How much of intergenerational immobility can be attributed to differences in childhood circumstances?

Rafael Carranza*

INET and Department of Social Policy and Intervention
University of Oxford

This version: February 27, 2021

Preliminary draft: Please do not cite.

*rafael.carranzanavarrete@spi.ox.ac.uk.

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 (PSID) for the US, 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.
JEL Classification: D31, D63, J62.

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 the same outcome for the parent (Jäntti and Jenkins, 2015). IOp estimates quantify the explanatory power – for example, through the R-squared of a linear regression – of a set of factors over which we have no control, typically referred to as circumstances (Roemer and Trannoy, 2015). If parental income is the only circumstance, then the IGE and the IOp estimate share the same functional form and Bourguignon (2018, pp. 114–115) shows how the IGE and IOp are directly associated. In this paper, however, 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.

The IGE literature does not delve on the sources of persistence and thus avoids discussions on the 'optimal' level of mobility. On the other hand, achieving equality of opportunity means an IOp index of zero. This has explicit implications for how the influence of parental income is treated in each case. In the IGE case only part of the influence of parental income is treated as an illegitimate source of persistence (a 'circumstance'), whereas all of its influence – and indeed more than that – is considered as circumstance.

The influence of circumstances interacts with 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 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. Third, circumstances can directly influence the income of the offspring. 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 ways.

I base my framework on the recursive models of Conlisk (1974, 1977), Leibowitz (1974), Atkinson (1983), Jenkins (1985), among others (see Haveman and 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 Figure 1.

Figure 1: Parental income as the only circumstance

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

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

Mediating circumstances (C_2) intervene in this relationship splitting the association between parental and offspring income into two: a direct and and an indirect path, as shown in Figure 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).

Preceding circumstances (C_1) pre-date parental income. If we focus solely on the IGE, that is, the relationship between parental and offspring income, then preceding circumstances can only have an influence to the extent that they are

Figure 2: Parental income and mediating circumstances

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

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

correlated to parental income, as shown in Figure 3.

Figure 3: Parental income, preceding, and mediating circumstances

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

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

Figures 2 and 3 tell us how much of intergenerational immobility (in income) can attributed to differences in childhood circumstances but there are be other factors at play. In an empirical exercise, for example, unobserved circumstances will not be considered. There might be other factors that also influence parental income, such as factors not deemed as circumstances. Jencks and Tach (2006) argue that innate talent is one such factor, in which case innate talent might contribute to the IGE but would not be considered a source of IOp. To account for these factors, Figure 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.

Figure 4: Parental income, preceding, and mediating circumstances

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

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 model in Figure 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. Hence 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.

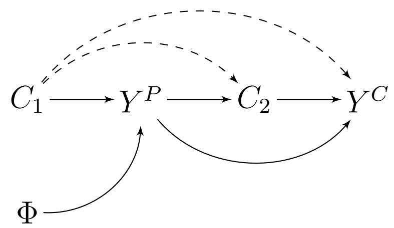
The idea of an 'optimal' level of intergenerational immobility relates to whether we can interpret these estimates as a measure of inequality of opportunity or not. Black and Devereux (2011) state that while people tend to favour equality of opportunity as a goal, zero intergenerational correlation is 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.

It is important to note that most (if not all) inequality of opportunity studies treat parental income as a circumstance. This is because most IOp estimates (whether by choice or due to lack of additional data on circumstances) follow a 'conventional' definition of IOp where outcomes depend on people's ability and effort, but not on their socioeconomic background (Cohen, 2009; Swift, 2013). This interpretation is inconsistent with the idea that the 'optimal' level of intergenerational immobility is anything but zero, as equality of opportunity is achieved when the influence of all circumstances is eliminated.[1] While there are nuances to this argument, for example, that we might tolerate some aspects of family influence (see Swift (2013, pp. 181–188) for a discussion) I treat parental income as a circumstance. In light of that, the residual term U in Figure 5 can be interpreted as a measure of unobserved circumstances.

[1] One way for the treatment of parental income as a circumstances to be consistent with

The final step of this model is to address the direct influence of circumstances. Concretely, preceding circumstances can influence mediating circumstances (for example, if the parent's occupations requires them to move to a different area) or the offspring income (if their children opt for the same occupation), as shown in Figure 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.

Figure 5: Direct and indirect influence of preceding 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. The dashed paths represent the influence of preceding circumstances outside that of parental income.

Such a decomposition is highly demanding in terms of data. It requires information on the income of the offspring and their parents, ideally at a similar age. It also requires information on circumstances, preferably measured or reported by the parents themselves when they happened rather than retrospectively by their offspring. For that reason, I use Panel Study of Income Dynamics (PSID). The PSID is a longitudinal panel survey in the US, starting on 1968 with 4,800 families and following them, their offspring, and all future generations, with the last survey carried out on 2017. Because of its long-running and exhaustive nature, the PSID has been extensively used to estimate intergenerational mobility patterns in the US (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 to 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 to 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 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% 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 Figures 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 (in years) explaining over a third of that contribution. Both high savings and parental education make substantial contributions to the IGE, but the influence of parental education on savings accounts for a negligible share of the their total contribution. Overall, few circumstances account for most of the IGE, with very little interaction among them.

The direct influence of circumstances (specifically, of preceding circumstances) accounts for a large part of their total influence the income of the offspring. Over half of the contribution of parental education – the circumstance that accounts for most of the IGE – does not 'pass' through parental income (55% in the case of earnings, 64% in the case of income). While childhood circumstances explain most of the IGE, they also have an influence beyond the correlation for the income of the parents and their children. If we care about equality of opportunity, we need to consider that influence when discussing intergenerational immobility patterns.

This paper contributes to the literature on intergenerational persistence in two ways. First, I expand on the literature of IGE decomposition that has focused on mediators between parents and their offspring. I 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 paper have noted their isomorphism and similarities (Brunori et al., 2013; Ferreira and Gignoux, 2014; Bourguignon, 2018), but no paper to date has provided a systematic way to study the relationship between parental income and other circumstances, and their influence of the income of the offspring.

2 An 'IOp' decomposition of the intergenerational elasticity and beyond

2.1 Decomposition framework

In this section I model the interaction between the income of the parent, the income of the offspring and childhood circumstances. 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 approach and accounts for the share of the total influence of preceding circumstances that is uncorrelated 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); Washbrook et al. (2014); Gregg et al. (2017), 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 parent's 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 and Wolfe (1995)). This line of research also studies the determinants of children's attaintment, albeit in a broader way, allowing for other 'paths' outside of parental income. For example, in the model of Leibowitz (1974) parental abilities and education influences family income (as preceding circumstances do, in my model) but they also influence heredity (i.e., biological inheritance), that influences the ability of the offspring, their education, choices, and income. These models allow for a more comprehensive economic perspective that specifies different ways in which circumstances influence the income of the offspring.

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

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

In my model, $\ln Y_i$ 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 fall between parental income and offspring's income, being influenced by the former and influencing the latter. 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.[2] The inclusion of mediating circumstances results in two possible components of transmission, a mediated and an unmediated component.

The C_2 term in Figure 2 represents a vector of circumstances, a fact better represented in the following equations rather than in the Figure. Each circumstance within C_2 accounts for a separate part of the IGE and there are no interactions between them (i.e., if were to I expand C_2 into its components, there would be no arrows between them, see Figure 9 in the Appendix).

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 and Gignoux (2014)). If we have K_2 circumstances in C_2, indexed

[2] I also include robustness checks, capping the offspring's age in 1989 at 18 and 22 years of age with minor differences in the decomposition.

by k, there are 2 equations:

$$\begin{aligned} \ln Y^C &= \omega_1 + \sum_{k=1}^{K_2} \pi_{1k} C_{2k} + \theta_1 \ln Y^P + u_1 && (2) \\ C_{2k} &= \alpha_{2k} + \lambda_{1k} \ln Y^P + \varepsilon_{2k}, \ \forall \ k = 1, \ldots, K_2. && (3) \end{aligned}$$

By including equation 3 into equation 2, I get:

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

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:

$$\beta = \frac{\text{Cov}(\ln Y^C, \ln Y^P)}{\text{Var}(\ln Y^P)}. \quad (5)$$

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:

$$\beta = \overbrace{\theta_1}^{Y^C \to Y^P} + \overbrace{\sum_{k=1}^{K_2} \pi_{1k} \lambda_{1k}}^{Y^C \to C_2 \to Y^P}. \quad (6)$$

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_k, the regression coefficient for mediating circumstance C_{2k} on offspring's income and λ_{1k}, 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 Figure 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)[3], the years of education of the parent with the highest education and the occupation of the parent (measured in 1989 using the 3-digit 1970 Census codes and then grouped into seven categories), the ethnicity of the parent (binary category: white or person of colour) and the size of 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. Similarly 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. Figure 9 in the Appendix is an extended version of Figure 4, including all existing interactions in the following equations.

