changes in employment status, housing tenure and family structure that occur between the two periods (see online appendix from Gregg et al. (2017b) for further details). The log of the average is then taken.[10]

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 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 earnings 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 online appendix Gregg et al. (2017b) for further details).

Finally, we consider a measure of average lifetime earnings that includes periods spent out of work. Ignoring jobless spells can lead to substantial biases in estimating IGEs (Gregg et al. 2017b). 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 allowance and income support), deflated to 2001 prices (see online appendix Gregg et al. (2017b) 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.[11]

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). Education measures combine information on years of schooling, standard in the

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[10] To explore the possible issue of differential measurement error across the distribution of sons' earnings, Appendix Table 5 summaries income observations by earnings quintile. A similar proportion of the sample report income twice compared to once at each earnings quintile.
[11] While averaging across earnings measures and including those who are rarely in work minimises the effects of attrition relative to using a measure at a point in time (Gregg et al. 2017b), Appendix Table 6 explores the pattern of attrition in the BCS using measures of parental education at birth. This indicates that those who are missing any earnings information look similar to median earners in terms of their parental education background. We have also explored the extent of attrition by parental education and find very similar proportions are missing earnings data across the distribution of parental education (results available on request).

literature on returns to education across the distribution of earnings, with more finely graded measures of qualifications obtained including the number of GCSE grades A*–C, number of A levels, degree attainment, degree subject studied[12] and higher education institution attended.[13] The information on GCSE qualifications and A levels is taken from reports at age 16 where available and ages 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 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 least one parental income observation and over 5 years of monthly work history available from 26 to 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. Here, the first column presents summary measures for the whole distribution while columns 2–6 present summary measures for each quintile of the distribution of sons' earnings. The mid-point of these quintiles is where each UQR will be estimated. 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 more likely to apply themselves 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 bottom to top quintiles of earnings. There is interestingly little variation in the proportion of time spent in employment above the bottom quintile 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% from the 20th percentile upwards.

5 Results

We begin by focusing on UQR estimates of the IGE using childhood parental income[14] and earnings at different point in time across sons' adulthood to consider the changing patterns of any nonlinearities across the lifecycle. The first column of Table 2 shows the

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[12] 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'.

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

[14] 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.

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	0–20th	21st–40th	41st–60th	61st–80th	81st–100th
Average parental income (2001 £s monthly)	1360.90 (569.21)	1146.53 (419.22)	1249.76 (465.54)	1329.47 (519.85)	1418.49 (550.22)	1660.54 (709.67)
IQ at 10	0.11 (0.88)	−0.21 (0.83)	−0.05 (0.88)	0.12 (0.82)	0.23 (0.83)	0.46 (0.87)
Maths at 10	0.15 (0.88)	−0.23 (0.90)	−0.02 (0.88)	0.15 (0.81)	0.27 (0.83)	0.55 (0.80)
Reading at 10	0.05 (0.88)	−0.29 (0.86)	−0.11 (0.88)	0.05 (0.83)	0.19 (0.83)	0.43 (0.79)
Application at 10	−0.05 (0.86)	−0.36 (0.89)	−0.22 (0.87)	−0.06 (0.83)	0.10 (0.81)	0.28 (0.74)
Hyperactive at 10	0.13 (0.98)	0.29 (1.05)	0.22 (1.02)	0.13 (0.98)	0.03 (0.93)	−0.03 (0.90)
Clumsy at 10	0.06 (0.88)	0.28 (0.98)	0.19 (0.95)	0.02 (0.83)	−0.09 (0.79)	−0.11 (0.78)
Extrovert at 10	0.00 (0.89)	−0.20 (0.90)	−0.04 (0.92)	0.02 (0.88)	0.08 (0.86)	0.14 (0.88)
Anxious at 10	−0.05 (0.90)	0.11 (0.91)	0.05 (0.94)	−0.07 (0.89)	−0.14 (0.90)	−0.20 (0.84)
Years of education	12.56 (2.29)	11.80 (1.60)	11.94 (1.63)	12.31 (2.09)	12.81 (2.42)	13.96 (2.80)
Number of GCSEs	4.01 (3.13)	2.69 (2.24)	2.95 (2.44)	3.68 (2.87)	4.61 (3.20)	6.12 (3.43)
Number of A levels	0.88 (1.10)	0.66 (0.71)	0.58 (0.72)	0.74 (0.95)	0.92 (1.14)	1.47 (1.52)
Degree	0.22 (0.40)	0.09 (0.26)	0.10 (0.28)	0.16 (0.35)	0.28 (0.44)	0.49 (0.49)
Proportion time employed	0.94 (0.15)	0.85 (0.27)	0.96 (0.12)	0.96 (0.09)	0.96 (0.07)	0.95 (0.07)

