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One size doesn't fit all: a quantile analysis of intergenerational income mobility in the U.S. (1980–2010)

Juan C. Palomino[1,2,3] · **Gustavo A. Marrero**[2,3,4] · **Juan G. Rodríguez**[1,2,3]

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Abstract Conventional wisdom and previous literature suggest that economic mobility is lower at the tails of the income distribution. However, the few studies that have estimated intergenerational income elasticity (IGE) at different points of the distribution in the U.S. were limited by small samples, arrived at disparate results, and had not estimated the trend of elasticity over time. Using the PSID database, a large sample of income observations in the 1980–2010 period for the U.S. is built, which allows us to obtain robust quantile estimates of the IGE both for the pooled sample and for each wave. For the pooled sample, the IGE shows a U-shaped relation with the income distribution, with higher values at the tails (0.64 at the tenth percentile and 0.48 at the ninety-fifth percentile) and a minimum value –highest mobility- of 0.38 at the seventieth percentile. The trend evolution of the IGE also varies across the income distribution: at the lower and mid quantiles, income mobility increased during the 80s and 90s but declined in the 00s, while for the higher quantiles it remained

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✉ Juan C. Palomino
juancpal@ucm.es

Gustavo A. Marrero
gmarrero@ull.es

Juan G. Rodríguez
juangabr@ucm.es

1 Universidad Complutense de Madrid, Madrid, Spain

2 EQUALITAS, Madrid, Spain

3 CEDESOG, San Cristóbal de La Laguna, Spain

4 Universidad de la Laguna, San Cristóbal de La Laguna, Spain

relatively stable along the whole period. Finally, the impact of education and race on mobility is evaluated. Both factors are found to be important and related to the position at the income distribution.

Keywords Intergenerational mobility · Income elasticity · Quantile regression

1 Introduction

The perception that the US is a "land of opportunities" has often served to overlook its levels of income inequality, considering that the economy enjoyed a high level of economic mobility.[1] In recent decades, however, this commonplace perception has been questioned. Studies estimating the connection between parent and child income through the Intergenerational Income Elasticity (IGE) put the level of opportunity in the US into perspective, both comparing it with other nations and, more recently, showing its trend evolution. Thus, the pioneering works of Solon (1992) and Zimmerman (1992) alerted about a much higher value for IGE than what had been obtained in the scarce previous research on this issue.[2] This finding spurred subsequent research analyzing the IGE in the US and around the world, with the US quite consistently ranking higher than other countries with similar degrees of development (Corak 2006; Björklund and Jäntti 2009; Blanden 2013).

However, partly because of data availability and computational requirements, most IGE studies derive it from a regression-to-the-mean model using ordinary least squares (OLS), and little attention has been paid to the possible differences in the level of elasticity at different points of the income distribution.[3] The few works that have estimated the IGE in the US at different quantiles of the distribution have not found a clear relation between the IGE and the income distribution, and have considered a cross section with relatively small samples (Eide and Showalter 1999; Grawe 2004; Cooper 2011), which may cast doubt on the accuracy of their estimates. With regard to the trend evolution of IGE, research up to date has focused only on the OLS evolution of IGE and has arrived at disparate results (Hertz 2007; Aaronson and Mazumder 2008; Lee and Solon 2009).

This paper contributes to the debate about the level and evolution of IGE in the US in three different ways. First, it shows how IGE estimates progressively change across the income distribution following a quite clear U-shaped pattern: parental income influence on children's income is thus greater at the tails of the income distribution. Using family income data from the Panel Study of Income Dynamics (PSID), we apply conditional Quantile

[1]The "American Dream" refers to opportunity rather than equality. As J. T. Adams said, it is "that dream of a land in which life should be better and richer and fuller for everyone, with opportunity for each according to ability or achievement" (Adams 2012). In fact, according to the International Social Survey (2012), 94.4% of the Americans think that hard work is essential or very important to get ahead, while this percentage is 75.8% for the average of respondents from all countries. Analogously, 91.4% percent of US respondents think that ambition is essential or very important to get ahead, while this percentage falls to 71% for the world average.

[2]Former studies for the U.S. highlighted IGE values around 0.2 (see Zimmerman 1992 for a review of these studies). Using better databases and correcting for measurement errors, Solon (1992) and Zimmerman (1992) found IGE estimates of about 0.4. Later on, methodological refinements aimed to better correct for transitory shocks and life cycle bias (Mazumder 2005) estimated values of about 0.5 which are closer to our results.

