THE CONTRIBUTION OF EARLY-LIFE VS. LABOUR MARKET FACTORS TO INTERGENERATIONAL INCOME PERSISTENCE: A COMPARISON OF THE UK AND SWEDEN*

(SHORT TITLE: EARLY-LIFE VS. LABOUR MARKET FACTORS)

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We explore whether differences in intergenerational income mobility between the UK and Sweden show up early in life, finding stronger associations between parental income and birth weight, height and school performance in the UK. We investigate whether these differentials can account for the country difference in income mobility. While differences in the associations in birth weight and height are too weak to matter, school performance does account for a substantial part of this difference. However, country differences in the earnings returns to these skills are at least as important as the differences in the link between parental income and skills.

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Since the early 1990s, economists have contributed to a growing literature on intergenerational earnings and income mobility (or its inverse, persistence). This literature speaks to important academic questions about parents' investments in their children, but also to the political debate about the performance of different economic systems. The results have received considerable media attention.[1] Alan Krueger – in his capacity as chairman of the US Council of Economic Advisors – sparked this public interest by, somewhat provocatively, claiming that the cross-national pattern of mobility estimates reveals a relationship that he called "The Great Gatsby Curve".[2] This curve shows a positive relationship between intergenerational persistence of earnings (as measured by the intergenerational earnings elasticity of sons' earnings with respect to fathers' earnings) and a standard measure of cross-sectional disposable income inequality during the time when the child generation grew up. We show an updated version of this curve in Figure 1. Although the observations are somewhat scattered, the general pattern is that countries with greater inequality of incomes also tend to be countries in which a greater fraction of economic advantage and disadvantage is passed on between fathers and sons.[3] For example, the United States and United Kingdom belong to the countries with high cross-sectional income inequality and strong persistence of incomes from one generation to the next. The Nordic countries, on the other hand, reveal the opposite pattern with weaker intergenerational persistence and more equal outcomes.[4]

What are the underlying mechanisms behind these country differences in intergenerational persistence of economic advantage? Are they related to policy? And if policies matter, are they related to investments in early childhood or to labour-market institutions? The most popular theoretical framework among economists – the so-called

[1] See, for example, The Economist (October, 2012) and the recent series on the Great Divide in the New York Times. Goldthorpe (2013) offers a discussion of the recent political debate in Britain.
[2] See Krueger (2012) and the 2012 Economic Report of the President.
[3] Unfortunately, there are fewer comparable estimates for daughters and fathers, and even fewer estimates using mothers' income.
[4] The curve has also been drawn in different varieties by, *e.g.*, Corak (2006; 2013) Andrews and Leigh (2009), Björklund and Jäntti (2009), and Blanden (2013). See also Solon (2002), Jäntti *et al.* (2006), and Jäntti and Jenkins (2015) for cross-national surveys of intergenerational income and earnings estimates.

Becker-Tomes model (1979; 1986) – suggests that a number of quite different mechanisms can potentially account for country differences. Solon's (2004) parameterisation of this model points at four broad factors: (i) "mechanical" (*e.g.*, genetic) transmission of income-generating traits, (ii) the efficacy of investments in children's human capital, (iii) the earnings return to human capital, and (iv) the progressivity of public investment in children's human capital.

In our view, existing research has very little to say about the relative importance of such, quite different, factors. Therefore, the step from the Great Gatsby curve to policy conclusions is a long one. Our starting point is that both academic and policy discussions would benefit from learning whether the country differences show up early in life, or when the offspring generation has entered the labour market. Such insights would also speak to the current discussion about early interventions in child development, cf. Knudsen *et al*. (2006).

While much research has examined the relative importance of different life-cycle factors in within-country studies, there exists much less work that does so in a cross-country setting. Our contribution is to account for cross-national differences in intergenerational income correlations by examining the importance of parental income in different phases of the offspring's early life. We compare Sweden, a high-mobility country, with the United Kingdom, a low-mobility country, to study at what stage during the life cycle the country differences emerge. Do they show up already early in life so that parental income matters more for early childhood characteristics, such as health and school performance in the UK compared to Sweden? Or do the country differences primarily appear when the offspring generation reaches the labour market?

We use the British Cohort Study (BCS) of children born in 1970 and Swedish register data. These two data sources give us a high degree of comparability that we cannot obtain for other countries with different locations on the Great Gatsby Curve. An advantage of the Swedish data is that they allow us to mimic the BCS data in terms of key variables and sample selection. We explore the role of parental income for (1) birth weight, (2) height at late teen ages, (3) grades at the end of compulsory school at age 16 and (4) final educational attainment.

We start by presenting comparable estimates of intergenerational income persistence for the two countries. Our estimates show that intergenerational income elasticities and correlations are significantly higher in the UK than in Sweden. For sons, the elasticities are 0.271 vs. 0.176 and the correlations are 0.249 vs. 0.177. For daughters, the difference in the elasticities is slightly larger but the difference in the correlations slightly lower. These results are in conformity with those reported in the previous literature.[5]

Our analysis of the country differences then proceeds in two steps. First, we explore whether these differences show up already early in life in outcomes (1)-(4) mentioned

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[5] See, *e.g.*, Blanden *et al*. (2004), Blanden *et al*. (2013) and Blanden *et al.* (2014), who for the UK find elasticities that are roughly similar but correlations that are slightly higher. As we explain below, we use income and earnings definitions to fit both countries. As a consequence, the Swedish estimates are not comparable to previous ones, including the one used in Figure 1. In Björklund *et al.* (2012) we compare the gradients in child outcomes with respect to parental education in Sweden and the UK using the same data source.

above. We find that there are, indeed, significant country differences early in the life cycle, and that the associations between parental income and offspring traits are stronger in the UK than in Sweden. In the second step, we ask whether these differences are large enough to account for the country differences in intergenerational income transmission. For this purpose, we decompose the intergenerational income correlation into the covariance between parental income and the child traits, as well as the earnings returns to these traits that the offspring generation obtain in the labour market. We experiment with this decomposition and let the UK get the Swedish covariance (and vice versa) and the UK get the Swedish returns (and vice versa). While mechanical, this exercise suggests that the country differences in birth-weight and height associations are so weak that they account for hardly any of the UK-Sweden difference in intergenerational income persistence. For grades and final education, on the other hand, we find that country differences in intergenerational associations can account for a substantial part of the difference in income persistence. We also find that country differences in earnings returns are in this respect at least as important as country differences in covariances between parental income and children's grades and education. As returns to skills and income inequality are closely related, our findings also help explain the Great Gatsby curve.

The paper is structured as follows. Section 1 offers a literature background. We explain our data in section 2. Section 3 reports our estimates of intergenerational associations. In section 4, we perform our decomposition analyses to investigate the relative importance of intergenerational transmission from parental income to early-life traits and the labour-market returns to these traits. We report some robustness checks in section 5. We end the paper by summarising our results and discussing their implications for policy and future research.