Standard deviation in parentheses. $N = 4312$

average estimated IGEs across the lifecycle at various ages. As is commonly found in the literature, the estimated IGEs increase as sons' age, with an average IGE of 0.23 at age 26 increasing to 0.50 by age 42.[15] The remaining columns of Table 2 show how the age at which adult earnings are assessed changes the distributional picture of the association between childhood family income and adult earnings. Figure 1 plots the estimated IGE from UQR at each age, 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 pattern in the steepness of the IGE as individuals' age. At age 26 for example, the IGE at the 10th percentile is 0.16 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 kick up at the top of earnings distribution with an IGE of 0.79 and 0.94 at ages 38 and 42 respectively at the 90th percentile of the distribution. At the 10th percentile, the IGE remains around 0.27–0.30.[16]

This pattern implies that when sons' earnings are observed in the lifecycle matters for observing nonlinearity in the IGE across the distribution of earnings.

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[15] Ages 36 to 38 are typically seen as ideal point in time to proxy lifetime earnings as here, the measurement error is approximately classical (see Bohlmark and Lindquist 2006).

[16] Appendix Table 7 repeats this analysis on a balanced sample (individuals who are employed and report positive earnings in every wave). The pattern of results is similar with flat IGE estimates at age 26 and an increasing relationship as individuals' age. By age 42, the IGE is 0.34 at the 10th percentile and 1.08 at the 90th percentile.

Further, the potential lifecycle bias from using earnings at a single age will not be the same across the distribution and cannot be assessed from experience at the mean. The implication is that using a single-year measure as a proxy for lifetime earnings is not appropriate when considering variation 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 CQR (Bratsberg et al. (2005) for Norway, Eide and Showalter (1999) and Palomino et al. (2018) for the USA and Grawe (2004) for Canada). Our findings are, however, in line with recent studies from Björklund et al. (2012) for Sweden and Schnitzlein (2016) for Germany and the USA.

Given the sensitivity of estimates of the IGE across the distribution to the age the son is observed, we focus on a lifetime estimate of IGE, considering average earnings across the observed part of the lifecycle from ages 26 to 42. This approach has the additional advantage of allowing us to assess the role that the exclusion of periods of joblessness plays in affecting estimates of the IGE across the distribution of lifetime earnings. Table 3 and Fig. 2 show the association between log parental childhood income and log sons' lifetime adult earnings across the distribution, first excluding and then including spells out of work from our measure of lifetime earnings.[17] Focusing first on lifetime earnings excluding workless spells, there is an 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 0.24, increasing to 0.62 at the 90th percentile. This mimics the pattern seen in Fig. 1, illustrating the substantial increase in the IGE as we move up the distribution of earnings. Here, there are significant differences between the estimates at the 10th percentile compared to the rest of the distribution and between the estimates at the 90th percentile compared to the rest of the distribution.

When spells out of work are included in our lifetime earnings measure, in the second row of Table 3, the association with parental childhood income shows a marked increase at the lower end of the distribution of earnings. This captures the correlation between low earnings and spells out of work as highlighted by Stewart and Swaffield (1999) and has become known as the low-pay no-pay cycle. There is now a 'J'-shaped relationship in the intergenerational elasticity 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 0.41 at the 10th percentile) and then to a greater extent at the very top of the earnings distribution (0.65 at the 90th percentile). The estimated IGE at the top of the distribution is significantly different from the rest of the distribution in this setting but the estimate at the bottom is more similar to the estimates at the 30th, 50th and 70th percentiles. The highest reward to coming from an affluent family is for those who get into top-earning jobs and the penalty in coming from a

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[17] See Gregg et al. (2017b) 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.