[3]Previous research using probabilities transition matrices already pointed at a significant inertia for individuals at the tails of the income distribution. Jantti et al. (2006) show that the chances of remaining in the same quintile for individuals with parents from the bottom of the income distribution are significantly higher in the US than in the UK or the nordic countries.

Regression (QR) to estimate the IGE in the US in the whole 1980-2010 period.[4] In particular, we combine QR computation with the model proposed in Lee and Solon (2009), to enlarge the available data and, in this manner, obtain accurate estimations at the tails of the distribution while controlling for measurement error and life cycle bias.[5]

In order to study whether the observed high levels of IGE in the US are a recent or a structural phenomenon, and to check whether the trend evolution of the IGE is homogenous across the income distribution of adult sons, our second contribution is a time series analysis of IGE along the 1980-2010 period at different income percentiles. To the best of our knowledge, this is the first time that the trend of IGE is estimated at different points of the income distribution, and we find that the top quantiles and the mid-bottom quantiles of the distribution seem to have followed different trajectories in the three decades considered. However, as explained in the results section, the null hypothesis that IGE values are equal in all years considered for each given quantile is not rejected in most of the quantiles, which calls for caution when interpreting the trend results.

Finally, we explore the role of sons' education and race as intergenerational transmission channels of parental income, both across the income distribution and along the time trend. In this respect, we find that the impact of both factors, education and race, depends on the point of the distribution under consideration.

The rest of the paper is structured as follows. In Section 2 we present our methodology to estimate IGE across the income distribution for the entire pool and year by year. Section 3 details our choices and treatment of the PSID database, while Section 4 presents our main IGE results for the pooled sample and for its trend from 1980 to 2010, and Section 5 concludes. A sensitivity analysis including different data choices and the unconditional quantile regression estimation is available in an Online Appendix.

2 Methodology

The intergenerational income elasticity refers to the influence of parental income in children's adult income. In the canonical (Galton 1886) regression of a child's income $y_{s_{it}}$ on the parent's income $y_{p_{it}}$,

$$\ln y_{s_i} = \alpha + \beta \ln y_{p_i} + \varepsilon_{it} \tag{1}$$

the constant term α captures the trend in average incomes across generations due for example to changes in labor market institutions, international trade or technology, while the β coefficient, called intergenerational elasticity, measures the degree of persistence in family's income across generations. The higher the value of β, the larger the capacity of parental income to predict son's economic achievement. Accordingly, $1 - \beta$ is a measure of intergenerational income mobility. Finally, the error term ε_{it} represents all other influences on the child's adult income not correlated with parental income.[6]

[4] We also apply the new unconditional quantile regression method proposed by Firpo et al. (2009) in our sensitivity analysis (see Online Appendix).

[5] See appendix Table 4 for a review of elasticity estimates for the US using OLS in the literature. In appendix Table 5 we review the existing IGE literature using QR in the US. Previous works had not found the clear U-shape pattern connecting IGE with the son's position at the income distribution. As we will discuss in the results section, this could be due to their small samples and to the use of earnings instead of income as the elasticity variable.

[6] Although the relation between parental income and son's income cannot be affected by reverse causality, there could be omitted variables that prevent us from establishing a causal relationship. Also, the value of IGE

The use of this basic model presents some important limitations. First, trying to avoid the life cycle bias, scholars have traditionally restricted the sample to observations at a precise children's age, thus overlooking a lot of information from income at other ages. As a result, the number of observations to estimate intergenerational mobility has typically been small. Second, the intergenerational income elasticity has been usually estimated by ordinary least squares (OLS), which yields an estimate at the mean of the distribution, but ignores the possible variation of intergenerational mobility across income quantiles, as pointed out by Bishop et al. (2014). Finally, when only parental income is included as an explanatory variable, the model in Eq. 1 is incapable of analyzing channels of income transmission between parents and children. Next, we explain the main strategies we have adopted to overcome these limitations.