1. Literature Background

1.1 Birth Weight

A large recent literature, efficiently surveyed by Currie (2009), has shown that birth weight in general and low birth weight in particular is related to parental socio-economic status. There are several reasons to expect such an association. The quality of nutritional intake during pregnancy is one obvious candidate explanation. Parents of higher socioeconomic status may also be better informed about health-related hazards that impact on the growth of the fetus. Such mechanisms have come to be known as the “fetal origin hypothesis”, associated with the British epidemiologist David J. P. Barker. In addition, one can expect that biological mechanisms (genetic inheritance) cause a relationship between parental socio-economic status and birth weight. The country’s health care system might very well have an impact on how strong these mechanisms are. A more compensatory system for care of pregnant mothers may attenuate these biological links. This is indeed a counterpart to what Goldberger (1979) had in mind with his famous eye-glasses example; policy can be used to counteract initial genetic effects.

Birth weight, in turn, has been shown to predict several later and adult outcomes. The literature surveyed by Currie is full of examples showing that birth weight predicts outcomes related to health, including mortality, as well as cognitive and noncognitive skills and thus also labour market performance. These relationships may show up because of the specific health problems that are related to low birth weight. However, it is also possible that low birth weight has direct effects on the acquisition of skills. Parents' reactions to the problems related to the underlying health problems are also likely to affect the impact of early health problems on subsequent skill acquisition. The same applies to the health-care and school systems in the country.

Much of the recent literature focuses on the issue whether the associations between parental resources and birth weight and between birth weight and adult outcomes are causal or not, see, *e.g.*, Black *et al.* (2007) and Torche and Echevarria (2011). For our purposes, causality it is not a major concern. We treat this variable as an indicator of several traits that are related to parental income and own performance later in life. Our main research question is cross-national: we ask whether parental income is a stronger predictor of adult outcomes in one country than another.

1.2 Height During Adolescence

As explained below, we have access to data on height measured at ages 16 and 29 for the UK, and at age 18 for Sweden. Obviously, these height measures reflect the cumulative growth up to these ages. This means that the combined genetic and environmental factors that contribute to birth weight also affect our height measures. Indeed, Black *et al.* (2007) find strong associations between birth weight and height during adolescence, and suggestive evidence that some effects are causal ones. But our height measures are also sensitive to a number of environmental conditions experienced during childhood. In their thorough survey of height determinants, Case and Paxson (2008) emphasise that the period from birth to age 3 is considered as the postnatal period that is most critical to height. Nutritional needs are greatest at this point in life, as is sensitivity to infections of different types. Such factors are, of course, likely to be related to family background, and in ways that might differ across countries.

Case and Paxson also emphasise that conditions during childhood affect the *timing* of children's growth. The timing of the typical pubertal growth spurt has been found to be sensitive to the child's health conditions and therefore also to parental background. Case and Paxson demonstrate that the growth spurt comes earlier for children of high socio-economic background. Thus, at some stages during adolescence, the pubertal growth spurt tends to magnify height differences between economic classes. Observing height at different ages in adolescence across countries could therefore give misleading estimates of country differences. In our analysis below, we avoid this problem by complementing our main analysis of height at age 16 for the UK and age 18 for Sweden – the first ages at which we have data – with results for height at age 29 for the UK.

The bivariate correlation between height and labour market earnings is quite strong. Using US PSID data, Case and Paxson report that the observed difference of 4 inches in men's heights at the 25th and the 75th percentiles is associated with an expected earnings differential of 9.2%. Furthermore, this association is observed throughout the whole height distribution. Lundborg *et al.* (2014), using the same Swedish data source as we do, find only somewhat weaker bivariate associations.

Case and Paxson and Lundborg *et al.* also explore the mechanisms behind this bivariate height-earnings association. Indeed, the candidate mechanisms are several and include self-esteem, social dominance and discrimination. It might also be that height captures omitted variables such as cognitive and noncognitive skills and strength. Case and Paxson find, using US and UK data, that most of the height-earnings association is eliminated when cognitive skills are controlled for, whereas Lundborg *et al.* find that physical strength is a more important underlying factor. Just as for birth weight, it is not crucial for our purposes whether height is important per se or if it is an indicator of several underlying productivity traits. However, we also report estimates of earnings returns to height (and birth weight) that condition on other observed factors, and thus we expect them to primarily proxy returns to physical and health-related traits.

1.3 Grades at the end of Compulsory School

Our next mediating variable is grades at age 16 at the end of compulsory school. This variable has a straightforward motivation for our purposes: grades are strongly associated with parental resources and early predictors of adult outcomes. The grades at the end of compulsory school are particularly important since they determine access to both study fields and schools at the upper-secondary level. A common result from research about the predictive performance of such grades is that they not only capture cognitive skills, as measured by typical test scores, but also noncognitive skills, such as motivation and persistence; see, *e.g.*, Borghans *et al.* (2011) for recent research.

1.4 Final Education

Like compulsory school grades, final education is a key variable when trying to understand intergenerational income correlations. Parental and public investment in the human capital of children is a central transmission mechanism in the theoretical work of Becker and Tomes (1979; 1986). From the perspective of intergenerational mobility, it is important to stress that final education captures both performance in school, as also captured by our grade variable, and the set of choices of further education made after compulsory school. A large literature in sociology (see, *e.g.*, Erikson *et al.*, 2005) has shown that family background has a strong influence on both school performance (primary social-origin effects) and school choices (secondary social-origin effects).

2. Data

2.1 Sources and Sample Restrictions

The British Cohort Study (BCS) is a survey of all children born in England, Scotland and Wales in one particular week in April 1970. The BCS is a very rich data set with surveys performed right after birth and at ages 5, 10, 16, 26, 30, 34 and 38. The first sweep covered the births and families of about 17 200 children. In the two last sweeps the number of observations fell to 11 200 (in 2000) and 9 600 (in 2004). With each sweep, the scope of enquiry has broadened from a strictly medical focus at birth to encompass physical and educational development during the child's growth, and later on economic and labour market outcomes as adults.

For Sweden, we use register data from several sources, which have been merged by Statistics Sweden using unique personal identifiers. For intergenerational research purposes, this is a very flexible data source. In this study, we use the information for Sweden to mimic the UK data set as closely as possible. Our sample for Sweden consists of all who were born in the country in 1973. We restrict our analysis to this cohort, as it is the first one for which birth-weight data are accessible. Several data sources are merged in order to obtain our variables of interest: the Swedish census in 1985 is used to identify each child's rearing parents in the fall of that year; birth-weight data are obtained from the National Board of Health and Welfare (Socialstyrelsen); height data are obtained from the compulsory military enlistment tests (administered by The National Service Administration in Sweden, Pliktverket); and separate registers at Statistics Sweden provide data on compulsory school grades at age 16 (*Årskurs-9 registret*), final education (the Education Register, *Utbildningsregistret*), and income and earnings based on tax declarations for both parents and offspring.

