CHAPTER 3

HOW MUCH OF INTERGENERATIONAL IMMOBILITY CAN BE ATTRIBUTED TO DIFFERENCES IN CHILDHOOD CIRCUMSTANCES?

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ABSTRACT

Can an estimate of the intergenerational elasticity (IGE) be interpreted as a measure of inequality of opportunity (IOp)? If parental income is the only childhood circumstance, then the answer is yes. However, parental income is one of many potential circumstances that can shape IOp. These circumstances can influence the offspring's income indirectly – by influencing parental income – or directly, bypassing the IGE altogether. I develop a model to decompose the interaction between childhood circumstances, parental income and offspring income. Using the Panel Study of Income Dynamics for the United States, I find that childhood circumstances account for 55% of the IGE for individual earnings and 53% for family income, with parental education explaining over a third of those shares. Furthermore, the IGE misses a large part of the influence of circumstances: only 45% of the influence of parental education on the offspring's income goes through parental income (36% for earnings).

Keywords: Intergenerational mobility; equality of opportunity; decomposition methods; circumstances; labour earnings; household income

JEL classifications: D31; D63; J622

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1. INTRODUCTION

What is the relationship between inequality of opportunity (IOp) and a measure of intergenerational immobility, such as the intergenerational elasticity (IGE)? The IGE is the slope coefficient ('Beta') from a least squares linear regression of the log of the offspring income (or earnings) and the log of the same outcome for the parent (Jäntti & Jenkins, 2015). IOp estimates quantify the explanatory power – for example, through the R-square of a linear regression – of a set of factors over which we have no control, typically referred to as circumstances (Roemer & Trannoy, 2015). If parental income is the only circumstance, then the IGE and the IOp estimate share the same functional form and are directly associated (Bourguignon, 2018, pp. 114–115).

In this article, I focus on the case where parental income is not the only circumstance. Both estimates of IOp and of the IGE summarise the influence of parental background on the offspring's outcome, albeit in different ways. The IGE considers the relationship between the income of the parent and their offspring. IOp estimates, on the other hand, represent parental background through multiple variables. While the IGE makes no assumptions on the legitimacy of intergenerational persistence, IOp explicitly states that all circumstances are sources of illegitimate inequality. While the IGE literature tends to avoid discussions on the 'optimal' level of mobility, achieving equality of opportunity requires an IOp index of zero.

Circumstances can account for the association between parental and offspring income in multiple ways. First, they can act as mediators between parents and their children. For example, high-income parents can invest in housing or other assets, providing a financial buffer for their offspring. Second, certain circumstances can precede parental income. Parental occupation and education are strong predictors of their income, which then influences their offspring's income. Circumstances can also influence the income of the offspring directly, bypassing parental income. The first two ways described here are part of the IGE, whereas the third one is not. I propose an empirical way of decomposing the influence of circumstances into each of these different paths.

I base my framework on the recursive models of Bowles and Nelson (1974), Conlisk (1974, 1977), and Atkinson (1983), among others (see Haveman & Wolfe, 1995, for a review of this literature). These models use diagrams to describe how different factors account for the relationship between parental and offspring income. They include factors that account for background characteristics, parental investment choices, as well as choices taken by the offspring. I follow this approach to describe the three ways in which circumstances and income interact.

I start with parental income being the only circumstance. As mentioned before, in this case, the IGE and IOp estimates are equivalent, as shown in Fig. 1.

Mediating circumstances (C_2) intervene in this relationship splitting the association between parental and offspring income into two: a direct path and an indirect (or mediated) path, as shown in Fig. 2. Previous papers have used such a model to decompose the IGE (Blanden et al., 2007; Palomino et al., 2018) or the relationship between family income and children's outcomes (Washbrook et al., 2014).

$$Y^P \longrightarrow Y^C$$

Note: Y^P: parental income. Y^C: offspring income.

Fig. 1. Parental Income as the Only Circumstance.

$$\begin{tikzcd} Y^P \arrow[r] \arrow[rr, bend right] & C_2 \arrow[r] & Y^C \end{tikzcd}$$

Note: Y^P: parental income. Y^C: offspring income. C_2: mediating circumstances.

Fig. 2. Parental Income and Mediating Circumstances.

Preceding circumstances (C_1) predate parental income chronologically and can only have an influence to the extent that they are correlated to parental income, as shown in Fig. 3.

Figs. 2 and 3 tell us how much of intergenerational immobility (in income) can be attributed to differences in childhood circumstances, but there are other factors at play.

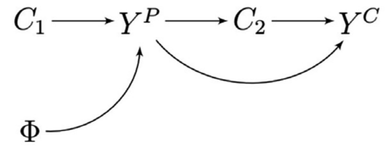
Parental income can be influenced by unobserved circumstances and factors not deemed as circumstances. Jencks and Tach (2006) argue that innate talent is one such factor. In that case, innate talent might contribute to the IGE but would not be considered a source of IOp. To account for these factors, Fig. 4 includes the term Φ into the model, which, by construction, has a residual nature: it accounts for all determinants of parental income that are not included in C_1.

The model in Fig. 4 includes two departures from previous studies that decompose the IGE (see, e.g., Blanden et al., 2007). First, I focus exclusively on factors that are conventionally defined as circumstances in the IOp literature. I exclude individual characteristics that are determined later in life and that might be construed as choices, such as going into higher education or labour market outcomes. Second, I allow some circumstances to precede the relationship between parental and offspring's income, as well as for parental income to influence the offspring's income directly, not only through its influence on mediators. Fig. A1 provides an extended version of Fig. 4, including all existing interactions in the following equations.

$$\begin{tikzcd} C_1 \arrow[r] & Y^P \arrow[r] \arrow[rr, bend right] & C_2 \arrow[r] & Y^C \end{tikzcd}$$

Note: Y^P: parental income. Y^C: offspring income. C_1: preceding circumstances. C_2: mediating circumstances.

Fig. 3. Parental Income, Preceding, and Mediating Circumstances.



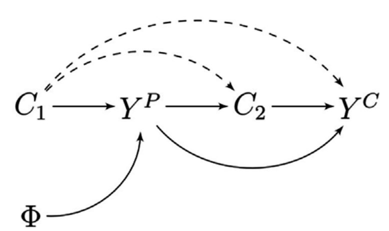
Note: Y^P: parental income. Y^C: offspring income. C_1: preceding circumstances. C_2: mediating circumstances. Φ: all determinants of parental income not included in C_1.

Fig. 4. Parental Income, Preceding, and Mediating Circumstances, including additional determinants.

The final step is to acknowledge the direct influence of preceding circumstances (C_1). Concretely, preceding circumstances can influence mediating circumstances (e.g. if the parent's occupation requires them to move to a different area) or the offspring income (if their children opt for the same occupation), as shown in Fig. 5. By including this component, I go beyond the decomposition of the IGE to fully account for the influence of preceding circumstances on the income of the offspring.

I use Panel Study of Income Dynamics (PSID) to measure intergenerational persistence and to decompose it. The PSID is a longitudinal panel survey in the United States, starting in 1968 with 4,800 families and following them, their offspring, and all future generations, with the last survey carried out in 2019. Because of its long-running and exhaustive nature, the PSID has been extensively used to estimate intergenerational mobility patterns in the United States (Mazumder, 2018).

I focus on two outcomes: individual earnings (where I study father–sons couples) and family income (where I include both women and men). Both outcomes are averaged over 6–9 survey waves: 1981–1989 for the parent's generation and 2001–2017 for the offspring, as the survey became biennial in 1997. I observe the offspring generation in 2017 and the parent generation almost 30 years before that, in 1989, when the offspring were 0–20 years old (median age: 9). Studying earnings captures intergenerational persistence in the labour market. On the other hand, persistence in family income allows for a broader measure of economic welfare that, unlike earnings, does not suffer from selection issues and can



Note: Y^P: parental income. Y^C: offspring income. C_1: preceding circumstances. C_2: mediating circumstances. Φ: all determinants of parental income not included in C_1. The dashed paths represent the influence of preceding circumstances outside that of parental income.

Fig. 5. Direct and Indirect Influence of Preceding Circumstances.

account for other dynamics such as the earnings of their partners and the working status of their offspring, which might reinforce or weaken existing inequalities in earnings.

The IGE for individual earnings is 0.35 (95% confidence interval (CI): [0.23; 0.47]) and the IGE for family income is 0.53 (95% CI: [0.47; 0.58]). I report the decomposition in steps, following Figs. 2, 4, and 5. First, circumstances mediate around a third of the relationship between parental and offspring income (32% for earnings, 36% for income). Among the mediating circumstances, families having above-median savings accounts for almost all of the total contribution (19% and 25% of the IGE, respectively). Preceding circumstances make a big difference, accounting for over half of the IGE (55% and 53%), with parental education (years) explaining over a third of that contribution. Both high savings and parental education make substantial contributions to the IGE, but their interaction accounts for a negligible share of their total contribution. Overall, few circumstances account for most of the IGE, with very little interaction among them.

This article contributes to the literature on intergenerational persistence in two ways. First, I expand on the literature of IGE decomposition to include factors that precede parental income as well as treating parental income (and thus, the IGE) as a mediator of the larger relationship between childhood circumstances and offspring income, as presented in IOp studies. Second, I bridge the gap between the work on IGE and IOp estimates. Previous papers have noted their isomorphism and similarities (Bourguignon, 2018; Brunori et al., 2013; Ferreira & Gignoux, 2014), but no study to date has provided a systematic way to study the relationship between parental income and other circumstances, highlighting the role of parental income.

This article puts in perspective the role played by a measure of immobility such as the IGE in the context of the IOp literature: parental income is a circumstance that cannot be fully accounted for by other more 'traditional' circumstances, and at the same time, these other circumstances play a role that goes beyond that of parental income. As such, equality of opportunity would imply an IGE of zero, while the converse might not be true.

2. AN 'IOP' DECOMPOSITION OF THE IGE ELASTICITY AND BEYOND

2.1. Decomposition Framework

I present the decomposition framework in three steps, following the description in the introduction. First, I account for mediating circumstances that lie between parental and offspring income and account for part of the IGE. Second, I include preceding circumstances, that is, circumstances that influence parental income. Keeping the focus on the IGE, I study the role of these circumstances to the extent that they correlate with parental income. Lastly, I account for factors that lie outside of the IGE by allowing for preceding circumstances to have a direct influence on the income of the offspring.

By following this order, I first determine the extent to which childhood circumstances account for intergenerational immobility and then move to their influence beyond parental income. As Roemer (2004) puts it, the first two decompositions are an appropriate measure of IOp if the influence of parental income on the income of the offspring summarises all transmission mechanisms between parents and their children. However, in the IOp literature parental income is one of many potential circumstances that influence children's income. The last step of my decomposition follows this notion and accounts for the share of the total influence of preceding circumstances, whether or not it is correlated with parental income.

The first part of my framework, the decomposition of the IGE, is based on the literature of determinants of intergenerational persistence (see Blanden et al., 2007; Gregg et al., 2017; Washbrook et al., 2014, among others). This literature uses a system of equation to describe a 'quasi-structural' model of the different paths through which parental income can influence the children's outcomes such as income, education, or early childhood tests. These 'paths' account for a share of the total association between parents and their children, usually measured through the IGE or an equivalent metric.

I also draw from previous work on recursive models (see, e.g., Haveman & Wolfe, 1995). This line of research also studies the determinants of children's attainment, albeit in a broader way, allowing for other 'paths' outside of parental income. Another similar approach is that of Palomino et al. (2019), who look at the interaction between education and occupation (and thus, a path where education shapes occupation) and its influence on IOp. These methods not only quantify the influence of certain factors but also how they interact with each other in shaping income inequality.

The decomposition approach, as described in the introduction, begins with an estimate of intergenerational persistence. I use an estimate of the IGE, β, measured as the slope coefficient from an ordinary least squares (OLS) regression of the log of offspring income (or earnings) on the log of parental income (or earnings), described in equation 1.

$$ln Y^{C} = \alpha + \beta ln Y^{P} + \varphi. \tag{1}$$

In my model, $\ln Y$ is either the log of individual earnings or the log of total family income. The superscript C or P represents the offspring or the parent, respectively. α is a constant and φ is an error term. For simplicity's sake, I refer to Y^C and Y^P as income in this section.

2.2. Accounting for Mediating Circumstances

Mediating circumstances are influenced by parental income and influence the income of the offspring. I include as mediating circumstances the region of birth of the offspring, measures of assets of the parents (owning a house, stocks, businesses, or savings), and whether the family used food stamps, all measured in 1989 when the offspring were between 0 and 20 years old. The inclusion of mediating circumstances results in two possible components of transmission, a mediated component and an unmediated component.

The C_2 term in Fig. 2 represents a vector of circumstances, a fact better represented in the following equations rather than in this figure. Each circumstance within C_2 accounts for a separate part of the IGE, and there are no interactions between them (i.e. if I were to expand C_2 into its components, there would be no arrows between them, see Fig. A1).

