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The Different Sources of Intergenerational Income Mobility in High and Low Income Families

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Abstract

This paper studies intergenerational income mobility using register data for 630,000 Danish children and their parents. We document substantial mobility differences across parents' income levels. Decomposing the mobility estimates shows that for children from low-income families, intergenerational income persistence is exclusively explained by parents' influence on children's employment. As parents' income increases, education becomes an increasingly dominant factor, except among children from the top-5% where intergenerational income persistence is driven by capital income likely through bequests and business contacts. Finally, we find that progressive public transfers such as those in Denmark suppress the importance of intergenerational transmission of employment. (99)

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1 Introduction

A large literature has studied intergenerational income mobility documenting substantial cross-country differences (Black and Devereux, 2011; Corak, 2013). Recent contributions to the literature have increasingly focused on within-country differences in mobility such as across areas of upbringing (e.g., Chetty et al., 2014; Deutscher and Mazumder, 2019; Eriksen and Munk, 2020; Guell et al., 2018) and across parents' income levels (Bratsberg et al., 2007; Chen et al., 2017; Helsø, 2021; Landersø and Heckman, 2016). Yet, our knowledge about the sources behind differences in income mobility across different family types remain limited.

This paper seeks to fill part of this gap by analyzing the mechanisms that explain income mobility across parental income levels. The paper uses full population administrative data from Denmark with information on income and all its underlying components (such as earnings, capital income, and welfare benefits) of more than 630,000 children and their parents.

We present two main findings. First, we show that persistence in income across generations is driven by very different mechanisms across parental income levels. For children from low income families, income persistence is solely driven by variation in employment rates and not by factors such as education. As parental income increases, children's education plays a growing role in shaping income persistence. Among top-income families, however, neither education nor employment rates explain the intergenerational income persistence. Instead, capital income (from income based on transferred wealth from parents) and business income stand out as the main drivers. Notably, these three mechanisms almost completely account for the relationship between parents' and children's income. These findings highlight that potential policies to improve income mobility may differ strongly depending on the families in focus. For children from disadvantaged background, for example, the extensive margin problem of finding a job appears to be a large barrier for social mobility.[1]

Our second main finding relates to the role of welfare transfers (such as social assistance and UI benefits) in shaping income mobility estimates. We show that the highly generous income transfers in Denmark substantially attenuate the intergenerational persistence in income. This effect is largest for children from low and middle income families. We show that the generosity of public transfers in Denmark effectively removes any mediating role of employment when estimating income mobility.[2]

We contribute to the broad literature on intergenerational income mobility in three dimensions (see e.g., Black and Devereux, 2011; Mogstad and Torsvik, 2021, for reviews of the literature). First, we show that the drivers of intergenerational income mobility differ strongly across parents' income levels (as Markussen and Røed, 2019, do for trends in rank-rank correlations in earnings). Second, while the role of employment for mobility in low-income families and education for mobility at higher levels of parental income have clear implications for potential policies focusing on skills and human capital, the finding that income persistence at the very top of the income distribution is driven solely by capital income (as Björklund et al., 2012, show for Sweden) introduces the importance of integrating studies of social mobility with those of asset accumulation and bequests to children. And third, the finding that transfer income largely removes the role of employment as a mechanism behind

[1]We mainly focus on estimates from regressions of children's log income on parents' log income (IGE), but we show that our conclusions are qualitatively similar when considering estimates based on children's and parents' income rank and absolute upward mobility.

[2]The variation in income mobility by income measure has previously been shown in e.g., Landersø and Heckman (2016) and Deutscher and Mazumder (2019). We expand their findings by showing that the differences between the different income measures largely stem from the mediating role of employment.

mobility estimates highlights the difficulties of comparing mobility estimates across countries with different levels of redistribution. Cross-sectional associations between children's and parents' income may proxy a host of different mechanisms (as shown in e.g., Nybom and Stuhler, 2022) where some relate to, for example, equality of opportunity in human capital formation while others relate to returns to human capital in the labor market.

2 Data

This paper uses Danish administrative register data. These data include a unique individual identifier that allows us to link information on individual income, education, and employment. Furthermore, the registers also include unique individual identifiers of parents, allowing us to identify parental characteristics as well. We define our sample as the full population of birth cohorts from 1972 to 1982. We exclude immigrants and descendants from our sample to ensure that we have information on child and parent income for as many years as possible, resulting in a final sample of 630,354 observations.[3]

The paper's key variables from the income register contain information on individual income from 1980 onward, including information on a range of different income items such as wage earnings, self-employment income, capital income, business income, and transfer income. Based on this information, we construct two income measures, which we use throughout the paper: i) *Market income*, which contains all pre-tax income excluding public

[3]Appendix Section B describes the data construction in detail, and Table A.1 presents the attrition at each stage of the sample selection in detail.

transfers; ii) *Gross income*, which equals market income plus public transfers.[4] We measure child income as an average at ages 31-37 to reduce bias from transitory shocks to income (Solon, 1992) and minimize lifecycle bias (Nybom and Stuhler, 2016).[5] We similarly construct measures of parents' market and gross income using the same definitions as above by averaging mother's and father's income at child age 8-14.

In the final step of our data construction, we add information on children's education and employment from the education and labor market registers, respectively. We measure education as the years of schooling required to attain the highest level of education of the child and measure employment as the fraction of time in employment between ages 31-37. Table B.1 shows descriptive statistics on education, employment, and each income measure used in the paper.

3 Results

We present our results in four steps. First, Section 3.1 establishes the baseline income mobility estimates in line with previous studies, and introduces how we decompose the estimates. Next, focusing first on income before redistribution in Denmark, Section 3.2 presents how intergenerational mobility in market income varies across parental income levels, and how children's education and employment mediate most of these nonlinearities. In Section 3.3

[4] Throughout the paper, we treat individuals with income below $1 as having zero income as these outliers would inflate the variance of log-income disproportionately. The paper is based on a balanced sample, where we exclude any individual with zero income in one or more of the two income measures. This sample restriction only reduces the sample size by 2% (see Table A.1) because we consider income averaged over seven years. Fig. A.1 in the appendix replicates the main result without this sample selection and is qualitatively similar.

[5] Figs. A.2 and A.3 illustrate the robustness of our results when varying the age at which children's and parents' income is measured. Similarly, Fig. A.4 shows that our results are robust to measuring parents' income based on their own age rather than their child's.

we turn to specific income types and show how the sources behind estimated income mobility vary strongly across parental income levels. Finally, Section 3.4 shows how public transfers reshape income mobility estimates and how this relates to children's labor market attachment.

3.1 Population average estimates

In line with many previous studies, we focus on the intergenerational income elasticity (IGE), which relates child log-income $y^C = ln(Y^C)$ to parental log-income $y^P = ln(Y^P)$.[6] However, as commonly recognized, income mobility estimates likely comprise several underlying mechanisms and heterogeneities. Factors such as education and employment likely mediate the relationship between parents' and children's income. We decompose the canonical mobility estimate using a mediation analysis (see Gelbach, 2016; Mackinnon, 2000; MacKinnon et al., 2007) to parse out how much of the relationship between children's and parents' income that can be attributed to factors influencing child income. We first estimate a baseline IGE equation:

$$y_i^C = \alpha_{IGE} + \beta_{IGE} y_i^P + \varepsilon_i \tag{1}$$

We then re-estimate the relationship between parents' and children's log market income in a model that conditions on child education and employment, our two mediators of interest:

$$y_i^C = \tilde{\alpha} + \beta_{EDUC} EDUC_i^C + \beta_{EMPL} EMPL_i^C + \beta_{RES} y_i^P + \tilde{\varepsilon}_i \tag{2}$$

[6]Deutscher and Mazumder (2021) present a comprehensive summary of commonly used measures of intergenerational income mobility.

β_{RES} captures the remaining relationship between parents' and children's income not explained by education and employment, and we dub this the residual component. The difference between this coefficient and the full IGE estimate, $\delta = \beta_{RES} - \beta_{IGE}$, is a combination of the role of education and employment as mediators: $\delta = \delta_{EDUC} + \delta_{EMPL}$. To estimate δ_{EDUC} and δ_{EMPL} — the mediating effect of the two components — we run two auxiliary regressions:

$$EDUC_i^C = \alpha_{EDUC} + \Gamma_{EDUC} y_i^P + \varepsilon_{i2} \tag{3}$$

$$EMPL_i^C = \alpha_{EMPL} + \Gamma_{EMPL} y_i^P + \varepsilon_{i3} \tag{4}$$

The two parameters Γ_{EDUC} and Γ_{EMPL} show the association between parents' income, and child education and employment, respectively. We then weight the parameters β_{EDUC} and β_{EMPL} from Eq. (2) by Γ_{EDUC} and Γ_{EMPL} to estimate the respective components:

$$\delta_{EDUC} = \Gamma_{EDUC} \beta_{EDUC} \tag{5}$$

$$\delta_{EMPL} = \Gamma_{EMPL} \beta_{EMPL} \tag{6}$$

This decomposition methodology allows us to estimate the mediating effects of child education and employment on β_{IGE}. We eschew the conventional approach of sequential control, i.e. gradually expanding the control set and attributing changes in β_{IGE} to the latest included variable. The sequential approach, while correctly estimating the total mediation of the control set ($\delta_{EDUC} + \delta_{EMPL}$) runs the risk of attributing too much influence to the earliest variables included in the sequence (Gelbach, 2016).

Panel a) of Table 1 shows conventional estimates of β_{IGE} for market income and applies the decomposition outlined above. The first column shows the IGE estimate, β_{IGE}, the second column shows the size of the education component, δ_{EDUC}, the third column shows the employment component, δ_{EMPL}, and the fourth column shows the residual influence of parent's income conditional on children's education and employment, β_{RES}. The estimates show that β_{IGE} is — to a very large extent — mediated by the education and employment components: Variation in children's education explains approximately 16% of β_{IGE} while variation in children's employment explains around 59%. The last 25% of β_{IGE} is related to other channels than education and employment and is captured by the residual component, β_{RES}.[7]

While our preferred approach is agnostic about the interdependence between the mediating variables, it could be argued that education influences both income directly and through its effect on employment. Table A.3 shows the results if we allow education to play such role. With this method for market income, the education component becomes more important, to the point where it is similar in size to the employment component. When using gross income, the importance of employment is likewise shifted towards the education component.

Panel b) of Table 1 shows the same set of estimates as panel a) using instead gross income rather than market income. Here, the overall mobility is estimated to be higher (as in e.g., Deutscher and Mazumder, 2019; Landersø and Heckman, 2016), with a β_{IGE} of 0.197 compared to 0.305 for market income. The most substantial difference, however, is the importance of the employment component, which is markedly attenuated: For market income, employment mediates around 59% of the relationship, which is reduced to around 26% when using gross income instead with δ_{EMPL} decreasing from 0.179 to 0.052. The

[7] Our preferred estimation of IGE, Eq. (1), includes no controls. In Table A.2 we replicate our results from Table 1 adjusting for gender and birth cohort fixed effects and show no substantive differences.

estimates reported in Table 1 are similar to those reported for Denmark in previous research.[8] Table A.4 shows the corresponding mobility estimates and decomposition for rank-rank mobility.[9]

3.2 Nonlinearity and the role of education and employment

The results presented above focus on the average relationship across the entirety of parents' income distribution. Yet, several papers have shown large nonlinearities in IGE estimates[10] suggesting that the relationship between parents' and children's income, as well as the mediating role of education and employment, could be more complex.