2.2 Variables

Parental income. In the BCS data set, parental income is defined as “all earned and unearned income of both father and mother” in 1980 and 1986. Moreover, it refers to the income of custodial parents (i.e., not necessarily biological parents) and is measured before taxes. To mimic this variable with the Swedish data, we use a measure of total income that includes income before taxes from all sources, except means-tested benefits and universal child benefits (*sammanräknad inkomst*). We use data from the years 1983 and 1989 for Sweden, as we want to measure parental income at identical ages of the child. In order to take into account only the income of present parents, we define parental income for those adults who lived in the same household as the child according to the census in 1985. We use as our measure of parental income for both countries the log of the average parental income across ages 10 and 16. We use a single data point for those cases when parental income is available at one age but missing at the other.[6]

A difference between the parental income data in the two countries is that the UK data are available only as discrete intervals of the income distribution. We use the centre of each of the respective intervals as the measure of parental income. Moreover, the top interval is not bounded from above and consequently there is no centre for this interval. For those in the top interval, we use the median gross family income within that interval according to the Luxemburg Income Study (LIS) database. To ensure comparability, we use the Swedish data on parental income in the same way, i.e., by dividing the data into corresponding intervals and using the centre values. For the unbounded top interval, we use its actual median. These income measures are used in our main analyses, but we have also conducted a sensitivity analysis with the Swedish data by comparing the main results based on intervals with results from using its actual data. The differences are small and do not affect any of our conclusions.

[6] Our results are stable to including dummy controls for whether income is missing at either of the two ages. Thus, we do not include such controls in our main analysis.

Offspring earnings. The BCS includes data on offspring labour earnings for ages 30 and 34.[7] From the Swedish tax register we extract information on labour earnings (*arbetsinkomst*) for the same ages. For both countries, we use the log of the average of these two annual earnings observations as our measure of long-run earnings. As with parental income, we use a single earnings observation when information is missing at one age but not at the other.

For the UK, both income and earnings information refers to weekly data at the time of the interview, whereas Swedish data sets contain annual measures of income and earnings. We convert both measures to 2005 US dollars and divide the Swedish numbers by 52 in order to show comparable data in our descriptive tables. More important are the potential selection issues that come with these differing data definitions. In the UK data, an individual needs to record positive earnings in a given week to be included in the sample. In the Swedish data, an individual only needs to record positive earnings any time during the calendar year to be included. The UK sample is therefore likely to be more selective, with a lower share of individuals with intermittent labour-market behavior. Therefore, we restrict the samples to those with weekly earnings greater than 100 US dollars. This limit is clearly lower than a full-time salary at minimum wage rates in both countries, but at least ensures that we drop those observations with obvious signs of sporadic labour-market attachment. While the descriptive statistics are altered by this restriction, our main regression results are largely robust to variations in this limit.

[7] A recent update of the BCS provides earnings data at age 38. In footnote 16 below, we report estimates of intergenerational elasticities and correlations that use this information as well as comparable estimates for Sweden. The country differences remain the same.

To sum up, the income and earnings measures we use are far from ideal. They are most certainly causing some attenuation bias in our estimated intergenerational associations, as the parental income measure is an average of only two annual income observations.[8] Further, we measure offspring's earnings a couple of years too early in order to minimize so-called life-cycle bias, at least according to evidence for Sweden.[9] This probably also contributes to some downward bias in our intergenerational income estimates. Our maintained assumption in this study is that these two sources of bias are of a similar magnitude in the two countries.[10]

Birth weight. For the UK, the birth-weight data stem from the initial sweep of the BCS and are based on reports from hospitals. For the Swedish dataset, the birth-weight variable is also obtained from hospital reports delivered to the National Board of Health and Welfare. In our regressions, we use as dependent variables birth weight in kilos, log of birth weight and a dummy for low birth weight, defined as less than 2.5 kilos.

Height. The UK height data stem from a professional medical examination of the survey respondents at age 16. For Sweden, we obtain information on height from data collected at the military enlistment that is compulsory for all Swedish men. Most men do these tests at age 18. Thus we cannot do this analysis for women. Because we measure height

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[8] See Mazumder (2005), for an examination of the relationship between the number of annual observations and the bias due to transitory income variation.

[9] Böhlmark and Lindquist (2006) and Nybom and Stuhler (2016) show that, for men, annual earnings approximate lifetime earnings in age ranges 33-40. There is no comparable evidence on this for the UK. Women's life-cycle earnings trajectories are more complex and thus there are no corresponding rules of thumb for women.

[10] Another issue is related to the fact that we measure parental income at a specific age of the child and thus at different ages of the parents depending on the age of parents at child's birth. We therefore control for parental age throughout, and additionally assume that any remaining bias is similar in Sweden and the UK.

at different ages in the two countries, we standardise the variable when we use it as dependent variable in our regressions. As noted in the previous section, we also complement our analysis for the UK by looking at height data from age 29 as a robustness check.

School grades. In order to use grades in a comparable way, we transform each grade of selected subjects of every person into a percentile rank, and then take the average percentile rank across subjects as each individual's grade measure. For the UK, we use the grades in the O-level (or CSE) examinations in the English language, English literature, mathematics, science, physics, chemistry, biology, history, geography, French, German and business studies.[11] We have spliced together the O-levels and GCSE according to the following ranking: (1) O level A, (2) O level B, (3) O level C/CSE 1, (4) O level D/CSE 2, (5) O level E/CSE 3, (6) CSE 4, (7) CSE 5, and (8) Fail.[12] We invert the scale so that better grades get coded higher, and assign to each person for each subject the percentile that corresponds to the tabulated percentile at the grade he or she received.

For Sweden, we use the grades at the end of compulsory school (i.e., at age 16 after nine years of compulsory schooling) in English, biology, physics, chemistry, technology, geography, history, religion, social studies and Swedish. We choose these subjects since they are taken by all students according to an identical curriculum. Next, we compute average percentile ranks across all subjects in the same way as for the UK.

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[11] We use only the subjects for which a majority in the respective samples have grades recorded. That implies that for the UK we need to exclude some subjects such as classical languages, religious studies, Spanish, music, etc.

[12] This splicing together of the grades for the UK was implemented for Björklund *et al.* (2012) after conversations with Jo Blanden and John Ermisch.

We have experimented with variations of this procedure, and while the exact estimates vary, the qualitative conclusions we reach do not. However, we must concede that the results with respect to the parental income gradient in grades are likely to be the least comparable, for the simple reason that the schooling institutions in Sweden and the UK are quite different. As an example, student tracking by field of study occurs at an earlier age in the UK than in Sweden. Although this is, on the one hand, problematic for our analysis, it is, on the other hand, exactly these types of institutional differences that motivate our UK-Sweden comparison.

Final education. Since educational systems differ across countries it is not as straightforward how to use data on final education in comparative studies as data on income and earnings. We apply the International Standard Classification of Education (ISCED) developed by UNESCO. ISCED was designed with the purpose to make educational levels internationally comparable. Our categorical variables correspond to “at least high school” (ISCED 3), “at least some college or post-secondary school” (ISCED 4), and “completed college” (ISCED 5). We combine ISCED 1 and 2 into a single omitted category, “less than high school”, since ISCED 1 is almost empty for our cohorts. By using such decumulative variables, rather than, *e.g.*, exclusive dummies, we avoid ambiguity in the expected association between parental income and offspring education.[13] The Swedish data on final education in 2007 stem from Statistics Sweden’s education register. The UK data are self-reported and we use the BCS wave from 2004. Thus, final education is measured at age 34 in both samples.[14]

[13] A similar specification is used by Blanden *et al.* (2014).
[14] For a few UK observations with missing data in 2004, we use information from the year 2000 sweep.