Equation 2 represents the influence of mediating circumstances and of parental income on the offspring's income. Equation 3 represents the association between parental income and each of the circumstances in C_2. Note that equation 2 is the standard reduced-form equation that researchers use to derive a version of the lower bound estimates of IOp if parental income and C_2 are the only circumstances (see, e.g., Ferreira & Gignoux, 2014). If we have K_2 circumstances in C_2, indexed by k, there are $K_2 + 1$ equations:

$$\ln Y^{C} = \omega_1 + \sum_{k=1}^{K_2} \pi_{1k} C_{2k} + \theta_1 \ln Y^{P} + u_1 \tag{2}$$

$$C_{2k} = \alpha_{2k} + \lambda_{2k} \ln Y^{P} + \varepsilon_{2k} \tag{3}$$

By including equation 3 into equation 2, I get:

$$\ln Y^{C} = \omega_1 + \sum_{k=1}^{K_2} \pi_{1k} \alpha_{2k} + \left(\theta_1 + \sum_{k=1}^{K_2} \pi_{1k} \lambda_{2k}\right) \ln Y^{P} + \sum_{k=1}^{K_2} \pi_{1k} \varepsilon_{2k} + u_1 \tag{4}$$

Equation 4 shows the two components through which parental income influences offspring income. To decompose β from equation 1 into these two components, I use the definition for the regression coefficient under a linear model:

$$\beta = \frac{\mathrm{Cov}\left(\ln Y^{P}, \ln Y^{C}\right)}{\mathrm{Var}(\ln Y^{P})} \tag{5}$$

By substituting equation 4 into equation 5 and given that the correlation between $\ln Y^{P}$ and the predicted error term is zero, I get the following decomposition of the IGE coefficient β:

$$\beta = \overbrace{\theta_1}^{Y^{C} \to Y^{P}} + \overbrace{\sum\nolimits_{k=1}^{K_2} \pi_{1k} \lambda_{2k}}^{Y^{C} \to C_2 \to Y^{P}}. \tag{6}$$

Equation 6 shows how β is decomposed into two components, each represented as a combination of regression coefficients. The first term θ_1 accounts for the association between parental and offspring's income, once we control for mediating circumstances. The second term accounts for mediating circumstances C_2 and comprises π_{1k}, the regression coefficient for mediating circumstance C_{2k} on offspring's income and λ_{2k}, the regression coefficient for parental income on mediating circumstance C_{2k}.

2.3. Accounting for Preceding and Mediating Circumstances

By including preceding circumstances, I describe the model shown in Fig. 4. C_1 denotes the set of preceding circumstances: circumstances that come before parental income chronologically. In this group, I include the IQ of the head of the family (measured in 1972),[1] the years of education of the parent with the highest education and the occupation of the parent (measured in 1989 using the three-digit 1970 census codes and then grouped into seven categories), the ethnicity of the parent (binary category: white or other), and the place in which they grew up in (farm, town, city, other).

Under preceding circumstances, the framework decomposes the IGE into four components. First, the mediated and unmediated channels discussed before – whether the component passes through C_2 or not. Second, influence can stem from preceding circumstances (C_1) or through the residual term Φ. Similar to the definition of 'effort' for most IOp estimates, Φ has a residual nature: whatever is not considered a preceding circumstance falls within Φ, including unobserved circumstances or factors that might not be considered circumstances. As with C_2, C_1 is also a vector of circumstances with no interaction among them. However, every circumstance in C_2 is associated with every circumstance in C_1.

By including C_1 in the decomposition of β, I add three new equations (technically, I add one new equation and extend equations 2 and 3 to account for C_1). If we have K_2 circumstances in C_2, indexed by k, we get a set of K_2+2 equations:

$$\ln Y^{\mathrm{P}} = \alpha_1 + \sum_{j=1}^{K_1} \kappa_j C_{1j} + \phi_2. \tag{7}$$

$$C_{2k} = \alpha_{2k} + \lambda_{2k} \ln Y^P + \sum_{j=1}^{K_1} \delta_{kj} C_{1j} + \varepsilon_{2k}. \tag{8}$$

$$\ln Y^C = \omega_2 + \sum_{j=1}^{K_1} \rho_{2j} C_{1j} + \sum_{k=1}^{K_2} \pi_{2k} C_{2k} + \theta_2 \ln Y^P + u_2. \tag{9}$$

The final set of equations represented in Fig. 4 includes equations 7–9. Equation 7 represents the influence of preceding circumstances on parental income (i.e. $C_1 \to Y^{\mathrm{P}}$) and that of the residual term ($\Phi \to Y^{\mathrm{P}}$). Equation 8 represents the mediated components and includes the influence of parental income ($Y^{\mathrm{P}} \to C_2$) and that of preceding circumstances ($C_1 \to C_2$). Lastly, equation 9 represents the influence of all factors on offspring's income: the unmediated influence of preceding circumstances ($C_1 \to Y^{\mathrm{C}}$), the influence of mediating circumstances ($C_2 \to Y^{\mathrm{C}}$), and the influence of parental income ($Y^{\mathrm{P}} \to Y^{\mathrm{C}}$). Just like equation 2, equation 9 is the standard way to measure IOp when parental income, C_1, and C_2 are circumstances.

By substituting equations 7 and 8 into equation 9 and using the same approach as in the previous section, I decompose β into the four components of Fig. 4.

$$\beta = \overbrace{\theta_2}^{\Phi \to Y^P \to Y^C} + \overbrace{\sum_{k=1}^{K_2} \pi_{2k}\lambda_{2k}}^{\Phi \to Y^P \to C_2 \to Y^C} + \overbrace{\sum_{j=1}^{K_1} \rho_{2j} \frac{\mathrm{Cov}\left(C_{1j}, \ln Y^{\mathrm{P}}\right)}{\mathrm{Var}\left(\ln Y^{\mathrm{P}}\right)}}^{C_1 \to Y^P \to Y^C} \tag{10}$$

The first component θ_2, the influence of parental income conditional on all circumstances, is the only component not associated to circumstances. This component can be interpreted as the influence of Φ in Fig. 4: the residual influence of parental income, once I control for preceding and mediating circumstances. All other components are associated with preceding circumstances, mediating circumstances, or both.

The other three components account for the contribution of circumstances to the IGE. The term $\sum_{k=1}^{K_2}\pi_{2k}\lambda_{2k}$ represents influence of Φ on mediating circumstances. λ_{2k} is the regression coefficient for parental income on mediating circumstances and π_{2k} is the regression coefficient for mediating circumstances on offspring income, for each of the K_2 circumstances. The term ρ_{2j} represents the unmediated influence of each of the K_1 preceding circumstances. Lastly, the term $\sum_{k=1}^{K_2}\pi_{2k}\delta_{jk}$ represents the mediated influence of the same preceding circumstances. It combines δ_{jk}, the regression coefficient for preceding circumstances on mediating circumstances, and π_{2k}, the regression coefficient for mediating circumstances on offspring's income. The latter two terms are weighted by the correlation between preceding circumstances and parental income.

Note that up to now the association between preceding circumstances and offspring's income is exclusively mediated by parental income (i.e. $C_1 \rightarrow Y^{\mathrm{P}} \rightarrow Y^{\mathrm{C}}$). Given that I have focused on the IGE, preceding circumstances matter to the extent that they correlate with the income of the father. Even preceding circumstances have an important influence of the income of the offspring (captured by the P coefficient), their contribution to the IGE will be zero if they do not correlate with parental income ($\mathrm{Cov}\left(C_{1j}, \ln Y^{\mathrm{P}}\right) = 0$). I remove this restriction in the following section to study the total contribution of C_1 on Y^C.

2.4. Accounting for the Direct Influence of Preceding Circumstances

To account for the complete influence of preceding circumstances on the offspring of the income, I need to move beyond the relationship between parent and offspring's income. That means partitioning the contribution of preceding circumstances into the ones influencing the IGE (represented by equation 7) and their direct influence (as determined by the regression coefficient for C_1 in equations 8 and 9).

I start by including equations 7 and 8 into equation 9. Grouping all terms associated with C_1, I get all the potential ways in which preceding circumstances influence the income of the offspring.

$$\ln Y^{\mathrm{C}} = \Xi + \sum_{j=1}^{K_1}\left(\rho_{2j} + \theta_2\kappa_j + \left(1+\kappa_j\right)\sum_{k=1}^{K_2}\pi_k\delta_{kj}\right)C_{1j} + \Sigma. \tag{11}$$

where the constant term and the error term include:

$$\Xi = \omega_2 + \sum_{k=1}^{K_2}\pi_{2k}\alpha_{2k} + \left(\theta_2 + \sum_{k=1}^{K_2}\pi_{2k}\lambda_{2k}\right)\alpha_1, \tag{12}$$

$$\Sigma = u_2 + \sum_{k=1}^{K_2} \pi_{2k}\varepsilon_{2k} + \left(\theta_2 + \sum_{k=1}^{K_2} \pi_{2k}\lambda_{2k}\right)\phi_2. \tag{13}$$

Using the same decomposition approach as in the previous section, but now focusing on the regression coefficient for preceding circumstance C_{1j} on offspring income $\ln Y^C$, we get:

$$\frac{\operatorname{Cov}\left(\ln Y^{\mathrm{C}}, C_{1j}\right)}{\operatorname{Var}\left(C_{1j}\right)} = \underbrace{\overbrace{\rho_{2j}}^{C_1 \to Y^{\mathrm{C}}} + \overbrace{\theta_2 \kappa_j}^{C_1 \to C_2 \to Y^{\mathrm{C}}}}_{\text{Direct}} + \underbrace{\overbrace{\sum_{k=1}^{K_2} \pi_k \delta_{kj}}^{C_1 \to Y^{\mathrm{P}} \to Y^{\mathrm{C}}} + \overbrace{\kappa_j \sum_{k=1}^{K_2} \pi_k \delta_{kj}}^{C_1 \to Y^{\mathrm{P}} \to C_2 \to Y^{\mathrm{C}}}}_{\text{Indirect (through the IGE)}}. \tag{14}$$

The first two capture the 'direct' influence of preceding circumstances. That is, the influence that does not pass through parental income, thus being excluded in the IGE. The last two terms, on the other hand, capture their influence passing through parental income, that is, their contribution to the IGE.

This decomposition only accounts for the influence of one preceding circumstances at time. That is, it is equivalent to decompose the regression coefficient of one particular circumstance on the income of the offspring:

$$\ln Y^{\mathrm{C}} = \omega_3 + \psi_j C_{1j} + u_3. \tag{15}$$

where the ψ_j coefficient is equal to the definition in equation 14. As a result, I do not provide a summary of the 'total' contribution of circumstances, nor of their relative importance. To provide some measure of the relative importance each circumstance plays, I include the *R*-square of the OLS regression of equation 15.[2]

2.5. On the Similarities Between IGE and IOp

Through this decomposition, we can discuss the similarities between IGE and IOp. The idea of an 'optimal' level of intergenerational immobility relates to whether we can interpret these estimates as a measure of IOp or not. Black and Devereux (2011) state that while people tend to favour equality of opportunity as a goal, zero intergenerational correlation is not necessarily the optimum. Major and Machin (2018) argue that few people would advocate for a world of zero intergenerational immobility. However, these arguments do not account for the fact that circumstances – the driving force of IOp – can also have an influence beyond that of parental income. While the influence of circumstances might not account for the complete IGE, their influence might go beyond that of parental income.

In addition, we could have different opinions on what we define as circumstances. Most IOp estimates follow a 'conventional' definition of IOp, where socio-economic background is considered a circumstance while innate talent is not (Swift, 2013). However, an 'optimal' level of intergenerational immobility of anything but zero would mean that we are not achieving equality of opportunity.

It could be the case that we tolerate some aspects of family influence, even if they are captured by our set of circumstances. A more nuanced interpretation of IOp will require that we not only quantify the total influence of certain factors but also through which channels they shape income inequality.

There are certain factors for which the distinction between effort and circumstance can be blurry. For example, education and occupation are typically treated as efforts – or at least efforts partially influenced by circumstances. But they become circumstances for the next generation. Atkinson (2015) makes the converse point, as income inequality today will become an important input for IOp of the next generation, such that all determinants of inequality will eventually become circumstances. If we think of 'dynasties' rather than individuals, as in Kanbur and Stiglitz (2016), then the distinction becomes irrelevant. What matters in this context is the initial position.[3]

For the purpose of this article, the relevant question is whether we should think of an IGE of zero as the policy goal. That is, whether policy should aim to 'nullify' the influence of all circumstances, including parental education or occupation, which at some point were considered efforts in themselves. Inequality of effort is positively associated with economic growth (see, e.g., Marrero & Rodríguez, 2019), and so we would like to allow for it and, indeed, promote it. However, we would like to reduce or minimise its influence on their children outcomes, as it is still a source of inequality for future generations.

Swift (2013, pp. 108–109) develops this argument in detail. The idea behind equal opportunities is that individuals are free to use their abilities and effort however they want, which could include giving their children better opportunities than the rest. But even in that case we could seek to prevent actions taken by the parents for the sake of equal opportunities. We could still redistribute income through taxation and spending on public schools, thus rendering parental investments on their children less 'effective'. More generally, we should aim to prevent 'opportunity hoarding' in all of its forms (Rury & Saatcioglu, 2015), not only for normative reasons but also because they lead to an inefficient allocation of resources. In other words, we should treat parental characteristics as circumstances if they lead to unfair (and inefficient) advantages, say access to unpaid internships at high-status firms but not if they lead to transmission of preferences, for example, if a parent wants their children to follow their trade. Making that distinction will require much more information on the causal mechanisms that drive the associations between our current measures of circumstance and the income of the children.