Fig. 1a illustrates the strong nonlinearity by plotting child log-market income by parental log-market income. The slope of the straight solid line is the coefficient β_{IGE} from Table 1. As evident from the figure, the slope between the various bins often vary substantially from the solid line. At low and high levels of parental income, the slope is lower than the population average, whereas the local slope is steeper for medium parental income levels. To capture these nonlinearities, we will estimate the nonlinear IGE (NL-IGE) as:

$$\underset{\alpha[Y_0^P],\beta[Y_0^P]}{min} \sum_{i=1}^{N} K_{h_\lambda}(Y_0^P, Y_i^P) \cdot \{y_i^C - \alpha_{NL-IGE}[Y_0^P] - \beta_{NL-IGE}[Y_0^P] y_i^P\}^2 \tag{7}$$

as outlined in Landersø and Heckman (2016), which allows us to estimate the income mo-

[8]See Bonke et al. (2005); Harding and Munk (2019); Helsø (2021); Hussain et al. (2009); Landersø and Heckman (2016); Munk et al. (2016).

[9]Harding and Munk (2019) find that the association between children's and parents' income rank has increased in Denmark for cohorts born from 1957–1977, and conclude that most of this increase is explained by work experience at age 35 while education only plays a minor role in explaining the trend.

[10]See Bratsberg et al. (2007); Chen et al. (2017); Helsø (2021); Landersø and Heckman (2016).

bility at each local range of parental income with the population average IGE β_{IGE} being a weighted average of the NL-IGEs β_{NL-IGE}[11] As with the population average IGE, the NL-IGE estimates can be interpreted as the change in child income in percentages from an increase in parental income of 1%. However, the estimates express the associations at a local level — an estimate of zero, for example, does not imply that going from rags to riches is likely but only that within a local range of parental income there is no association between child income and parental income.

Fig. 1b shows the NL-IGE estimates as defined in Eq. (7) mirroring the pattern depicted in Fig. 1a: Local income mobility in market income is largest at the bottom and top of parents' income distribution and lowest at the middle of the distribution. The variation is considerable with β_{NL-IGE} estimates ranging from 0.22 to 0.65, comparable to the variation across OECD countries in IGE estimates reported in Corak (2013), which we illustrate in Fig. A.6. Thus, even in a small country such as Denmark, parents' income has very different bearings on child income depending on which part of the income distribution that parents' income is drawn from. This nonlinearity has several implications for mobility. First, it illustrates the limitations of using the population average IGE as a summarizing measure of mobility. For example, two countries sharing the same average IGE could differ substantially with respect to which income groups experience high and low levels of mobility. Second, given that IGE behaves in a nonlinear manner, the mechanisms driving IGE could behave nonlinearily as well.

Next, we plot the relationship between parents' income and child education and employ-

[11] Thus, $\beta_{IGE} = \int \omega_{Y^P} \beta_{NL-IGE} dY^P$ where Y^P is parents' income levels and ω_{Y^P} is a weight. In Eq. 7, $K_{h_\lambda}(Y_0^P, Y_i^P)$ is an Epanechikov kernel. We consider a bandwidth h of $26,000. Fig. A.5 replicates these estimations with a bandwidth h of $15,000 and shows similar results.

ment in Figs. 2a and b, respectively. From the figures it is clear that the relationships between parents' income and children's education and employment are nonlinear. For both variables, a marginal increase in parents' income is associated with substantial increases around the middle of parents' income distribution but less so at the top and bottom. Despite this similarity, the figure also shows an important difference: Education increases very rapidly when parents' log income increases from 11 to 12, whereas the most substantial increase in employment happens between parents' log income 10 and 11. Thus, as we move up through the distribution of parents' income, a marginal increase in income is initially mainly associated with higher employment rates and later mainly with more education. This implies that education and employment could act as mechanisms for income mobility in a nonlinear manner with employment being more important in the lower parts of parents' income distribution (where it increases most rapidly) and education being more important towards the middle and top of parents' income distribution.

To quantify the relationships between children's education and employment and parents' income, we apply the decomposition method outlined in Section 3.1 in combination with the local linear regression approach in Eq. (7). The goal is to estimate the total local IGE, β_{NL-IGE}, the education component, $\delta_{NL-EDUC}$, the employment component, $\delta_{NL-EMPL}$, and the residual component, β_{NL-RES} across levels of parents' income:

$$\beta_{NL-IGE} = \delta_{NL-EDUC} EDUC_i^C + \delta_{NL-EMPL} EMPL_i^C + \beta_{NL-RES} y_i^P \tag{8}$$

We therefore repeat the anayisis outlined in Eqs. 3–6 at each level of parental income as described for the estimated nonlinear IGE above (we still assume that education and employment affect income linearly—*nonlinear* refers to the variation across parental income levels). Appendix C details the estimation procedure.

The resulting estimates are presented in Fig. 2c. The figure shows that education and employment both act as mediators for intergenerational income persisitence, but in a highly heterogeneous manner at different levels of parental income. For children from low-income families, variation in education plays a negligible role in explaining the overall association between children's and parents' income while variation in employment acts as the crucial mediator.[12] Past the second decile of parental income, the mediating role of employment begins to diminish, eventually becoming zero, while the mediating role of education steadily becomes stronger.[13] Moreover, Fig. 2c also shows that while education and employment mediate nearly all of β_{NL-IGE} for low-income families, they gradually explain less as parents' income increases.[14] The remaining unexplained component, β_{RES}, in high income families is the focus of the following subsection.

[12]In line with this result, Markussen and Røed (2019) find that the declining income mobility coincides with a stronger employment gradient among individuals from low income families.

[13]Fig. A.7 replicates Fig. 2c using sequential controls (allowing education to influence income directly and through employment), first controlling for education and then for employment (thereby assigning more weight to the role of education in the mediation analyses), and shows the same substantive results. However, education appears to be a more crucial mechanism in this configuration, which follows from it being introduced first.

[14]Fig. A.8 shows the estimated rank-rank mobility and the mediating role of education and employment across parents' income deciles. Fig. A.9 shows similar estimates, but for absolute upward mobility. Any direct comparison of nonlinearities between IGE on the one hand and rank-rank or upward mobility analyses on the other are impossible. For ranks, this is due to the compression of the income distribution to a uniform distribution and for upward mobility, the nature of the measure not being expressed as a regression coefficient changes the decomposition method. However, the figures still show that the results relating to the role of education and employment are qualitatively similar: In low income families, employment is the predominant mediator, the role of education is stable or increases until the last decile of parents' income, and the residual (unexplained) component becomes increasingly dominant as parents' income increases.

3.3 The "residual" component and the role of capital income

This section analyzes the residual IGE component (the unexplained portion of β_{IGE} after adjusting for education and employment). To investigate this, we focus on the various types of income that make up our measure of market income: wages, profits from businesses, and capital income.[15] For this analysis, we exploit that any measure of log-child income can be written as an additive function of its underlying income components, such that $y_i^C = \ln(Y_{WAGE,i}^C + Y_{PROF,i}^C + Y_{CAP,i}^C + Y_{RES,i}^C)$ with $Y_{WAGE,i}$, $Y_{PROF,i}$, $Y_{CAP,i}$ and $Y_{RES,i}$ denoting, respectively, wages, business profits, capital income, and residual income levels. Fig. 3a shows these components across levels of parental log-income. The figure shows that, for all children, regardless of parents' income, wages are the dominant component of market income. Profits from businesses make up a consistent, but much smaller, portion of children's income, the size of which increases for the top five percentiles of parents' income. Capital income is almost non-existent as a source of income, except among children whose parents are in the top five percentiles of the income distribution. For the top percentile, the amount of capital income increases dramatically and makes up a sizable portion of market income. These descriptive results indicate that the sources of intergenerational income persistence could be fundamentally different for children from high-income families compared to children from low- and middle-income families.

In order to assess the importance of each income component for β_{IGE}, we first define income as wages only and then gradually expand this definition by adding profits from businesses and capital income, respectively. This allows us to isolate the association between

[15] Our measure of market income also includes a very minor portion of other "residual incomes" such as remunerations.

the individual child income components in the total IGE estimate as described in Section 3.1. We estimate the following:

$$
\begin{aligned}
y_i^C =& \beta_{IGE} y_i^P \\
y_i^C =& \beta_W y_i^P + \beta_1 \ln(Y_{WAGE,i}^C) \\
y_i^C =& \beta_{WP} y_i^P + \beta_2 \ln(Y_{WAGE,i}^C + Y_{PROF,i}^C) \\
y_i^C =& \beta_{WPC} y_i^P + \beta_3 \ln(Y_{WAGE,i}^C + Y_{PROF,i}^C + Y_{CAP,i}^C)
\end{aligned}
\tag{9}
$$

This decomposition departs from that used in the previous section in two dimensions:

First, we apply the sequential approach because child income is a *additive combination* of wages, profits, capital income, and residual income. Based on Eq. (9), we calculate the role for β_{IGE} of wages by $\delta_{WAGE} = \beta_{IGE} - \beta_W$. Similarly, we calculate the role of profits from businesses, capital income, and residual income, respectively, by $\delta_{PROF} = \beta_W - \beta_{WP}$, $\delta_{CAP} = \beta_{WP} - \beta_{WPC}$. and $\delta_{RES} = \beta_{WPC}$. In contrast, when we considered the role of education and employment in the previous section, the sequential approach would make us attribute too much influence to the earliest variables included in the sequence.

Second, we estimate results in separate analyses for the the first quartile, the second quartile, the third quartile, the fourth quartile except the top 5%, the top 5%, and the top 1% of parents' income. We do not estimate results in a local linear regression because this would dilute the dominant role of capital income among children from the top 5% and top 1%.

Fig. 3b shows the results: For the first, second, and third quartile of parents' income, the wage earnings component, δ_{WAGE} is the dominant channel for β_{IGE}, with profits from businesses, δ_{PROF} playing a minor role and δ_{CAP} being completely negligible. This is hardly surprising, given the near non-existence of capital income for these children in Fig. 3a. However, for the 75th to 95th percentile, the importance of wage earnings for β_{IGE} diminishes. Finally, children of parents in the top five percentiles of the income distribution exhibit a radically different pattern since β_{IGE} is in no substantial way driven by wage earnings and profits from businesses ($\delta_{WAGE}, \delta_{PROF} \approx 0$). Rather, income persistence for these children is dominated by the importance of capital income, δ_{CAP}, which accounts for nearly the entirety of β_{IGE}. This pattern is even more pronounced among children of parents from the top 1% of the income distribution. This prominent role of capital income for explaining β_{IGE} relates directly to the large unexplained component of IGE, β_{RES}, for children of high-income parents shown in Fig. 1c and suggests a third mechanism of inherited assets yielding capital income. This result complements Björklund et al. (2012), who show that wealth transmission plays a central role for income persistence among high income families in Sweden, and relates to Boserup et al. (2018), showing that the process of transferring wealth and capital from parents to children is initiated at a very early age in high-income families (Fig. A.12 illustrates this process for our data: The marked difference in assets by parents' income is evident even at ages 15-18).

3.4 Transfer income and nonlinearities

So far, we have focused on market income, but Denmark has one of the world's most generous transfer systems, and (almost) all individuals without employment are eligible for some type of public transfer income. In fact, the low income inequality in Denmark largely originates in the redistribution of income. For example, the Danish and U.S. Gini coefficients of market income differ by around 15%, whereas the corresponding Gini coefficients of post-redistribution income differ by around 50% (OECD, 2022).

As presented earlier in Table 1, the population average IGE decreases once we include redistribution through public transfers, i.e. when we move from market income to gross income. This difference begs two questions: Where in parents' income distribution are public transfers particularly important as a source of income mobility, and how do transfer incomes influence the role of education and employment?

Fig. 4a plots children's log-market income and log-gross income against parents' log-market income along with linear slopes representing the average IGE from Table 1.[16] The figure shows that the linear slope is closer to the log-log plots when considering gross income rather than market income. Moreover, as illustrated in Fig. 4b, average transfer income is monotonically decreasing across parents' income levels (reflecting the progressive redistribution from the Danish welfare state).