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

Percentile of earns dist.	OLS (β)	10th	30th	50th	70th	90th
Age of earnings						
Age 26	0.227	0.155	0.148	0.222	0.272	0.310
	(0.02)***	(0.03)***	(0.02)***	(0.02)***	(0.03)***	(0.05)***
Age 30	0.366	0.271	0.343	0.322	0.378	0.445
	(0.02)***	(0.03)***	(0.03)***	(0.02)***	(0.03)***	(0.05)***
Age 34	0.420	0.265	0.352	0.417	0.453	0.621
	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.07)***
Age 38	0.468	0.298	0.381	0.431	0.443	0.791
	(0.03)***	(0.04)***	(0.04)***	(0.03)***	(0.04)***	(0.08)***
Age 42	0.497	0.273	0.415	0.429	0.541	0.935
	(0.03)***	(0.04)***	(0.03)***	(0.03)***	(0.04)***	(0.09)***

$N = 2364, 3340, 2806, 2080, 2685$. Standard errors in parentheses, $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. Dummy variables included where incomes are imputed

deprived family also hits hard at the lower end of the lifetime earnings distribution when adult joblessness is included in the outcome measure. Given the evidence that growing up in workless family is strongly associated with adult joblessness and poverty (see Gregg et al. 2018) the importance of joblessness to the IGE at the bottom of the lifetime earnings distribution is not surprising.
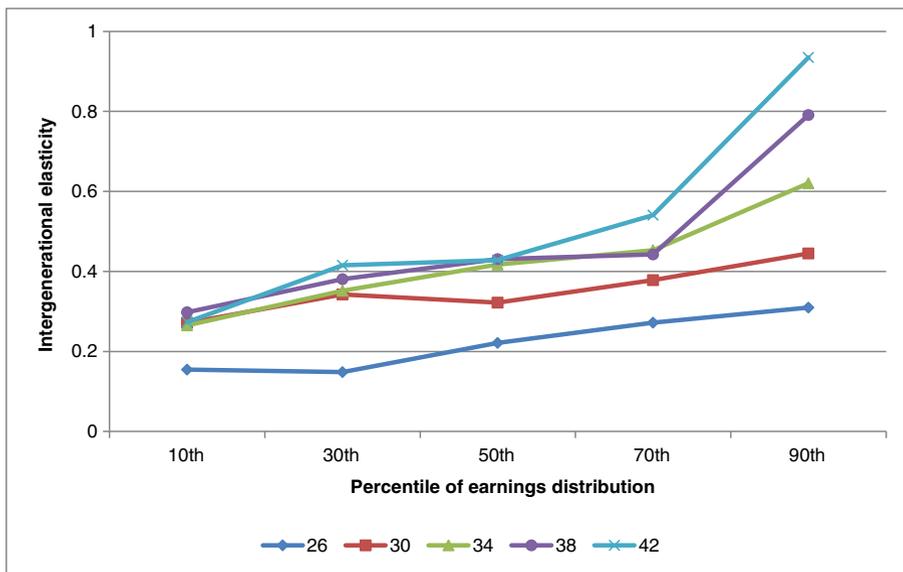
Fig. 1 Unconditional quantile regression estimates of the intergenerational association between log parental income and log earnings at various ages in the BCS 1970

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	0.240	0.307	0.358	0.412	0.620
	(.020)***	(0.03)***	(0.02)***	(0.02)***	(0.03)***	(0.05)***
Equal with 10th percentile			− 1.86	− 3.27*	− 4.05*	− 6.52*
Equal with 90th percentile		6.52*	5.81*	4.87*	3.57*	
Including workless spells	0.430	0.414	0.348	0.381	0.426	0.652
	(.020)***	(0.05)***	(0.02)***	(0.02)***	(0.03)***	(0.05)***
Equal with 10th percentile			1.23	0.61	− 0.21	− 3.37*
Equal with 90th percentile		3.37*	5.65*	5.03*	3.87*	