3. Results

3.1 Intergenerational Income Associations

The prototypical model in the economics literature on intergenerational income mobility is

$$Y^c = \alpha + \beta Y^p + \varepsilon, \qquad (1)$$

where Y^c denotes the log of offspring's long-run income and Y^p is the log of parental long-run income. Thus, the parameter β is the intergenerational elasticity (IGE). Because this parameter can be estimated with data on offspring's annual income as long as annual income proxies long-run income with classical measurement errors, there are now elasticity estimates for a substantial number of countries. Most estimates pertain to fathers and sons. These estimates have been used to draw the Great Gatsby Curve.

However, it has also been argued that intergenerational correlations (IGC) are preferred to intergenerational elasticities for the purpose of cross-national comparisons.[15] The IGC is obtained from (1) by using standardised variables, or equivalently by multiplying β by the ratio of the standard deviations of parental and offspring long-run incomes. By so doing, the cross-national intergenerational comparison is not affected by country-specific changes in long-run income inequality.

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[15] See, e.g., Björklund and Jäntti (2009), Goldthorpe (2013), and Jäntti and Jenkins (2015). Indeed, the latter authors advocate rank correlations for comparative purposes. For other reasons, Chetty *et al*. (2014) also advocate rank correlations. However, using rank correlations is not an option for us, since UK parental income data are available in intervals only.

Although the results from previous studies are our point of departure, we estimate new intergenerational elasticities and correlations on our own samples. Table 1 shows descriptive statistics for our samples. UK parents are about one year younger when their income is measured, a rather small difference. For the UK, we note that the standard deviation of log of parental income is lower than the standard deviation of the log of offspring's earnings. This difference implies that our estimated intergenerational correlations will differ from our estimated intergenerational elasticities. For Sweden, these standard deviations are identical for sons' earnings and parental income, whereas for daughters inequality is higher among parents.

We report intergenerational income persistence estimates in Table 2. As expected from previous research, the intergenerational income associations are lower for Sweden than for the UK. The standard errors are reasonably small, so the null hypothesis of equality across countries is rejected. For sons, the point estimates of the elasticities are 0.176 for Sweden and 0.271 for the UK, and the corresponding correlations – regressions with standardised income measures for both parents and offspring – are 0.177 and 0.249. For daughters, the country differences are somewhat lower, and for the correlation, the difference between the countries is only barely significant. As discussed above, all these estimates are downward biased but hopefully equally much in both countries.[16]

[16] This conclusion is confirmed by estimates using offspring's earnings at age 38 as well as 30 and 34. We use the recently available BCS data on earnings at age 38. Further, we use earnings at ages 30, 34 and 38 for Swedes born in 1969. For sons, the elasticities (correlations) are 0.181 and 0.271 (0.153 and 0.238). For daughters, the corresponding estimates are 0.133 and 0.329 (0.130 and 0.201). See our online appendix Table A.1 for full results.

In row 3, we also report estimates for a model that adds a quadratic term for the log of parental income (unstandardised). The estimates suggest that the functional form is not very different in the two countries. Thus, we stick to the simple linear framework to explore the cross-national differences in intergenerational persistence.

3.2 Birth Weight

We estimate simple models with birth weight as the dependent variable and the log of long-run parental income as the explanatory variable. In the literature, different measures of birth weight have been used, for example, birth weight in kilos, the log of birth weight, a dummy indicator for low birth weight (*e.g.*, less than 2.5 kg), and fetal growth (defined as birth weight divided by weeks of gestation). Black *et al*. (2007) examine the explanatory power of these variables and report that the log of birth weight provides the best fit for their outcome variables, which included adult earnings.[17] Nevertheless, we report results for birth weight in kilos, the log of birth weight, and low birth weight.[18]

Table 3 reports sample descriptives. Here and in subsequent analyses of the other traits, we use the maximum sample size in the data set. In an online appendix, we report sensitivity analyses based on a balanced sample for all outcomes. We note that birth weight for the 1973 cohort in Sweden exceeds the birth weight for the 1970 cohort in the UK by around 150-180 grams (see Panel A). Otherwise the standard deviations are similar. Thus, not surprisingly, the prevalence of low birth weight is higher in the UK

[17] We note though that they draw their conclusion from twin fixed-effects regressions.
[18] We do not use variables with adjustment for gestation length although our data sources contain this information. The reason is that data on gestation (by the National Board of Health and Welfare) are considered unreliable and would introduce measurement error.

than in Sweden; around 6% compared to around 3% for boys, and 6 compared to 4% for girls.

Table 4 reports estimates for birth weight, log of birth weight, and low birth weight, respectively. Our basic conclusions are robust with respect to the three measures, and also to whether we standardise the variables or not. A first basic conclusion is that there is indeed a significant parental income gradient, in both countries, in birth weight for both sons and daughters. A second conclusion is that the associations are significantly stronger in the UK than in Sweden; the gradients are about twice as high for the UK. Nonetheless, the magnitude of all the estimated intergenerational associations is rather low. For example, the highest elasticity is only 0.035 for UK daughters, and the correlation between the log of birth weight and the log of parental income is 0.108.

3.3 Height

Panel B in Table 3 reports sample descriptives for our height samples. Because we measure height at age 16 for the UK and at age 18 for Swedish sons, it is natural that Swedish sons are taller than the UK sons in our data. Because of this difference in measurement, we must treat estimates of country differences based on unstandardised height with caution. Thus, we focus on the estimated correlations.

All estimates for height in Table 4 are significantly different from zero.[19] Again, we also find a significant country difference, with twice as large a correlation for the UK. Yet, the

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[19] The estimates for age 29 in the UK are virtually identical to those for age 16 so we do not report these here. See our online appendix Table A.2.

magnitude of the correlations between parental income and height is modest, at most 0.136 at age 16 in the UK.

3.4 School Grades

We report sample descriptives for our grade samples in Panel C of Table 3. The overall mean of the average percentile is slightly above 0.5 for daughters and slightly below that for sons. This reflects a general and well-known gender gap in school performance. A difference between the countries, however, is that the standard deviation in grades is markedly higher in Sweden. This reflects the fact that the grade systems are different in the two countries; the standard deviation of such an average percentile rank variable that we use is affected by the number of fields that are graded and by the number of steps for each graded field. Because of this difference, we focus on the results with standardised variables (correlations) in Table 4.

It is not surprising that all single parameters are strongly significantly different from zero. Interestingly, however, we also find significant country differences in the transmission estimates, and again the UK ones are the largest for the standardised variables.

3.5 Final Education

Our basic education information is available in the form of levels of education. One option would be to transform these levels into years of schooling in order to estimate simple models with years of schooling as the dependent variable for both countries. However, we prefer to use the original data since the transformation from levels to years might create country-specific errors. Thus, we estimate separate models using the categorical variables described in the previous section as dependent variables.

We report sample descriptives in Panel D in Table 3. The distribution of individuals across the four education levels differs somewhat across the countries, which could be a consequence of institutional differences. There is a larger share with “at least high school” (level 3) in Sweden than in the UK. Yet, the share reaching the highest level is relatively higher in the UK. We also note a quite clear gender gap in educational attainment, although this is more obvious in Sweden than in the UK.

The estimates in Table 4 show, as expected, that the parental income gradients in educational attainment are significantly different from zero in both countries. As for the other traits, the point estimates of the intergenerational coefficients are higher for the UK than for Sweden. However, the differences only pertain to level 3 (“at least high school”), whereas the coefficients are of a similar magnitude for the higher levels.