3. DATA

I use the PSID, a household panel survey for the United States that has followed the same individuals and their descendants since 1968. The PSID has been used extensively to study the intergenerational mobility of many different outcomes (Mazumder, 2018). Being a long-running panel, it also includes extensive information on multiple generations, particularly childhood circumstances as reported by the parents themselves when they happened, in contrast with most cross-sectional surveys where circumstances are reported retrospectively by the offspring. Because of its detailed characterisation of the socio-economic background while growing up, the PSID is among the best surveys to study IOp and intergenerational transmission in the context of high-income countries.[4]

To maximise comparability, I use similar definitions and samples as previous research on IGE estimations (see Mazumder, 2018, for a survey). For individual earnings, I study only fathers and sons. For family income, I include both men and women. I restrict the sample to the head of the family unit, as most circumstances are only measured for them. My outcome variables are individual earnings and family income, averaged over six to nine years of data. Long-term averages reduce the attenuation bias from measurement error or transitory fluctuations (Solon, 1992). Overall, my IGE estimates – 0.35 for earnings and 0.53 for income – fall within the range of previous estimates. For example, Gouskova et al. (2010) report IGE estimates ranging from 0.3 and 0.4 for individual earnings and Lee and Solon (2009) report estimates ranging from 0.35 to 0.55 for family income.

I match parents and their offspring using the PSID's Family Identification Mapping System (FIMS). The FIMS assigns the ID of every parent to each offspring. I merge each offspring to their biological or adoptive parents. The 2017 sample includes individuals from the second PSID generation (with a median age of 50 years) up to the seventh generation (with a median age of six years). Of the 2017 offspring sample, 85% have an FIMS map (i.e. the offspring of a previous PSID respondent). Within that group, 77% have at least one parent in the 1989 sample. The remaining sample (equivalent to 45% of the 2017 sample) includes 2017 respondents with no observed parents in the 1989 wave of the PSID. This could happen for two reasons. First, individuals could be part of the 1997 or 2017 immigrant refresher samples, which were first interviewed in those years with the goal of sampling the immigrant population, in which case they would not have an FIMS map. Second, their parents had died or retired from the sample by 1989, in which case, they have an FIMS map but no parent data.[5]

3.1. Outcome Variables

I look at two outcomes: individual labour earnings and total family income. Individual labour earnings reflect the intergenerational persistence of skills and characteristics that are valued in the labour market. Family income includes other sources besides earnings as well as income from other people in the family, if present. The IGE for family income reflects the intergenerational persistence of other non-labour market attributes, such as capital income, social transfers, or income from the spouse. While earnings focus on labour market advantages, Mazumder (2018) argues that family income is much closer to consumption and therefore to the concepts of 'utility' or 'welfare'.

To reduce transitory fluctuations and measurement error, I average both outcomes over multiple years. Mazumder (2005, 2016) shows that these fluctuations can result in a downward bias of up to 30%. I include nine years of data for both the parents and offspring generations. In the parents' case, the period covers 1981–1989. For the offspring's generation, it covers the period 2001–2017, as the PSID changed from annual to biannual interviewing in 1997. I include all respondents with at least six observations over this period. On average, each respondent in the offspring's generation has 8.6 observations for earnings and 8.8 for income.

The outcomes were measured in 1989 for the parent's generation and in 2017 for that of the offspring. Circumstances were measured in 1989, with the exception of the parent's IQ score that was measured in 1972 (see Footnote 2). For circumstances to be considered as such, I only include offspring that were 20 years of age or younger in 1989, as older offspring might be able to influence their own circumstances (e.g. if they buy a house for their parents). For that reason, my sample consists of offspring aged 28–48 in 2017. I limit the sample of parents to those older than 25 years of age in 1989 to exclude younger respondents whose incomes could be substantially below their 'permanent' or long-term income (Haider & Solon, 2006; Jenkins, 1987), and I cap their age at 64, as the share of parents with positive earnings decreases rapidly after that. Fig. 6 plots the age distribution for the offspring generation in 2017 (left plot) and the parental generation in 1989 (right plot). This figure shows that offspring age is more constrained and uniformly distributed than the parents. Both the average age and the median age for both generations are around 39 years of age.

My earnings variable is the total labour income of the head of household. This includes farm and business income, wages, bonuses and overtime, and income from independent professional practice. It also includes the labour part of market gardening (farm or gardening businesses) and of roomers and boarders (hospitality businesses). The PSID assigns 75% of the gardening business income to labour income (the rest being asset income) and 50% of the roomers and boarders income to labour income if they own the house (100% if the owners rent the house). If the respondent's business reports a loss, there is no labour income (i.e. there is no negative labour part of business income). I focus only on the earnings of the fathers and sons, to replicate previous estimates of IGE.

Family income includes total taxable income and transfers for all family members.[6] This includes taxable income, that is, wages and salaries, bonuses, overtime, and/or commissions, wife's labour income, farm and business income, income from rent, dividends, interest, trust funds, and royalties, alimony, and other income from assets. It also includes transfer income, which comprises Aid to Dependent Children (ADC) or Aid to Families with Dependent Children (AFDC) – and after 1997 the Temporary Assistance for Needy Families (TANF) – supplemental security income, other welfare, social security payments, veterans' administration pensions, other retirement, pensions, and annuities, unemployment pay, workers' compensation, child support, help received from relatives, and other transfers. I assign to each respondent the family income of their family unit in the corresponding year (1989 or 2017). For respondents with parents living in different households in 1989 and with both households in the survey, I opt for the household with the highest income.

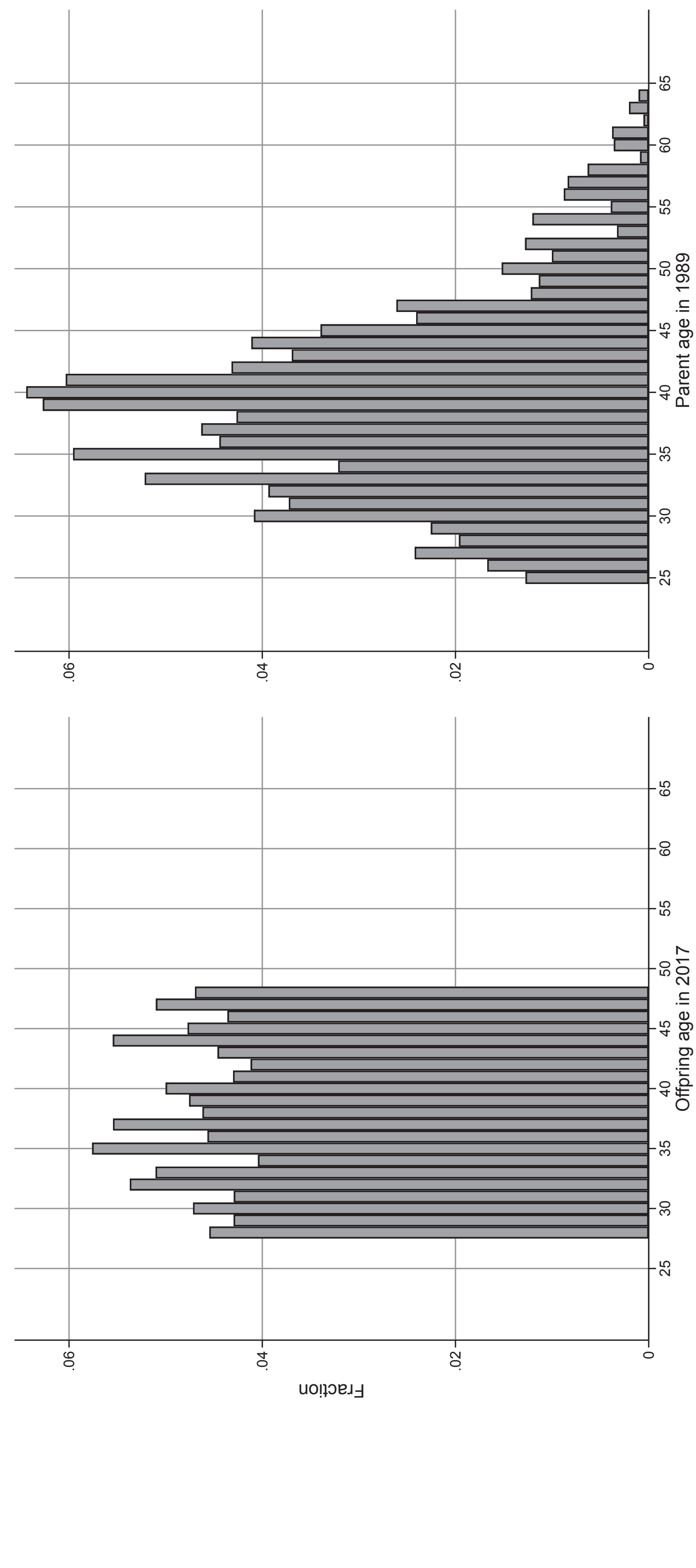


Fig. 6. Age Distribution for Parents and Offspring.

I measure all outcomes in 2017 US dollars using the consumer price index (CPI) provided by the US Bureau of Labor Statistics. The reference period is the calendar year prior to the survey year (e.g. the 1989 survey includes all earnings from 1988). I drop all missing values for any of the variables (outcomes and circumstances). I keep siblings in the sample and assign to each the outcome of the same parent, thus clustering the bootstrap at the parental family level. I use the 2017 cross-sectional sample weight to account for differential attrition.

My final sample includes 2,021 parent–offspring pairs for family income and 721 for individual earnings.[7] The complete PSID sample includes 41,901 respondents for the 1989 sample and 26,445 for 2017. After using the FIMS to map parents and their offspring, the sample includes 16,453 parent–offspring pairs. By restricting the age range for both parents and offspring, the sample decreases to 3,224 observations. Excluding the survey of economic opportunity (SEO) sample results in a sample size of 2,056. Finally, constraining the sample to those offspring with circumstance data and, in the case of earnings, to only sons and fathers, leaves us with the final sample.

3.2. Circumstance Variables

In the IOp literature, circumstances are involuntarily inherited factors that influence offspring's income and earnings. All of the circumstances used for my decomposition analysis are listed in Table 1. Except for the IQ score and the years of education of the parent with the highest education, all other variables are categorical. All circumstances were measured in 1989, except for the IQ score which was measured in 1972, and the state where the offspring was born, measured at the time of birth.

Preceding circumstances (C_1) are allowed to influence mediating circumstances (C_2). However, the circumstances within each group do not influence each other (as shown in Fig. A1). This is because the temporal order is not as clear as it is between preceding and mediating circumstances. Also, given the large number of circumstances, adding these interactions would add an unnecessary amount of complexity to the model. Each new interaction would require an additional equation, rapidly increasing the number of individual components to be described. For example, if a circumstance C_{1a} (say, parental education) were allowed to influence another circumstance C_{1b} (parental occupation), both being part of C_1 the component $C_1 \to Y^C$ would need to be decomposed into $C_{1a} \to Y^C$ and $C_{1a} \to C_{1b} \to Y^C$, as would any other component in C_1. Such a detailed model is beyond the scope of this article.

A more complex model of intergenerational transmission would also need to include factors that might not be considered circumstances, for example, post-school investments (as in Fig. 1 in Haveman & Wolfe, 1995). I intentionally exclude these factors from my analysis. For example, the education of the offspring is an important factor when accounting for the intergenerational transmission of income, but I do not control for, nor for measured cognitive skills or the formation of preferences, as not everyone would consider them to be circumstances. As my focus is on the relationship between IOp and the IGE, I focus on circumstances that can be unequivocally interpreted as circumstances.[8]

Table 1. Description of All Circumstance Variables.

Name	Description
Preceding circumstances	
IQ score	Score on sentence completion test taken in 1972 (13 multiple choice questions – score goes from 0 to 13)
Education (years)	Years of education of the parent with the highest education (0–17 years)
Ethnicity	1 if Black, American Indian, Aleut, Eskimo, Asian, Pacific Islander, other. 0 if White
Occupation (main occupation/most important activity using three-digit code 1970 census)	
	Grouped into seven categories: professional, manager, clerical, craftsman, operative, farmer, and services
Parent grew up in (four categories)	
Farm	Farm, rural area, and country
Small town	Small town, any size town, and suburb
Large city	Large city and any size city
Other	Other, several different places, and combination of places
Mediating circumstances	
Homeowner	Family owns or is buying home, fully or jointly (includes mobile home owners who rent lots)
Over median: business	Family owns above-median market value of farm or business
Over median: stocks	Family owns above-median market value of shares of stock, mutual funds, or investment trusts (including stocks in individual retirement account (IRAs))
Over median: savings	Family owns above-median money in checking or savings accounts, money market bonds, or treasury bills (including IRAs)
Over median: food stamps	Family received above-median food stamp benefits
State where born`	State where the offspring was born (50 states plus DC, US territory/outside United States, and no response)

Notes: All circumstances are measured in 1989 (when the offspring were 0–20 years of age) with the 'parent grew up in' measured retrospectively. The two exceptions are the state where the offspring was born (measured at the year of birth) and the IQ score (test taken by the 1972 head of the family).

4. IGE ESTIMATES AND DECOMPOSITION ANALYSIS

This section is organised into four subsections. I first report the IGE estimates and contrast them with previous studies. Then I move to the first decomposition of the IGE, by accounting for the influence of mediating circumstances. In the third part, I also include preceding circumstances. The last subsection moves beyond the IGE decomposition to account for the complete influence of preceding circumstances.

4.1. IGE Estimates

Table 2 reports the IGE estimates for individual earnings and family income. The IGE is 0.35 for earnings and 0.53 for income. These estimates are within the range of previous estimates that have used the same database. Two good references for that comparison are Mazumder (2016, 2018). Mazumder (2016) estimates the IGE for both earnings and income by averaging these outcomes over a different number of waves. He restricts the PSID sample to all father–son pairs with

Table 2. IGE Estimate for Individual Earnings and Family Income.