2.1 The model

To use all the available information, and still tackle the life cycle bias, we follow the approach in Lee and Solon (2009). This methodology permits the exploitation of the entire pool of data, estimating the IGE with all available pairwise observations of adult sons and parents' income, while controlling for the influence of the life cycle on income of both parents and children. The equation to be estimated is the following:

$$\ln y_{s_{it}} = \alpha + \beta \ln y_{p_i} + \sum_{n=1}^{4} \gamma_n A_i^n + \sum_{n=1}^{4} \delta_n C_{it}^n + \sum_{n=1}^{4} \theta_n [\ln y_{p_i}] C_{it}^n + \varepsilon_{it} \tag{2}$$

where $y_{s_{it}}$ is the real household income (in logs) of adult sons from family i at year t = 1980, 1981, …, 2010; y_{p_i} is the averaged parental household income (in logs) of family i when the son was a child between 13 and 19 years old; the rest of terms control for the influence of the life cycle on parental and son's income. Variable A_i^n, parameters γ_1 to γ_4 , represents the age of the parent in family i when the children was 16 years old. Variable C_{it}^n, parameters δ_1 to δ_4 , controls for the son's age when his income is measured. It is expressed as the difference between the age of the son and the age of 40 years old at each year t in which income is computed, thus centering our estimates at the age of 40. If c is the birth cohort of the individual, $t - c$ is the age at which income is reported, and thus $C = t - c - 40$. The third variable $[\ln y_{p_i}]C_{it}^n$, parameters θ_1 to θ_4, represents the interaction between parental income and the age of the son, and it tries to account for the possible divergences in life-income patterns depending on parental income. Age related variables (A and C) are quartic in order to control for different possible functional shapes when time interacts with income.

We first estimate (2) for the entire pool of data, thus obtaining IGE in the US for the entire sample. Later, we estimate the time trend of β between 1980 and 2010 using all available information. For this purpose, we need to modify (2) as follows:

$$\ln y_{s_{it}} = \alpha_t D_t' + \beta_t [\ln y_{p_{it}} D_t'] + \sum_{n=1}^{4} \gamma_n A_i^n + \sum_{n=1}^{4} \delta_n C_{it}^n + \sum_{n=1}^{4} \theta_n [\ln y_{p_{it}}] C_{it}^n + \varepsilon_{it} \tag{3}$$

where D_t is a vector of yearly dummy variables whose first element takes the value of 1 for 1980 and 0 otherwise, the second element takes the value of 1 for 1981 and 0 for all the rest,

can be influenced by other variables involved (education quantity, education quality, race, location, social connections, etc.) In fact, our study of education and race discloses part of the role of these variables on IGE: controlling for race and for the amount of education reduces our measure of IGE in more than 30% at most quantiles and even more than 60% at the 5th percentile (see Table 2).

and so on. Thus, estimating (3) gives us a different intercept α and slope β for each PSID wave at t = 1980, 1981...2010. The age-controlling variables are estimated for the pooled data and the model assumes they are time invariant.

2.2 Quantile regression

We use Quantile Regression to examine whether intergenerational mobility varies across the income distribution. This method offers the possibility of obtaining point estimates at any selected quantile of the son's conditional income distribution. Using the entire pool of data, we run QR for Eq. 2 and estimate IGE at every ventile, i.e. quantiles 0.05, 0.10...0.95. Initially, the QR estimates are obtained for the pooled 1980-2010 sample. The large size of this sample allows us to obtain highly accurate QR estimates at the tails. Later, we estimate the QR version of Eq. 3 and characterize the time trend evolution of IGE at different percentiles for the 1980 – 2010 period. Although these estimations are less accurate because the sample must be split, they allow us to analyze the particular trend of IGE at different quantiles all along the 1980–2010 period.

In contrast with OLS, which minimizes squared errors and yields the estimates at the mean of the distribution, QR minimizes absolute errors at any particular quantile of the conditional $Y|X$ distribution (Koenker and Bassett 1978; Koenker 2005).[7] Suppose that we want to calculate the QR estimate of the quantile τ. Then, those absolute errors corresponding to observations below the quantile τ are weighted with the weight $1 - \tau$, while the absolute errors for those observations above the quantile τ are weighted (asymmetrically) with τ. This asymmetrical weighting can make the QR estimates less robust at the tails of the distribution. This is not a problem for samples that are sufficiently large, but with small samples, a change in only some of the data might alter the coefficient quite significantly. For this reason, we apply the proposal in Lee and Solon (2009), which allows us to use the entire 1980-2010 pool of data to estimate IGE at all ventiles of the distribution. In our yearly IGE trend estimates, when the estimation is 'split' by years, we have excluded the most extreme quantiles ($\tau = 0.05$ and $\tau = 0.95$) from the graphical representation of the results due to the high standard errors of the estimation at those quantiles.