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

[3] I assign to the parent in 1989 the IQ score of whoever is the head of family in 1972, and therefore should be interpreted as a rough measure of 'family abilities'.

have K_2 circumstances in C_2, indexed by k, we get a set of $K_2 + 2$ equations:

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

$$C_{2k} = \alpha_{2k} + \lambda_{2k} \ln Y^P + \sum_{j=1}^{K_1} \delta_{kj} C_{1j} + \varepsilon_{2k}, \ \forall\ k = 1, \ldots, K_2. \tag{8}$$

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

The final set of equations represented in Figure 4 includes equation 7, 8, and 9. Equation 7 represents the influence of preceding circumstances on parental income (i.e, $C_1 \rightarrow Y^P$) and that of the residual term ($\Phi \rightarrow Y^P$). Equation 8 represents the mediated components and includes the influence of parental income ($Y^P \rightarrow C_2$) and that of of preceding circumstances ($C_1 \rightarrow C_2$). Lastly, equation 9 represents the influence of all factors on offspring's income: the unmediated influence of preceding circumstances ($C_1 \rightarrow Y^C$), the influence of mediating circumstances ($C_2 \rightarrow Y^C$) and the influence of parental income ($Y^P \rightarrow Y^C$). 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 Figure 4.

$$\beta = \theta_2 + \sum_{k=1}^{K_2} \pi_{2k} \lambda_{2k} + \sum_{j=1}^{K_1} \left[\left(\rho_{2j} + \sum_{k=1}^{K_2} \pi_{2k} \delta_{jk} \right) \frac{\mathrm{Cov}(C_{1j}, \ln Y^P)}{\mathrm{Var}(\ln Y^P)} \right]. \tag{10}$$

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 Figure 4: the residual influence of parental income, once I control for preceding and mediating circumstances. All other components are associated with either 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.

We can get a clearer idea of the contribution of preceding circumstances by comparing the decomposition in equation 6 to that of equation 10. It shows how both the mediated and the unmediated components are divided into two terms each: one stemming from C_1 and one stemming from Φ.

$$\theta_1 = \theta_2 + \sum_{j=1}^{K_1} \rho_{2j} \frac{\mathrm{Cov}(C_{1j}, \ln Y^P)}{\mathrm{Var}(\ln Y^P)} \tag{11}$$

$$\sum_{k=1}^{K_2} \pi_{1k}\lambda_{1k} = \sum_{k=1}^{K_2} \pi_{2k}\lambda_{2k} + \sum_{j=1}^{K_1}\sum_{k=1}^{K_2} \pi_{2k}\delta_{jk} \frac{\mathrm{Cov}(C_{1j}, \ln Y^P)}{\mathrm{Var}(\ln Y^P)} \tag{12}$$

I can also rearrange the final decomposition in equation 10 to reflect each of the components into which the IGE is decomposed.

$$\beta = \overbrace{\theta_2}^{\Phi \to Y^P \to Y^C} + \overbrace{\sum_{k=1}^{K_2} \pi_{2k}\lambda_{2k}}^{\Phi \to Y^P \to C_2 \to Y^C} + \overbrace{\sum_{j=1}^{K_1} \rho_{2j} \frac{\mathrm{Cov}(C_{1j}, \ln Y^P)}{\mathrm{Var}(\ln Y^P)}}^{C_1 \to Y^P \to Y^C} + \underbrace{\sum_{j=1}^{K_1}\sum_{k=1}^{K_2} \pi_{2k}\delta_{jk} \frac{\mathrm{Cov}(C_{1j}, \ln Y^P)}{\mathrm{Var}(\ln Y^P)}}_{C_1 \to Y^P \to C_2 \to Y^C}. \tag{13}$$

Note that up to now the association between preceding circumstances and offspring's income is exclusively mediated by parental income (i.e., $C_1 \to Y^P \to Y^C$). 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 ρ coefficient), their contribution to the IGE will be zero if they do not correlate with parental income $\big(\text{Cov}(C_{1j}, \text{ln}Y^P) = 0\big)$. 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 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 to C_1, I get all the potential ways in which preceding circumstances influence the income of the offspring.

$$\text{ln}Y^C = \Xi + \sum_{j=1}^{K_1} \left(\rho_{2j} + \theta_2 \kappa_j + (1 + \kappa_j) \sum_{k=1}^{K_2} \pi_k \delta_{kj} \right) C_{1j} + \Sigma. \tag{14}$$

Where the constant term and the error term include:

$$\begin{aligned} \Xi &= \omega_2 + \sum_{k=1}^{K_2} \pi_{2k} \alpha_{2k} + \left(\theta_2 + \sum_{k=1}^{K_2} \pi_{2k} \lambda_{2k} \right) \alpha_1, & (15) \\ \Sigma &= u_2 + \sum_{k=1}^{K_2} \pi_{2k} \varepsilon_{2k} + \left(\theta_2 + \sum_{k=1}^{K_2} \pi_{2k} \lambda_{2k} \right) \phi_2. & (16) \end{aligned}$$

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 lnY^C , we get:

$$\frac{\text{Cov}(\text{ln}Y^C, C_{1j})}{\text{Var}(C_{1j})} = \underbrace{\overbrace{\rho_{2j}}^{C_1 \to Y^C} + \overbrace{\theta_2 \kappa_j}^{C_1 \to C_2 \to Y^C}}_{\text{Direct}} + \underbrace{\overbrace{\sum_{k=1}^{K_2} \pi_k \delta_{kj}}^{C_1 \to Y^P \to Y^C} + \overbrace{\kappa_j \sum_{k=1}^{K_2} \pi_k \delta_{kj}}^{C_1 \to Y^P \to C_2 \to Y^C}}_{\text{Indirect (through the IGE)}}. \tag{17}$$

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 at time. That is, it is equivalent to decompose the regression coefficient of one particular circumstance on the income of the offspring:

$$\text{ln}Y^C = \omega_3 + \psi_j C_{1j} + u_3. \tag{18}$$

Where equation 17 is equal to ψ_j. 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-squared of the OLS regression of equation 18.[4]

3 Data

I use the Panel Study of Income Dynamics (PSID), a household panel survey for the USA that has followed the same individuals and their descendants since 1968. The PSID has been used extensively to study the intergenerational mobil-

[4]Bourguignon (2018) shows that the R-squared can be interpreted as a measure of relative IOp if our inequality index is the variance of the logarithm of the predicted outcome, $\texttt{Var}\left(log(\hat{\beta}C_i)\right)$.

ity 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 repored retrospectively by the offspring. Because of its detailed characterization of the socioeconomic background while growing up, the PSID is among the best surveys to study inequality of opportunity and intergenerational transmission in the context of high-income countries.

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 6 to 9 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) reports IGE estimates ranging from 0.3 and 0.4 for individual earnings and Lee and Solon (2009) reports 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 2nd PSID generation (with an median age of 50 years) up to the 7th generation (with an median age of 6 years). Of the 2017 offspring sample, 85% have a FIMS map (i.e., is 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, either because they do not have a FIMS map (as their parents were not interviewed, for example in the case the 1997 or 2017 immigrant refresher sample), or because their parents had died or attrited by 1989, in which case they have a 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. Unfortunately, to avoid dealing with the low labour market participation among women most IGE estimates are derived from samples that exclude mothers and daughters (see Chadwick and Solon (2002) for a case in which they do address it). 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. Whereas earnings focus on labour market advantages, Mazumder (2018) arguers that family income is much closer to consumption and therefore to the concepts of 'utility' or 'welfare'.