	Earnings	Income
IGE	0.347	0.526
	(0.063)	(0.028)

Notes: Individual earnings for fathers and sons only ($N = 721$) and family income for all offspring and the head of household in 1989 ($N = 2{,}021$). Bootstrapped standard errors in parenthesis.

available individual earnings or family income between the ages of 25 and 55 from 1967 to 2010. Mazumder (2018) provides an extensive review of IGE estimates using the PSID and other data sources.

The IGE estimates for earnings in Mazumder (2016) range from 0.3 for a one-year measure, to over 0.65 for 15-year averages for fathers and 10-year averages for sons. If we look at the equivalent of my estimate, nine-year averages for fathers and sons, the estimate is 0.39, while the arithmetic average for estimates with six- to nine-year averages is 0.40. Mazumder (2018) reports the estimates from several papers. Among these estimates, most account for lifecycle bias resulting in IGE estimates of around 0.65.[9] For example, Gouskova et al. (2010) restrict the sample to the male head of the household and their fathers and report an IGE for earnings of 0.41, which increases to 0.63 once they correct for age-varying attenuation bias. My estimates account for a transitory variation by averaging the outcomes over a large number of years but do not account for lifecycle bias as that would require accounting for the adjusted estimation process (e.g. the inclusion of a polynomial of age) when decomposing the IGE.

For income, Mazumder (2016) reports IGE estimates ranging from 0.38 to 0.66. The nine-year averages for fathers and sons result in an IGE of 0.49, while the simple average for estimates with six- to nine-year averages is 0.44. These estimates are particularly sensitive to the different samples. For example, the estimate using eight-year averages is 0.37. For that reason, Mazumder (2016) repeats his analysis for income using a fixed sample, keeping only individuals with 10 years of data. Using one-year measures for sons and fathers with 10 years of data, the IGE estimates are around 0.58. Among the selected papers in Mazumder (2018), the IGE for income ranges from 0.53 to 0.62. For example, Hertz (2005) restricts the PSID sample to all children born between 1942 and 1972 and observes their income when they were between 25 and 55 years of age. He reports an IGE estimate for the age-adjusted family income of around 0.5.

These estimates – and, indeed, most IGE estimates – might suffer from different sources of bias due to the data quality. Following Jäntti and Jenkins (2015), there are two main issues when looking for 'long-term' measures of economic status to estimate β. The first one is the presence of transitory variations in income measures, resulting in attenuation bias. This issue results in a downward bias for IGE estimates, and based on Solon (1992), it is typically solved by averaging multiple years of income data for both parents and their offspring, as I do in this paper. The second is lifecycle bias, which states that observed income is below permanent or long-term income earlier in life, while being above it later in life. One solution is to observe incomes at similar ages for both parents and children

(Grawe, 2006), which is why I cap the age of both parents and their offspring. To these two issues, I add an additional source of bias, due to co-residency of parents and their children (Francesconi & Nicoletti, 2006). While this is an issue in short panels, the long-running nature of the PSID helps in addressing it. Inevitably, these sources of bias might still persist despite my efforts to attenuate. However, the purpose of this article is not to amend each source of bias but to obtain estimates as close as possible to those that have already been estimated, as to focus on the following decomposition.

4.2. Decomposing the IGE: Mediating Circumstances

The inclusion of mediating circumstances splits the IGE into two components. A mediated component, where parental income influences these circumstances, and they in turn influence offspring income, and a second one where parental income influences offspring income directly. By construction, the latter component is a residual: it accounts for all other factors that are not included among mediating circumstances.[10]

Table 3 presents the decomposition, including the contribution of each mediating circumstance. I also include the 95% CI obtained from a bootstrap with replacement that iterated the whole decomposition process 1,000 times, clustered at the parental family level. In total, the mediating component accounts for 32% of the IGE for individual earnings and 36% for family income. The relative size is similar for both outcomes, but the IGE is much higher for family income. These shares as a part of each IGE are shown in Fig. 7.

A pattern that arises from this decomposition (and the next) is that a few circumstances account for most of the share attributed to circumstances. The most relevant circumstance is whether the family had above-median savings in 1989. It accounts for 19% of the IGE for earnings and 25% for income. Family savings – and more generally, wealth and assets – act both as a stock for human capital or other investments and a buffer for external shocks such as medical risks (De Nardi & Fella, 2017). Savings also have a direct intergenerational transfer, through bequests and inheritances (Killewald et al., 2017), reinforcing wealth inequalities across generations.

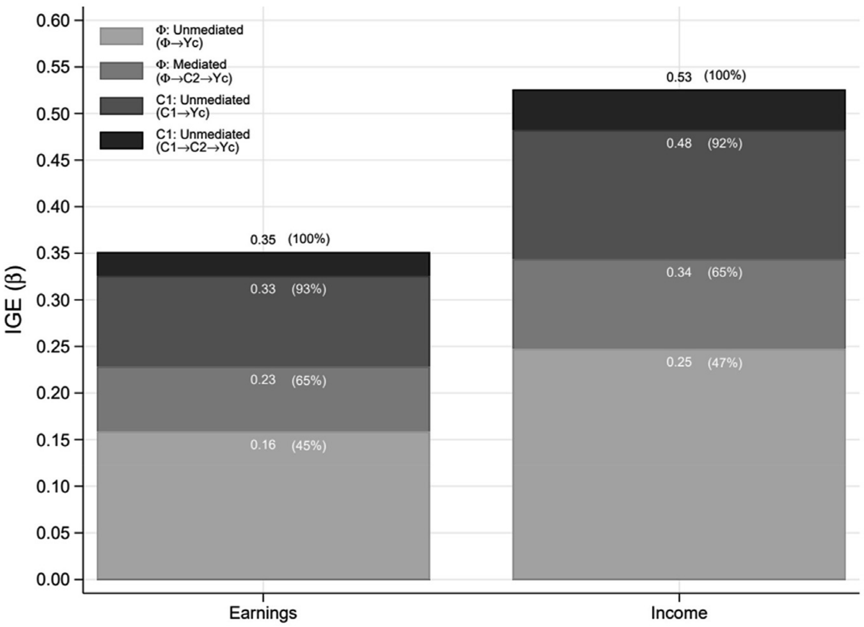
The only other circumstance with a statistically significant contribution at the 95% level is having above-median investment in stocks, albeit only for earnings immobility. This circumstance accounts for 5% of the IGE for earnings but less than a percentage point for income. Financial investments can act as a similar buffer as savings but are more highly concentrated at the top of the distribution.

Another important circumstance is whether families used food stamps (now called Supplemental Nutrition Assistance Program, SNAP) in 1989. It accounts for 4.4% of the IGE for earnings and 5.8% for income, although neither is statistically significant. The high share accounted for by this circumstance reflects that intergenerational persistence happens not only at the top of the distribution (as suggested by the importance of savings and investment) but also at the bottom.

Table 3. IGE Decomposition (Mediating Circumstances).

	Earnings						Income					
	Coefficient	95% CI		% of IGE	95% CI		Coefficient	95% CI		% of IGE	95% CI	
Mediating circumstances												
Homeowner	0.009	−0.02	0.04	1.64	−3.95	7.23	0.006	−0.03	0.04	1.74	−8.32	11.81
Region: Mideast	−0.000	−0.01	0.01	−0.01	−1.03	1.02	0.006	−0.02	0.03	1.81	−4.72	8.34
Region: Great lakes	0.001	−0.00	0.01	0.14	−0.90	1.19	0.001	−0.01	0.01	0.17	−3.25	3.60
Region: Plains	0.001	−0.00	0.01	0.14	−0.72	0.99	0.008	−0.02	0.04	2.19	−6.86	11.24
Region: Southeast	0.014	−0.00	0.03	2.64	−0.54	5.83	0.005	−0.01	0.03	1.51	−4.52	7.53
Region: Southwest	−0.002	−0.01	0.00	−0.42	−1.77	0.94	0.000	−0.02	0.02	0.02	−6.06	6.11
Region: Rocky mountains	0.000	−0.00	0.00	0.01	−0.31	0.33	0.001	−0.01	0.01	0.15	−1.92	2.22
Region: Far west	−0.003	−0.01	0.00	−0.61	−1.96	0.75	−0.006	−0.03	0.01	−1.81	−9.95	6.33
Region: Outside United States	0.000	−0.00	0.00	0.05	−0.32	0.42	−0.005	−0.02	0.01	−1.35	−7.32	4.62
Region: No answer	−0.000	−0.00	0.00	−0.00	−0.27	0.27	−0.000	−0.00	0.00	−0.00	−0.49	0.49
Over Median: business	0.001	−0.01	0.01	0.12	−2.52	2.75	0.000	−0.01	0.01	0.05	−2.47	2.57
Over Median: stocks	0.026	0.00	0.05	5.01	0.63	9.39	0.002	−0.04	0.05	0.64	−13.76	15.03
Over Median: savings	0.100	0.07	0.13	19.00	12.68	25.33	0.088	0.04	0.14	25.25	8.84	41.67
Used food stamps	0.023	−0.01	0.05	4.39	−1.34	10.12	0.020	−0.01	0.05	5.78	−3.37	14.92
Summary												
$Y^P \rightarrow C_2 \rightarrow YY^C$	0.169	0.12	0.22	32.11	21.84	42.37	0.125	0.05	0.20	36.15	14.57	57.73
$Y^P \rightarrow Y^C$	0.357	0.28	0.43	67.89	57.63	78.16	0.222	0.11	0.33	63.85	42.27	85.43
Total	0.526	0.47	0.58	100.00	100.00	100.00	0.347	0.23	0.47	100.00	100.00	100.00

Notes: Individual earnings for fathers and sons only ($N = 721$) and family income for all offspring and the head of household in 1989 ($N = 2{,}021$). All circumstances measured for the head of family in 1989. Homeowner: parent owning a house in 1989. Region where born has 'New England' as the reference category. 'Outside US' category includes US territories. The asset variables (including the use of the Food Stamp programme, renamed SNAP in 2008) takes the value 1 for those parents above the median in 1989 (e.g. by being above the median value of the food stamp benefit or by having above-median savings). CI based on a 1,000-iteration bootstrap, clustered at the parental family level, using random sampling with replacement over the whole estimation and decomposition process.



Note: Individual earnings for fathers and sons only ($N = 721$) and family income for all offspring and the head of household in 1989 ($N = 2,021$).

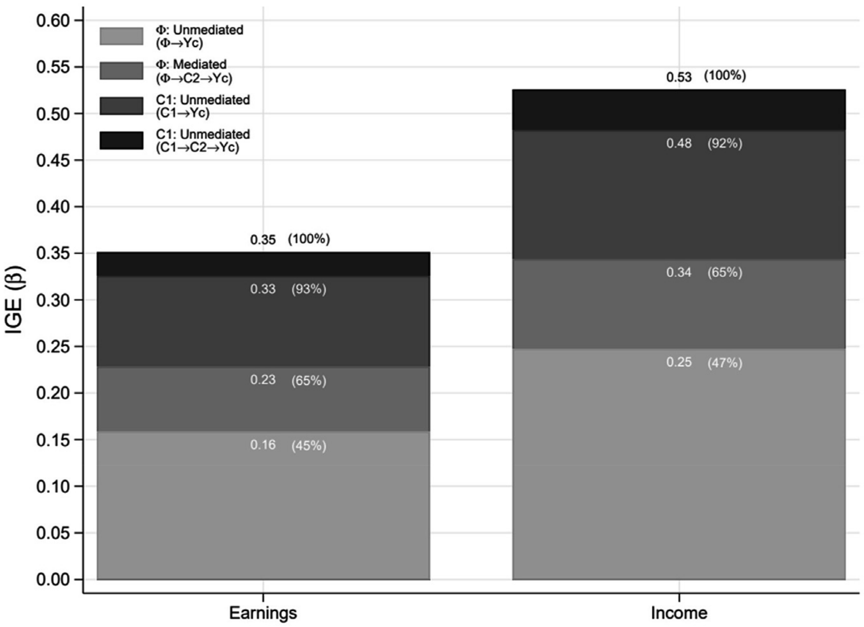
Fig. 7. IGE Decomposition: Mediating Circumstances.

4.3. Decomposing the IGE: Preceding and Mediating Circumstances

I expand the previous decomposition by adding circumstances that precede the relationship between parental and offspring's outcomes. As a result, each of the two components discussed in the previous section is divided into two: One component that follows from preceding circumstances, and another component stemming for all other sources of immobility.

As both sets of preceding and mediating circumstances include a large number of components, I report a summary of the complete decomposition reporting only preceding circumstances. I present the opposite table, reporting only mediating circumstances, in Table A1.

Tables 4 and 5 report the decomposition for individual earnings and family income, respectively. I also include the 95% CI obtained from a bootstrap with replacement that iterated the whole decomposition process 1,000 times, clustered at the parental family level. After controlling for preceding and mediating circumstances, the coefficient of the logarithm of individual earnings of the parent ($\ln Y^P$) goes from 0.35 to 0.16, while the coefficient for the logarithm of parental family income goes from 0.53 to 0.25 (see Columns 3 and 6 of Table A4). Overall, circumstances account for 55% of the IGE of earnings and 53% for the IGE of income. Fig. 8 summarises the decomposition.



Note: Individual earnings for fathers and sons only ($N = 721$) and family income for all offspring and the head of household in 1989 ($N = 2,021$).

Fig. 8. IGE Decomposition: All Circumstances.