4. Accounting for Labour-Market Returns

So far we have found that there are indeed UK-Sweden differences in the associations between parental income and child outcomes already early in life. But how important are these differences? Can they possibly account for a considerable part of the country difference in intergenerational income associations that we reported in section 3.1? And if they are important, what is the role for country differences in the returns to the productive traits that we have examined? To explore these issues we use a straightforward analytical framework that distinguishes between, on the one hand, the intergenerational covariances between parental income and children's productivity traits, and, on the other hand, the returns to these productivity traits.[20]

Denote a single productivity trait for the child generation by X^c, and the relevant income measures for parents and children by Y^p and Y^c respectively. Further, divide Y^p and Y^c by their standard deviations to focus on the intergenerational income correlation (IGC), instead of the elasticity. We make use of a linear regression of the child's earnings on each productivity trait that we study

$$Y^c = \varpi + \delta X^c + u, \qquad (2)$$

where X^c in the first case represents birth weight. Using (2) and Y^p, the estimated intergenerational income correlation (IGC) becomes

$$IGC = Cov(Y^p, Y^c)/\sigma^2 = \delta Cov(Y^p, X^c)/\sigma^2 + Cov(Y^p, u)/\sigma^2, \qquad (3)$$

where σ^2 denotes the variance of parental income (which here is standardised to one). Note that these formulas apply both when we include a single trait (scalar-valued X^c) and multiple ones (vector-valued X^c).

[20] For similar exercises, see Österbacka (2001), Björklund *et al*. (2005) and Blanden *et al*. (2007; 2014)

We can examine the contribution of each of our productivity traits to the intergenerational income correlation by estimating equation (2), retrieving the residuals, and computing the components of (3). It is the first component – the product of the monetary return to the trait and the covariance between the trait and parental income – that can be attributed to the trait we consider, whereas the second component represents everything else. We can also separately examine the importance of the monetary returns (δ) and the intergenerational covariance between parental income and the trait.

In Table 5, we report the results from this accounting exercise for Sweden and the UK.[21] Since height is missing for daughters in the Swedish sample, we restrict the analysis to sons.[22] We first report the results when we include each trait separately and then the results that include all traits at the same time last. Neither birth weight nor height can account for hardly any of the Sweden-UK difference in the IGC. We can see that the components attributed to these traits are very small compared to the total correlation in the two countries. Thus, the small absolute cross-national differences in these components cannot explain a substantial part of the cross-national difference in intergenerational income persistence.

When we turn to grades, another pattern emerges. First, we see that the components attributed to grades make up about one third of the IGC in both countries. In absolute

[21] Note that the IGCs differ slightly from the ones in Table 2. The reason is that we have estimated the IGCs in Table 5 on samples that also contain valid measures of the respective traits. Note also that we report estimates of the δ-coefficients and their associated standard errors in our online appendix Table A.3.
[22] We report the corresponding results (excluding height) for daughters in our online appendix Table A.4 and A.5. The results for the respective traits are largely similar. The difference in the IGC for daughters, however, can be fully accounted for by our decomposition, which is not the case for the sons.

terms, this component is 0.085 for the UK and 0.060 for Sweden. Thus, one can say that roughly one third of the cross-national difference can be attributed to factors associated with grades at age 16. When considering this difference, it is interesting to look separately at the contributions of the monetary returns to grades (δ) and the covariance between the trait and parental income. The country difference is created by both these components, but with a greater contribution from the covariance. When we let Sweden have the UK return, its IGC goes up to 0.178 (from 0.173), and when we let Sweden have the UK covariance, it goes up to 0.192. Similarly, when we let the UK have the Swedish return, its IGC goes down to 0.249 (from 0.255), and when we let the UK have the Swedish covariance it goes down to 0.235.

The last single trait that we examine is education. The component attributed to this trait also makes up about one third of the total IGC.[23] As was the case with grades, the UK IGC is reduced by giving the UK the Swedish return or covariance, with a higher contribution from the former. The Swedish IGC, in turn, goes up more with UK returns than with the UK covariances (from 0.177 to 0.202 and 0.187 respectively).

The final panel of table 5 shows the results from entering all traits simultaneously in the second step. Note that in the decomposition formulae, the X^c are still regressed on parental income without conditioning on other traits, while in the second step we regress offspring earnings on vector-valued X^c. With this approach, birth weight and height

[23] Note that we here take into account the three categorical variables jointly.

become somewhat cleaner indicators of health, and grades and education become somewhat cleaner indicators of skills.

As expected, we do now capture a greater share of the IGC in the components attributable to the traits: about 0.066 for Sweden and 0.124 for the UK in absolute terms. However, we do only marginally better in terms of closing the gap between the UK and Sweden in our counterfactual correlations than we did for grades and education alone. In total, we close nearly half the gap in the IGC when entering all traits simultaneously. Returns turn out to be slightly more important than the covariances. Giving the UK the Swedish returns closes 40% of the gap in the IGC, and giving Sweden the UK returns closes 33% of the gap. The corresponding numbers for the covariance are 29% and 21%.

5. Robustness Checks

5.1 Balanced vs. Unbalanced Samples

So far we have used the largest possible sample for each separate analysis. By so doing, we have maximised the precision and minimised the sample selection bias for each estimated parameter. It could, however, be argued that our comparisons of the relative importance of different traits becomes flawed by the fact that we compare estimates from different samples. Therefore, we have also reestimated all parameters in Tables 2 and 4 as well as the decompositions in Table 5 on one balanced sample; see our online appendix Tables A.6-A.8. The requirement that all variables are simultaneously available reduces the samples by some 10% for Sweden, but from 3153 to 1820 for UK daughters and from 3304 to 1606 for UK sons. As a consequence, the precision of the estimates falls.

However, the main pattern of the results remain the same. The differences between the intergenerational income associations in Table 2 remain about the same. The country differences in the parameters of the trait variables are also roughly the same except for height, which is no longer significantly different across the two countries. The decomposition also tells the same story with the balanced sample as in Table 5; see our online appendix Table A.8. If anything, returns tend to become slightly more important.

5.2 Treatment of Parental Income Data

To ensure comparability across countries, we used the Swedish data on parental income in the same way as for the UK, *i.e.*, by dividing the data into intervals of the parental income distribution and using the center values in each interval. We briefly examine the sensitivity of the results to this feature of the data by comparing our main results with results from using the actual data (*i.e.*, continuous measures for Sweden). We report descriptive statistics and estimates for this sensitivity analysis in our online appendix Tables A.9 and A.10. The discrepancies are small and do not affect any of our conclusions.

5.3 Attrition in the UK Data

Finally, we conducted a sensitivity analysis with respect to attrition in the UK sample. If attrition is non-random, for example related to socio-economic characteristics, then our results for the UK could be biased. The sensitivity analysis is based on comparisons of our baseline intergenerational elasticities and correlations with corresponding estimates based on a simple weighting procedure. Since there is little attrition in the first sweep of the UK survey, we use various socio-economic indicators from this survey to predict whether an individual ends up in our final samples. We use the following variables as predictors of non-attrition: birth weight, birth weight squared, and an indicator for low birth weight (less than 2500 grams), indicators for mother's age at delivery, mother's marital status, father's employment, and father's social class. The variables are all strongly significant predictors of non-attrition.