$N = 4170, 4312$. Standard errors in parentheses, $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. Dummy variables included where income and earnings are imputed. Testing equality across coefficients using a standard Wald Test, star indicates that confidence intervals do not overlap

5.1 The role of early skills, education and early labour market experiences

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 here illustrate the association between sons' lifetime earnings and parental childhood income for a marginal change in log parental childhood income conditional on ability, education and early labour market experiences. They also show the association between sons' lifetime earnings and measures of ability for a marginal
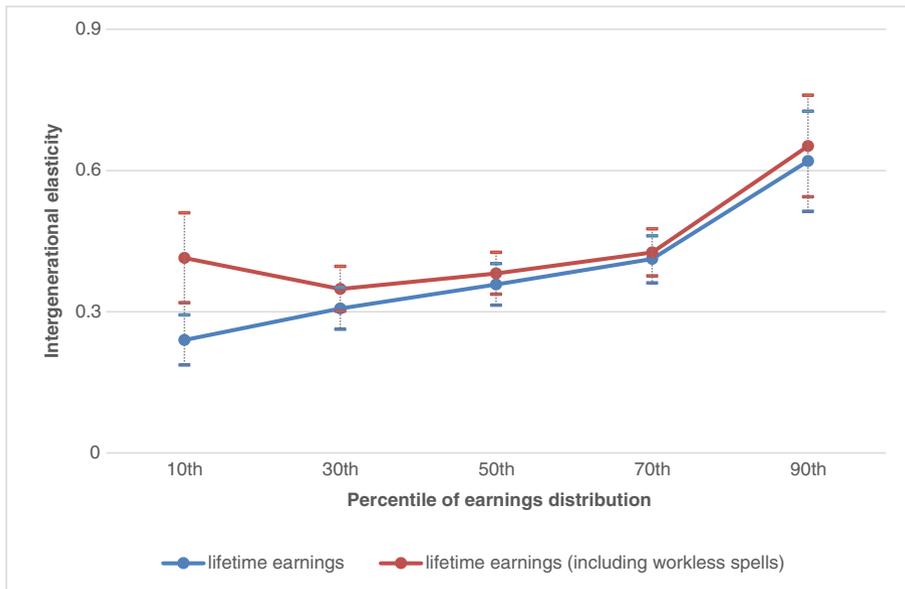
Fig. 2 Unconditional quantile regression estimates of the intergenerational association between log parental income and log lifetime earnings with and without workless spells (26–42) in the BCS 1970

change in ability and test scores, conditional on childhood family income. The interpretation of discreet variables such as years of schooling and holding a degree cannot be interpreted in the same way and this is discussed in detail below.[18]

These estimates address two distinct literatures. First, they show how the intergenerational association is mediated by educational attainment (Blanden et al. 2007; Björklund et al. 2017) 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. Throughout this analysis, the top row of each panel, the IGE conditional on early skills, education and early labour market attachment, can be contrasted to the baseline estimates, the unconditional IGE shown in the second row of Table 3, as illustrated in Fig. 3. This indicates whether the baseline '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.

Panel A of Table 4 shows the OLS and UQR estimates of the conditional associations between IQ test scores and family income, and sons' earnings across the distribution of sons' lifetime earnings (including spells out of work). The IGE diminishes slightly with the inclusion of IQ at age 10 in a linear manner (around five percentage points across the distribution). The returns to IQ exhibit a slight 'U' shape of stronger returns in the lower and upper parts of the distribution although 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. Interestingly, there is no evidence that there are larger returns to IQ at the top of the earnings distribution.

Early maths and literacy test scores (measured at age 10) are introduced to the model in panel B along with a number of non-cognitive traits. 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 three to five percentage points, again uniformly across the distribution of sons' earnings. As illustrated in Fig. 3, the total contribution of early skills reduces the IGE but does not change the shape across the distribution of sons' earnings, with a 'J' shape remaining after conditioning on these measures. The estimated IGE at the top of the distribution remains significantly different from those at other parts of the earnings distribution (see Appendix Table 8).

These attributes dominate the role of IQ, which is now insignificant. The returns to maths scores at age 10 are strongly 'U' patterned across the distribution of lifetime earnings, with marginally higher maths ability gaining higher 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.