After including preceding circumstances, the share accounted for by circumstances increases from 32% to 55% for earnings and from 36% to 53% for income. By looking at equation 14, we know that this increment is accounted for by the 'direct' (or unmediated) influence of preceding circumstances ($C_1 \rightarrow Y^P \rightarrow Y^C$). A part of the unmediated influence of parental income is now determined by preceding circumstances. This decomposition shows that this influence is substantial and account for a part of the IGE that goes above and beyond the influence of mediating circumstances.

Among the three components that comprise the influence of circumstances, the largest one is the unmediated influence of preceding circumstances ($C_1 \rightarrow Y^P \rightarrow Y^C$), accounting for around 27% of the IGE in both cases. The second largest component is the mediated influence of non-circumstance factors ($\text{NC} \rightarrow Y^P \rightarrow C_2 \rightarrow Y^C$), accounting for almost 20% of the IGE. The third component, the mediated influence of preceding circumstances ($C_1 \rightarrow Y^P \rightarrow C_2 \rightarrow Y^C$) accounts for around 8% of the IGE. This decomposition indicates that both preceding and mediating circumstances account for an important share of the IGE, but there is little interaction between the two. Preceding circumstances have a direct influence on offspring's outcomes, and mediating circumstances play an important role in the relationship between non-circumstance factors and offspring's income, but preceding circumstances have a very weak association with mediating circumstances.

Table 4. IGE Decomposition for Individual Earnings (All Circumstances).

	Earnings					
	Coefficient	95% CI	% of IGE	95% CI	Coefficient	95% CI
Unmediated influence of Φ:						
$\Phi \rightarrow Y^{P} \rightarrow Y^{C}$	0.157	0.04	0.28	45.27	16.21	74.34
Mediated influence of Φ						
$\Phi \rightarrow Y^{P} \rightarrow C_2 \rightarrow Y^{C}$	0.068	−0.00	0.14	19.52	−0.74	39.78
Unmediated influence of C_1: $C_1 \rightarrow Y^{P} \rightarrow Y^{C}$						
IQ score	0.011	−0.01	0.03	3.27	−2.38	8.92
Education (years)	0.063	0.01	0.12	18.03	0.59	35.47
Ethnicity: Non-white	−0.003	−0.01	0.00	−0.99	−3.28	1.30
Occupation: Manager	0.009	−0.01	0.03	2.64	−4.03	9.31
Occupation: Clerical	0.006	−0.01	0.02	1.80	−2.27	5.88
Occupation: craftsman	−0.009	−0.03	0.01	−2.66	−9.36	4.05
Occupation: Operative	0.004	−0.03	0.03	1.26	−8.28	10.80
Occupation: Farmer	0.008	−0.01	0.03	2.28	−3.04	7.59
Occupation: Services	−0.001	−0.01	0.01	−0.30	−2.49	1.90
Occupation: Other	0.001	−0.02	0.02	0.34	−4.87	5.56
Parent grew in small town	0.001	−0.01	0.01	0.33	−2.57	3.22
Parent grew in large city	0.005	−0.01	0.02	1.57	−3.57	6.71
Parent grew in other	0.001	−0.00	0.01	0.36	−1.22	1.95
Mediated influence of C_1: $C_1 \rightarrow Y^{P} \rightarrow C_2 \rightarrow Y^{C}$						
IQ score	0.001	−0.01	0.01	0.39	−1.80	2.58
Education (years)	0.010	−0.02	0.04	2.93	−6.52	12.38
Ethnicity: Non-white	0.001	−0.00	0.01	0.43	−0.78	1.64
Occupation: Manager	0.001	−0.00	0.01	0.24	−1.12	1.61
Occupation: Clerical	0.001	−0.00	0.00	0.31	−0.58	1.20

Occupation: craftsman	0.002	−0.01	0.01	0.67	−1.66	3.00
Occupation: operative	0.002	−0.01	0.02	0.47	−3.87	4.80
Occupation: Farmer	0.001	−0.00	0.01	0.30	−0.88	1.47
Occupation: Services	0.000	−0.00	0.00	0.10	−1.19	1.38
Occupation: Other	0.003	−0.00	0.01	1.00	−1.52	3.53
Parent grew in small town	0.000	−0.00	0.00	0.05	−1.21	1.31
Parent grew in large city	0.000	−0.01	0.01	0.10	−1.55	1.76
Parent grew in other	0.001	−0.00	0.00	0.28	−0.69	1.26
Summary						
$\Phi - Y^P \rightarrow Y^C$	0.157	0.04	0.28	45.27	16.21	74.34
$\Phi - Y^P \rightarrow C_2 \rightarrow Y^C$	0.068	−0.00	0.14	19.52	−0.74	39.78
$C_1 \rightarrow Y^P \rightarrow Y^C$	0.097	0.03	0.17	27.94	6.93	48.94
$C_1 \rightarrow Y^P \rightarrow C_2 \rightarrow Y^C$	0.025	−0.01	0.06	7.27	−3.09	17.63
Sum circumstances	0.190	0.09	0.29	54.73	25.66	83.79
Total	0.347	0.23	0.47	100.00	100.00	100.00

Notes: Individual earnings for fathers and sons only ($N = 721$) and family income for all offspring and the head of household in 1989 ($N = 2{,}021$). The parent's IQ test (0–13) was taken by the head of family in 1974. Education is a continuous variable going from 1 to 17 for the parent with the highest education in 1989. All other parental characteristics are for the head of the family in 1989. Parent's ethnicity is a binary variable that takes the value 1 for a person of colour (POC) and where the reference category is 'White'. Occupation of the head of household has 'Professional' as reference category. The reference category for where the parent grew up in is 'Farm'. Confidence interval based on a 1,000-iteration bootstrap, clustered at the parental family level, using random sampling with replacement over the whole estimation and decomposition process.

Table 5. IGE Decomposition for Family Income (All Circumstances).

	Income					
	Coefficient	95% CI	% of IGE	95% CI	Coefficient	95% CI
Unmediated influence of Φ:						
$\Phi - Y^{P} \rightarrow Y^{C}$	0.247	0.17	0.32	47.03	35.14	58.92
Mediated influence of Φ						
$\Phi - Y^{P} \rightarrow C_2 \rightarrow Y^{C}$	0.096	0.05	0.14	18.31	9.96	26.67
Unmediated influence of C_1: $C_1 \rightarrow Y^{P} \rightarrow Y^{C}$						
IQ score	0.019	−0.00	0.04	3.62	−0.42	7.65
Education (years)	0.094	0.06	0.13	17.83	11.33	24.33
Ethnicity: Non-white	−0.004	−0.03	0.02	−0.71	−4.95	3.52
Occupation: Manager	0.012	−0.00	0.03	2.32	−0.54	5.18
Occupaion: Clerical	−0.000	−0.00	0.00	−0.06	−0.55	0.44
Occupation: craftsman	0.000	−0.00	0.00	0.05	−0.33	0.43
Occupation: Operative	0.008	−0.01	0.02	1.48	−1.09	4.05
Occupation: Farmer	0.000	−0.00	0.01	0.07	−0.84	0.97
Occupation: Services	0.005	−0.01	0.02	0.91	−1.40	3.22
Occupation: Other	0.000	−0.02	0.02	0.03	−3.99	4.06
Parent grew in small town	0.002	−0.00	0.01	0.32	−0.50	1.14
Parent grew in large city	0.002	−0.00	0.01	0.39	−0.62	1.39
Parent grew in other	0.000	−0.00	0.00	0.09	−0.40	0.58
Mediated influence of C_1: $C_1 \rightarrow Y^{P} \rightarrow C_2 \rightarrow Y^{C}$						
IQ score	0.004	−0.00	0.01	0.81	−0.38	2.00
Education (years)	0.014	0.00	0.03	2.68	0.01	5.36
Ethnicity: Non-white	0.007	0.00	0.01	1.38	0.04	2.73
Occupation: Manager	0.001	−0.00	0.01	0.28	−0.60	1.15
Occupation: Clerical	0.000	−0.00	0.00	0.04	−0.12	0.19

Occupation: Craftsman	−0.000	−0.00	0.00	−0.03	−0.21	0.14
Occupation: Operative	0.003	−0.00	0.01	0.58	−0.34	1.51
Occupation: Farmer	0.001	−0.00	0.00	0.23	−0.11	0.58
Occupation: Services	0.002	−0.00	0.01	0.43	−0.38	1.24
Occupation: Other	0.011	0.00	0.02	2.03	−0.01	4.06
Parent grew in small town	−0.000	−0.00	0.00	−0.01	−0.31	0.30
Parent grew in large city	−0.000	−0.00	0.00	−0.09	−0.45	0.27
Parent grew in other	−0.000	−0.00	0.00	−0.02	−0.20	0.15
Summary						
$\Phi \rightarrow Y^P \rightarrow Y^C$	0.247	0.17	0.32	47.03	35.14	58.92
$\Phi \rightarrow Y^P \rightarrow C_2 \rightarrow Y^C$	0.096	0.05	0.14	18.31	9.96	26.67
$C_1 \rightarrow Y^P \rightarrow Y^C$	0.139	0.10	0.18	26.34	18.22	34.47
$C_1 \rightarrow Y^P \rightarrow C_2 \rightarrow Y^C$	0.044	0.02	0.06	8.31	4.24	12.38
Sum circumstances	0.279	0.22	0.34	52.97	41.08	64.86
Total	0.526	0.47	0.58	100.00	100.00	100.00

Notes: Individual earnings for fathers and sons only ($N = 721$) and family income for all offspring and the head of household in 1989 ($N = 2{,}021$). The parent's IQ test (0–13) was taken by the head of family in 1974. Education is a continuous variable going from 1 to 17 for the parent with the highest education in 1989. All other parental characteristics are for the head of the family in 1989. Parent's ethnicity is a binary variable that takes the value 1 for a person of colour (POC) and where the reference category is 'White'. Occupation of the head of household has 'Professional' as reference category. The reference category for where the parent grew up in is 'Farm'. Confidence interval based on a 1,000-iteration bootstrap, clustered at the parental family level, using random sampling with replacement over the whole estimation and decomposition process.

Among preceding circumstances, parental education accounts for the largest share of the IGE, accounting for around 21% of the IGE in total by adding up its mediated and unmediated influence. Most of this influence is unmediated: parental education does influences the income of the offspring through factors outside of mediating circumstances. For example, parental education influences choices of the offspring later in life, such as their occupation or type of job, which are strong predictors of their income.

Other preceding circumstances with an unmediated influence include the IQ score of the head of household in 1972 (around 3.5% of the IGE) and whether the father worked as a manager in 1989 (around 2.5% of the IGE). On the other hand, the ethnicity of the parent reports a mediated influence, particularly for family income (1.4%). Unfortunately, none of these circumstances are statistically significant at the 95%, so that the sample size does not allow me to draw robust conclusions from these circumstances.

Table A1 reports the same decomposition – including preceding and mediating circumstances – but detailing the latter. Consistent with the previous section, the most important circumstances relate to the holding and lack of wealth and assets. Families holding above-median savings in 1989 account for 13% of the IGE for individual earnings and 10% for family income. Families receiving food assistance in 1989 account for 6% of the IGE for individual earnings and 4% for family income. Overall, the relative contribution of mediating circumstances is fairly similar for both outcomes.

4.4. The Direct and Indirect Influence of Preceding Circumstances

In this section, I go beyond the decomposition of the IGE to account the full contribution of preceding circumstances. From Fig. 5, we see that C_1 can influence the income of the offspring 'directly', that is, outside of its contribution to parental income. This contribution does not contribute to the IGE, which focuses solely on the relationship between parent and offspring income.

From an IOp of view, we are interested in the full influence of circumstances. In most cases, that includes their influence on efforts, which is why most papers estimate a reduced-form equation similar to equation 9 (see, e.g., Ferreira & Gignoux, 2011). Therefore, a measure of IOp does not only account for the influence of parental income but also for the influence of all other circumstances. The extent to which these other circumstances influence the income of the offspring can help understand the relationship between the IGE and IOp.

Table 6 reports the decomposition into a direct component and an indirect component, as shown in equation 14. The indirect component comprises the influence of each preceding circumstance on parental income, which in turn influences offspring income and thus on the IGE. The direct component is the influence of each preceding circumstance on offspring income, not accounted for in the IGE. I report the decomposition for both earnings and for income.

To provide a measure of the 'relevance' of each circumstance, I include the R-square of an OLS regression of that circumstance on the income of the offspring. Consistent with the IGE decomposition, parental education is the most

Table 6. Influence of Preceding Circumstances Not in the IGE (% Share).