We then use the predicted probability of non-attrition to reestimate our intergenerational models with inverse probability weights (IPW). Observations which, based on observable characteristics in the first sweep of the survey, are regarded as having a higher probability of non-attrition will have a lower weight in the estimation, and vice versa. We then simply compare our baseline estimates with the estimates based on IPW. We perform the analysis using two different sample selection criteria. The first, our income sample, consists of all observations with non-missing offspring earnings and parental income and is larger in size (see Tables 1 and 2). The second, our balanced sample, consists of those observations that also have non-missing data on all the intermediate variables (birth weight, height, grades, education) and is considerably smaller in size. If non-random attrition is a problem, then the consequences are likely to be larger for the latter sample. Thus, it is useful to look at both these samples. Finally, we also perform the analysis separately for sons and daughters.

The results in Table 6 indicate that attrition is not an important factor behind our results. The differences between our baseline estimates and the weighted estimates are small and not systematic; in some cases the weighted estimates are marginally higher, and in others they are marginally lower. The differences are never larger than 10% of the baseline estimates and most often much lower. Even though our models predicting non-attrition might be missing some important aspects of the attrition process due to omitted variables, the results clearly suggest that attrition is not a major concern. Blanden *et al.* (2011) reach the same conclusion with another analysis of attrition in the BCS data.

6. Conclusions and Discussion

We have presented an approach to exploring the mediating factors behind cross-national differences in intergenerational income persistence. We applied this approach on data from Sweden and the UK, but we argue that it can serve as a model also for other cross-national comparisons.

We first explored the importance of two variables that have received much attention in recent research by economists, namely birth weight and height during adolescence. Indeed, birth weight is probably the most widely used measure of the early life environment. Our results are mixed. First, we did find a significant parental-income gradient in both countries and for both variables. This finding adds to the evidence presented by Currie (2009). Indeed, the finding for birth weight confirms that there is “inequality at birth”. Further, we did find a significant country difference in the family-income gradient of both variables; the gradients are more than twice as strong in the UK. These results suggest that differences in policy and other circumstances can make a difference very early in life, i.e., that already at birth health is malleable.

However, we also found that only a trivial magnitude of the intergenerational income correlation (and of the country difference in this correlation) could be attributed to birth weight and height. The monetary return in adulthood to these traits and the covariance between these traits and parental income were simply too small to be important for the observed intergenerational transmission parameters. This is not to say that early childhood is not important for intergenerational income mobility, but our results suggest that these variables do not capture enough of important mechanisms. Future research should therefore look for stronger early predictors of adult outcomes. Unfortunately, the often-praised rich Swedish register data do not contain such information. This is in contrast to the much richer British birth-cohort studies. See, *e.g.*, Blanden *et al*. (2007), who use information about noncognitive skills and ability to explore changes over time in intergenerational mobility in the UK.

When we turned to the more conventional human-capital variables, school grades at age 16 and final education, the results were different. We found that factors associated with either of these variables could account for about a third of the intergenerational income correlation. Further, a substantial part of the country difference in intergenerational income mobility could be accounted for by grades and final education. In particular, the results for school grades suggest that early-intervention policies can potentially increase intergenerational mobility.

Nonetheless, it was striking that grades and final education turned out to be more important for intergenerational income persistence in the UK, both because of higher monetary returns in the labour market to these traits, and because of a higher covariance between each trait and parental income. Our estimates suggest that differences in returns to these skills contribute to 33-40% of the gap in the intergenerational income correlation, whereas the contribution from differences in covariances is somewhat lower. Blanden *et al. (*2014) find similar results in their comparison of intergenerational mobility in the UK and the United States using traits from early adulthood. They find that, primarily because of the higher returns to education and skills, the pathway through offspring education is relatively more important in the United States. These results suggest that what happens in the labour market is also important for country-differences in intergenerational income mobility.

We argue that a comprehensive model of income mobility that can help understand the cross-national patterns should focus not only on the link between parental resources and offspring's skills, but also on the link between skills and labour-market rewards. The popular Becker-Tomes model focuses primarily on the first link by modelling parental investment behaviour. As a matter of fact, an early (but neglected) intergenerational model by Conlisk (1974) is more elaborate about the link between skills and income, and therefore offers an interesting complement to the Becker-Tomes model, which primarily treats the wage returns as an investment incentive for the parents. We also want to stress that recent results from the OECD's Program for the International study of Adult Competencies (PIAAC) show large country differences in the relationship between adults’ skills and their wages. Hanushek *et al.* (2015) report that in Sweden, a one standard deviation increase in (within-country) cognitive skills is associated with a wage premium of 13% compared to 28% in the US. The UK is close to the US with 23%, and Sweden’s number is close to its neighbour countries Denmark and Norway (with 14%). It would be surprising if these differences do not have implications for the cross-national pattern of intergenerational income correlations.

Further, there are other labour market factors – potentially unrelated to skills – that can influence income mobility. For example, Corak and Piraino (2011) have found a strong intergenerational transmission of employers between fathers and sons, suggesting an important role for networking in the labour market. Their results and ours suggest that comparative intergenerational income mobility research should also consider differences in labour-market institutions.

We conclude that our study suggests that both factors early in life and labour-market characteristics, such as the returns to skills, can help explain cross-national differences in intergenerational income mobility. Further, given the relationship between returns to skills and cross-sectional income inequality, our findings also help us understand the Great Gatsby curve. Thus, future research should look broadly for possible causal mechanisms behind the cross-national differences in intergenerational income mobility.