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[18] As the technique assumes rank invariance or similarity and hence can only be thought of in this way for incremental changes.

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

Table 4 (continued)

Percentile of earns dist.	OLS	10th	30th	50th	70th	90th
	(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	0.301	0.200	0.197	0.214	0.361
	(0.02)***	(0.05)***	(0.03)***	(0.02)***	(0.03)***	(0.06)***
Years of education	0.018	−0.003	0.010	0.018	0.031	0.053
	(0.00)***	(0.01)	(0.00)**	(0.00)***	(0.01)***	(0.01)***
Number of GCSEs	0.034	0.001	0.027	0.038	0.045	0.058
	(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	0.305	0.202	0.199	0.214	0.357
	(0.02)***	(0.05)***	(0.03)***	(0.02)***	(0.03)***	(0.06)***
Years of education	−0.001	−0.002	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	0.006	0.027	0.034	0.036	0.037
	(0.00)***	(0.01)	(0.00)***	(0.00)***	(0.00)***	(0.01)***
Number of A levels	0.001	−0.062	−0.024	−0.011	0.013	0.110
	(0.01)	(0.02)***	(0.01)***	(0.01)	(0.01)	(0.03)***
Degree	0.188	0.103	0.107	0.224	0.245	0.307
	(0.03)***	(0.05)**	(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 university						
Average parental income	0.255	0.324	0.216	0.207	0.221	0.337
	(0.02)***	(0.05)***	(0.03)***	(0.02)***	(0.03)***	(0.05)***
Years of education	−0.004	−0.002	0.005	−0.003	0.002	−0.009
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Number of GCSEs	0.027	0.007	0.027	0.033	0.034	0.030
	(0.00)***	(0.01)	(0.00)***	(0.00)***	(0.00)***	(0.01)***
Number of A levels	−0.012	−0.071	−0.027	−0.014	0.006	0.074
	(0.01)	(0.02)***	(0.01)***	(0.01)	(0.01)	(0.03)***
Degree	0.168	0.132	0.097	0.235	0.276	0.085
	(0.05)***	(0.09)	(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	0.208	0.181	0.185	0.207	0.329
	(0.02)***	(0.05)***	(0.03)***	(0.02)***	(0.03)***	(0.05)***

Table 4 (continued)

Percentile of earns dist.	OLS	10th	30th	50th	70th	90th
Proportion time employed	0.915	2.450	0.750	0.463	0.279	0.161
	(0.05)***	(0.19)***	(0.06)***	(0.04)***	(0.04)***	(0.06)***
Constant	5.839	4.326	5.439	6.269	6.796	6.480
	(0.34)***	(0.80)***	(0.43)***	(0.38)***	(0.39)***	(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	4312	4312	4312	4312	4312	4312

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

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 further impact on the IGE at the bottom of the distribution of earnings beyond test scores. Part of the greater association between parental income and adult earnings for those who make it to the top of the earnings distribution is therefore accounted for by extended schooling among those from richer compared to poorer families.
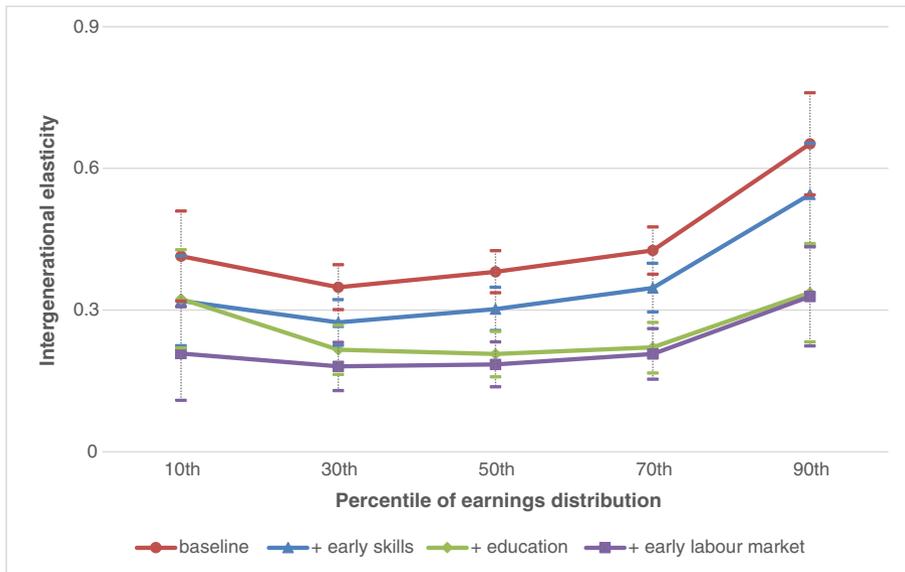
Fig. 3 Unconditional quantile regressions of the intergenerational associations between log parental income and log lifetime earnings (including workless spells) (26–42), conditional on early skills, education and early labour market experience