	Earnings							Income						
	Direct			Indirect			R^2	Direct			Indirect			R^2
	Coefficient	95% CI		Coefficient	95% CI			Coefficient	95% CI		Coefficient	95% CI		
IQ score	52.2	30.4	74.1	47.8	25.9	69.6	3.8	41.5	28.0	55.0	58.5	45.0	72.0	7.6
Education (years)	64.2	49.7	78.7	35.8	21.3	50.3	12.3	55.1	45.7	64.5	44.9	35.5	54.3	19.4
Ethnicity: Non-white	30.4	−108.8	169.7	69.6	−69.7	208.8	1.7	20.6	−6.4	47.7	79.4	52.3	106.4	4.7
Occupation: Professional	48.1	−60.7	156.9	51.9	−56.9	160.7	2.3	42.5	22.1	62.9	57.5	37.1	77.9	3.8
Occupation: manager	63.3	39.6	87.1	36.7	12.9	60.4	2.8	44.6	29.0	60.1	55.4	39.9	71.0	4.1
Occupation: Clerical	–	–	–	–	–		0.0	28.6	–	–	71.4	–	–	0.0
Occupation: craftsman	−30.5	–	–	130.5	–	–	0.0	143.8	–	–	−43.8	–	–	0.0
Occupation: operative	68.4	50.6	86.2	31.6	13.8	49.4	3.2	55.0	38.1	72.0	45.0	28.0	61.9	3.9
Occupation: Farmer	51.3	−58.4	161.0	48.7	−61.0	158.4	0.7	26.6	−571.7	624.8	73.4	−524.8	671.7	0.6
Occupation: services	54.2	−328.4	436.7	45.8	−336.7	428.4	1.6	36.1	−26.8	99.0	63.9	1.0	126.8	1.6
Occupation: Other	25.0	−29.5	79.6	75.0	20.4	129.5	1.7	18.3	−6.4	43.0	81.7	57.0	106.4	3.5
Parent grew in farm	43.1	–	–	56.9	–	–	1.5	47.6	−26.9	122.1	52.4	−22.1	126.9	1.2
Parent grew in small town	−17.0	–	–	117.0	–	–	0.1	48.4	–	–	51.6	–	–	0.2
Parent grew in large city	67.6	–	–	32.4	–	–	0.3	43.6	–	–	56.4	–	–	0.2
Parent grew in other	84.0	–	–	16.0	–	–	0.1	35.7	–	–	64.3	–	–	0.0

Notes: Individual earnings for fathers and sons only ($N = 721$) and family income for all offspring and the head of household in 1989 ($N = 2{,}021$). The parent's IQ test (0–13) was taken by the head of family in 1974. Education is a continuous variable going from 1 to 17 for the parent with the highest education in 1989. All other parental characteristics are for the head of the family in 1989. Parent's ethnicity is a binary variable that takes the value 1 for a person of colour (POC) and where the reference category is 'White'. Missing values reflect shares below −1,000% or above 1,000%. R^2 is the R-square of the OLS regression of that circumstance (C_j) on the income of the offspring (Y^C). Confidence interval based on a 1,000-iteration bootstrap, clustered at the parental family level, using random sampling with replacement over the whole estimation and decomposition process.

relevant circumstance under this metric. Other relevant circumstances (although much less so than education) are the IQ score of the parent, the ethnicity of the parent (only for income), and some parent's occupations, namely being a professional, a manager, or an operative. Almost all of these circumstances report statistically significant estimates at the 95% level.

The influence of parental education – the circumstance with the highest *R*-square – is mostly direct. For earnings, 64% of the contribution of education is associated with its direct contribution (55% for income). Even though parental education accounts for a large share of the IGE, most of its influence on the income of the offspring is not part of the IGE. The education of the parent has is a strong determinant of IOp, both due to its influence on the income of the parent and of the offspring.

Contrary to parental education, the ethnicity of the parent acts mostly as an indirect phenomenon, albeit with a much smaller *R*-square. Also, 70%–80% of its influence on the income of the offspring is accounted for in the IGE. This means that the ethnicity of the parent influences intergenerational persistence in income mostly through its influence on the income of the parent.

The rest of the circumstances shows a mixed picture, depending on the outcome. The IQ of the head of household in 1972 is split halfway for earnings (52% vs. 48%) but the indirect influence is stronger for income, accounting for 59% of its total influence. Having parents with a professional occupation has a similar decomposition than that of parental IQ. Having parents with an operative occupation, on the other hand, reports a mostly indirect influence (68% for earnings and 55% for income).

The two most important circumstances in terms of the *R*-square, parental education and IQ score, report an important indirect effect. Only in the case of the IQ score for income, we see a higher direct influence. Despite these circumstances accounting for a large share of the IGE, most of their influence lies outside of the relationship between parental and offspring income.

5. DISCUSSION

In this chapter, I study the relationship between estimates of the IGE and of IOp. If parental income were the only circumstance, they then would be mechanically equivalent, but this is rarely the case. I find that circumstances can explain just over half of the IGE for income and earnings. This influence is accounted for factors that precede the parent–offspring relation, namely parental individual characteristics, and factors that mediate this relation such as measures of parental wealth and their interaction. Moreover, preceding factors can have an influence that 'skips' parental income and that would be included in a measure of IOp but not in the IGE. This direct influence can be substantial in some cases, for example, accounting for two thirds of the total influence of parental education on offspring income. These findings highlight that parental income is an important circumstance on its own, but it does not summarise the full influence of parental influence as it is sometimes assumed in IGE studies.

Given these findings, can we interpret the IGE as a measure of IOp? For that to be true, Roemer (2004) proposes two conditions. That we follow a 'radical' view of IOp and that parental income perfectly summarises all circumstances. The set of circumstances in this article is closer to what Swift (2013) calls a 'conventional' view of IOp, where we include measures of socio-economic background and parental characteristics but –contrary to the radical view– we exclude measures of individual talent or innate abilities for the children's generation. Moreover, I find that circumstances such as parental education have an important influence on the income of the offspring, above and beyond that of the parent.

While closely correlated, as shown in Brunori et al. (2013), the fact that parental income does not fully capture all circumstances means that we could see changes in IOp that would not be reflected as changes in the IGE. For example, high-education parents could spent more hours playing or studying with their kids, creating a path between parental education and offspring income that is not mediated by the income of the parents. These departures not only explain why IOp and IGE estimates are not perfectly correlated but also that there are other important channels beyond income through which socio-economic background can shape inequality in the next generation.

One important caveat relates to omitted or unobserved circumstances. Due to the residual nature of this approach, omitted circumstances will contribute to the 'unexplained' part of the IGE (the part stemming from Φ). This problem is common in the IOp literature and results in 'lower bound' estimates of IOp (Carranza, 2020). Additional circumstances will change the decomposition to the extent that they do not correlate with currently observed circumstances. Future research could include additional circumstances to explain this decomposition.

One avenue of future research to pursue is whether intergenerational mobility in other outcomes could provide a better proxy of IOp. Roemer (2004) suggests that education could be one. Wealth is another outcome that could better reflect circumstances. One way to think of this challenge is to frame it as a prediction problem, as Brunori et al. (2018) have done for the measurement of IOp. In this context, the 'best' outcome – and thus the best measure of mobility – would be the best at predicting a large set of circumstances on its own.

In addition, the decomposition of the IGE could be further expanded to acknowledge different paths. Haveman and Wolfe (1995) and Bowles and Gintis (2002) develop models with such structures, where paths can reflect investments in time, monetary investments, and genetic transmission, among others, and these factors mediate the association between parental and offspring income through education or training. Decomposing the paths through which parents characteristics and choices shape the outcomes of their children could help in understanding the mechanisms behind the IGE, potentially bringing important insights on how and why parental circumstances shape children's outcomes.

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NOTES

1. The IQ test was taken in 1972 by all heads of family at the time (aged 17 and older, 43 years on average). It includes 13 basic logic questions such as *we only see (blank) at night*, offering five potential responses (the answer being 'stars' in this case). I assign this value to the parents in 1989. The test was not necessarily taken by the 1989 head of the family, for example, if a 1989 head of family lived with their parents in 1972. In such a case, that 1989 head of family will have had the test taken by one of their parents, that is, the grandparent of my offspring cohort. Among all heads in 1989, around half were not the head of family in 1972. This is the group that reports the IQ score of their parent. As such, it should be interpreted as a rough measure of 'family abilities'.
2. Bourguignon (2018) shows that the R-square can be interpreted as a measure of relative IOp if our inequality index is the variance of the logarithm of the predicted outcome, Varlog.
3. I discuss the implications of following such a view in Section D of the Appendix 1.
4. The PSID includes two samples, the Survey Research Center (SRC), a national sampling frame, and the Survey of Economic Opportunity (SEO), aimed at oversampling low income households. I exclude the SEO sample due to certain irregularities in its sampling. This choice has also been taken in previous articles such as Lee and Solon (2009) and Mazumder (2016).
5. Among the matched sample, 0.04% of respondents have three or more parents in the data (e.g. two biological parents and one adoptive parent). There are seven cases with three parents in the same household, with at least one parent with no information on its relation to the 1989 head of the family unit (ER30608 = 0). I exclude these cases from the final sample.
6. Following Mazumder (2016, 2018) and with the goal of comparability in mind, I focus on total rather than equivalised income.
7. The large difference in number of observations has to do with two reasons. First, earnings only look at father–sons pairs. Second, the earnings sample include individuals with positive earnings while the income sample includes individuals with positive household income.
8. For a detailed discussion on what constitutes a circumstance, see, for example, Cohen (1999), Bowles and Gintis (2002), Roemer (2004), Swift (2004), Jencks and Tach (2006), and Torche (2015).
9. Life cycle adjustments can make an important difference when estimating the IGE, particularly for earnings. For example, Lee and Solon (2009) control for the interaction between parental income and a quartic polynomial of parental and offspring's age. Using their approach and centring the estimates around age 35, my IGE estimates increase to 0.58 for earnings and 0.61 for income. Accounting for this adjustment in my decomposition would require the inclusion of an additional term to reflect the inclusion of the age variables and their interactions.
10. I report a series of robustness checks and extensions in Appendix 1. My findings are robust to different age cut-offs, to income and earnings being averaged across different numbers of years. I extend the analysis to explore the presence of potential non-linearities across the distribution.

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APPENDIX 1. ROBUSTNESS CHECKS AND EXTENSIONS

A. The IGE Decomposition

The main assumption in this decomposition approach is that parental characteristics can be interpreted as circumstances as they are measured when the offspring was at most 20 years of age. That restriction imposes a trade-off between sample size and the cut-off age. For that reason, I re-estimate the decomposition for two additional samples based on two different cut-offs: 18 and 22 years of age – roughly speaking, at the end of secondary education and the end of post-secondary education, respectively. The 18 years of age cut-off reinforces the idea that circumstances should be measured when the offspring was young, while the 22 years of age cut-off allows for a larger sample while still falling within a reasonable 'responsibility threshold'.

I also explore the minimum number of years used to average earnings and income. My decomposition restricts the sample to individuals with at least six years of data (and with a maximum of nine years). As a robustness check, I re-estimate the decomposition by including individuals with five, four, and three years of outcome data. Given that most respondents have nine years of data, the increment in the sample size of including additional individuals is limited. Nonetheless, I present the results of both robustness checks in Table A2.

I first compare the different age cut-offs for the sample of individuals with six to nine years of data, shown in the last rows of Table A2. Columns 3 and 4 ('20 or younger in 1989') report the benchmark findings for the sample of offspring who were at most 20 years of age in 1989. There is a slight increase in the IGE for earnings the older the sample, going from 0.33 to those 18 or younger in 1989 to 0.37 for those 22 or younger in 1989. However, the share accounted for by circumstances remains relatively unchanged and around 54%. For income, the IGE almost does not change for the sub-18, sub-20, or sub-22 samples. There is a slight decrease in the share accounted for by circumstances in the first sample, falling from around 53% to 50%. Overall, the change in the age cut-off when the offspring was young makes a small difference in the IGE decomposition for earnings and almost no difference for income.

Including individuals with less than six years of data makes almost no difference for the IGE estimates. As expected, the IGE decreases slightly (1 percentage point) when including individuals with three years of data, as outcome measures are less precise hence reducing the association between parents and offspring. For income, the inclusion of individuals with fewer years of data does not change the share accounted for by circumstances, but it does increase for earnings. Circumstances account for up to eight more percentage points (from 55% to 63% for the sub-20 sample) when including individuals with three years of data. One explanation could be the smaller size of the earnings sample. However, these changes fall well within the confidence intervals of the earnings decomposition (see Table 4).

B. The Total Influence of Preceding Circumstances

In this section, I re-estimate Table 6 with the sub-18 and sub-22 years of age samples. Results are shown in Table A3. The different age cut-offs make little to no difference in the direct/indirect decomposition. The direct influence of parental education lies between 62% and 64% for earnings and 53%–57% for income. The direct influence of the IQ score lies between 52% and 56% for earnings and 39% and 46% for income. Overall, and similar to the previous subsection, these changes fall well within the confidence intervals of the benchmark decomposition.

C. Non-linear Decomposition: A Quantile Regression Approach

As a final extension, I explore the existence of non-linear effects. In a recent paper, Palomino et al. (2018) study how the IGE changes across the income distribution, finding that the IGE is highest at the bottom of the distribution. Following their approach, I re-estimate my decomposition using quantile regressions for different percentiles of the income distribution. I focus on family income as an outcome, because the small sample size for earnings does not allow for a proper quantile analysis.

I present two results. First, I report the share of the IGE accounted by circumstances (i.e. the components associated with circumstances in equation 14). That is, the total contribution of circumstances to the IGE. Second, I focus solely on the most relevant circumstance – parental education – and study its direct influence (i.e. the influence not passing through parental income in equation 14). For each, I also report the 95% confidence interval.

Concretely, Fig. A2 reports the share of the IGE not attributed to parental income. Given equations 7–9, this share is represented by $1-\left(\hat{\theta}_2 / \hat{\beta}\right)$, where the 'hat' represents the OLS estimate.

Similarly, Fig. A3 reports the share of the total contribution of parental education not accounted for by the IGE. If we call ω the regression coefficient of parental income on the income of the offspring, then this share is represented by $\left(\hat{\rho}_{2j}+\hat{\theta}_2\hat{\kappa}_j\right)/\hat{\omega}$.