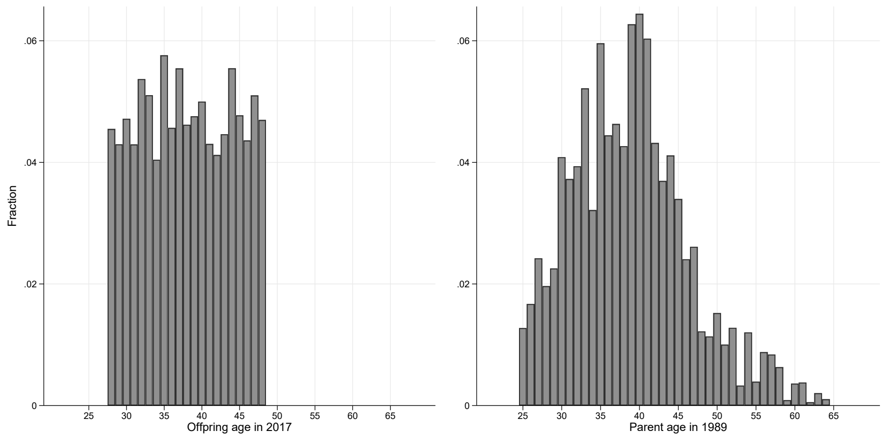
To reduce transitory fluctuations and measurement error I average both outcomes over multiple years. Mazumder (2005, 2016) shows that these fluctuations can result in a downward bias of up to 30%. I include 9 years of data for both the parents and offspring generations. In the parents' case, the period covers 1981 to 1989. For the offspring's generation, it covers the period 2001 to 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

[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.

of the parent's IQ score that was measured in 1972. 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 (for example, if they buy a house for their parents). For that reason, my sample consists of offspring aged 28 to 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 (Jenkins, 1987; Haider and Solon, 2006) and I cap their age at 64, as the share of parents with positive earnings decreases rapidly after that. Figure 6 plots the age distribution for the offspring generation in 2017 (left plot) and the parental generation in 1989 (right plot). The Figure shows that offspring age is more constrained uniformly distributed than the parents. Both the average and the median age for both generations is around 39 years of age.

Figure 6: Age distribution for parents and offspring



Note: Family income sample ($N = 2,021$).

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.

I measure all outcomes in 2017 US dollars using the CPI provided by the U.S. 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 in the SRC sample (the SEO sample is excluded).

My final sample includes 2,021 parent-offspring pairs for family income and 721 for individual earnings. 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

[6]Following Mazumder (2016, 2018) and with the goal of comparability in mind, I focus on total rather than equivalised income.

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 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. Except for the IQ score, which was measured in 1972, and the state where the offspring was born, all other circumstances were measured in 1989. The IQ score is only available for 1972 (and earlier dates) and it is assigned to the head of the family of the test-taker in 1989. That means that this 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.[7]

[7]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.

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 to 17 years).
Ethnicity	1 if Black, American Indian, Aleut, Eskimo, Asian, Pacific Islander, other. 0 if White.
Occupation (Main occupation/Most important activity using 3-digit code 1970 Census)	Grouped into 7 categories: Professional, Manager, Clerical, Craftman, Operative, Farmer and Services.
Parent grew up in (Four categories)	
Farm	Farm, rural area, country.
Small town	Small town, any size town, suburb.
Large city	Large city, any size city.
Other	Other, several different places, combination of places, doesn't answer.
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 (incl. stocks in IRAs).
Over median: Savings	Family owns above-median money in checking or savings accounts, money market bonds, or Treasury bills (incl. IRAs).
Over median: Food stamps	Family received above-median food stamp benefits (now SNAP).
State where born	State where the offspring was born (50 states plus D.C., U.S. territory/outside U.S., and no response)

Note: All circumstances are measured in 1989 (when the offspring were 0 to 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 (taken by the head of the family unit in 1972).

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 Figure 9 in the Appendix). 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 $C_1 \rightarrow Y^C$ would need to be decomposed into $C_{1a} \rightarrow Y^C$ and $C_{1a} \rightarrow C_{1b} \rightarrow Y^C$, as would any other component in C_1. Such a detailed model is beyond the scope of this paper.

A more complex model of intergenerational transmission would also need to include factors that might not be considered circumstances, e.g., post-school investments (as in Figure 1 in Haveman and 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]

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.

[8]For a detailed discussion on what constitutes a circumstance, see e.g., Cohen (1999); Bowles and Gintis (2002); Roemer (2004); Swift (2004); Jencks and Tach (2006); Torche (2015).

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 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.

Table 2: IGE estimate for individual earnings and family income

	Earnings	Income
IGE	0.347	0.526

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

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-years averages for sons. If we look at the equivalent of my estimate, 9-year averages for fathers and sons, the estimate is 0.39, while the arithmetic average for estimates with 6 to 9-year averages is 0.40. Mazumder (2018) reports the estimates from several papers. Among these estimates, most account for life-cycle 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 transitory variation by averaging the outcomes over a

[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.

large number of years but do not account for life-cycle 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 9-year averages for fathers and sons result in an IGE of 0.49, while the simple average for estimates with 6 to 9-year averages is 0.44. These estimates are particularly sensitive to the different samples. For example, the estimate using 8-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.

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.

Table 3 presents the decomposition, including the contribution of each mediating circumstance. I also include the 95% confidence interval 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. This shares as a part of each IGE are shown in Figure 7.

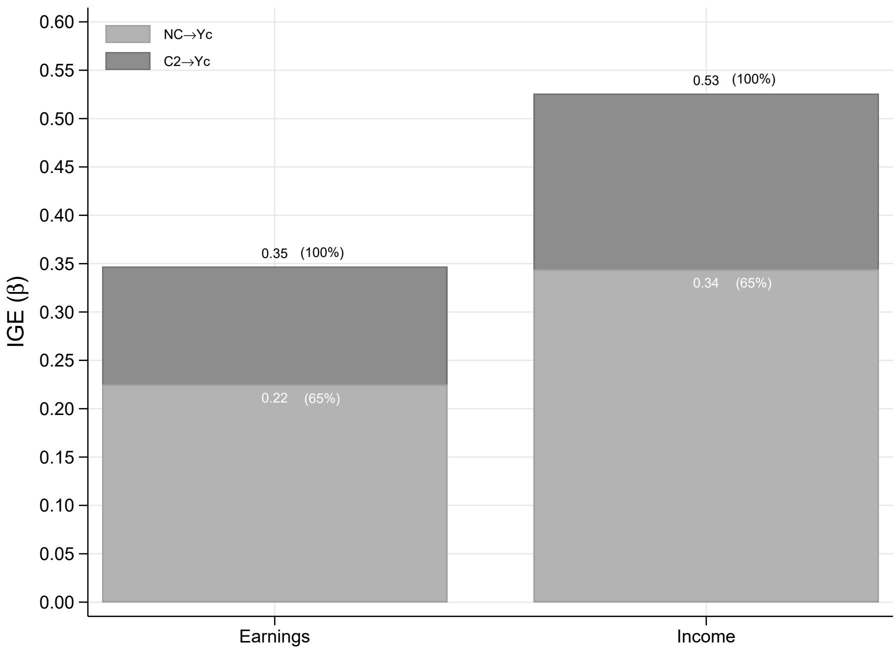
Table 3: IGE decomposition (Mediating circumstances)

	Earnings						Income					
	Coef.	95% CI		% of IGE	95% CI		Coef.	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 Mount.	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 U.S.A.	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												
Yp → C2 → Yc	0.169	0.12	0.22	32.11	21.84	42.37	0.125	0.05	0.20	36.15	14.57	57.73
Yp → Yc	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

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

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 as well as a buffer for external shocks such as medical risks (De Nardi and Fella, 2017). Savings also have a direct intergenerational transfer, through bequests and inheritances (Killewald et al., 2017), reinforcing wealth inequalities across generations.

Figure 7: IGE decomposition: Mediating circumstances



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

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 circumstances reflects that intergenerational persistence happes not only at the top of the distribution (as suggested by the importance of savings and investment) but also at the bottom.

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 are divided in two: One component that follows from preceding circumstances, and another component stemming for all other sources of immobility.

As both the sets of preceding and mediating circumstances include a large number of components, I report a summary of the complete decomposition. For each of the K_1 circumstance C_1, there are two components, one unmediated and another one mediated from C_2 that includes K_2 different components. The same is true for the component starting from Φ. That means that there are $(1 + K_1) \cdot (1 + K_2)$ specific decomposition components to report (182 components in my case). In Tables 4 and 5 I report the decomposition estimates only for C_1 by adding up the influence of each mediating circumstance. For example, I report the total influence of education over parents being homeowners, over being born in the Mideast, over having used food stamps, and all other mediating circumstances. I present the opposite table – where the influence of each preceding circumstance has been added up – in Table 7 in the Appendix.