As the measure of years of schooling is discrete rather than continuous, interpreting the coefficient as the individual return to extra education is inappropriate, as discussed in section 3. Here, the estimate gives the association for an increase in the proportion of people with an extra year of education at that quintile. At the 10th percentile, there is no significant return to additional schooling in the population, increasing to 4% at the median and twice this at the 90th percentile. Additional education therefore matters to a greater degree among higher earning jobs, which is consistent with previous findings that show that the returns to an extra year of schooling are markedly larger in the upper portion of the wage distribution (Angrist et al. 2006). The inclusion of this common indicator of education also reduces the impact of earlier test scores, 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 detailed 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 effect at the bottom of the earnings distribution (top row, panel F). The estimated intergenerational elasticities are now markedly U shaped: strongest at the 10th and 90th percentiles and more modest in the middle of the distribution of earnings as illustrated in Fig. 3. Importantly, 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 at university, the IGE is still very strong, particularly at the top and bottom of the distribution.[20] This suggests that equal levels of educational attainment are not enough to level the playing field, particularly for those in the tails of the distribution of earnings.

The pattern of coefficients for GCSEs attained mirrors that of years of schooling, in that there is a strong increase across the earnings distribution (panel D). Increases in years of education have far less effect once conditional on GCSE attainment as these are important predictors of continued study. Extending measures of education to include measures of post-compulsory schooling, A levels and degree attainment (panel E), removes 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 GCSEs, increases in the proportion of the population with these measures of continued study have no effect (or even negative in the case of A levels) at the bottom of the earnings distribution but

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[19] GCSEs in English and maths are particularly important for continued study but the subject specific data is often incomplete in the data.
[20] While the Wald test for equality suggests we can reject the null for the estimated coefficients at the 30th, 50th and 70th percentile being equal to the 10th and 90th, the confidence intervals overlap (Appendix Table 8).

have a marked effect on wages at the top.[21] Adding in finer-graded measures of degree attainment including the subject studied and the institution attended (panel F) completely wipes out the payoff to degree attainment at the 90th percentile of the lifetime earnings distribution. This suggests that for those who make it to the top of the earnings distribution, it is the subject studied at university (accounting for around 40% of the degree association) and the institution attended (accounting for the remaining 60% 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 months 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 often referred to as 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 bottom of the distribution of sons' lifetime earnings, reducing the association between parental childhood income and lifetime earnings at the 10th percentile by over ten percentage points (see Fig. 3). The IGE, after conditioning on early skills, education and early labour market attachment, is linear across the distribution of sons' lifetime earnings until the 90th percentile, where the IGE is 13 percentage points higher.[22] 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. Youth unemployment has regularly been found to have long-term scars on wages and future employment (Gregg 2001; 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. This finding, along with the importance of spells out of work in creating the portion of 'J' shape at the 10th percentile (Fig. 2), highlights that early joblessness is a strong predictor of ending up trapped in the low-pay no-pay cycle (Stewart and Swaffield 1999).