2.2.1 Conditional and unconditional quantile regression

Unlike the OLS estimator, which is valid for both the conditional and unconditional distribution, conditional QR estimates cannot be used to represent the estimates at the unconditional quantiles of the distribution. Trying to address this problem, Firpo et al. (2009) have proposed a new 'unconditional quantile regression' method to estimate the impact of the different X covariates at the unconditional quantiles. In order to check the robustness of our results, in the Online Appendix we have compared conditional and unconditional quantile estimations of IGE for an age restricted-subsample. We find the results in the conditional and unconditional regressions to be overall quite similar and that our main qualitative findings (i.e. the U-shape pattern of the IGE and the different role of education and race across the distribution) still hold.

[7] The use of absolute errors instead of squared errors makes QR less sensitive to outliers than OLS. Also, as pointed out by Mitnik et al. (2015) OLS estimates of elasticity using log transformed income are in fact centered at the geometric mean instead of the arithmetic mean; however, in contrast to the mean, the median and the quantiles estimated by QR are unaffected by a log transformation of the variables.

2.3 Factors of intergenerational income transmission

It is a challenging issue to understand the main channels and factors that condition the transmission of income from parents to children. In principle, education, connections, race and other genetic traits are potential candidates. Unfortunately, the availability of data to test some of these factors is limited.[8]

We focus on two possible explanatory variables that are time-consistent over the PSID panel: son's 'years of education' and 'race'. We attempt to measure the importance of these factors in the transmission of income across the children's income distribution, first for the entire pool of data, and then at each PSID wave over the last three decades.

To estimate the impact of education for the entire pool, we first add in equation 2 the 'years of education' variable e_{s_i}.

$$\ln y_{s_{it}} = \alpha + \beta \ln y_{p_i} + \lambda e_{s_i} + \sum_{n=1}^{4} \gamma_n A_i^n + \sum_{n=1}^{4} \delta_n C_{it}^n + \sum_{n=1}^{4} \theta_n [\ln y_{p_i}] C_{it}^n + \varepsilon_{it} \quad (4)$$

where λ_{s_i} is the partial direct impact of the variable e_{s_i} on son's income, given parental income and all other controls in Eq. 4. How can we interpret a possible change in the β coefficient after the inclusion of the variable e? Let us consider an extreme situation in which the education variable e is uncorrelated with parental income. In this case, even when the variable e is significant to explain children income, including this variable in the regression does not modify the influence that parental income has on son's income, thus the primitive β (as estimated in Eq. 2) will remain unchanged. In the opposite case, if the variable e is strongly correlated with parental income, the new β will significantly drop when the variable e is included in the regression. Hence, we can interpret that the smaller the change in β when we include variable e in the regression, the weaker the role of this variable as a transmission channel. Analogously, comparing the elasticity (β) from Eq. 4 with the one obtained in Eq. 2 can measure the share of elasticity 'mediated' by education: $(\beta_{baseline} - \beta_{edu})/\beta_{baseline}$

To control for the additional effect of race, we have added the race variable in Eq. 5. Variable r_{s_i} is a dummy variable that takes the value 1 for white individuals and is 0 otherwise. Then, the impact of race can be calculated comparing the elasticity β from Eq. 5 and the β from Eq. 4, and relating it with the original baseline beta: $(\beta_{edu} - \beta_{race+edu})/\beta_{baseline}$

$$\ln y_{s_{it}} = \alpha + \beta \ln y_{p_i} + \lambda e_{s_i} + \varphi r_{s_i} + \sum_{n=1}^{4} \gamma_n A_i^n + \sum_{n=1}^{4} \delta_n C_{it}^n + \sum_{n=1}^{4} \theta_n [\ln y_{p_i}] C_{it}^n + \varepsilon_{it} \quad (5)$$

Finally, we have analogously included the variables e_{s_i} and r_{s_i} in our trend estimation (3), in order to analyze the influence of son's education and race in the time evolution of IGE.