Tables 4 and 5 report the decomposition for individual earnings and family income, respectively. I also include the 95% confidence interval obtained from a

Table 4: IGE decomposition for individual earnings (All circumstances)

	Earnings					
	Coef.	95% CI		% of IGE	95% CI	
Unmediated influence of Φ:						
$\Phi \rightarrow$ Yp $\rightarrow$ Yc	0.157	0.04	0.28	45.27	16.21	74.34
Mediated influence of Φ:						
$\Phi \rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc	0.068	-0.00	0.14	19.52	-0.74	39.78
Unmediated influence of C1: C1 $\rightarrow$ Yp $\rightarrow$ Yc						
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
Occup: Manager	0.009	-0.01	0.03	2.64	-4.03	9.31
Occup: Clerical	0.006	-0.01	0.02	1.80	-2.27	5.88
Occup: Craftsman	-0.009	-0.03	0.01	-2.66	-9.36	4.05
Occup: Operative	0.004	-0.03	0.03	1.26	-8.28	10.80
Occup: Farmer	0.008	-0.01	0.03	2.28	-3.04	7.59
Occup: Services	-0.001	-0.01	0.01	-0.30	-2.49	1.90
Occup: Other	0.001	-0.02	0.02	0.34	-4.87	5.56
P grew in Small town	0.001	-0.01	0.01	0.33	-2.57	3.22
P grew in Large city	0.005	-0.01	0.02	1.57	-3.57	6.71
P grew in Other	0.001	-0.00	0.01	0.36	-1.22	1.95
Mediated influence of C1: C1 $\rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc						
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
Occup: Manager	0.001	-0.00	0.01	0.24	-1.12	1.61
Occup: Clerical	0.001	-0.00	0.00	0.31	-0.58	1.20
Occup: Craftsman	0.002	-0.01	0.01	0.67	-1.66	3.00
Occup: Operative	0.002	-0.01	0.02	0.47	-3.87	4.80
Occup: Farmer	0.001	-0.00	0.01	0.30	-0.88	1.47
Occup: Services	0.000	-0.00	0.00	0.10	-1.19	1.38
Occup: Other	0.003	-0.00	0.01	1.00	-1.52	3.53
P grew in Small town	0.000	-0.00	0.00	0.05	-1.21	1.31
P grew in Large city	0.000	-0.01	0.01	0.10	-1.55	1.76
P grew in Other	0.001	-0.00	0.00	0.28	-0.69	1.26
Summary						
$\Phi \rightarrow$ Yp $\rightarrow$ Yc	0.157	0.04	0.28	45.27	16.21	74.34
$\Phi \rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc	0.068	-0.00	0.14	19.52	-0.74	39.78
C1 $\rightarrow$ Yp $\rightarrow$ Yc	0.097	0.03	0.17	27.94	6.93	48.94
C1 $\rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc	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

Note: Individual earnings for fathers and sons only ($N = 721$) and family income for all offspring and the head of household in 1989 ($N = 2,021$). The parent's IQ test (0 to 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 color (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.

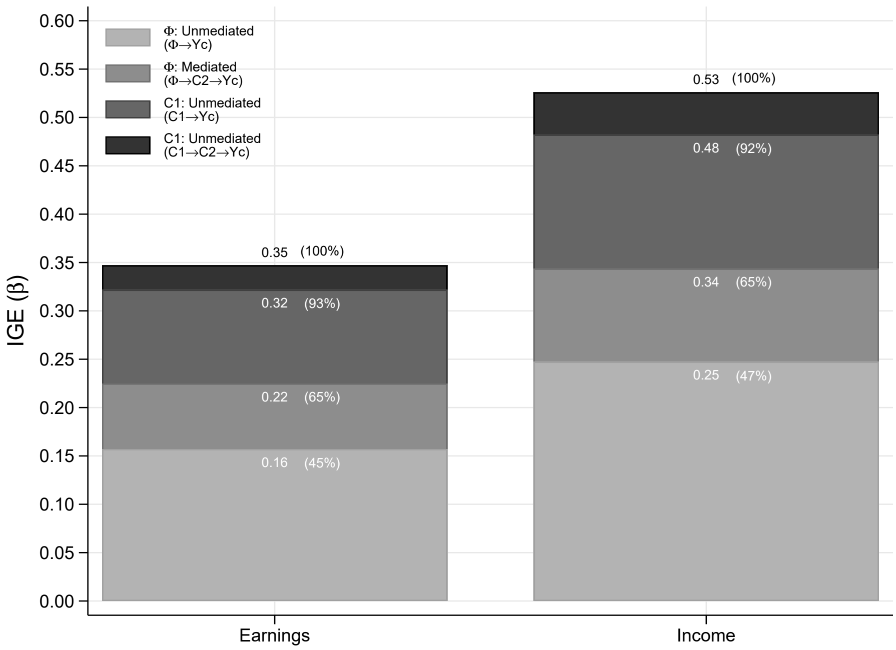
Table 5: IGE decomposition for family income (All circumstances)

	Income					
	Coef.	95% CI		% of IGE	95% CI	
Unmediated influence of Φ:						
$\Phi \rightarrow$ Yp $\rightarrow$ Yc	0.247	0.17	0.32	47.03	35.14	58.92
Mediated influence of Φ:						
$\Phi \rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc	0.096	0.05	0.14	18.31	9.96	26.67
Unmediated influence of C1: C1 $\rightarrow$ Yp $\rightarrow$ Yc						
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
Occup: Manager	0.012	-0.00	0.03	2.32	-0.54	5.18
Occup: Clerical	-0.000	-0.00	0.00	-0.06	-0.55	0.44
Occup: Craftsman	0.000	-0.00	0.00	0.05	-0.33	0.43
Occup: Operative	0.008	-0.01	0.02	1.48	-1.09	4.05
Occup: Farmer	0.000	-0.00	0.01	0.07	-0.84	0.97
Occup: Services	0.005	-0.01	0.02	0.91	-1.40	3.22
Occup: Other	0.000	-0.02	0.02	0.03	-3.99	4.06
P grew in Small town	0.002	-0.00	0.01	0.32	-0.50	1.14
P grew in Large city	0.002	-0.00	0.01	0.39	-0.62	1.39
P grew in Other	0.000	-0.00	0.00	0.09	-0.40	0.58
Mediated influence of C1: C1 $\rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc						
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
Occup: Manager	0.001	-0.00	0.01	0.28	-0.60	1.15
Occup: Clerical	0.000	-0.00	0.00	0.04	-0.12	0.19
Occup: Craftsman	-0.000	-0.00	0.00	-0.03	-0.21	0.14
Occup: Operative	0.003	-0.00	0.01	0.58	-0.34	1.51
Occup: Farmer	0.001	-0.00	0.00	0.23	-0.11	0.58
Occup: Services	0.002	-0.00	0.01	0.43	-0.38	1.24
Occup: Other	0.011	0.00	0.02	2.03	-0.01	4.06
P grew in Small town	-0.000	-0.00	0.00	-0.01	-0.31	0.30
P grew in Large city	-0.000	-0.00	0.00	-0.09	-0.45	0.27
P grew in Other	-0.000	-0.00	0.00	-0.02	-0.20	0.15
Summary						
$\Phi \rightarrow$ Yp $\rightarrow$ Yc	0.247	0.17	0.32	47.03	35.14	58.92
$\Phi \rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc	0.096	0.05	0.14	18.31	9.96	26.67
C1 $\rightarrow$ Yp $\rightarrow$ Yc	0.139	0.10	0.18	26.34	18.22	34.47
C1 $\rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc	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

See note in Table 4.

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 (lnY^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 11 in the appendix). Overall, circumstances account for 55% of the IGE of earnings and 53% for the IGE of income. Figure 8 summarises the decomposition.

Figure 8: IGE decomposition: All circumstances



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

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 11, 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 ($NC \rightarrow Y^P \rightarrow C_2 \rightarrow Y^C$), accounting for almost 20% of the IGE. The third component, the mediated influence of preceding circumstances ($C_1 \rightarrow Y^P \rightarrow C_2 \rightarrow Y^C$ or) 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.

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.

4.3.1 Contribution of mediating circumstances

Table 7 in the Appendix reports the same decomposition – including preceding and mediating circumstances – but for detailing the latter. I have already mentioned that preceding and mediating circumstances report very little interaction in accounting for the IGE. Mediating circumstances matter when explaining the influence of factors other than preceding circumstances (Φ).