Among low-income families, the NL-IGE for gross income in Fig. 4c is around 0.10-0.20, while the corresponding estimates in Fig. 1 range from approximately 0.25-0.50 for market income. For high-income families, however. we only see minor differences between NL-IGE estimates with and without public transfers. In consequence, the differences in estimated income mobility across parents' income are substantially attenuated once transfer income

[16] To ease comparability between results across parental income levels, we only vary how children's income is measured.

is included.[17] The main reason is that the role of employment is strongly attenuated. For market income, β_{EMPL} varied from 0 to 0.47 across parents' income levels — for gross income, β_{EMPL} only varies from 0 to 0.1 (compare Fig. 2c to Fig. 4c).

In sum, Fig. 4 shows that transfer income leads to substantial increases in estimated income mobility among children from low-income families because transfer income largely nullifies the role of employment as an underlying mechanism. The role of education is also attenuated for children from middle- and high-income families when public transfers are included in the income measure, but not in the same dimension as seen for the role of employment.

4 Discussion and conclusion

This paper studies nonlinearities in intergenerational income mobility across parental income levels using Danish register data for more than 630,000 children and their parents. In line with previous work, we find strong nonlinearities in income mobility: For children born into low-income and high-income families, the estimated intergenerational income elasticity is around 0.3, while for children from middle-income families the estimates are as high as 0.6.

We show that for children from low-income families almost all of the association between

[17] Fig. A.13 shows that it is not one specific transfer component that drives this finding, but instead *the Danish transfer system in its entirety.* As we observe the fraction of years individuals receive each of the specific public transfer components, we can gradually widen the set of transfer components we condition on until we effectively condition on the individuals' employment rates. Fig. A.13a shows the results for gross income, where we split the sample by parents' income. Not surprisingly, conditioning on the specific transfer components do not affect estimates since gross income includes transfer income. The figure, however, serves as a contrast to Fig. A.13b, which shows how mobility in market income changes once we gradually control for transfer reception. There is no single component that drives the results and the high income mobility in Denmark when we consider gross income. Furthermore, we also show in Fig. 4a, the increase in mobility after adding public transfers is most pronounced for children from the lowest quartile of the distribution of parents' income.

parents' and children's market income (i.e. excluding public transfers) is explained by variation in employment while education only plays a minor role. As parents' income increases, the role of variation in employment decreases while the importance of education increases. For children from high-income families, however, neither education nor employment exhibit any substantial importance in explaining income mobility. Instead, our results point to capital income (likely from bequests and inherited wealth) and business income as the most important aspects behind intergenerational persistence in income.

Furthermore, we find that transfer income reduces the role of employment in the association between parents' and children's income. In a country with generous transfers such as Denmark, the role of employment vs. non-employment is almost offset by the progressive redistribution through transfer programs such as social assistance, unemployment insurance benefits, and disability pensions among others.

It is noteworthy that the simple mechanisms we present in this paper mediate almost the entire relationship between parents' and children's income. The three categories, however, should be considered *types of mechanisms* rather than definitive or causal explanations. as each of the three are complex and dynamic phenomena, which are bound to function heterogeneously depending on context. While we have shown that the three aspects provide an almost full account of persistence in income between parents and children, we leave the study of the dynamics and sub-mechanisms of education, employment, and capital income to future research.

Nevertheless, our paper points to the importance of how income is measured and the context when estimating intergenerational income mobility and persistence. Our findings further highlight that for children from disadvantaged backgrounds, the extensive margin problem of finding a job appears to be the most predominant barrier for social mobility. For children from middle-income families, the main driver of social mobility is education. For children from the most affluent families, however, wealth accumulation – which is initiated at an early stage of the children's lives – appears to be the main mechanism at play.

Tables and Figures

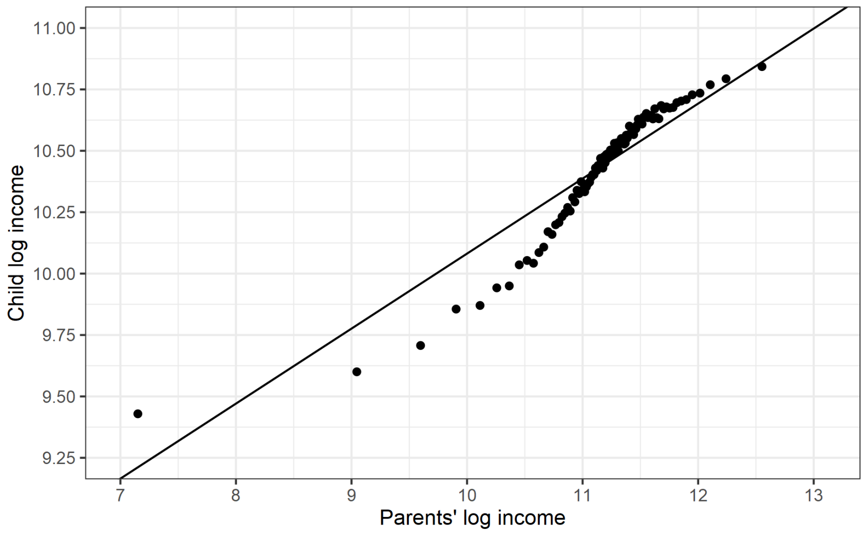
Table 1: Linear IGE estimates

	β_{IGE}	δ_{EDUC}	δ_{EMPL}	β_{RES}
Panel a) Market income IGE estimates and decomposition				
	β_{IGE}	δ_{EDUC}	δ_{EMPL}	β_{RES}
	Income mobility	Education component	Employment component	residual component
Estimate	0.305	0.049	0.179	0.077
	(0.002)	(0.001)	(0.003)	(0.002)
Rel. size		16.1 %	58.7 %	25.2 %
Observations	630,354	630,354	630,354	630,354
Panel b) Gross income IGE estimates and decomposition				
	β_{IGE}	δ_{EDUC}	δ_{EMPL}	β_{RES}
	Income mobility	Education component	Employment component	residual component
Estimate	0.197	0.041	0.052	0.105
	(0.001)	(0.000)	(0.001)	(0.002)
Rel. size		20.8 %	26.4 %	52.8 %
Observations	630,354	630,354	630,354	630,354

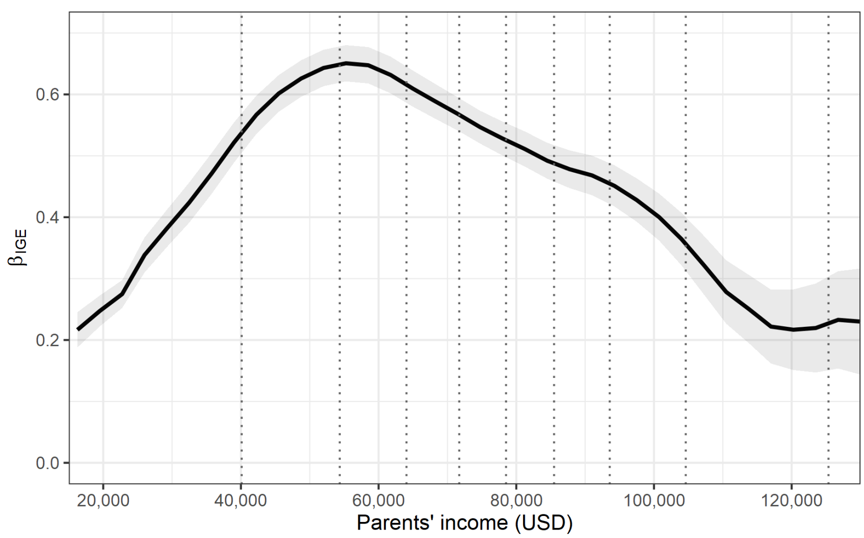
Note: Panel a) shows the coefficients (β_{IGE}) and standard errors from regressions of child log income on parents' log income for market income. The panel also shows the composition of β_{IGE} for market income when decomposing the estimate into components pertaining to education (δ_{EDUC}), employment (δ_{EMPL}), and the residual IGE (β_{RES}). Decomposition estimates are obtained by the method discussed in Section 3.1 and standard errors have been constructed by 250 bootstraps. Panel b) shows estimates and decomposition when using gross income.

Figure 1: Local associations between children's and parents' market income

a) Children's log-market income plotted against parents' log-market income

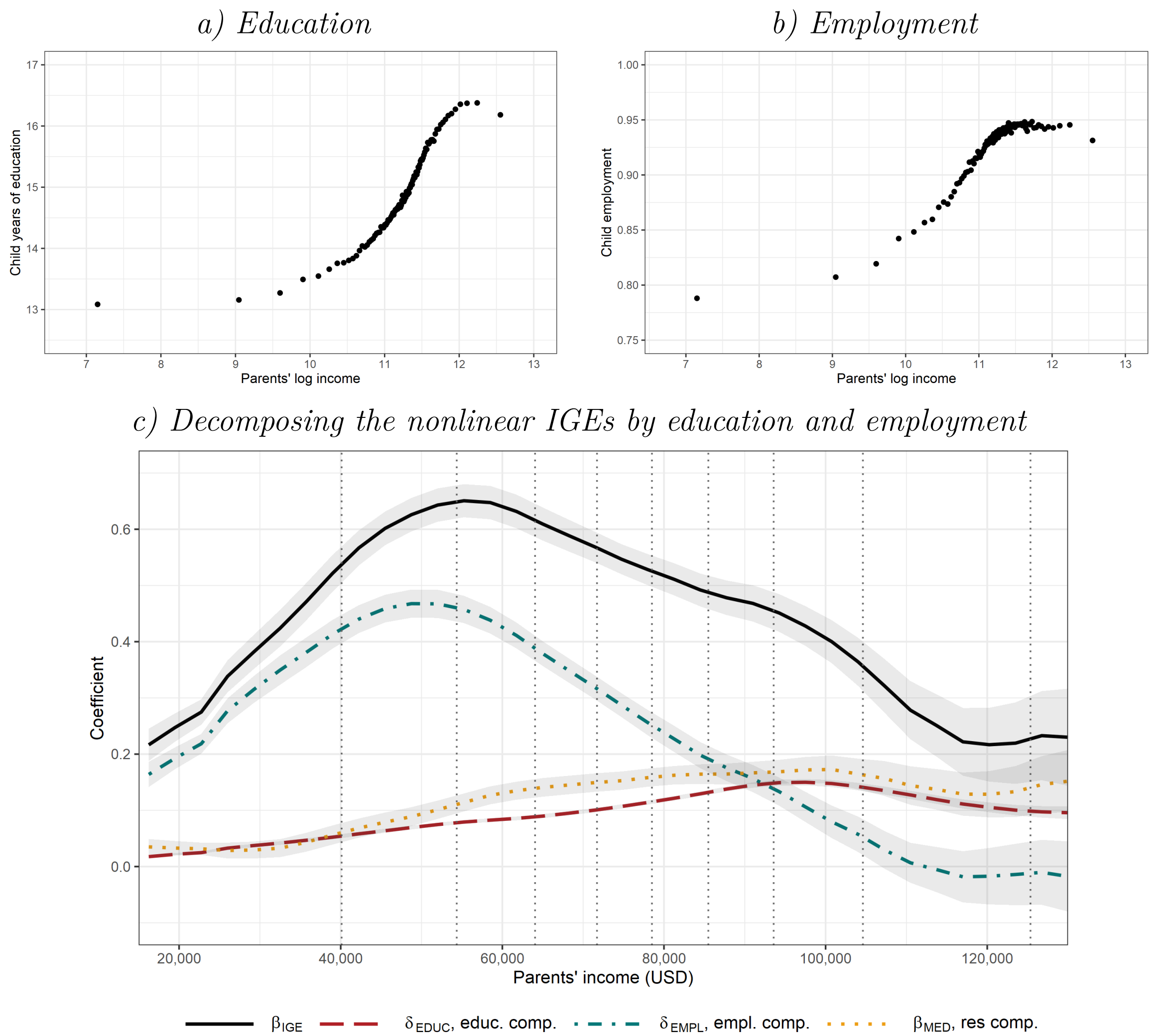


b) Nonlinear IGEs across parental income levels



Note: Panel a) shows child log market income by parents' log market income. The solid line shows the linear IGE estimate. Panel b) shows nonlinear estimates of IGE (NL-IGE) by parents' market income obtained using local linear regression, as discussed in Section 3.2. Standard errors in b) obtained by 250 bootstraps. Dashed vertical lines in b) show deciles of parents' market income.