The share of the IGE accounted for by all circumstances is higher around the third decile and at the top of the distribution. However, the overall distribution appears to be homogeneous around the average. As the confidence intervals for these estimations are quite large – due to the small sample size – no point departure from the average is statistically significant.

The direct contribution of parental education is smaller at the bottom of the distribution. This finding is consistent with Palomino et al. (2018), who find that the mediating share of education (i.e. its indirect influence) is higher at the bottom of the distribution. Nonetheless, the confidence intervals are too large to say anything substantial about the distribution.

D. Treating Circumstances as 'Parental Effort'

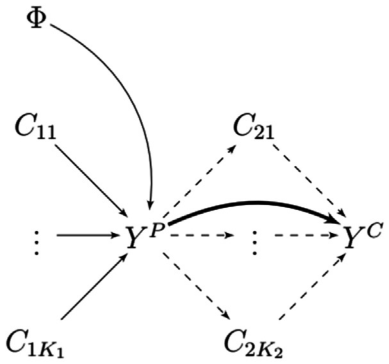
In Section 2.5, I discussed the distinction between circumstances and effort, and how it might not be clear-cut for some factors. This is the case for certain circumstances that can be labelled as 'parental effort', namely education, occupation, and IQ score. From a multigenerational view – also called by Kanbur and Stiglitz (2016) a dynastic perspective – only 'exogenous' factors would be truly circumstances. In such a case, the 'optimal' level for the IGE would allow differences in children's income due to differences in parental effort.

We can repeat the analysis presented in Section 4.3, excluding education, occupation, and IQ score as circumstances. I report these findings in Table A5. We see that the remaining circumstances now account for 35%–40% of the IGE and that mediating circumstances gain in relative importance, now accounting for over 30% of the IGE. This means that the two remaining preceding circumstances, ethnicity and place of birth, have very little predictive power and that the contribution of preceding circumstances is driven by parental effort.

We can confirm these findings by looking at the second panel of Table A5. If we only include parental effort among preceding circumstances, we get very similar findings to those reported in this article, with circumstances accounting for one percentage point less than in my main findings. In other words, 'exogenous' circumstances such as ethnicity and place of birth provide very little additional information to (i.e. they are strongly correlated with) parental efforts.

The remaining question is why does parental effort have such an important role in shaping income inequalities for the next generation. We can think of reasons with very different normative implications. If high-status parents are over-investing to secure a privileged position, we can think of this mechanism as morally illegitimate. Indeed, opportunity hoarding is not only viewed as unfair but also as inefficient. On the other hand, parents who exerted high effort instil preferences for effort on their children can be construed as tolerable mechanism. The challenge ahead is to better understand these mechanisms, explaining why do high-education parents tend to have high-income children.

APPENDIX 2: ADDITIONAL TABLES AND FIGURES



Note: Extended version of Figure 3 with each one of the K_1 circumstances in C_1 and the K_2 circumstances in C_2. Circumstances in each vector do not influence other circumstances within the same vector. Circumstance in C_1 influence every elements of C_2. The dashed lines represent the mediated components (that pass through C_2). The bold line between Y^P and Y^C represents the unmediated components.

Fig. A1. Channels of Transmission Including Two Factors (Extended).

Table A1. IGE Decomposition (Mediating Circumstances).

	Earnings						Income					
	Coefficient	95% CI		% of IGE	95% CI		Coefficient	95% CI		% of IGE	95% CI	
$\Phi \rightarrow Y^{P} \rightarrow Y^{C}$	0.157	0.038	0.276	45.27	16.21	74.34	0.247	0.172	0.323	47.03	35.14	58.92
$\Phi \rightarrow Y^{P} \rightarrow C_2 \rightarrow Y^{C}$												
Homeowner	0.011	−0.020	0.043	3.24	−6.23	12.72	0.016	−0.010	0.042	3.07	−1.91	8.06
Region: Mideast	0.007	−0.013	0.027	2.02	−4.01	8.05	0.000	−0.005	0.006	0.04	−1.00	1.09
Region: Great lakes	0.000	−0.013	0.014	0.07	−4.18	4.31	−0.001	−0.007	0.005	−0.20	−1.33	0.93
Region: Plains	0.002	−0.026	0.030	0.57	−8.23	9.37	0.001	−0.010	0.012	0.18	−1.87	2.23
Region: Southeast	0.000	−0.011	0.012	0.06	−3.41	3.52	0.002	−0.006	0.011	0.45	−1.13	2.04
Region: Southwest	0.000	−0.015	0.016	0.11	−4.78	5.00	0.000	−0.006	0.007	0.07	−1.21	1.35
Region: Rocky mountains	0.003	−0.012	0.017	0.74	−3.68	5.16	0.002	−0.005	0.010	0.44	−1.05	1.93
Region: Far west	−0.007	−0.035	0.020	−2.15	−12.45	8.14	−0.003	−0.014	0.009	−0.53	−2.73	1.66
Region: Outside United States	−0.009	−0.031	0.013	−2.71	−10.17	4.75	−0.003	−0.008	0.003	−0.48	−1.48	0.51
Region: No answer	0.000	−0.001	0.001	0.01	−0.31	0.32	−0.000	−0.001	0.001	−0.00	−0.21	0.21
Over median: Business	−0.000	−0.007	0.007	−0.03	−2.06	2.00	−0.002	−0.011	0.008	−0.29	−2.14	1.57
Over median: Stocks	−0.005	−0.035	0.025	−1.48	−10.96	7.99	0.012	−0.004	0.029	2.29	−0.84	5.42
Over median: Savings	0.044	0.010	0.079	12.78	2.11	23.46	0.051	0.029	0.074	9.74	5.39	14.09
Used food stamps	0.022	−0.008	0.052	6.31	−3.62	16.24	0.019	−0.004	0.042	3.53	−0.90	7.96
$C_1 \rightarrow Y^{P} \rightarrow Y^{C}$	0.097	0.026	0.168	27.94	6.93	48.94	0.139	0.095	0.182	26.34	18.22	34.47
$C_1 \rightarrow Y^{P} \rightarrow C_2 \rightarrow Y^{C}$												
Homeowner	0.000	−0.004	0.004	0.08	−1.08	1.24	0.001	−0.002	0.005	0.25	−0.45	0.95
Region: Mideast	0.002	−0.008	0.011	0.53	−2.45	3.50	0.000	−0.003	0.003	0.01	−0.61	0.63
Region: Great lakes	−0.000	−0.014	0.014	−0.14	−4.45	4.18	0.001	−0.004	0.007	0.28	−0.83	1.39
Region: Plains	0.000	−0.005	0.006	0.06	−1.56	1.68	−0.001	−0.008	0.007	−0.12	−1.50	1.25
Region: Southeast	0.000	−0.014	0.015	0.14	−4.33	4.61	0.007	−0.005	0.018	1.30	−0.97	3.56

(*Continued*)

Table A1. (Continued)

	Earnings						Income					
	Coefficient	95% CI		% of IGE	95% CI		Coefficient	95% CI		% of IGE	95% CI	
Region: Southwest	0.000	−0.008	0.008	0.05	−2.38	2.49	−0.003	−0.008	0.003	−0.48	−1.54	0.57
Region: Rocky mountains	−0.002	−0.013	0.009	−0.58	−3.80	2.64	−0.002	−0.009	0.005	−0.41	−1.76	0.94
Region: Far west	0.003	−0.009	0.014	0.73	−3.07	4.52	0.001	−0.004	0.007	0.23	−0.81	1.26
Region: Outside United States	0.005	−0.004	0.013	1.36	−1.39	4.11	0.003	−0.002	0.007	0.53	−0.35	1.41
Region: No answer	−0.000	−0.001	0.001	−0.01	−0.22	0.21	−0.000	−0.001	0.001	−0.01	−0.13	0.11
Over median: Business	−0.001	−0.008	0.007	−0.22	−2.40	1.96	−0.001	−0.005	0.004	−0.13	−1.01	0.75
Over median: Stocks	−0.002	−0.016	0.011	−0.67	−4.95	3.61	0.004	−0.002	0.010	0.81	−0.38	1.99
Over median: Savings	0.020	0.002	0.039	5.89	−0.34	12.12	0.025	0.012	0.037	4.66	2.26	7.06
Used food stamps	0.000	−0.004	0.005	0.06	−1.44	1.56	0.007	−0.003	0.018	1.40	−0.57	3.37
Summary												
$\Phi \rightarrow Y^{P} \rightarrow Y^{C}$	0.157	0.038	0.276	45.27	16.21	74.34	0.247	0.172	0.323	47.03	35.14	58.92
$\Phi \rightarrow Y^{P} \rightarrow C_2 \rightarrow Y^{C}$	0.068	−0.002	0.137	19.52	−0.74	39.78	0.096	0.053	0.139	18.31	9.96	26.67
$C_1 \rightarrow Y^{P} \rightarrow Y^{C}$	0.097	0.026	0.168	27.94	6.93	48.94	0.139	0.095	0.182	26.34	18.22	34.47
$C_1 \rightarrow Y^{P} \rightarrow C_2 \rightarrow Y^{C}$	0.025	−0.006	0.057	7.27	−3.09	17.63	0.044	0.023	0.065	8.31	4.24	12.38
Sum circumstances	0.190	0.086	0.294	54.73	25.66	83.79	0.279	0.218	0.339	52.97	41.08	64.86
Total	0.347	0.225	0.469	100.00	100.00	100.00	0.526	0.469	0.583	100.00	100.00	100.00

Notes: Individual earnings for fathers and sons only ($N = 721$) and family income for all offspring and the head of household in 1989 ($N = 2{,}021$). All circumstances measured for the head of family in 1989. Homeowner: parent owning a house in 1989. Region where born has 'New England' as the reference category. 'Outside US' category includes US territories. The asset variables (including the use of the Food Stamp programme, renamed SNAP in 2008) takes the value 1 for those parents above the median in 1989 (e.g. by being above the median value of the food stamp benefit or by having above-median savings). Confidence interval based on a 1,000-iteration bootstrap, clustered at the parental family level, using random sampling with replacement over the whole estimation and decomposition process.

Table A2. Robustness Check – Outcome Averages and Age Cut-offs.

	Earnings Income		Income		Earnings Income		Income		Earnings Income		Income	
	Coeffient Share	Share	Coeffient Share	Share	Coeffient Share	Share	Coeffient Share	Share	Coeffient Share	Share	Coeffient	Share
3–9 Years average												
$\Phi \rightarrow Y^C$	0.11	35.8	0.26	49.9	0.13	37.1	0.24	46.6	0.15	41.9	0.25	47.5
$\Phi \rightarrow C_2 \rightarrow Y^C$	0.08	24.3	0.08	15.7	0.08	23.3	0.09	18.1	0.07	19.4	0.09	16.9
$C_1 \rightarrow Y^C$	0.11	33.2	0.14	27.2	0.10	30.8	0.14	26.7	0.11	32.1	0.15	28.1
$C_1 \rightarrow C_2 \rightarrow Y^C$	0.02	6.7	0.04	7.2	0.03	8.7	0.04	8.5	0.02	6.7	0.04	7.4
Circumstances	0.21	64.2	0.26	50.1	0.21	62.9	0.28	53.4	0.20	58.1	0.27	52.5
Total	0.32	100.0	0.53	100.0	0.34	100.0	0.52	100.0	0.35	100.0	0.52	100.0
4–9 Years average												
$\Phi \rightarrow Y^C$	0.13	39.3	0.27	50.4	0.14	40.0	0.25	46.9	0.16	44.0	0.25	47.7
$\Phi \rightarrow C_2 \rightarrow Y^C$	0.07	23.0	0.08	15.5	0.08	22.1	0.09	18.1	0.07	18.6	0.09	17.0
$C_1 \rightarrow Y^C$	0.10	31.1	0.14	27.0	0.10	29.3	0.14	26.6	0.11	30.9	0.14	28.0
$C_1 \rightarrow C_2 \rightarrow Y^C$	0.02	6.7	0.04	7.2	0.03	8.6	0.04	8.4	0.02	6.5	0.04	7.3
Circumstances	0.20	60.7	0.26	49.6	0.20	60.0	0.28	53.1	0.20	56.0	0.27	52.3
Total	0.32	100.0	0.53	100.0	0.34	100.0	0.52	100.0	0.35	100.0	0.52	100.0
5–9 Years average												
$\Phi \rightarrow Y^C$	0.13	39.0	0.27	50.5	0.14	40.4	0.25	47.0	0.16	44.1	0.25	47.7
$\Phi \rightarrow C_2 \rightarrow Y^C$	0.07	23.0	0.08	15.6	0.07	21.7	0.10	18.2	0.07	18.8	0.09	17.0
$C_1 \rightarrow Y^C$	0.10	31.3	0.14	26.7	0.10	30.0	0.14	26.4	0.11	31.2	0.14	27.9
$C_1 \rightarrow C_2 \rightarrow Y^C$	0.02	6.7	0.04	7.2	0.03	7.9	0.04	8.4	0.02	5.9	0.04	7.4
Circumstances	0.20	61.0	0.26	49.5	0.20	59.6	0.28	53.0	0.20	55.9	0.27	52.3
Total	0.32	100.0	0.53	100.0	0.34	100.0	0.52	100.0	0.36	100.0	0.52	100.0
6–9 Years average												
$\Phi \rightarrow Y^C$	0.15	46.8	0.27	50.5	0.16	45.3	0.25	47.0	0.18	48.0	0.25	47.7
$\Phi \rightarrow C_2 \rightarrow Y^C$	0.06	19.3	0.08	15.7	0.07	19.5	0.10	18.3	0.06	16.9	0.09	17.1
$C_1 \rightarrow Y^C$	0.09	27.9	0.14	26.7	0.10	27.9	0.14	26.3	0.11	29.3	0.14	27.8
$C_1 \rightarrow C_2 \rightarrow Y^C$	0.02	5.9	0.04	7.0	0.03	7.3	0.04	8.3	0.02	5.8	0.04	7.3
Circumstances	0.17	53.2	0.26	49.5	0.19	54.7	0.28	53.0	0.19	52.0	0.27	52.3
Total	0.33	100.0	0.53	100.0	0.35	100.0	0.53	100.0	0.37	100.0	0.52	100.0

Notes: Sample size differs for each estimation. For the sub-18 sample, for earnings and income, respectively: 720 and 1,911 (3+ years), 760 and 2,036 (4+ years), 812 and 2,159 (5+ years), 708 and 1,909 (6 years). For the sub-20 samples: 747 and 2,034 (3+ years), 799 and 2,157 (4+ years), 697 and 1,902 (5+ years), 734 and 2,027 (6 years). For the sub-22 samples: 783 and 2,148 (3+ years), 683 and 1,896 (4+ years), 720 and 2,021 (5+ years), 769 and 2,142 (6 years).