6 Conclusions

Research has established that there is a strong average intergenerational association between parental income in childhood and sons' labour market earnings, increasing as sons' age in the UK (Gregg et al. 2017b). Such mean-based estimates are informative for making comparisons across countries (Corak 2013) and across time (Blanden et al. 2004) and have been very influential in establishing that the UK has a social mobility problem that has stimulated political debate and policy action. The particular focus of UK policy makers has been on three issues that reflect different parts of the distribution of incomes: (a) access to elite jobs, (b) those who are stuck on low pay and (c) the role of educational attainment in improving life chances for poor children. While mean-

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

[22] Although the Wald test suggests that we can reject the null of equal coefficients at the 10th, 30th, 50th and 70th percentile compared to the 90th, the confidence intervals overlap here for each estimate (Appendix Table 8).

based estimates of intergenerational mobility offer little insight here, our new approach adds value by exploring such distributional dimensions of social mobility within a common framework allowing important comparisons and inference to be made.

Using measures of lifetime earnings to allow us to also account for spells spent out of work in adulthood illustrates a distinct 'J' shape in the association between parental childhood income and sons' adult lifetime earnings. Coming from a more affluent family is more valuable 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 USA, Norway and Canada that find a decreasing intergenerational relationship as they move up the earnings distribution based on the problematic, in this context, conditional quantile regression technique. They are however consistent with literature in the UK about the strong role of family background in access to and progression within top jobs (Macmillan 2009; Macmillan et al. 2015; Laurison and Friedman 2016), persistence in jobless spells across generations (Macmillan 2014; Gregg et al. 2018) and patterns of IGEs across sons' earnings from Björklund et al. (2012) for Sweden and Schnitzlein (2016) for both Germany and the USA.

Importantly, we find that even conditioning on a wealth of measures of human capital including IQ, early skills, years of schooling, GCSE, A level and degree attainment, university institution and subject studied and similar early labour market attachment, there remains a strong IGE at the top of the distribution of sons' lifetime earnings. This suggests that education is not as meritocratic as we might hope, even when considering who gets into top universities and studies highly rewarded subjects, with access to elite jobs being as much about what happens outside of education as it is about what happens in schools and universities. While identifying what exactly is going on here is beyond the scope of this research, the policy challenge has strong parallels with the evolution of the gender pay gap, which is as much (if not more) about happenings outside of education as it is about skills and attainment. This has been the focus of on-going public policy for 50 years and while still unfinished business has seen substantial improvements. The challenge in seeking to move toward greater equality of opportunity outside of the education system, or within levels of education attained, has been rather neglected to date.

When we consider patterns in returns to early skills, education and early labour market attachment 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 and, in particular, avoiding youth unemployment. Although the estimated effects are not causal, they are conditional on a range of measures including parental income, ability as measured by an IQ test score and fine-graded educational attainment. The findings suggest that functional maths is valuable even among those who do not have high educational achievement in terms of educational qualifications or continued study. It also emphasises the importance of early labour market attachment and would imply large returns to policy development to tackle youth unemployment in terms of addressing the intergenerational persistence of who ends up with low lifetime earnings. The school to work transition in the UK remains chaotic for those not pursuing higher education (see among many others Social Mobility Commission (2014a)) compared to most Northern European countries with their strong apprenticeship systems.

By contrast, educational attainment influences earnings most 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 underpin

around half of the estimated IGE. In particular, for those at the top of the distribution, it is the subject studied and the institution attended, rather than the degree attainment, which drive differences in high earnings. This highlights a need to open up elite university places to more students from poorer families to promote mobility. It also highlights that it may be helpful to reduce the importance of such criteria in recruitment practices so that employers can access a wider talent pool. Nybom (2017), for Sweden, suggests that high returns to education for those from more affluent families really reflect higher returns to education among those with higher cognitive and non-cognitive abilities. The models here are very different in construction but may suggest this is less true for the UK.