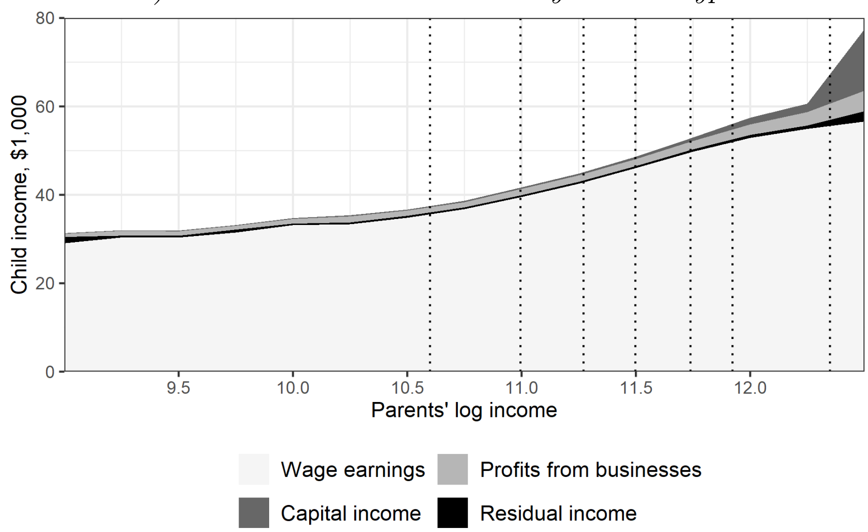
Figure 2: Child education and employment by parental market income



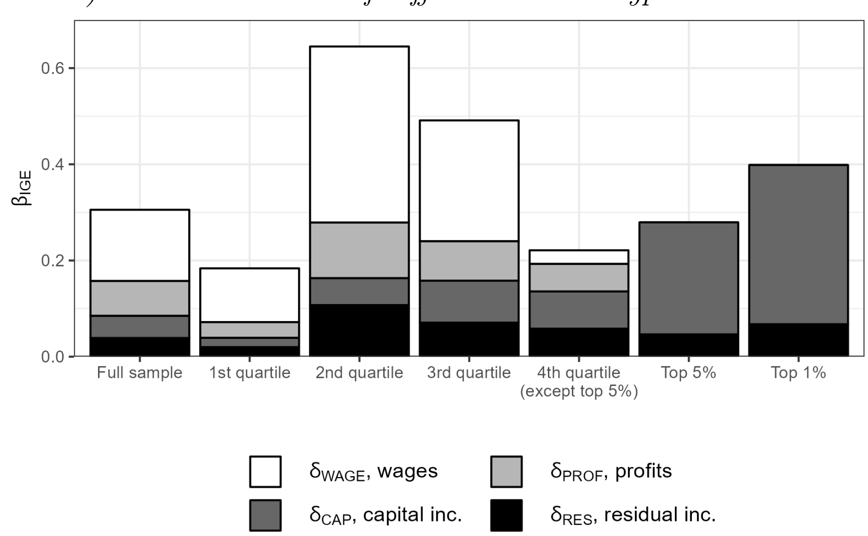
Note: Panel a) shows child years of completed education by parents' log market income. Panel b) shows child employment (measured as the share of years from ages 31-37 with positive wages or profits from businesses) by parents' log market income. Panel c) shows the decomposition of the nonlinear IGE estimates by parents' market income. The solid line represents the NL-IGE as per Fig. 1b and the three remaining lines show the education, employment, and residual component across parents' market income. Standard errors in c) obtained by 250 bootstraps. Dashed vertical lines in c) show deciles of parents' market income.

Figure 3: Child market income and IGEs by parental market income

a) Children's market income by income type



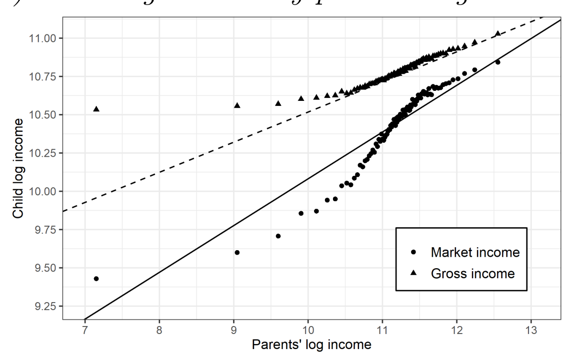
b) The contribution of different income types in IGEs



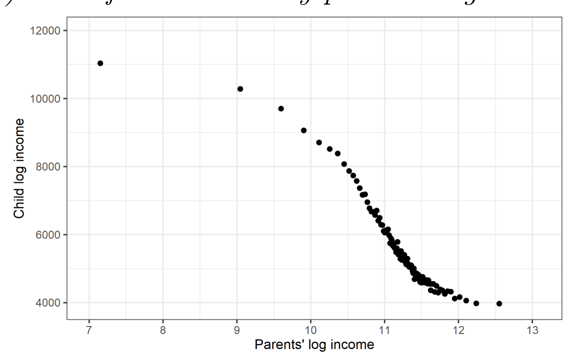
Note: Panel a) shows the composition of child market income by parents' log market income. Dashed lines in a) indicate the 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentile of parents' income. Panel b) shows how the components of market income — wages, profits from businesses, and capital income — each contribute to market income IGE and how this composition varies by parents' market income.

Figure 4: The role of transfer income in the IGE

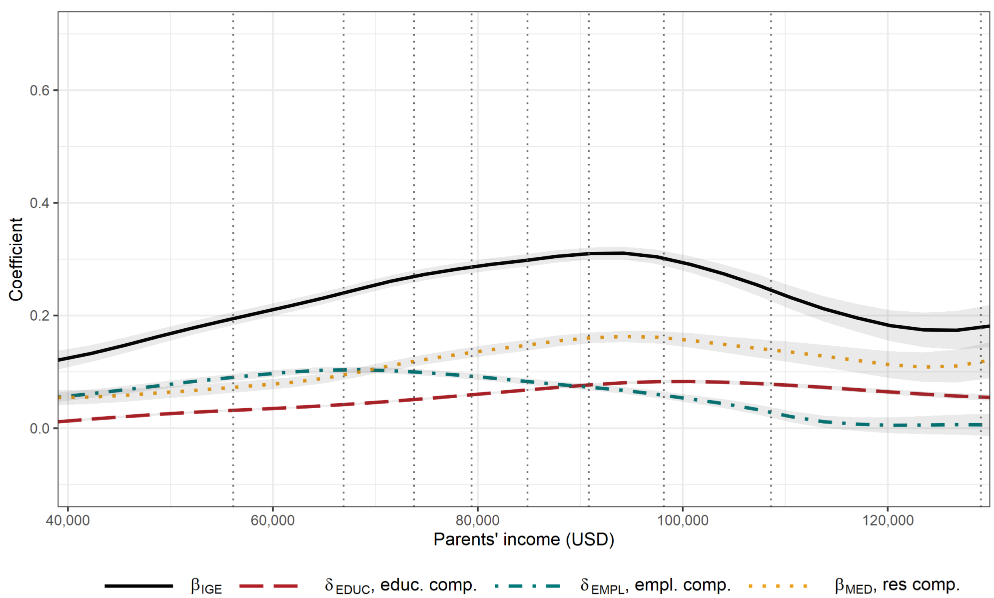
a) Child log income by parents' log income



b) Transfers received by parents' log income



c) Decomposing the nonlinear IGEs by education and employment - gross income



Note: Panel a) shows child log market and gross income by parents' market income. The solid line shows the linear IGE estimate for market income, the dashed line shows the corresponding estimate for gross income. Panel b) shows child log income from public transfers by parents' log market income. Panel c) shows the decomposition of the nonlinear IGE estimates by parents' gross income for child gross income. The solid line represents the NL-IGE and the three remaining lines show the education, employment, and residual component across parents' income. Standard errors in c) obtained by 250 bootstraps. Dashed vertical lines in c) show deciles of parents' gross income.

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A Additional results (for online publication only)

Table A.1: Sample selection

Birth cohorts 1972–1982	655,216
Exclude children without linked parents	-6,141
Exclude children without education/employment information	-2,964
Exclude parental income $\leq$ \$1 or missing	-3,150
Exclude child income $\leq$ \$1 or missing	-12,607
Final sample	630,354

Note: The table shows the definition of our analytical sample and the amount of observations dropped for each step. Our gross sample is the full population of Danish birth cohorts 1972-1982 excluding immigrants and descendants. The sample is balanced across market and gross income: children are dropped if they or their parents have a missing value or a value less than \$1 on market or gross income.

Table A.2: Linear IGE estimates adjusted for gender and birth cohort

Panel a) Market income IGE estimates and decomposition				
	β_{IGE}	δ_{EDUC}	δ_{EMPL}	β_{RES}
	Income mobility	Education component	Employment component	residual component
Estimate	0.307	0.055	0.178	0.074
	(0.002)	(0.001)	(0.003)	(0.002)
Rel. size		17.8 %	58.0 %	24.2 %
Observations	630,354	630,354	630,354	630,354
Panel b) Gross income IGE estimates and decomposition				
	β_{IGE}	δ_{EDUC}	δ_{EMPL}	β_{RES}
	Income mobility	Education component	Employment component	residual component
Estimate	0.199	0.045	0.053	0.101
	(0.001)	(0.001)	(0.001)	(0.002)
Rel. size		22.7 %	26.4 %	50.9 %
Observations	630,354	630,354	630,354	630,354

Note: Panel a) shows the coefficients (β_{IGE}) and standard errors from regressions of child log income on parents' log income for market income adjusted for gender and birth cohort fixed effects. The panel also shows the composition of β_{IGE} for market income when decomposing the estimate into components pertaining to education (δ_{EDUC}), employment (δ_{EMPL}), and the residual IGE (β_{RES}). Decomposition estimates are obtained by the method discussed in Section 3.1 and standard errors have been constructed by 250 bootstraps. Panel b) shows estimates and decomposition when using gross income.

Table A.3: Linear IGE estimates – decomposed by sequential controls

Panel a) Market income IGE estimates and decomposition				
	β_{IGE}	δ_{EDUC}	δ_{EMPL}	β_{RES}
	Income mobility	Education component	Employment component	residual component
Estimate	0.305	0.126	0.102	0.077
	(0.002)	(0.003)	(0.002)	(0.002)
Rel. size		41.3 %	33.5 %	25.2 %
Observations	630,354	630,354	630,354	630,354
Panel b) Gross income IGE estimates and decomposition				
	β_{IGE}	δ_{EDUC}	δ_{EMPL}	β_{RES}
	Income mobility	Education component	Employment component	residual component
Estimate	0.197	0.075	0.017	0.105
	(0.001)	(0.002)	(0.001)	(0.002)
Rel. size		38.1 %	9.1 %	52.8 %
Observations	630,354	630,354	630,354	630,354

Note: Panel a) shows the coefficients (β_{IGE}) and standard errors from regressions of child log income on parents' log income for market income. The panel also shows the composition of β_{IGE} for market income when decomposing the estimate into components pertaining to education (δ_{EDUC}), employment (δ_{EMPL}), and the residual IGE (β_{RES}). Decomposition estimates are obtained by the method of sequential inclusion of mediators discussed in Section 3.1 and standard errors have been constructed by 250 bootstraps. Panel b) shows estimates and decomposition when using gross income.