Table A3. Robustness Check for Influence of C_1: Age Cut-offs.

	18 or Younger in 1989				20 or Younger in 1989				22 or Younger in 1989			
	Earnings		Income		Earnings		Income		Earnings		Income	
	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect
IQ score	53.4	46.6	39.0	61.0	52.2	47.8	41.5	58.5	56.3	43.7	45.5	54.5
Education (years)	64.2	35.8	52.5	47.5	64.2	35.8	55.1	44.9	62.1	37.9	56.7	43.3
Ethnicity: Non-white	31.2	68.8	16.7	83.3	30.4	69.6	20.6	79.4	24.8	75.2	20.0	80.0
Occupation: Professional	44.9	55.1	39.3	60.7	48.1	51.9	42.5	57.5	53.9	46.1	46.0	54.0
Occupation: Manager	65.3	34.7	44.1	55.9	63.3	36.7	44.6	55.4	59.4	40.6	47.5	52.5
Occupation: Clerical	213.0	−113.0	46.9	53.1	.	.	28.6	71.4	551.5	−451.5	−437.3	537.3
Occupation: Craftsman	35.9	64.1	128.9	−28.9	−30.5	130.5	143.8	−43.8	−38.8	138.8	110.8	−10.8
Occupation: Operative	66.9	33.1	51.5	48.5	68.4	31.6	55.0	45.0	66.3	33.7	55.5	44.5
Occupation: Farmer	15.6	84.4	30.0	70.0	51.3	48.7	26.6	73.4	48.3	51.7	24.0	76.0
Occupation: Services	56.3	43.7	37.3	62.7	54.2	45.8	36.1	63.9	50.6	49.4	41.7	58.3
Occupation: Other	26.9	73.1	15.3	84.7	25.0	75.0	18.3	81.7	27.3	72.7	20.2	79.8
Parent grew in farm	37.1	62.9	40.6	59.4	43.1	56.9	47.6	52.4	45.7	54.3	38.9	61.1
Parent grew in small town	−186.1	286.1	44.2	55.8	−17.0	117.0	48.4	51.6	15.8	84.2	62.2	37.8
Parent grew in large city	68.9	31.1	29.8	70.2	67.6	32.4	43.6	56.4	53.6	46.4	−10.2	110.2
Parent grew in other	96.2	3.8	30.7	69.3	84.0	16.0	35.7	64.3	102.2	−2.2	11.3	88.7

Note: Sample size differs for each estimation. For the sub-18 sample, for earnings and income, respectively: 708 and 1,909. For the sub-20 samples: 734 and 2,021. For the sub-22 samples: 769 and 2,142. The parent's IQ test (0–13) was taken by the head of family in 1974. Education is a continuous variable going from 1 to 17 for the parent with the highest education in 1989. All other parental characteristics are for the head of the family in 1989. Parent's ethnicity is a binary variable that takes the value 1 for a person of colour (POC) and where the reference category is 'White'. Missing values reflect shares below −1,000% or above 1,000%.

Table A4. Linear Regression for Each Outcome.

Variables	(1) Earnings	(2) Earnings	(3) Earnings	(4) Income	(5) Income	(6) Income
Parental earnings	0.351***	0.228***	0.158***			
		(0.057)	(0.057)			
Parental income				0.526***	0.344***	0.247***
				(0.025)	(0.028)	(0.034)
IQ score		0.025	0.022		0.022**	0.018**
		(0.015)	(0.015)		(0.009)	(0.009)
Education (years)		0.044**	0.038**		0.056***	0.049***
		(0.019)	(0.016)		(0.009)	(0.008)
Ethnicity: Non-white		0.095	0.165		−0.021	0.022
		(0.109)	(0.106)		(0.063)	(0.061)
Occupation: Professional		−0.156	−0.144		−0.094**	−0.084*
		(0.100)	(0.095)		(0.047)	(0.045)
Occupation: Clerical		0.059	0.034		−0.102*	−0.107*
		(0.127)	(0.125)		(0.062)	(0.062)
Occupation: Craftsman		−0.078	−0.038		−0.082*	−0.047
		(0.066)	(0.065)		(0.042)	(0.043)
Occupation: Operative		−0.200**	−0.176**		−0.193***	−0.155***
		(0.088)	(0.075)		(0.052)	(0.050)
Occupation: Farmer		−0.590	−0.532		−0.182	−0.103
		(0.406)	(0.372)		(0.115)	(0.106)
Occupation: Services		−0.116	−0.082		−0.211***	−0.163**
		(0.134)	(0.126)		(0.081)	(0.081)
Occupation: Other		−0.317*	−0.205		−0.180***	−0.085
		(0.180)	(0.204)		(0.066)	(0.071)
Parent grew in farm		–	–			
Parent grew in small town		0.028	0.028		0.088	0.106
		(0.073)	(0.071)		(0.087)	(0.081)
Parent grew in large city		0.087	0.085		0.088	0.117
		(0.073)	(0.072)		(0.089)	(0.083)
Parent grew in other		0.175	0.102			
		(0.128)	(0.114)			
Homeowner			0.062			0.051
			(0.062)			(0.037)

(*Continued*)

Table A4. (Continued)

Variables	(1) Earnings	(2) Earnings	(3) Earnings	(4) Income	(5) Income	(6) Income
Region: Mideast			0.145			0.014
			(0.143)			(0.077)
Region: Great lakes			0.023			−0.060
			(0.137)			(0.074)
Region: Plains			−0.017			−0.016
			(0.147)			(0.078)
Region: Southeast			−0.002			−0.105
			(0.141)			(0.076)
Region: Southwest			0.013			−0.195**
			(0.151)			(0.095)
Region: Rocky mountains			−0.063			−0.062
			(0.166)			(0.091)
Region: Far west			−0.140			−0.047
			(0.224)			(0.088)
Region: Outside United States			0.553**			0.317
			(0.263)			(0.203)
Region: No answer			−0.064			−0.055
			(0.136)			(0.287)
Over median: Business			−0.022			−0.016
			(0.078)			(0.046)
Over median: Stocks			−0.021			0.058
			(0.064)			(0.036)
Over median: Savings used food stamps			0.188*** (0.068)			0.190*** (0.038)
			−0.216* (0.117)			−0.128* (0.069)
Parent grew in farm					0.047	0.064
					(0.088)	(0.084)
Parent grew in other					–	–
Constant	7.036***	7.542***	8.212***	5.317***	6.381***	7.427***
	(0.623)	(0.614)	(0.640)	(0.276)	(0.308)	(0.373)
Observations	725	725	725	2,021	2,021	2,021
R-squared	0.093	0.152	0.200	0.257	0.315	0.346

Note: Standard errors in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

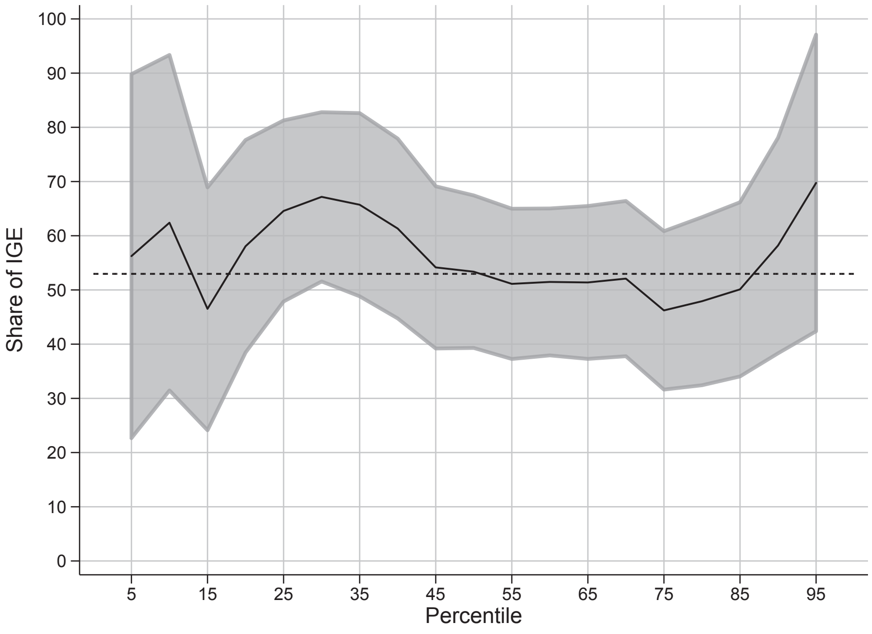


Fig. A2. IGE Decomposition: Quantile Regression.

Notes: Quantile regression estimation for parental family income on offspring family income, with and without controlling for all other circumstances ($N = 2{,}021$). Confidence interval based on a 100-iteration bootstrap, clustered at the parental family level, using random sampling with replacement over the whole estimation process.

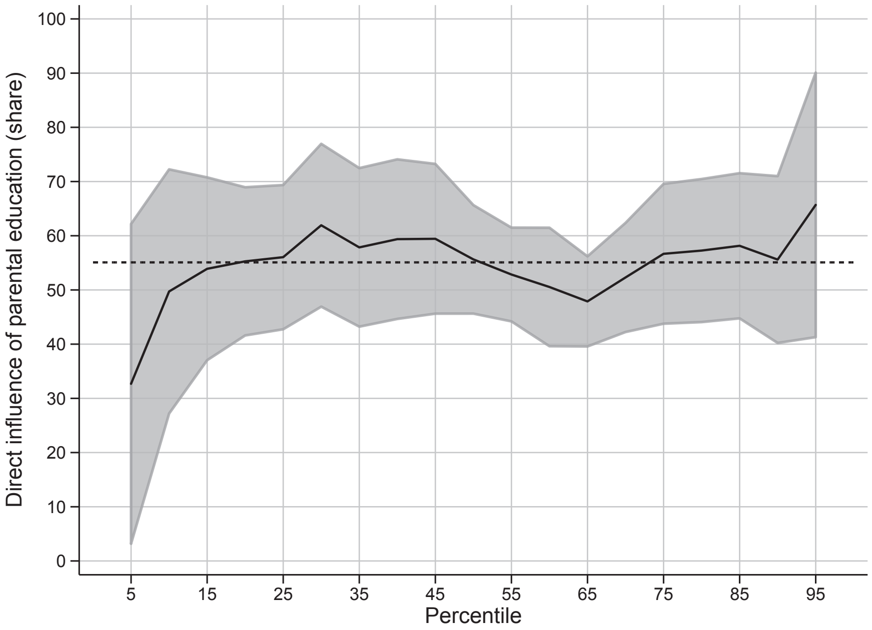


Fig. A3. Direct Influence of Parental Income: Quantile Regression.
Notes: Quantile regression estimation for parental education on offspring family income, with and without controlling for parental family income ($N = 2{,}021$). Confidence interval based on a 100-iteration bootstrap, clustered at the parental family level, using random sampling with replacement over the whole estimation process.

Table A5. Treating Circumstances as 'Parental Effort'.

	Coefficient	Shares	Coefficient	Shares
Decomposition excluding 'parental effort' in C_1				
$\Phi \rightarrow Y^{P} \rightarrow Y^{C}$	0.21	59.5	0.34	65.1
$\Phi \rightarrow Y^{P} \rightarrow C_2 \rightarrow Y^{C}$	0.13	35.8	0.16	30.3
$C_1 \rightarrow Y^{P} \rightarrow Y^{C}$	0.01	3.1	0.01	2.1
$C_1 \rightarrow Y^{P} \rightarrow C_2 \rightarrow Y^{C}$	0.01	1.7	0.01	2.5
Sum indirect	0.14	40.5	0.18	34.9
IGE	0.351	100	0.526	100
Decomposition including 'parental effort' only in C_1				
$\Phi \rightarrow Y^{P} \rightarrow Y^{C}$	0.16	46.4	0.25	48.1
$\Phi \rightarrow Y^{P} \rightarrow C_2 \rightarrow Y^{C}$	0.07	18.5	0.10	18.3
$C_1 \rightarrow Y^{P} \rightarrow Y^{C}$	0.10	28.3	0.14	26.3
$C_1 \rightarrow Y^{P} \rightarrow C_2 \rightarrow Y^{C}$	0.02	6.7	0.04	7.4
Sum indirect	0.19	53.6	0.27	51.9
IGE	0.351	100	0.526	100