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. Similarly, parents being homeowners account for around 3% of the IGE for both outcomes. Overall, the relative contribution of mediating circumstances is fairly similar for both outcomes.

Table 7 highlights how factors that might not be considered circumstances – and thus included in Φ – can contribute to IOp. One common example of such a factor are the instillation of preferences on children (Roemer, 2004; Dardanoni et al., 2006). However, the same factors that drive our intention to instill preferences can have an influence on other aspects of the intergenerational transmission process. Say we want to instil the importance of saving to our children, that same interest could drive our own intentions and capacity to accumulate savings. Even though we consider a driver of intergenerational persistence as legitimate, that driver can also have an influence of other factors we consider illegitimate.

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 Figure 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 and 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 and an indirect component, as shown in equation 17. 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 (Table 8 in the Appendix includes the bootstrapped confidence intervals of these estimates).

To provide a measure of the 'relevance' of each circumstance, I include the R-squared of an OLS regression of that circumstance on the income of the offspring. Consistent with the IGE decomposition, parental education is the most 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 (see Table 8 in the Appendix).

Table 6: Influence of preceding circumstances not included in the IGE (% share)

	Earnings			Income		
	Direct (non-IGE)	Indirect (IGE)	R^2	Direct (non-IGE)	Indirect (IGE)	R^2
IQ score	52.2	47.8	3.8	41.5	58.5	7.6
Education (years)	64.2	35.8	12.3	55.1	44.9	19.4
Ethnicity: Non-white	30.4	69.6	1.7	20.6	79.4	4.7
Occup: Professional	48.1	51.9	2.3	42.5	57.5	3.8
Occup: Manager	63.3	36.7	2.8	44.6	55.4	4.1
Occup: Clerical	.	.	0.0	28.6	71.4	0.0
Occup: Craftsman	-30.5	130.5	0.0	143.8	-43.8	0.0
Occup: Operative	68.4	31.6	3.2	55.0	45.0	3.9
Occup: Farmer	51.3	48.7	0.7	26.6	73.4	0.6
Occup: Services	54.2	45.8	1.6	36.1	63.9	1.6
Occup: Other	25.0	75.0	1.7	18.3	81.7	3.5
P grew: in Farm	43.1	56.9	1.5	47.6	52.4	1.2
P grew in Small town	-17.0	117.0	0.1	48.4	51.6	0.2
P grew in Large city	67.6	32.4	0.3	43.6	56.4	0.2
P grew in Other	84.0	16.0	0.1	35.7	64.3	0.0

Note: Individual earnings for fathers and sons only ($N = 721$) and family income for all offspring and the head of household in 1989 ($N = 2,021$). The parent's IQ test (0 to 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 color (POC) and where the reference category is "White". Missing values reflect shares below -1000% or above 1000%. R^2 is the R-squared of the OLS regression of that circumstance (C_{1j}) on the income of the offspring (Y^C).

The influence of parental education – the circumstance with the highest R-squared – 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 inequality of opportunity, 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-squared. 70% to 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 show 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, report a mostly indirect influence (68% for earnings and 55% for income).

The two most important circumstances in term of the R-squared, 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.

4.5 Robustness checks and extensions

4.5.1 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 6 years of data (and with a maximum of 9 years). As a robustness check, I re-estimate the decomposition by including individuals with 5, 4, and 3 years of outcome data. Given that most respondents have 9 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 9 in the Appendix.

I first compare the different age cut-offs for the sample of individuals with 6 to 9 years of data, shown in the last rows of Table 9. 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 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 6 years of data makes almost no difference for the IGE estimates. As expected, the IGE decreases slightly (1 percentage point) when including individuals with 3 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 8 more percentage points (from 55% to 63% for the sub-20 sample) when including individuals with 3 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 in the Appendix).

4.5.2 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 10 in the appendix. The different age cutoffs make little to no difference in the direct/indirect decomposition. The direct influence of parental education lies between 62% to 64% for earnings and 53 to 57% for income. The direct influence of the IQ score lies between 52% to 56% for earnings and 39% to 46% for income. Overall, and similarly to the previous subsection, these changes fall well within the confidence intervals of the benchmark decomposition (see Table 8 in the Appendix).

4.5.3 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) studies the 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 to 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 17). For each I also report the 95% confidence interval.

Concretely, Figure 10 in the Appendix reports the share of the IGE not attributed to parental income. Given equations 7 to 9, this share is represented by $1-(\hat{\theta}_2/\hat{\beta})$, where the 'hat' represents the OLS estimate.

Similarly, Figure 11 in the Appendix 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 be 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 to the small sample size – no point departure from the average is statistically significant (Palomino et al. (2018) uses a sample of over 25 thousand observations for this exercise).

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.

5 Discussion

In this paper I study the relationship between estimates of the IGE and of IOp. I model the interaction between the income of the parent, the income of their offspring, and other childhood circumstances to understand to what extent can we consider the IGE to be a measure of IOp. My model proposes two main decompositions: One to determine how much much of the IGE can be explained by differences in these circumstances, and a second one to determine how much of the total contribution of circumstances is not included in the IGE.

My IGE estimates are constructed to be as consistent as possible with previous estimates. Using 2017 PSID data, the IGE for individual earnings – estimated only for fathers and sons – is 0.35, whereas the IGE for total family income is

0.53. Circumstances account for just over half of the IGE in both cases, with parental education and families having above-median savings being the most important circumstances. Conversely, around 45% of the IGE is not accounted for by circumstances. As a first approximation, this decomposition suggests that an 'optimal' IGE should be at least half of its current level in the USA.

This first decomposition is further split into two, to account for circumstances that mediate the relationship between parents and offspring, and circumstances that precede it. The decomposition reports that both mediating and preceding circumstances matter for the IGE, but that there is little interaction between the two. Mediating circumstances account for around 20% of the IGE while preceding circumstances account for over 25%. The combination of the two – the mediated influence of preceding circumstances – explains only around 8% of the IGE.

Contrary to the IGE, an IOp estimate not only accounts for the full influence of parental income but also also for the influence of other circumstances. For that reason my second decompositions focuses on the extent to which the influence of preceding circumstances is not accounted for in the IGE. I decompose the contribution of each preceding circumstances to the income of the offspring into a 'direct' (i.e., not mediated by parental income) and an 'indirect' (i.e., mediated by parental income and thus accounted for in the IGE) component.

The most relevant preceding circumstance (in terms of its contribution to offspring income and to the IGE) is parental education. Around two-thirds of its influence on offspring earnings is not mediated by parental earnings (58% for income). This decomposition suggests that ff we consider parental education as a circumstance (as is often the case in IOp studies), then the IGE is an insufficient measure of IOp, as the influence of other of other important circumstances is not wholly accounted for by parental income.

One important caveat of this analysis has to do with omitted or unobserved circumstances. My first decomposition accounts for the influence of observed circumstances. Due to the residual nature of this approach, all omitted circumstances 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 (Ferreira and Gignoux, 2011). Similarly, the estimates on the first decomposition should be interpreted as lower bounds of the share of the IGE attributable to circumstances.

Childhood circumstances account for most – but not all– of the IGE, and they also have an influence outside of the relationship between parent's and offspring's income. Overall, the influence of circumstances on the income of the offspring is substantial, and the IGE captures only a part of it. Conversely, not all the IGE is accounted for by circumstances.

What about the use of the IGE as a measure of IOp? Both decompositions help in clarifying this relationship. As Roemer (2004) puts it, complete intergenerational mobility – more precisely, origin independence – implies equality of opportunity under two conditions. First, if we follow the strongest definition of IOp, where natural or inborn talent is a circumstance (what Swift (2013) calls the 'radical' view of IOp). Second, if the influence of the parental background is summarised in its entirety by parental income. My first decomposition (the share of the IGE attributed to circumstances) relates to the former condition, while my second decomposition (the influence of circumstances excluded from the IGE) relates to the latter.

The first condition presents a normative choice and it shapes how we interpret the part of the IGE not attributed to circumstances. My choice of circumstances is closer to the 'conventional' view of IOp, which accounts for the influence of discrimination and socioeconomic background. As it stands, a radical view of IOp would suffer from several omitted circumstances, namely measures of the offspring's 'ability' at birth. While the discussion on views of IOp is outside the scope of this paper, I show that even with a 'conventional' view of IOp, more than half of the IGE is attributable to differences in circumstances.