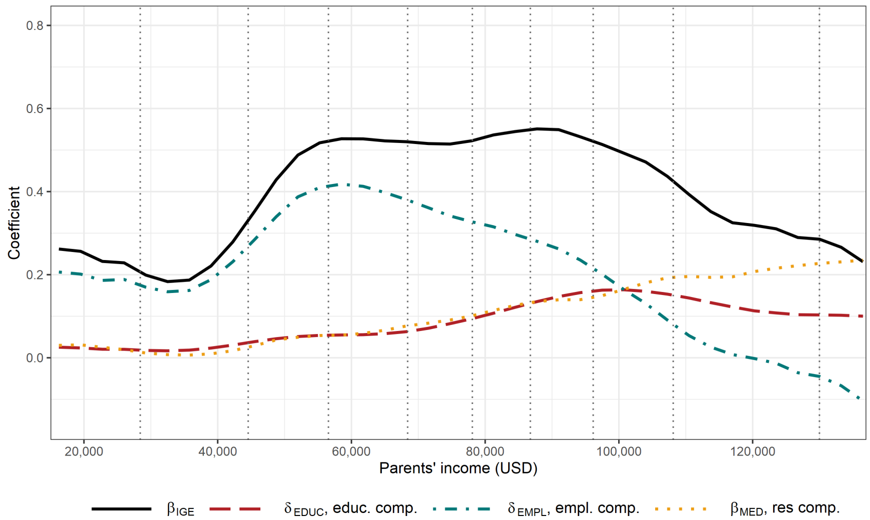
Table A.4: Linear rank-rank estimates

Panel a) Market income rank-rank estimates and decomposition				
	β_{RR}	δ_{EDUC}	δ_{EMPL}	β_{RES}
	RR mobility	Education component	Employment component	residual component
Estimate	0.247	0.058	0.058	0.131
	(0.001)	(0.000)	(0.001)	(0.001)
Rel. size		23.4 %	23.4 %	53.4 %
Observations	630,354	630,354	630,354	630,354
Panel b) Gross income rank-rank estimates and decomposition				
	β_{RR}	δ_{EDUC}	δ_{EMPL}	β_{RES}
	RR mobility	Education component	Employment component	residual component
Estimate	0.223	0.062	0.040	0.121
	(0.001)	(0.000)	(0.000)	(0.001)
Rel. size		27.8 %	17.9 %	54.3 %
Observations	630,354	630,354	630,354	630,354

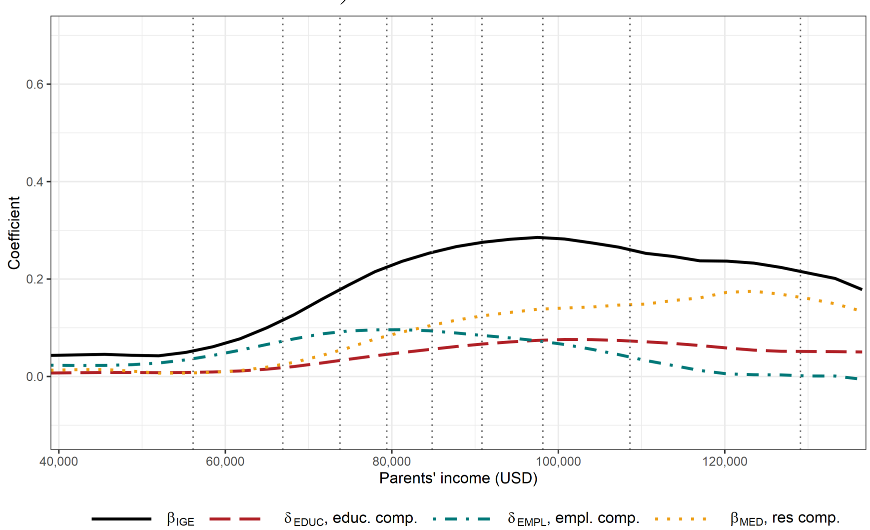
Note: Panel a) shows the coefficients (β_{RR}) and standard errors from regressions of child income rank on parents' income rank for market income. The panel also shows the composition of β_{RR} for market income when decomposing the estimate into components pertaining to education (δ_{EDUC}), employment (δ_{EMPL}), and the residual IGE (β_{RES}). Decomposition estimates are obtained by the method discussed in Section 3.1 and standard errors have been constructed by 250 bootstraps. Panel b) shows estimates and decomposition when using gross income.

Figure A.1: Robustness to income threshold: Nonlinear IGEs and decomposition

a) Market income



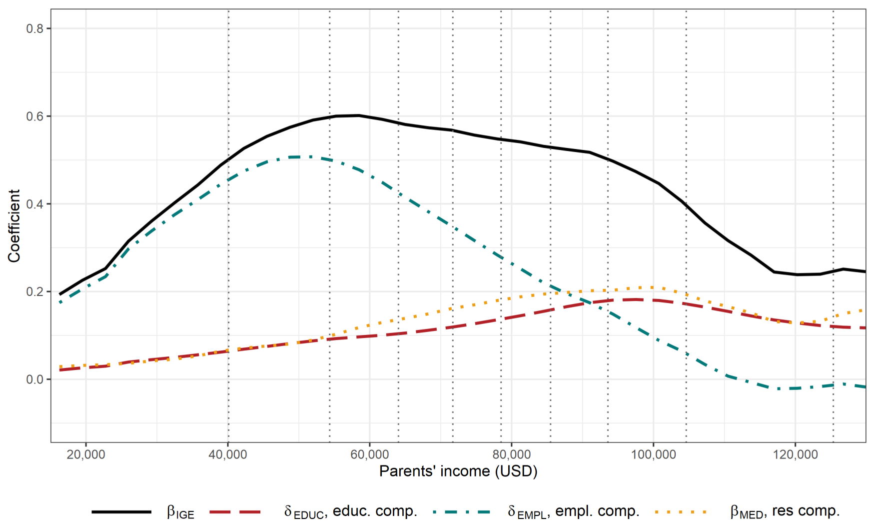
b) Gross income



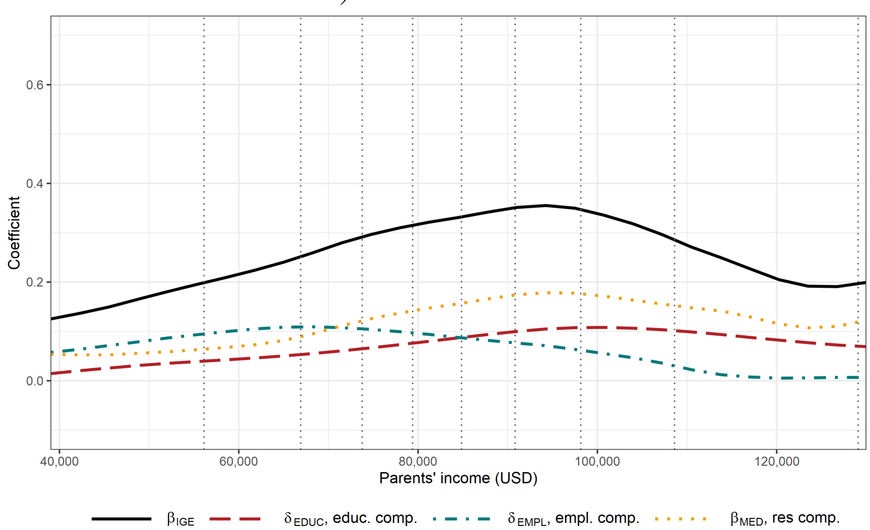
Note: This figure replicates Figs. 2c and 4c when lowering the threshold for incomes from >\$1 to >\$0. Panel a) shows the decomposition of the nonlinear IGE estimates by parents' market income. The solid line represents the NL-IGE as per Fig. 1b and the three remaining lines show the education, employment, and residual component across parents' market income. Panel b) shows similar results for gross income. Dashed vertical lines in a) and b) show deciles of parents' market and gross income, respectively.

Figure A.2: Robustness to timing of income measurement – child age 34-37: Nonlinear IGEs and decomposition

a) Market income



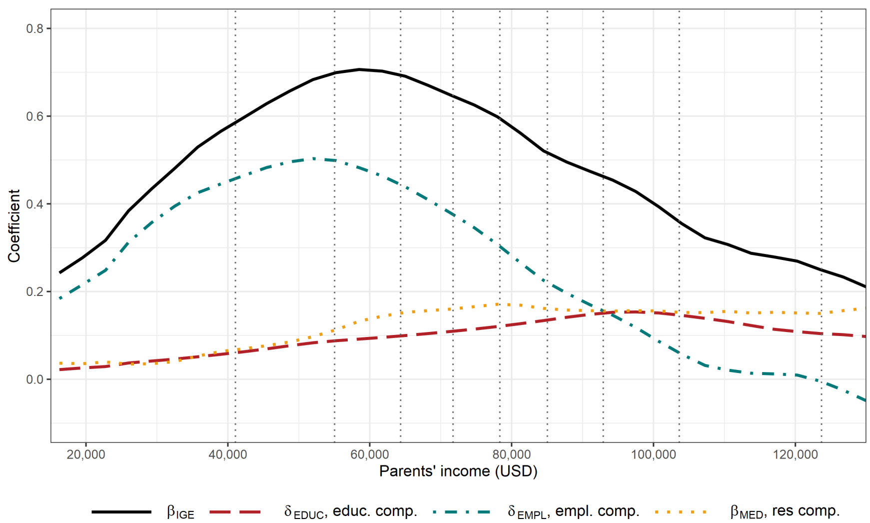
b) Gross income



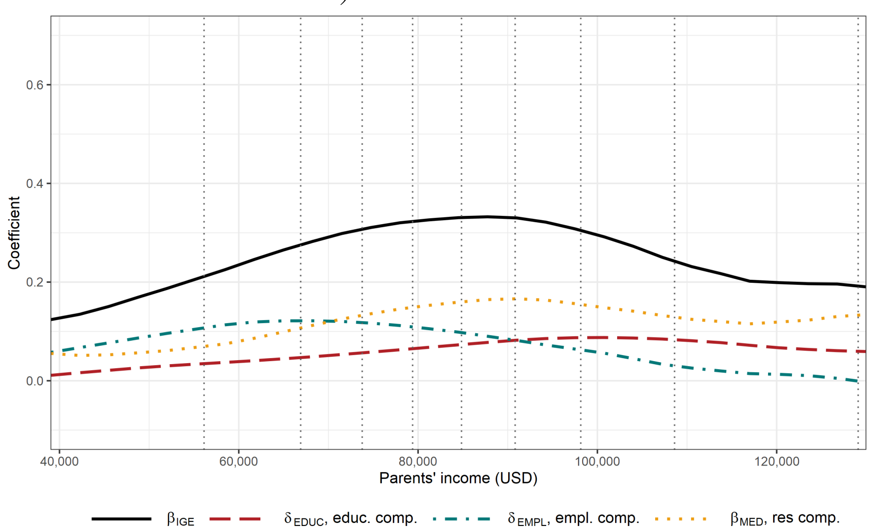
Note: This figure replicates Figs. 2c and 4c when measuring child income at ages 34-37 rather than 31-37. Panel a) shows the decomposition of the nonlinear IGE estimates by parents' market income. The solid line represents the NL-IGE as per Fig. 1b and the three remaining lines show the education, employment, and residual component across parents' market income. Panel b) shows similar results for gross income. Dashed vertical lines in a) and b) show deciles of parents' market and gross income, respectively.