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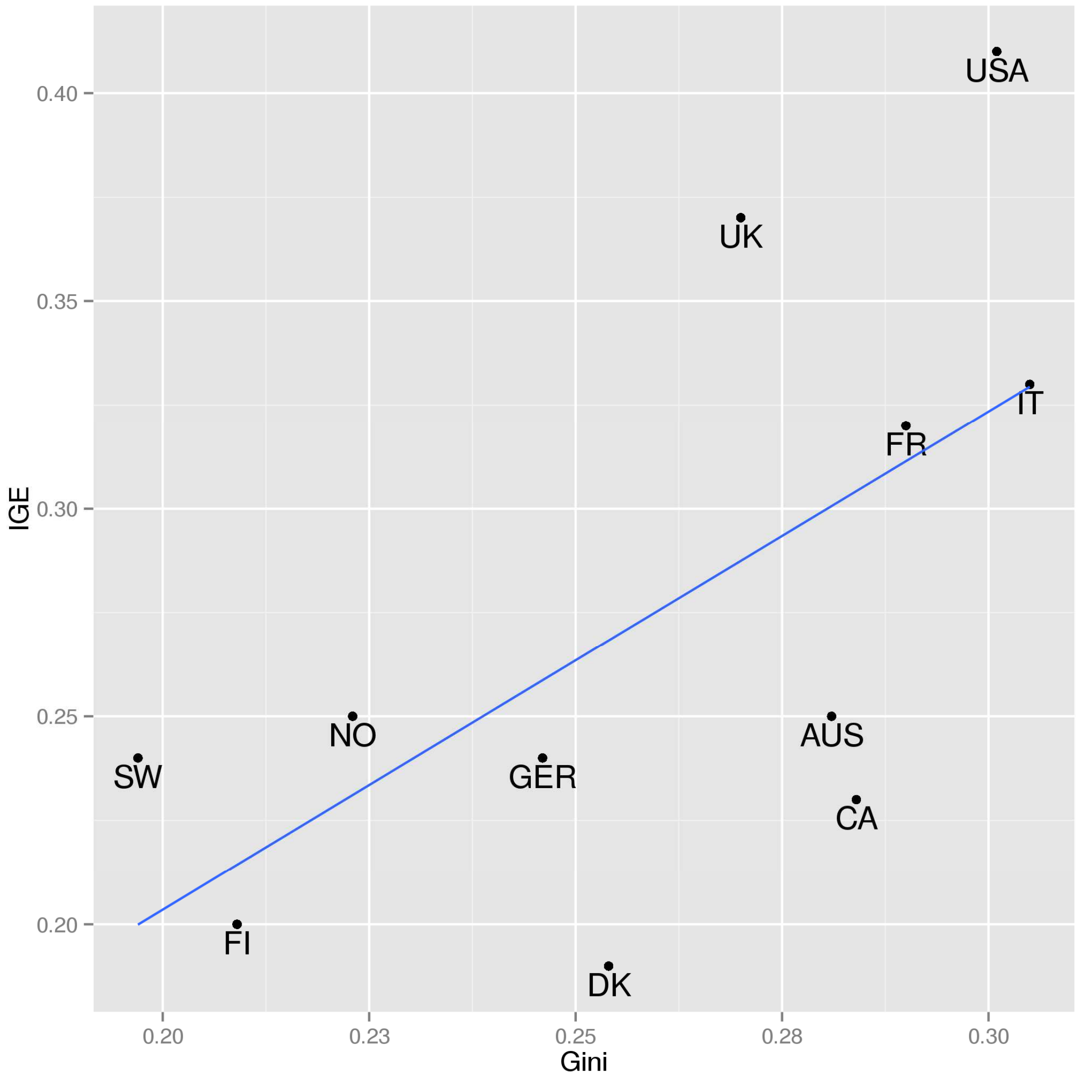
Figures and Tables

Figure 1

The Great Gatsby Curve



Note: This curve shows the relationship between cross-sectional disposable income inequality (GINI) and the intergenerational earnings elasticity (IGE). Sources: IGEs are taken from Blanden (2013), except for Denmark. We use Hussein et al.'s (2015) more recent estimate for Denmark. GINIs are taken from Luxembourg Income Study (LIS), Wave 1 (around 1980) when available and Wave 2 (around 1985) if the first wave is not available.

Table 1
Descriptive Statistics for Income Samples

	Sons		**Daughters**	
	Sweden	UK	Sweden	UK
Log earnings, offspring	6.33	6.59	6.03	6.11
	(0.46)	(0.56)	(0.42)	(0.71)
Log income, parents	6.52	6.19	6.52	6.20
	(0.46)	(0.51)	(0.46)	(0.50)
Parental age	40.80	39.44	40.71	39.50
	(4.98)	(5.76)	(4.99)	(5.75)
N	47324	3275	43132	2960

Note: The table shows means and standard deviations within parentheses. We use weekly income and earnings, PPP-adjusted to 2005 dollars. Swedish annual income and earnings are divided by 52 in order to make the data comparable. We condition on offspring's earnings > 100 dollars/week. Parental age (the mean of both parents) is measured at the time parental income is measured.

Table 2
Estimates of Intergenerational Income Associations

	Sons			***Daughters***		
	Sweden	UK	F-test	Sweden	UK	F-test
Elasticity	0.176	0.271	23.7	0.162	0.296	70.3
	(0.005)	(0.019)	[0.000]	(0.004)	(0.026)	[0.000]
Correlation	0.177	0.249	9.8	0.178	0.211	2.8
	(0.005)	(0.017)	[0.002]	(0.005)	(0.018)	[0.097]
Quadratic (linear)	-1.051	-1.213	57.2	-1.164	-0.966	1.6
	(0.068)	(0.272)	[0.000]	(0.066)	(0.370)	[0.200]
(square)	0.098	0.122		0.105	0.104	
	(0.005)	(0.022)		(0.005)	(0.030)	

Note: We use the average of the parents' age and its square as controls in the regression models in this and subsequent tables. Standard errors are within parentheses and p-values within brackets.

Table 3

Descriptive Statistics for Outcome Samples

		Sons		Daughters	
		Sweden	UK	Sweden	UK
A. Birth weight	Birth weight	3.56	3.38	3.42	3.27
		(0.54)	(0.54)	(0.52)	(0.50)
	Log birth weight	1.26	1.20	1.22	1.17
		(0.17)	(0.17)	(0.16)	(0.16)
	Low birth weight	0.03	0.05	0.04	0.06
		(0.17)	(0.23)	(0.19)	(0.23)
	Log parental income	6.52	6.18	6.52	6.20
		(0.46)	(0.51)	(0.46)	(0.51)
	Parental age	40.80	39.43	40.71	39.49
		(4.98)	(5.77)	(4.99)	(5.74)
	N	47297	3188	43103	2892
B. Height	Height	1.80	1.74	n.a.	n.a.
		(0.06)	(0.08)		
	Log parental income	6.52	6.23		
		(0.46)	(0.50)		
	Parental age	40.77	40.00		
		(4.97)	(5.64)		
	N	43670	1931		
C. Average grade	Average grade	0.47	0.51	0.53	0.54
		(0.21)	(0.14)	(0.20)	(0.13)
	Log parental income	6.52	6.20	6.52	6.21
		(0.46)	(0.51)	(0.46)	(0.50)
	Parental age	40.78	39.88	40.70	39.75
		(4.97)	(5.67)	(4.98)	(5.76)
	N	46459	2709	42349	2559
D. Education	At least high school (level 3)	0.91	0.72	0.95	0.77
	At least some college (level 4)	0.40	0.46	0.53	0.52
	At least completed college (level 5)	0.26	0.37	0.39	0.43
	Log parental income	6.52	6.20	6.52	6.21
		(0.46)	(0.51)	(0.46)	(0.50)
	Parental age	40.80	39.51	40.71	39.53
		(4.98)	(5.78)	(4.99)	(5.69)
	N	47227	2725	43057	2643

Note: The table shows means (with standard deviations within parentheses) of child outcomes, log parental income and parental age of the different outcome samples. Parental age (of both parents) is measured at the time the parental income is measured. Height is measured in meters and education is measured as ISCED levels, with levels 1 and 2 merged into one. Standard deviations are in parentheses.