Unlike the first condition, the second condition can be empirically verified for each of the observed circumstances. Under this condition, parental income is a summary measure that accounts for all potential circumstances. My decomposition shows that, but for one case, no circumstance is entirely accounted through the IGE. Parental income does not summarise all potential circumstances, it is one of many relevant circumstances. Following the two condition of Roemer (2004), an IGE of zero does not imply an IOp index of zero, due to there being other factors besides parental income than influence the latter but not the former.[10]

This does not mean than IGE estimates are poor proxies of IOp. I show that circumstances are an important part of the IGE, and that the IGE accounts for part of their influence. The similarities in functional form also highlight the similarities between the two. In a cross-country context, Brunori et al. (2013) show a positive correlation between indices of relative IOp and intergenerational correlations in income and education. In this paper, however, I focus on unpacking the IGE to explore why this correlation is not perfect.

Further research is needed to better understand the determinants and paths behind intergenerational persistence. Other countries, outcomes, and time periods should be explored to understand the role context plays in this decomposition. One such example is wealth transmission where the most important determinants happen later in life, such as receiving inheritances or inter vivos transfers, rather than while growing up (Nolan et al., 2021). Similarly, more complex structural models such as the ones proposed in Haveman and Wolfe (1995) can help understand the role and timing of different factors. These extensions might depart from the notion of 'circumstances' (or perhaps, move towards more demanding views of IOp), but will help in understanding what is accounted for in measures like the IGE.

[10]Indeed, Roemer (2004) argues that parental education – the most relevant circumstance in my decomposition – is a better proxy for the influence of parents on their offspring.

6 Bibliography

Atkinson, A. B. (1983). Income Distribution and Inequality of Opportunity. In A. B. Atkinson (Ed.), *Social Justice and Public Policy* (1 ed.)., Chapter 4, pp. 65–80. Cambridge, MA: MIT Press.

Black, S. E. and P. J. Devereux (2011). Recent developments in intergenerational mobility. In D. Card and O. Ashenfelter (Eds.), *Handbook of Labor Economics*, Volume 4, Chapter 16, pp. 1487 – 1541. Amsterdam: Elsevier.

Blanden, J., P. Gregg, and L. Macmillan (2007). Accounting for intergenerational income persistence: Noncognitive skills, ability and education. *The Economic Journal 117*(519), C43–C60.

Bourguignon, F. (2018). Inequality of Opportunity. In J. Stiglitz, J. Fitoussi, and M. Durand (Eds.), *For Good Measure: Advancing Research on Well-being Metrics Beyond GDP*, Chapter 5. Paris: OECD.

Bowles, S. and H. Gintis (2002). The inheritance of inequality. *Journal of Economic Perspectives 16*(3), 3–30.

Brunori, P., F. H. G. Ferreira, and V. Peragine (2013). Inequality of Opportunity, Income Inequality and Economic Mobility: Some international comparisons. In E. Paus (Ed.), *Getting Development Right*, Chapter 5, pp. 85–115. New York: Palgrave Macmillan.

Chadwick, L. and G. Solon (2002). Intergenerational Income Mobility Among Daughters. *American Economic Review 92*(1), 335–344.

Cohen, G. (2009). *Why Not Socialism?* Princeton: Princeton University Press.

Cohen, G. A. (1999). Socialism and Equality of Opportunity. In M. Rosen and J. Wolff (Eds.), *Political Thought*, Chapter 123, pp. 354–358. Oxford: Oxford University Press.

Conlisk, J. (1974). Can Equalization of Opportunity Reduce Social Mobility? *American Economic Review 64*(1), 80–90.

Conlisk, J. (1977). An Exploratory Model of the Size Distribution of Income. *Economic Inquiry 15*(3), 345–366.

Dardanoni, V., G. S. Fields, J. E. Roemer, and M. L. Sánchez Puerta (2006).

How Demanding Should Equality of Opportunity Be, and How Much Have We Achieved. In S. L. Morgan, D. Grusky, and G. S. Fields (Eds.), *Mobility and Inequality: Frontiers of Reasearch in Sociology and Economics*, Chapter 3, pp. 59–82. Palo Alto, CA: Stanford University Press.

De Nardi, M. and G. Fella (2017). Saving and Wealth Inequality. *Review of Economic Dynamics 26*, 280–300.

Ferreira, F. H. and J. Gignoux (2011). The Measurement of Inequality of Opportunity: Theory and an Application to Latin America. *Review of Income and Wealth 57*, 622–657.

Ferreira, F. H. G. and J. Gignoux (2014). The measurement of educational inequality: Achievement and opportunity. *World Bank Economic Review 28*(2), 210–246.

Gouskova, E., N. Chiteji, and F. Stafford (2010). Estimating the intergenerational persistence of lifetime earnings with life course matching: Evidence from the PSID. *Labour Economics 17*(3), 592 – 597.

Gregg, P., J. O. Jonsson, L. Macmillan, and C. Mood (2017). The Role of Education for Intergenerational Income Mobility: A comparison of the United States, Great Britain, and Sweden. *Social Forces 96*(1), 121–152.

Haider, S. and G. Solon (2006). Life-Cycle Variation in the Association between Current and Lifetime Earnings. *American Economic Review 96*(4), 1308–1320.

Haveman, R. and B. Wolfe (1995). The Determinants of Children's Attainments: A Review of Methods and Findings. *Journal of Economic Literature 33*(4), 1829–1878.

Hertz, T. (2005). Rags, Richers, and Race: The Intergenerational Economic Mobility of Black and White Families in the United States. In S. Bowles, H. Gintis, and M. O. Groves (Eds.), *Unequal Chances: Family Background and Economic Success* (1 ed.)., Chapter 5. Princeton, NJ: Princeton University Press.

Jäntti, M. and S. P. Jenkins (2015). Income Mobility. In A. B. Atkinson and F. Bourguignon (Eds.), *Handbook of Income Distribution*, Volume 2, Chapter 10, pp. 807–935. Amsterdam: Elsevier.

Jencks, C. and L. Tach (2006). Would Equal Opportunity Mean More Mobility?

In S. L. Morgan, D. Grusky, and G. S. Fields (Eds.), *Mobility and Inequality: Frontiers of Reasearch in Sociology and Economics*, Chapter 2, pp. 23–58. Palo Alto, CA: Stanford University Press.

Jenkins, S. (1985). Future Trends in the Inequality and Intergenerational Inheritance of Income: Some Exploratory Results for Britain. *Paper presented at the 5th World Congress of the Econometric Society, Cambridge MA*.

Jenkins, S. (1987). Snapshots versus movies: 'Lifecycle biases' and the estimation of intergenerational earnings inheritance. *European Economic Review 31*(5), 1149 – 1158.

Killewald, A., F. T. Pfeffer, and J. N. Schachner (2017). Wealth Inequality and Accumulation. *Annual Review of Sociology 43*(1), 379–404.

Lee, C.-I. and G. Solon (2009). Trends in Intergenerational Income Mobility. *The Review of Economics and Statistics 91*(4), 766–772.

Leibowitz, A. (1974). Home Investments in Children. *Journal of Political Economy 82*(2, Part 2), S111–S131.

Major, L. and S. Machin (2018). *Social Mobility: And Its Enemies*. Pelican Books. London: Penguin Books Limited.

Mazumder, B. (2005). Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data. *Review of Economics and Statistics 87*(2), 235–255.

Mazumder, B. (2016). Estimating the Intergenerational Elasticity and Rank Association in the United States: Overcoming the Current Limitations of Tax Data. In *Research in Labor Economics*, Volume 43, pp. 83–129. Bingley: Emerald Group Publishing Limited.

Mazumder, B. (2018). Intergenerational Mobility in the United States: What We Have Learned from the PSID. *The ANNALS of the American Academy of Political and Social Science 680*(1), 213–234.

Nolan, B., J. C. Palomino, P. V. Kerm, and S. Morelli (2021). Intergenerational wealth transfers and wealth inequality in rich countries: What do we learn from Gini decomposition? *Economics Letters 199*, 109701.

Palomino, J. C., G. A. Marrero, and J. G. Rodríguez (2018). One size doesn't fit all: A quantile analysis of intergenerational income mobility in the US (1980–2010). *The Journal of Economic Inequality 16*(3), 347–367.