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 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 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 are high. Macmillan et al. (2015) 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. Laurison and Friedman (2016) illustrate that even within elite occupations, those from higher status families earn more than their lower status counterparts. This research and these other studies thus present a compelling picture of large rewards to coming from an affluent family, rather than ability and education, at the top of the earnings distribution.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

Table 5 Parental income observations across the distribution of lifetime earnings

Percentile of earns dist.	0–20th	21st–40th	41st–60th	61st–80th	81st–100th
Income in both periods	45.3	47.0	46.7	47.3	47.7
Only income at 10	44.0	40.6	40.4	42.0	38.1
Only income at 16	10.7	12.4	12.9	10.7	14.3

Table 6 Parental education observations across the distribution of lifetime earnings compared to those with missing earnings observations

Percentile of earns dist.	Missing	0–20th	21st–40th	41st–60th	61st–80th	81st–100th
Father's education						
School leaving age	66.4	76.3	76.0	67.5	61.4	43.1
GCSEs	14.0	12.0	11.4	14.7	15.5	18.7
A Levels	11.0	7.6	7.6	9.9	13.4	17.8
Degree	8.7	4.2	5.0	7.9	9.8	20.4
N	10,976	1046	1026	1066	1067	1032
Mother's education						
School leaving age	66.7	76.8	73.1	66.3	60.3	45.2
GCSEs	16.2	14.3	14.9	18.5	19.0	18.7
A Levels	11.3	6.6	8.5	10.4	14.5	21.2
Degree	5.8	2.3	3.5	4.8	6.2	14.9
N	11,613	1091	1066	1095	1091	1061

Table 7 Lifecycle bias in estimates of the intergenerational income elasticity (IGE) in the UK on a balanced sample

Percentile of earns dist.	OLS (β)	10th	30th	50th	70th	90th
Age of earnings						
Age 26	0.268	0.255	0.175	0.222	0.263	0.274
	(0.04)***	(0.06)***	(0.04)***	(0.04)***	(0.04)***	(0.06)***
Age 30	0.376	0.243	0.319	0.330	0.398	0.434
	(0.04)***	(0.06)***	(0.05)***	(0.05)***	(0.05)***	(0.09)***
Age 34	0.346	0.257	0.257	0.410	0.378	0.537
	(0.05)***	(0.06)***	(0.05)***	(0.05)***	(0.07)***	(0.13)***
Age 38	0.417	0.236	0.362	0.420	0.406	0.846
	(0.05)***	(0.07)***	(0.06)***	(0.05)***	(0.06)***	(0.15)***
Age 42	0.499	0.343	0.410	0.416	0.485	1.079
	(0.06)***	(0.08)***	(0.06)***	(0.06)***	(0.07)***	(0.19)***

$N = 748$. Standard errors in parentheses, $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. Dummy variables included where incomes are imputed

Table 8 Testing differences across log parental income coefficients compared to the 10th and 90th percentile of log sons' earnings for various model specifications

Percentile of earns dist.	OLS (β)	10th	30th	50th	70th	90th
Baseline	0.430	0.414	0.348	0.381	0.426	0.652
	(.020)***	(0.05)***	(0.02)***	(0.02)***	(0.03)***	(0.05)***
Equal with 10th percentile			1.23	0.61	− 0.21	− 3.37*
Equal with 90th percentile		3.37*	5.65*	5.03*	3.87*	
Including early skills	0.348	0.320	0.274	0.302	0.347	0.545
	(0.02)***	(0.05)***	(0.02)***	(0.02)***	(0.03)***	(0.06)***
Equal with 10th percentile			0.85	0.33	− 0.46	− 2.88*
Equal with 90th percentile		2.88*	7.02*	6.50*	5.23*	
Including education	0.255	0.324	0.216	0.207	0.221	0.337
	(0.02)***	(0.05)***	(0.03)***	(0.02)***	(0.03)***	(0.05)***
Equal with 10th percentile			1.78	2.10	1.69	− 0.24
Equal with 90th percentile		0.24	2.08	2.41	1.99	
Including labour market	0.212	0.208	0.181	0.185	0.207	0.329
	(0.02)***	(0.05)***	(0.03)***	(0.02)***	(0.03)***	(0.05)***
Equal with 10th percentile			0.46	0.43	0.02	− 1.71
Equal with 90th percentile		1.71	2.54	2.67	2.09	

$N = 4170$, 4312. Standard errors in parentheses, $*p < 0.1$; $**p < 0.05$; $***p < 0.01$. Dummy variables included where income and earnings are imputed. Testing equality across coefficients using a standard Wald Test, star indicates that confidence intervals do not overlap

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