Figure A.3: Robustness to timing of parents' income measurement – child age 6-14: Non-linear IGEs and decomposition

a) Market income

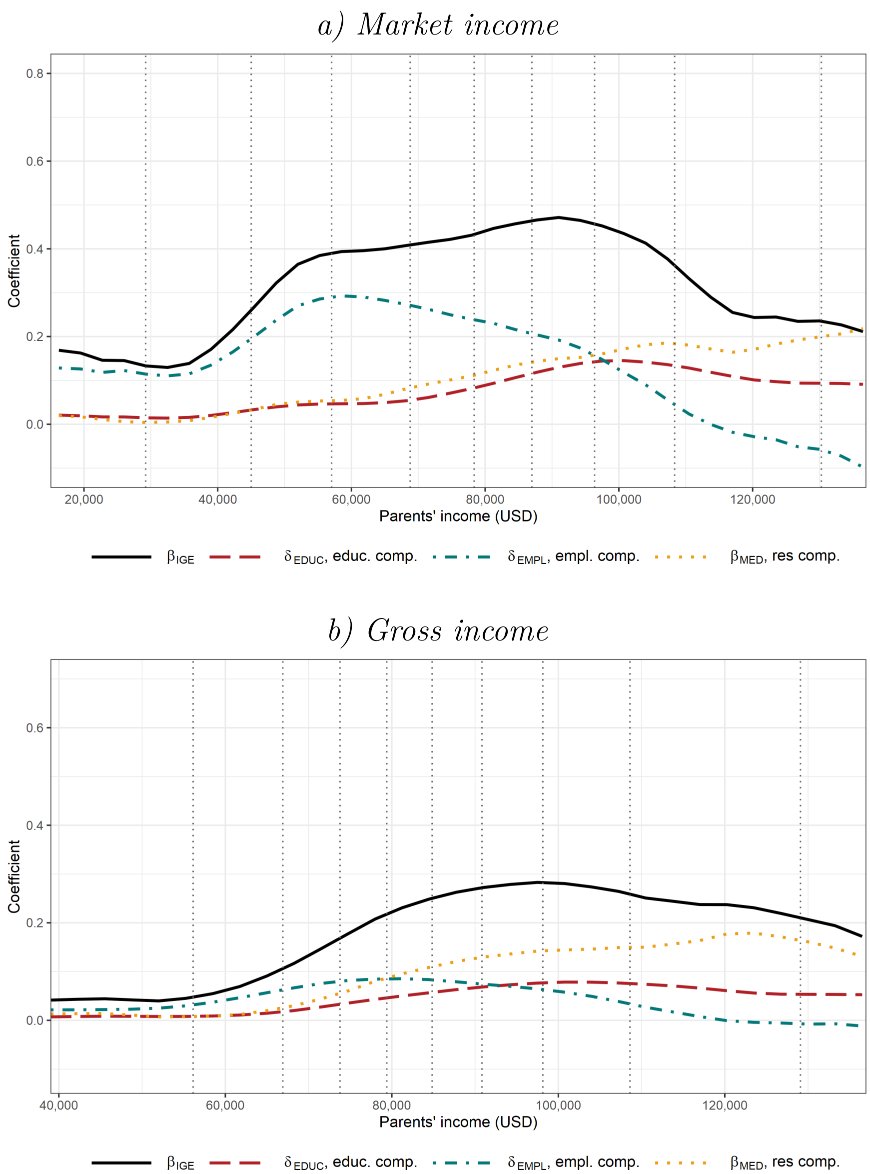


b) Gross income



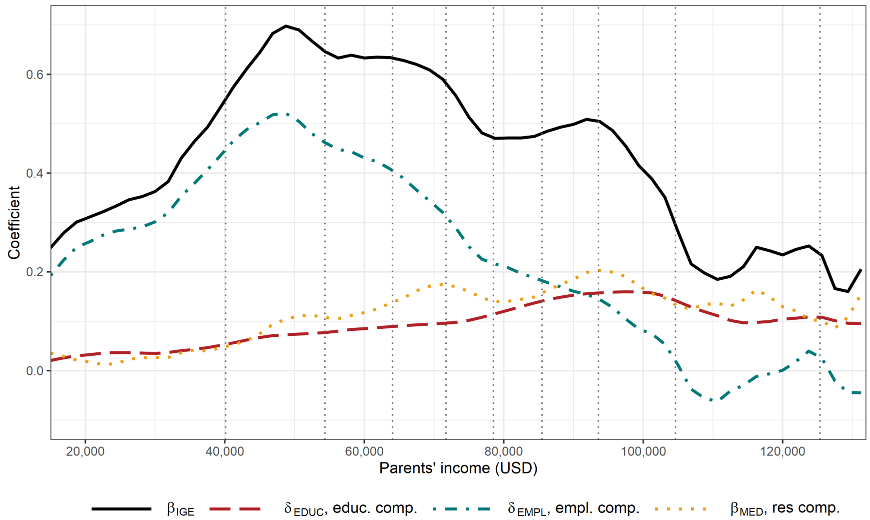
Note: This figure replicates Figs. 2c and 4c when measuring parents' income when the child was 6-14 rather than 8-14. Panel a) shows the decomposition of the nonlinear IGE estimates by parents' market income. The solid line represents the NL-IGE as per Fig. 1b and the three remaining lines show the education, employment, and residual component across parents' market income. Panel b) shows similar results for gross income. Dashed vertical lines in a) and b) show deciles of parents' market and gross income, respectively.

Figure A.4: Robustness to timing of parents' income measurement – parents' own age 40-43: Nonlinear IGEs and decomposition



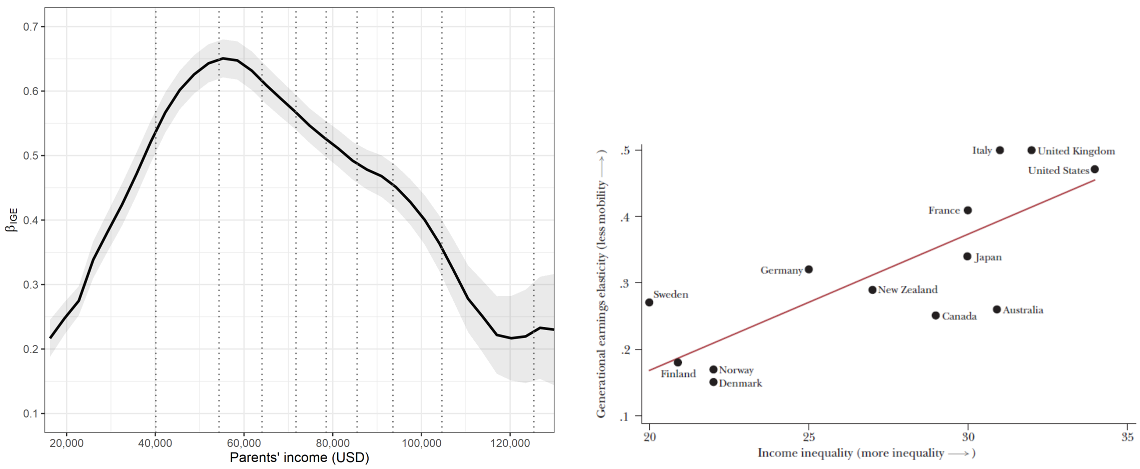
Note: This figure replicates Figs. 2c and 4c when measuring parents' income based their own age (40-43) rather than by child age. Panel a) shows the decomposition of the nonlinear IGE estimates by parents' market income. The solid line represents the NL-IGE as per Fig. 1b and the three remaining lines show the education, employment, and residual component across parents' market income. Panel b) shows similar results for gross income. Dashed vertical lines in a) and b) show deciles of parents' market and gross income, respectively.

Figure A.5: Decomposition of the nonlinear IGE by education and employment – narrower bandwidth



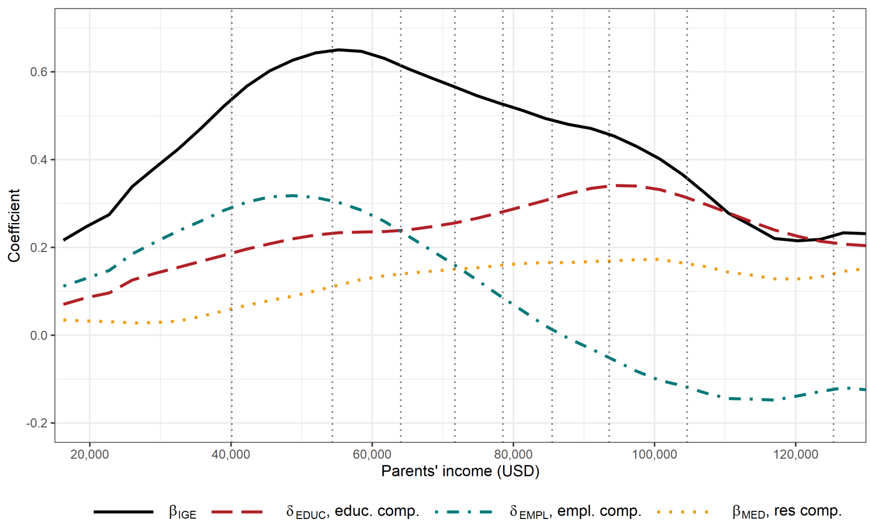
Note: The figure replicates Fig. 2c, applying a more narrow bandwidth h of \$15,000 rather than \$26,000. The figure shows the decomposition of the nonlinear IGE estimates by parents' market income. The solid line represents the NL-IGE as per Fig. 1b and the three remaining lines show the education, employment, and residual component across parents' market income. Dashed vertical lines show deciles of parents' market income.

Figure A.6: Comparing variation in estimated income mobility within Denmark to variation found across non-Western countries on average



Note: This figure compares nonlinear IGE estimates from Fig. 1b with cross-country IGE estimates reported in Corak (2013). Dashed vertical lines show deciles of parents' market income.

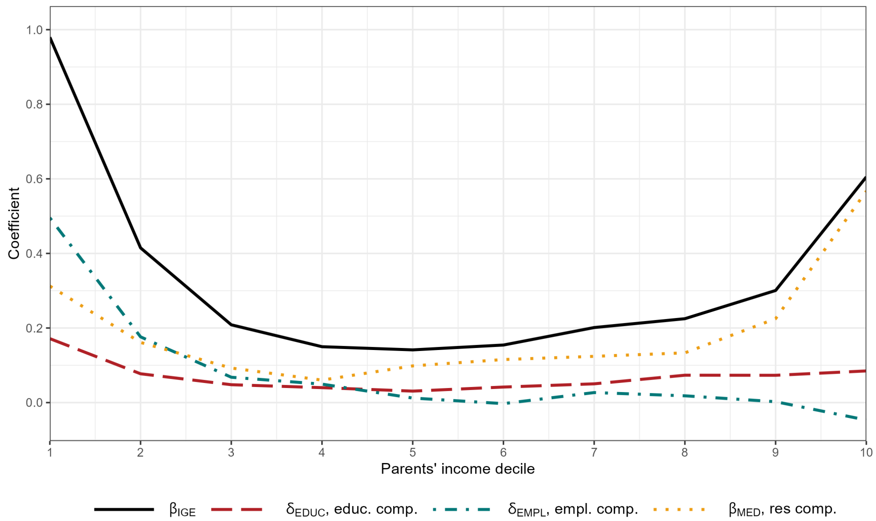
Figure A.7: Sequential decomposition of the nonlinear IGE by education and employment



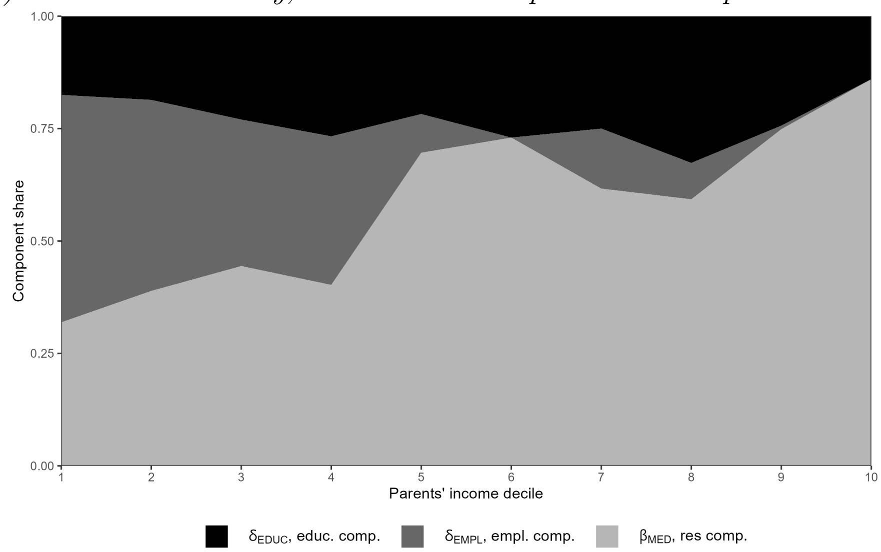
Note: The figure replicates Fig. 2c, applying sequential control decomposition rather than the parametric decomposition suggested in Gelbach (2016). The figure shows the decomposition of the nonlinear IGE estimates by parents' market income. The solid line represents the NL-IGE as per Fig. 1b and the three remaining lines show the education, employment, and residual component across parents' market income. Dashed vertical lines show deciles of parents' market income.