Roemer, J. E. (2004). Equal opportunity and intergenerational mobility: going beyond intergenerational income transition matrices. In Miles Corak (Ed.), *Generational Income Mobility in North America and Europe*, pp. 1–13. Cambridge: Cambridge University Press.

Roemer, J. E. and A. Trannoy (2015). Equality of Opportunity. In A. B. Atkinson and F. Bourguignon (Eds.), *Handbook of Income Distribution*, Volume 2, Chapter 4, pp. 217–300. Amsterdam: Elsevier.

Solon, G. (1992). Intergenerational Income Mobility in the United States. *The American Economic Review 82*(3), 393–408.

Swift, A. (2004). Would Perfect Mobility be Perfect? *European Sociological Review 20*(1), 1–11.

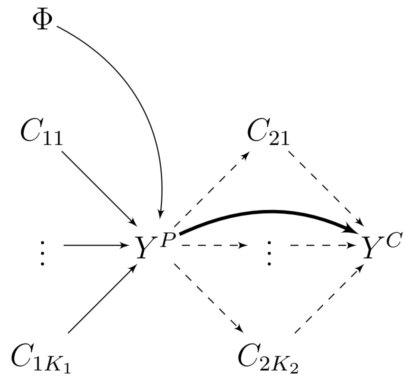
Swift, A. (2013). *Political Philosophy. A Beginners' Guide for Students and Politicians* (3rd ed.). Cambridge: Polity Press.

Torche, F. (2015). Intergenerational Mobility and Equality of Opportunity. *European Journal of Sociology 56*(03), 343–371.

Washbrook, E., P. Gregg, and C. Propper (2014). A decomposition analysis of the relationship between parental income and multiple child outcomes. *Journal of the Royal Statistical Society: Series A (Statistics in Society) 177*(4), 757–782.

7 Appendix

Figure 9: Channels of transmission including two factors (Extended)



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.

Table 7: IGE decomposition (mediating circumstances)

	Earnings						Income					
	Coef.	95% CI		% of IGE	95% CI		Coef.	95% CI		% of IGE	95% CI	
$\Phi \rightarrow$ Yp $\rightarrow$ Yc	0.157	0.038	0.276	45.27	16.21	74.34	0.247	0.172	0.323	47.03	35.14	58.92
$\Phi \rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc												
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 Mount.	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 U.S.A.	-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
C1 $\rightarrow$ Yp $\rightarrow$ Yc	0.097	0.026	0.168	27.94	6.93	48.94	0.139	0.095	0.182	26.34	18.22	34.47
C1 $\rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc												
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
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 Mount.	-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 U.S.A.	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												
$\Phi \rightarrow$ Yp $\rightarrow$ Yc	0.157	0.038	0.276	45.27	16.21	74.34	0.247	0.172	0.323	47.03	35.14	58.92
$\Phi \rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc	0.068	-0.002	0.137	19.52	-0.74	39.78	0.096	0.053	0.139	18.31	9.96	26.67
C1 $\rightarrow$ Yp $\rightarrow$ Yc	0.097	0.026	0.168	27.94	6.93	48.94	0.139	0.095	0.182	26.34	18.22	34.47
C1 $\rightarrow$ Yp $\rightarrow$ C2 $\rightarrow$ Yc	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

Note: Individual earnings for fathers and sons only ($N = 721$) and family income for all offspring and the head of household in 1989 ($N = 2,021$). 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 U.S.' category includes U.S. 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 8: Bootstrap for total contribution of preceding circumstances (% share)

	Earnings						Income					
	Direct			Indirect			Direct			Indirect		
	Coef.	95% CI		Coef.	95% CI		Coef.	95% CI		Coef.	95% CI	
IQ score	52.2	30.4	74.1	47.8	25.9	69.6	41.5	28.0	55.0	58.5	45.0	72.0
Education (years)	64.2	49.7	78.7	35.8	21.3	50.3	55.1	45.7	64.5	44.9	35.5	54.3
Ethnicity: Non-white	30.4	-108.8	169.7	69.6	-69.7	208.8	20.6	-6.4	47.7	79.4	52.3	106.4
Occup: Professional	48.1	-60.7	156.9	51.9	-56.9	160.7	42.5	22.1	62.9	57.5	37.1	77.9
Occup: Manager	63.3	39.6	87.1	36.7	12.9	60.4	44.6	29.0	60.1	55.4	39.9	71.0
Occup: Clerical	27343.0	25704.4	28981.6	-27243.0	-28881.6	-25604.4	28.6	-2378.4	2435.5	71.4	-2335.5	2478.4
Occup: Craftsman	-30.5	-3568.9	3507.9	130.5	-3407.9	3668.9	143.8	-1851.2	2138.7	-43.8	-2038.7	1951.2
Occup: Operative	68.4	50.6	86.2	31.6	13.8	49.4	55.0	38.1	72.0	45.0	28.0	61.9
Occup: Farmer	51.3	-58.4	161.0	48.7	-61.0	158.4	26.6	-571.7	624.8	73.4	-524.8	671.7
Occup: Services	54.2	-328.4	436.7	45.8	-336.7	428.4	36.1	-26.8	99.0	63.9	1.0	126.8
Occup: Other	25.0	-29.5	79.6	75.0	20.4	129.5	18.3	-6.4	43.0	81.7	57.0	106.4
P grew: in Farm	43.1	-1188.3	1274.6	56.9	-1174.6	1288.3	47.6	-26.9	122.1	52.4	-22.1	126.9
P grew in Small town	-17.0	-63161.5	63127.5	117.0	-63027.5	63261.5	48.4	-94081.1	94178.0	51.6	-94078.0	94181.1
P grew in Large city	67.6	-1427.7	1563.0	32.4	-1463.0	1527.7	43.6	-2410.2	2497.4	56.4	-2397.4	2510.2
P grew in Other	84.0	-5071.7	5239.6	16.0	-5139.6	5171.7	35.7	-2080.8	2152.1	64.3	-2052.1	2180.8

Note: Confidence intervals of Table 6. Family income for all offspring and the head of household in 1989 ($N = 2,021$). The parent's IQ test (0 to 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 color (POC) and where the reference category is "White". 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 9: Robustness check for IGE decomposition: Outcome averages and age cutoffs

	18 or younger in 1989				20 or younger in 1989				22 or younger in 1989			
	Earnings		Income		Earnings		Income		Earnings		Income	
	Coef.	Share	Coef.	Share	Coef.	Share	Coef.	Share	Coef.	Share	Coef.	Share
3–9 years average												
$\Phi \rightarrow$ Yc	0.11	35.8	0.26	49.9	0.13	37.1	0.24	46.6	0.15	41.9	0.25	47.5
$\Phi \rightarrow$ C2 $\rightarrow$ Yc	0.08	24.3	0.08	15.7	0.08	23.3	0.09	18.1	0.07	19.4	0.09	16.9
C1 $\rightarrow$ Yc	0.11	33.2	0.14	27.2	0.10	30.8	0.14	26.7	0.11	32.1	0.15	28.1
C1 $\rightarrow$ C2 $\rightarrow$ Yc	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												
$\Phi \rightarrow$ Yc	0.13	39.3	0.27	50.4	0.14	40.0	0.25	46.9	0.16	44.0	0.25	47.7
$\Phi \rightarrow$ C2 $\rightarrow$ Yc	0.07	23.0	0.08	15.5	0.08	22.1	0.09	18.1	0.07	18.6	0.09	17.0
C1 $\rightarrow$ Yc	0.10	31.1	0.14	27.0	0.10	29.3	0.14	26.6	0.11	30.9	0.14	28.0
C1 $\rightarrow$ C2 $\rightarrow$ Yc	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												
$\Phi \rightarrow$ Yc	0.13	39.0	0.27	50.5	0.14	40.4	0.25	47.0	0.16	44.1	0.25	47.7
$\Phi \rightarrow$ C2 $\rightarrow$ Yc	0.07	23.0	0.08	15.6	0.07	21.7	0.10	18.2	0.07	18.8	0.09	17.0
C1 $\rightarrow$ Yc	0.10	31.3	0.14	26.7	0.10	30.0	0.14	26.4	0.11	31.2	0.14	27.9
C1 $\rightarrow$ C2 $\rightarrow$ Yc	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												
$\Phi \rightarrow$ Yc	0.15	46.8	0.27	50.5	0.16	45.3	0.25	47.0	0.18	48.0	0.25	47.7
$\Phi \rightarrow$ C2 $\rightarrow$ Yc	0.06	19.3	0.08	15.7	0.07	19.5	0.10	18.3	0.06	16.9	0.09	17.1
C1 $\rightarrow$ Yc	0.09	27.9	0.14	26.7	0.10	27.9	0.14	26.3	0.11	29.3	0.14	27.8
C1 $\rightarrow$ C2 $\rightarrow$ Yc	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

Note: 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 10: Robustness check for influence of C_1: Age cutoffs

	18 or younger in 1989				20 or younger in 1989				22 or younger in 1989			
	Earnings		Income		Earnings		Income		Earnings		Income	
	Dir.	Ind.	Dir.	Ind.	Dir.	Ind.	Dir.	Ind.	Dir.	Ind.	Dir.	Ind.
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
Occup: 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
Occup: 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
Occup: Clerical	213.0	-113.0	46.9	53.1	.	.	28.6	71.4	551.5	-451.5	-437.3	537.3
Occup: 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
Occup: 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
Occup: 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
Occup: 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
Occup: 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
P 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
P 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
P 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
P 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 to 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 color (POC) and where the reference category is "White". Missing values reflect shares below -1000% or above 1000%.