Table 4

Estimates of Intergenerational Associations: Child Outcomes on Log Parental Income

		Sons			Daughters		
		Sweden	UK	F-test	Sweden	UK	F-test
Birth weight	Regression coeff.	0.021	0.081	9.7	0.027	0.109	15.8
		(0.006)	(0.019)	[0.002]	(0.006)	(0.019)	[0.000]
	Correlation	0.018	0.076	10.6	0.024	0.110	18.8
		(0.005)	(0.018)	[0.001]	(0.005)	(0.019)	[0.000]
Log birth weight	Regression coeff.	0.007	0.025	8.9	0.009	0.035	15.0
		(0.002)	(0.006)	[0.003]	(0.002)	(0.006)	[0.000]
	Correlation	0.021	0.073	8.4	0.026	0.108	16.6
		(0.005)	(0.018)	[0.004]	(0.005)	(0.019)	[0.000]
Low birth weight	Regression coeff.	-0.008	-0.016	1.0	-0.010	-0.034	10.4
		(0.002)	(0.008)	[0.325]	(0.002)	(0.009)	[0.001]
	Correlation	-0.004	-0.008	1.3	-0.005	-0.017	11.3
		(0.001)	(0.004)	[0.256]	(0.001)	(0.004)	[0.001]
Height	Regression coeff.	0.008	0.022	23.5	n.a.	n.a.	n.a.
		(0.001)	(0.004)	[0.000]			
	Correlation	0.058	0.136	11.7	n.a.	n.a.	n.a.
		(0.005)	(0.024)	[0.001]			
Average grade	Regression coeff.	0.105	0.080	14.3	0.087	0.065	10.3
		(0.002)	(0.005)	[0.000]	(0.002)	(0.005)	[0.001]
	Correlation	0.231	0.304	11.0	0.195	0.248	6.2
		(0.005)	(0.019)	[0.001]	(0.005)	(0.020)	[0.013]
Education – level 3	Regression coeff.	0.076	0.175	69.1	0.044	0.169	204.5
		(0.003)	(0.017)	[0.000]	(0.002)	(0.016)	[0.000]
	Correlation	0.123	0.199	12.4	0.097	0.203	27.3
		(0.005)	(0.019)	[0.000]	(0.005)	(0.019)	[0.000]
Education – level 4	Regression coeff.	0.246	0.226	2.9	0.204	0.206	0.0
		(0.005)	(0.018)	[0.089]	(0.005)	(0.019)	[0.944]
	Correlation	0.231	0.233	0.2	0.187	0.208	0.7
		(0.005)	(0.018)	[0.618]	(0.005)	(0.019)	[0.386]
Education – level 5	Regression coeff.	0.204	0.208	0.0	0.193	0.203	0.2
		(0.004)	(0.018)	[0.876]	(0.005)	(0.019)	[0.697]
	Correlation	0.214	0.222	0.0	0.182	0.207	1.3
		(0.005)	(0.019)	[0.954]	(0.005)	(0.019)	[0.253]

Note: Each panel reports the regression and correlation coefficients on log parental income from separate regressions for each child outcome controlling for the mean parental age and its square. Birth weight is measured in kilograms; low birth weight is an indicator for less than 2.5 kilograms. Height is in meters and education is measured as ISCED levels. Standard errors are in parentheses and p-values in brackets.

Table 5

Decompositions of the Intergenerational Income Correlation for Sons

	IGC	$\delta * Cov(Y^p, X^c)$	$Cov(Y^p, u^c)$	.	IGC	$\delta * Cov(Y^p, X^c)$	$Cov(Y^p, u^c)$
Birth weight				Average grade			
Swedish estimates	0.177	0.031*0.018=0.001	0.176	Swedish estimates	0.173	0.259*0.231=0.060	0.113
UK estimates	0.250	0.059*0.076=0.004	0.246	UK estimates	0.255	0.280*0.304=0.085	0.170
UK with Swedish returns	0.248	0.002	0.246	UK with Swedish returns	0.249	0.079	0.170
UK with Swedish covariance	0.247	0.001	0.246	UK with Swedish covariance	0.235	0.065	0.170
Sweden with UK returns	0.177	0.001	0.176	Sweden with UK returns	0.178	0.065	0.113
Sweden with UK covariance	0.178	0.001	0.176	Sweden with UK covariance	0.192	0.079	0.113
Log birth weight				Education			
Swedish estimates	0.177	0.035*0.021=0.001	0.176	Swedish estimates	0.177	0.12*0.12+0.09*0.23+0.07*0.21=0.050	0.127
UK estimates	0.250	0.063*0.073=0.005	0.246	UK estimates	0.253	0.14*0.20+0.13*0.23+0.13*0.22=0.087	0.166
UK with Swedish returns	0.249	0.003	0.246	UK with Swedish returns	0.226	0.060	0.166
UK with Swedish covariance	0.247	0.001	0.246	UK with Swedish covariance	0.241	0.075	0.166
Sweden with UK returns	0.177	0.001	0.176	Sweden with UK returns	0.202	0.075	0.127
Sweden with UK covariance	0.179	0.003	0.176	Sweden with UK covariance	0.187	0.060	0.127
Low birth weight				All traits			
Swedish estimates	0.177	-0.032*-0.023=0.001	0.176	Swedish estimates	0.173	0.066	0.107
UK estimates	0.250	-0.042*-0.073=0.001	0.249	UK estimates	0.267	0.124	0.143
UK with Swedish returns	0.250	0.001	0.249	UK with Swedish returns	0.229	0.086	0.143
UK with Swedish covariance	0.250	0.001	0.249	UK with Swedish covariance	0.240	0.097	0.143
Sweden with UK returns	0.177	0.001	0.176	Sweden with UK returns	0.204	0.097	0.107
Sweden with UK covariance	0.177	0.001	0.176	Sweden with UK covariance	0.193	0.086	0.107
Height							
Swedish estimates	0.174	0.072*0.058=0.004	0.170				
UK estimates	0.267	0.118*0.136=0.016	0.251				
UK with Swedish returns	0.261	0.010	0.251				
UK with Swedish covariance	0.258	0.007	0.251				
Sweden with UK returns	0.177	0.007	0.170				
Sweden with UK covariance	0.180	0.010	0.170				

Note: Each panel shows the intergenerational income correlation (IGC) in each country, decomposes this into a covariance of the intermediate offspring trait and its earnings return and the covariance of the residual with parental income. These terms are used to calculate the counterfactual IGCs by imputing the returns and observed covariances.

Table 6
Attrition Analysis of the UK Data Set

Elasticities	Sons		Daughters	
	Baseline	Weighted	Baseline	Weighted
Income sample	0.270 (0.020) [N=3051]	0.273 (0.021) [N=3051]	0.305 (0.027) [N=2736]	0.309 (0.026) [N=2736]
Balanced sample	0.270 (0.020) [N=1046]	0.250 (0.023) [N=1046]	0.304 (0.027) [N=1317]	0.291 (0.029) [N=1317]
Correlations	**Sons**		**Daughters**	
	Baseline	Weighted	Baseline	Weighted
Income sample	0.245 (0.018) [N=3051]	0.248 (0.019) [N=3051]	0.214 (0.019) [N=2736]	0.217 (0.019) [N=2736]
Balanced sample	0.245 (0.018) [N=1046]	0.227 (0.021) [N=1046]	0.214 (0.019) [N=1317]	0.205 (0.021) [N=1317]

Note: The table reports regression and correlation coefficients of log offspring earnings on log parental income controlling for mean parental age and its square. For the weighted estimates we use the predicted probability of non-attrition to re-estimate our intergenerational models with inverse probability weights. As predictors of non-attrition we use birth weight, birth weight squared, an indicator for low birth weight, indicators for mother's age at delivery, mother's marital status, father's employment, and father's social class. The sample sizes for the prediction step are N = 8181 for the sons and N = 7541 for the daughters. Standard errors are within parentheses and sample sizes for the final estimation in brackets.