Figure A.8: Nonlinear decomposition of mobility using rank-rank estimates

a) Rank-rank mobility, nonlinear decomposition - components

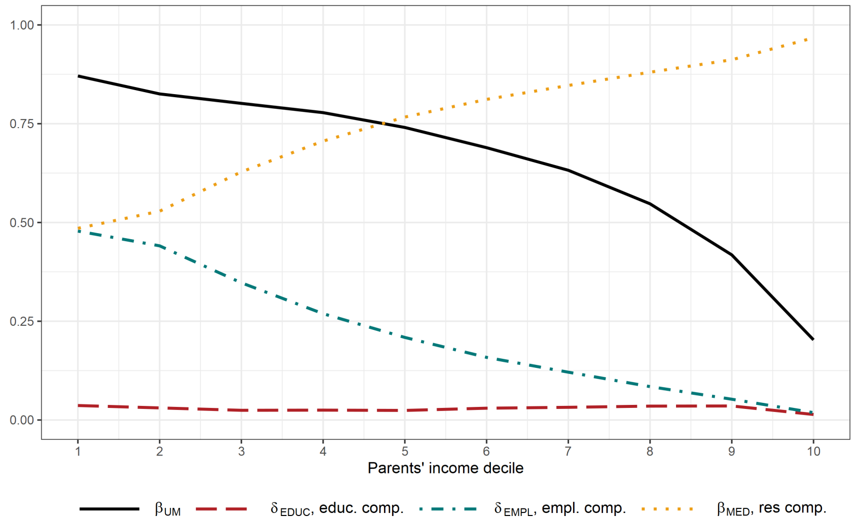


b) Rank-rank mobility, nonlinear decomposition - component share



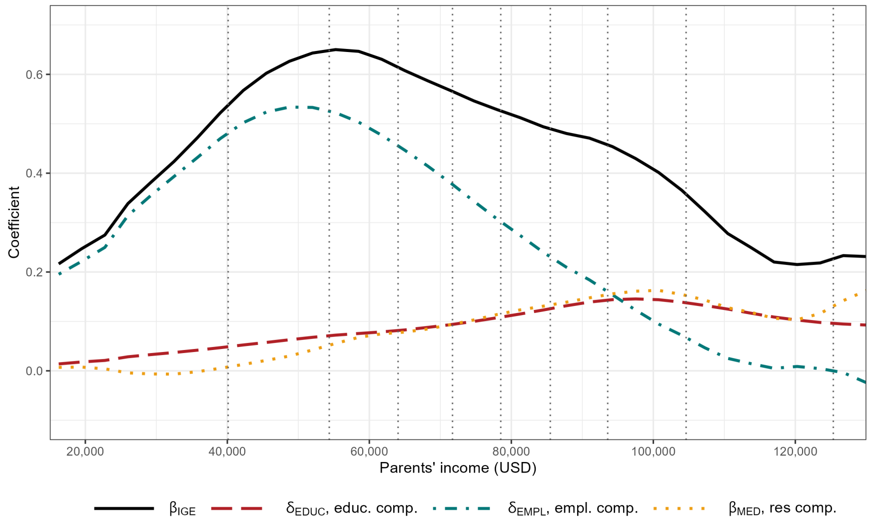
Note: The figure replicates the decomposition of the nonlinear IGE estimates in Fig. 2c using rank-rank mobility rather than IGE. Panel a) shows the size of each component when estimating them with the same methodology as the IGE estimates in Fig. 2c and Panel b) shows the relative sizes of the education, employment, and residual components to the rank-rank mobility estimate. In b) some values below zero are set to zero to avoid negative shares.

Figure A.9: Nonlinear decomposition of absolute upward mobility



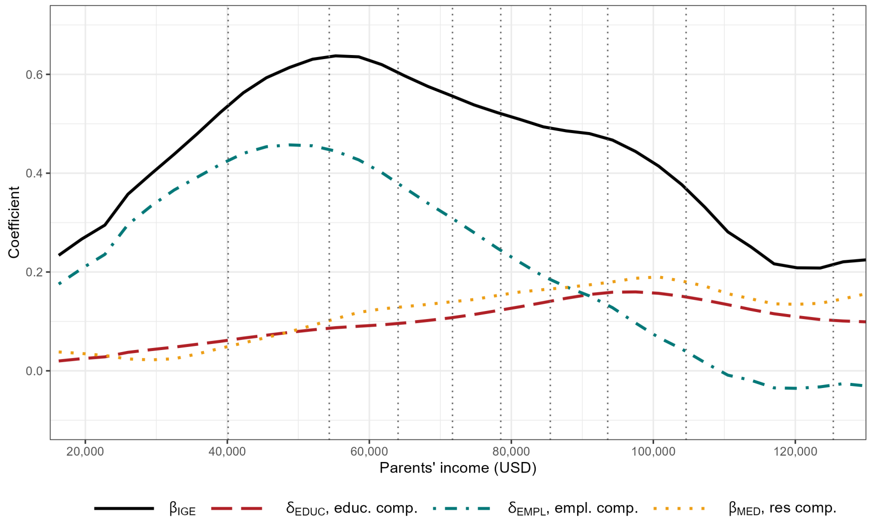
Note: The figure replicates the decomposition of the nonlinear IGE estimates in Fig. 2c using absolute upward mobility than IGE. The role of education and employment is estimated by their explanatory power, in this case R squared, from a regression of upward mobility on education or employment. The components are estimated using Owen-Shapley decomposition methods.

Figure A.10: Decomposition of the nonlinear IGE by education and employment – higher threshold for employment



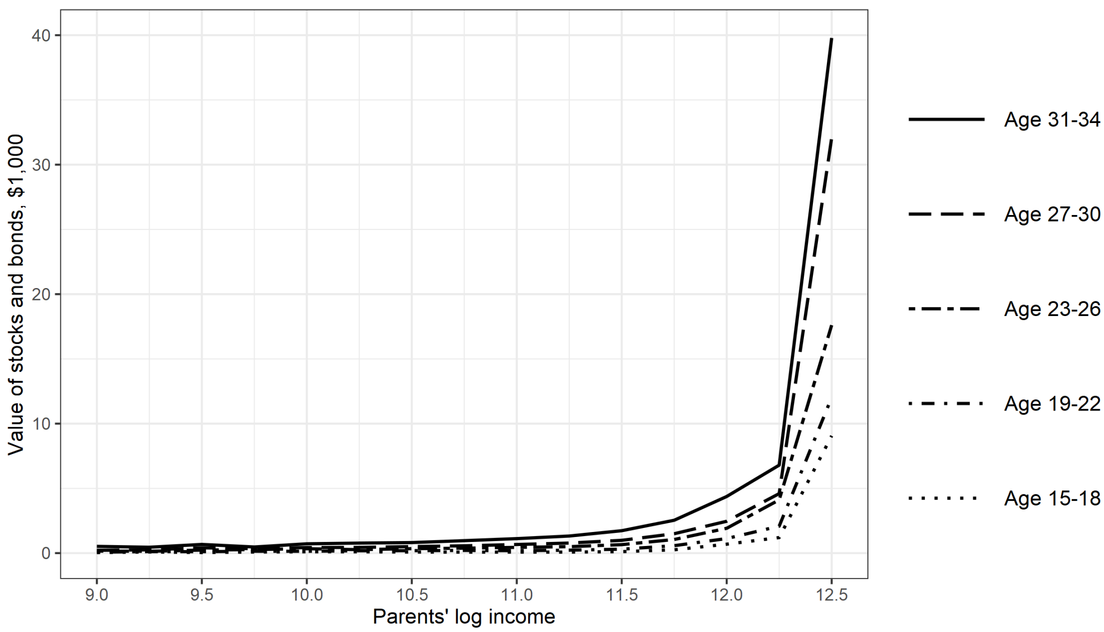
Note: The figure replicates the decomposition of the nonlinear IGE estimates in Fig. 2c and defines employment in a given year as having wage earings above app. $7,500 rather than positive income. The solid line represents the NL-IGE as per Fig. 1b and the three remaining lines show the education, employment, and residual component across parents' market income.

Figure A.11: Decomposition of the nonlinear IGE by education and employment – students excluded



Note: The figure replicates the decomposition of the nonlinear IGE estimates in Fig. 2c and excluding individuals who enrolled in any education in the 31-37 age span. The solid line represents the NL-IGE as per Fig. 1b and the three remaining lines show the education, employment, and residual component across parents' market income.

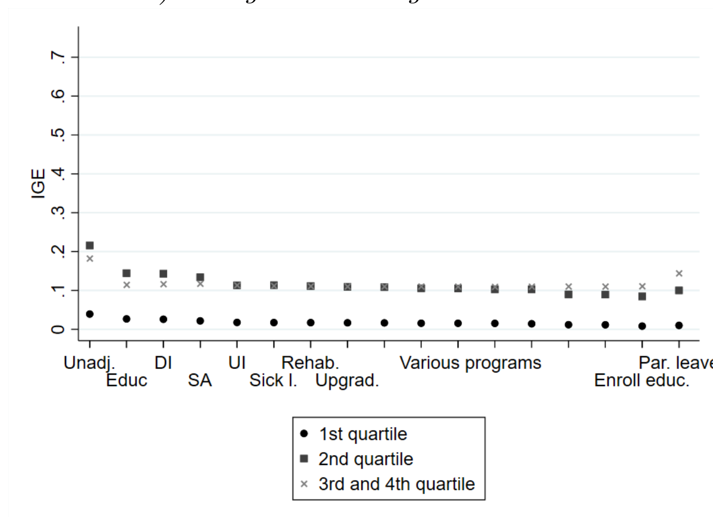
Figure A.12: Value of stocks and bonds by child age and parental income



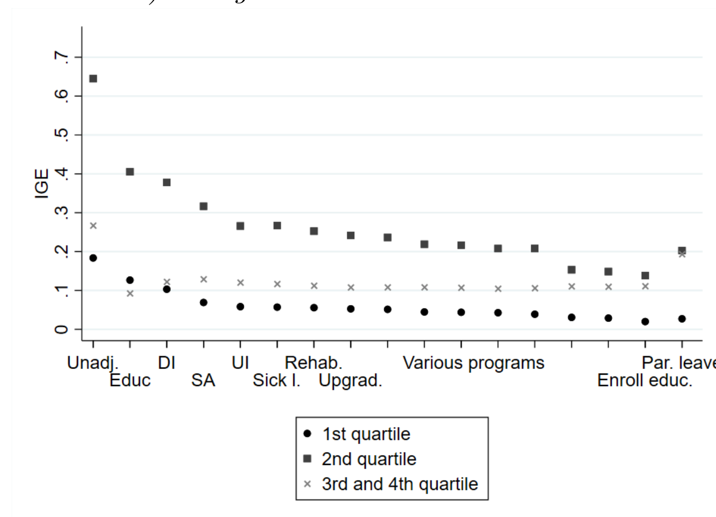
Note: The figure shows the value of owned stocks and bonds by parents' log market income and child age.