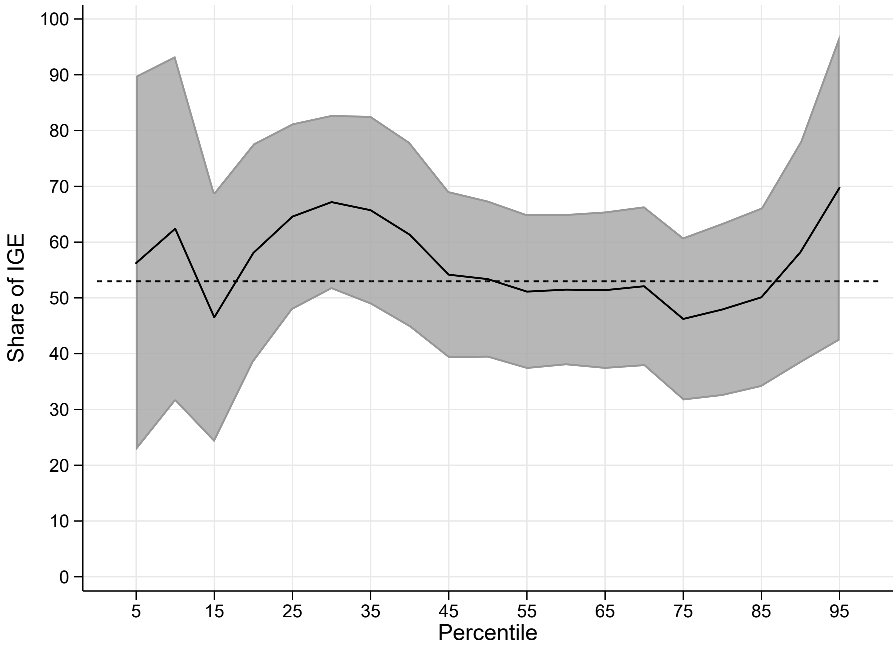
Table 11: Linear regression for each outcome

VARIABLES	(1) Earnings	(2) Earnings	(3) Earnings	(4) Income	(5) Income	(6) Income
Parental earnings	0.347***	0.225***	0.157***			
	(0.058)	(0.057)	(0.057)			
Parental income				0.526***	0.344***	0.247***
				(0.025)	(0.028)	(0.034)
IQ score		0.025*	0.023		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		0.103	0.181*		-0.021	0.022
		(0.112)	(0.109)		(0.063)	(0.061)
Occup: Professional		-0.157	-0.143		-0.094**	-0.084*
		(0.100)	(0.095)		(0.047)	(0.045)
Occup: Clerical		0.072	0.051		-0.102*	-0.107*
		(0.131)	(0.128)		(0.062)	(0.062)
Occup: Craftsman		-0.078	-0.038		-0.082*	-0.047
		(0.066)	(0.065)		(0.042)	(0.043)
Occup: Operative		-0.200**	-0.175**		-0.193***	-0.155***
		(0.088)	(0.075)		(0.052)	(0.050)
Occup: Farmer		-0.591	-0.528		-0.182	-0.103
		(0.406)	(0.375)		(0.115)	(0.106)
Occup: Services		-0.114	-0.080		-0.211***	-0.163**
		(0.135)	(0.127)		(0.081)	(0.081)
Occup: Other		-0.286	-0.176		-0.180***	-0.085
		(0.193)	(0.218)		(0.066)	(0.071)
P grew: in Farm		-0.176	-0.099		0.047	0.064
		(0.128)	(0.114)		(0.088)	(0.084)
P grew in Small town		-0.147	-0.074		0.088	0.106
		(0.130)	(0.105)		(0.087)	(0.081)
P grew in Large city		-0.084	-0.013		0.088	0.117
		(0.120)	(0.109)		(0.089)	(0.083)
Homeowner			0.051			0.051
			(0.063)			(0.037)
Region: Mideast			0.138			0.014
			(0.146)			(0.077)
Region: Great Lakes			0.012			-0.060
			(0.140)			(0.074)
Region: Plains			-0.027			-0.016
			(0.149)			(0.078)
Region: Southeast			-0.012			-0.105
			(0.143)			(0.076)
Region: Southwest			0.009			-0.195**
			(0.153)			(0.095)
Region: Rocky Mount.			-0.075			-0.062
			(0.168)			(0.091)
Region: Far West			-0.151			-0.047
			(0.227)			(0.088)
Region: Outside U.S.A.			0.541**			0.317
			(0.263)			(0.203)
Region: No Answer			-0.066			-0.055
			(0.136)			(0.287)
Over median: Business			-0.021			-0.016
			(0.078)			(0.046)
Over median: Stocks			-0.023			0.058
			(0.064)			(0.036)
Over median: Savings			0.196***			0.190***
			(0.068)			(0.038)

Used food stamps			-0.204*			-0.128*
			(0.115)			(0.069)
Constant	7.079***	7.742***	8.328***	5.317***	6.381***	7.427***
	(0.626)	(0.665)	(0.664)	(0.276)	(0.308)	(0.373)
Observations	720	720	720	2,021	2,021	2,021
R-squared	0.091	0.150	0.199	0.257	0.315	0.346

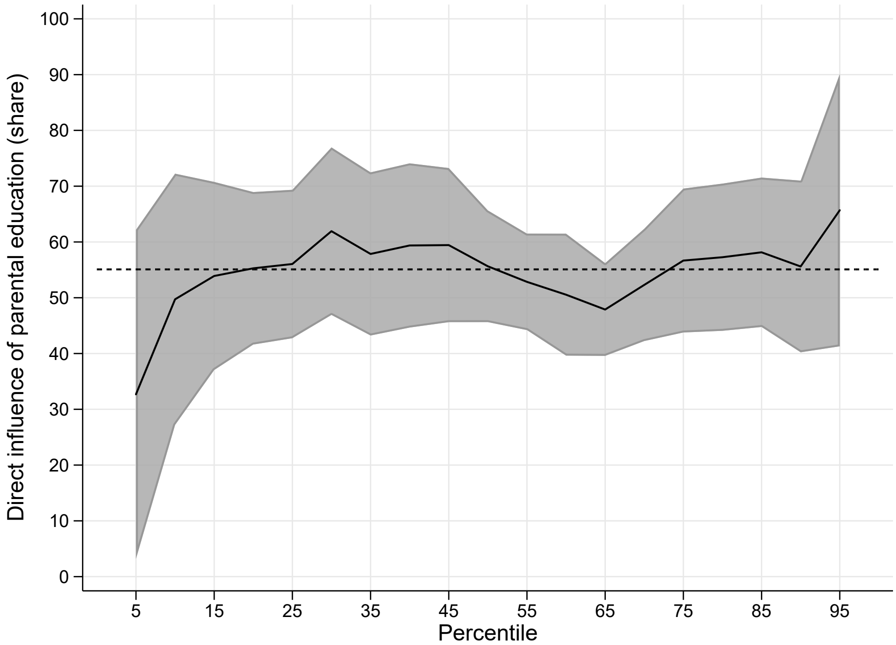
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 10: IGE decomposition: Quantile regression



Note: 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.

Figure 11: Direct influence of parental income: Quantile regression



Note: 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.