Figure A.13: The role of transfer income in the IGE

a) Using children's gross income

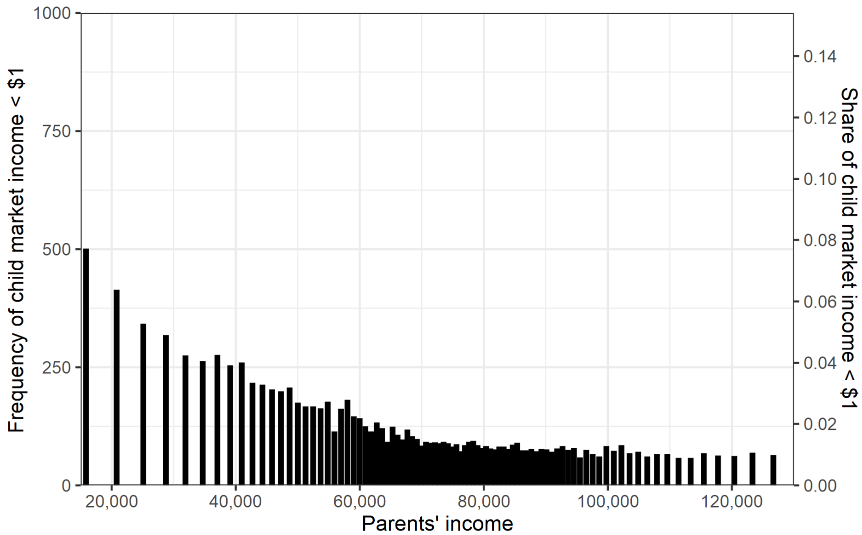


b) Using children's market income



Note: The conditioning set is (from left to right): No controls, Education, Disability pension, Social assistance, Unemployment insurance benefits, Sick leave benefits, Labor market rehabilitation programs, Labor market upgrading programs, Minor programs (see https://www.dst.dk/da/TilSalg/Forskningsservice/Dokumentation/hoejkvalitetsvariable/befolkningens-tilknytning-til-arbejdsmarkedet–ras-/soc-status-kode), Education support, Parental leave benefits. We measure each component as the rates averaged over age 31-37. Hence, each variable we include in the conditioning set takes the values $\{0; 0.25; 0.5; 0.75; 1\}$.

Figure A.14: Amount and share of children with incomes <$1 by parents' income



Note: This figure shows the amount and share of children with market income <$1 by parents' income. Both amount and share are calculated by parents' market income percentile rank.

For online publication:

B Data construction

We use Danish administrative register data provided by Statistics Denmark for our analyses. The register data include a unique individual identifier that allows us to link individual information on, for example, income, education, and employment. In addition, the register data also include unique individual identifiers of parents, allowing us to identify parental characteristics as well.

Using the demographic register, we define our sample as the full population of birth cohorts from 1972 to 1982 as well as their parents. We exclude immigrants and descendants from our sample to ensure that we have information on child and parent income for as many years as possible. We also discard individuals for whom we have no identification of the father or mother (around 0.9%), and individuals with missing information on any income measure, education, or employment (around 2%). This results in a final sample of 630,354 observations.[18]

We next add information from the income register, which contains information on individual income from tax authorities from 1980 onward. These data include detailed information on a wide range of different income items such as wage earnings, capital income, profits from businesses, transfer income, and tax payments. Based on this information, we construct two income measures, which we use throughout the paper: i) *Market income*, which contains all pre-tax income excluding public transfers; ii) *Gross income*, which equals market income plus public transfers.[19]

We measure child income as an average at ages 31-37 to reduce bias from transitory shocks to income (Solon 1992) and minimize lifecycle bias (Nybom and Stuhler, 2016).[20] We similarly construct measures of parents' market and gross income using the same definitions as above by summarizing mother's and father's average income at child ages 8-14. We then add information on children's education from the education registers. We measure education

[18]Table A.1 presents the attrition at each stage of the sample selection in detail.

[19]Throughout the paper, we exclude individuals with income below \$1 as these outliers would inflate the variance of log-income disproportionately. Fig. A.14 shows the distribution of child incomes below \$1 by parents' income. We apply the same rule to parents' income. All results are based on a balanced sample, where we exclude individuals with zero income in either of the two income measures. Fig. A.1 in the appendix replicates our main results without this sample selection and show no substantive differences.

[20]Figs. A.2 and A.3 illustrate the robustness of our results when varying the age at which children's and parents' income is measured. Similarly, Fig. A.4 further shows that our results are robust to measuring parents' income based on their own age rather than their children's.

as the years of schooling required to attain the highest level of education of the child.[21] We also measure employment as the child's share of years with positive wage income or profits from business at ages 31-37.[22] Table B.1 shows descriptive statistics on each income measure used in the paper as well as on education and employment.[23]

We report the average for each income measure as well as the average within each income quartile and separately for the top five percentiles. As expected, the variance in each income measure is much larger at the bottom and top of each income distribution. Table B.2 shows the distribution of gender and birth cohorts, respectively. The table reveals an almost equal gender distribution and shows that birth cohorts decline in size over time. The latter trend is not a product of our data and sampling choices, but reflects an overall demographic trend for these cohorts in Denmark.

[21] A fraction of the sample enrolls in education in the 31-37 age span. A.11 replicates our main result excluding these individuals and shows no substantive difference.

[22] A.10 shows our results when defining employment as having wage earnings above app. $7,500 rather than positive wages and shows no substantive differences.

[23] We use an exchange rate of $100 to 660 Danish Crowns (DKK).

Table B.1: Summary statistics: Income, education, employment

	Mean	1st quartile	2nd quartile	3rd quartile	4th quartile	Top 5%
Children's market income, $1,000	47.11	16.98	39.68	52.00	79.76	121.43
	(38.61)	(10.42)	(3.91)	(3.62)	(61.43)	(128.26)
Children's gross income, $1,000	52.76	30.37	44.82	54.77	81.10	122.12
	(36.09)	(8.00)	(2.82)	(3.20)	(61.28)	(128.25)
Parents' market income $1,000	83.39	40.15	69.63	87.74	136.05	215.67
	(57.31)	(15.80)	(5.39)	(5.68)	(89.32)	(176.66)
Children's years of schooling	14.89	13.87	14.60	15.15	15.92	16.22
	(2.38)	(2.56)	(2.10)	(2.09)	(2.26)	(0.06)
Children's employment	0.92	0.72	0.98	0.99	0.99	0.99
	(0.20)	(0.31)	(0.06)	(0.04)	(0.04)	(0.06)
Observations	630,354	157,589	157,588	157,589	157,588	31,517

Note: The table shows descriptive statistics for child education, child employment, child market and gross income and parents' market income. The first column shows the mean of each variable with standard deviations in parentheses. Columns 2-5 show means (and standard deviations) within quartiles of the variable and column 6 shows the statistics for the top five percentiles. For education and employment, means and standard deviations are shown by market income quartiles and top 5% market income.

Table B.2: Summary statistics: Gender and birth cohort

	Frequency	Share
Gender		
Male	317,656	50.39%
Female	312,698	49.61%
Birth cohort		
1972	67,796	10.76%
1973	64,187	10.18%
1974	63,909	10.14%
1975	64,890	10.29%
1976	59,042	9.37%
1977	55,800	8.85%
1978	55,509	8.81%
1979	53,048	8.42%
1980	51,254	8.13%
1981	47,455	7.53%
1982	47,464	7.53%
Observations	630,354	100.00 %

Note: The table shows descriptive statistics for child gender and birth cohort.The first column shows the frequency of each variable, the second column shows its share. The distribution of birth cohorts, including the declining cohort sizes, matches the demographic development for this time period in Denmark and is not affected by our choices of sample definition.

C Nonlinear mediation analysis

The goal is to estimate a nonlinear version of the mediation analysis described in Eq. (8).

To do so, we implement the strategy from Eq. (7) where we weight each observations by a kernel $K_{h_\lambda}(Y_0^P, Y_i^P)$ of parents' income Y_i^P by the distance to a kernel center Y_0 in regressions where we gradually change Y_0 across the entire distribution of parents' income.

The (overall) nonlinear IGE around a given level of parental income Y_0^P is estimated as:

$$\min_{\alpha_{NL-IGE}, \beta_{NL-IGE}} \sum_{i=1}^{N} K_{h_\lambda}(Y_0^P, Y_i^P) \cdot \{y_i^C - \alpha_{NL-IGE}[Y_0^P] - \beta_{NL-IGE}[Y_0^P] y_i^P\}^2 \tag{C.1}$$

In the next step, we rerun the analysis while conditioning on children's education and employment:

$$\min_{\tilde{\alpha}_{NL}, \beta_{NL-EDUC}, \beta_{NL-EMPL}, \beta_{NL-RES}} \sum_{i=1}^{N} K_{h_\lambda}(Y_0^P, Y_i^P) \cdot \{y_i^C - \tilde{\alpha}_{NL}[Y_0^P] - \beta_{NL-EDUC}[Y_0^P] EDUC_i^C - \beta_{NL-EMPL}[Y_0^P] EMPL_i^C - \beta_{NL-RES}[Y_0^P] y_i^P\}^2 \tag{C.2}$$

β_{NL-RES} captures the remaining residual relationship between parents' and children's income around a given level of parental income Y_0^P, which is not explained by education and employment. In the following steps, we estimate the association between parents' income and children's education and employment, respectively, around a given level of parental income

Y_0^P:

$$\min_{\alpha_{NL-EDUC},\Gamma_{NL-EDUC}} \sum_{i=1}^{N} K_{h_\lambda}(Y_0^P, Y_i^P) \cdot \{EDUC_i^C - \alpha_{NL-EDUC}[Y_0^P] - \Gamma_{NL-EDUC}[Y_0^P]y_i^P\}^2 \tag{C.3}$$

and

$$\min_{\alpha_{NL-EMPL},\Gamma_{NL-EMPL}} \sum_{i=1}^{N} K_{h_\lambda}(Y_0^P, Y_i^P) \cdot \{EMPL_i^C - \alpha_{NL-EMPL}[Y_0^P] - \Gamma_{NL-EMPL}[Y_0^P]y_i^P\}^2 \tag{C.4}$$

The two parameters $\Gamma_{NL-EDUC}$ and $\Gamma_{NL-EMPL}$ show the association between parents' income, and child education and employment, respectively, around a given level of parental income Y_0^P.

We then weight the parameters $\beta_{NL-EDUC}$ and $\beta_{NL-EMPL}$ from Eq. (C.2) by $\Gamma_{NL-EDUC}$ and $\Gamma_{NL-EMPL}$ to estimate the respective components:

$$\delta_{NL-EDUC} = \Gamma_{NL-EDUC}\beta_{NL-EDUC} \tag{C.5}$$

$$\delta_{NL-EMPL} = \Gamma_{NL-EMPL}\beta_{NL-EMPL} \tag{C.6}$$