[8] Anger and Heineck (2010) find a positive relation between parental and children cognitive abilities, even controlling for education and economic background. It is hard, however, to connect this transmission of abilities with the transmission of income, and studies about this transmission channel are rare. Data availabity has made scholars focus mainly on variables like education and race (Hertz 2006; Torche 2013). Bowles and Gintis (2002) is a prominent exception, finding the impact of intelligence on income transmission to be relatively small, accounting for a 12.5% share of the intergenerational correlation.

3 Database

To measure intergenerational income mobility, we use the 'core' sample of the PSID database. The PSID is a household panel maintained by the University of Michigan that began in 1968 and is still running. The survey was conducted annually from 1968 to 1997, and then every other year.

The income variable used is total family income, which aggregates the total income of the household, including taxable incomes and transfers received by the head, the head's spouse and other family members, and which is consistently included in the PSID since its creation (note that income reported refers to the year prior to the interview). All values are transformed to 2010 US dollars using the average Consumer Price Index (CPI) from the Bureau of Labor Statistics and outlier observations are removed. We follow Lee and Solon (2009) and exclude observations for which income is less than \$100 or more than \$150,000 in 1967 dollars. In total, around 200 observations (less than 1% of the sample) were dropped.[9]

We match sons and parents using the individual and family codes provided by the PSID, creating an unbalanced panel. Parental observations include family incomes of households with both male and female heads, and the sample of children is restricted to those sons that later become household heads.[10]

We have averaged yearly parental family income when the child was between 13 and 19 years old (seven years), provided there were at least three observations over this period (6.24 observations on average), in order to reduce transitory shocks (see Solon 1992, Zimmerman 1992), Mazumder 2005 or Mitnik et al. 2015).

In the Online Appendix we discuss the sensitivity of these data choices to different specifications. Our choice of the PSID 'core sample' seems robust to the use of only the Survey Rearch Component sample of the PSID. Also, we test our results to the use of different outliers thresholds and also include an illustrative example of the effect of different numbers of parental years averaged, which supports our choice of up to seven years averaged as a good measure of permanent income.

When observing the income of the adult children, a 'life cycle' bias can arise in the estimation depending on the age at which this income is observed. Previous works on intergenerational elasticity have concluded that observing income at the middle of the life cycle is the best proxy of permanent income (Black and Devereux 2011).[11] However, restricting the sample to observations at a precise children's age, implies ignoring a lot of information from income at other ages that might be available and could be exploited. To use this information, but still tackle the life cycle bias, we follow the approach in Lee and Solon (2009). As mentioned in Section 2, instead of shortening the age range of children, we use all available observations of income from the whole working life of individuals, but include

[9] Note that we also exclude outlier observations in which reported parental age -when the child was 16- is smaller than 30 or greater than 70.

[10] Our preliminary results showed that adult daughters' IGE depended strongly on their marital status. A rigorous analysis for women should consider assortative mating (Chadwick and Solon 2002; Black and Devereux 2011) and the structural change in women's access to the labor market occurred in the decades analyzed, which is beyond the scope of this paper. In this respect, note also that race data for wives is only available from 1984.

[11] Using Finnish data, Lucas and Kerr (2013) find that IGE estimates increase with the son's age considered until approximately the age of 40.

age-dependent covariates in the regression to control for the different age at which family income is observed, centering our estimates at the age of 40. For consistency, we control also for parental age in the regressions in order to tackle the potential parental life cycle bias. Since the age controls are estimated for the period 1980–2010 has a whole, it is important that there is no significant change in the age-income pattern across cohorts. We have checked that in our sensitivity analysis (see Online Appendix) and found no significant change.

In sum, at each year from 1980 to 2010, we keep the observations of sons who are between 25 and 65 years old, provided that they are the head of the household and live in the family home. By the year 1980 we already have sufficient individuals who were between 13 and 19 years old in 1968 (when the PSID began) and have already established their own household. In Table 1 we show the number of observations that abide all these criteria for all years in the period 1980-2010, and include the mean and standard deviation of age and real family income in logs for parents and sons. Our sample consists of a total of 25,084 observations from 3088 different individuals. On average, each individual appears in 8.12 waves of the survey, with a standard deviation of 6.39. As discussed in Section 4.1, we have taken this into account in the computation of standard errors (see Footnote 12).

In addition to the main total family income variable, we also consider from the PSID the individual variables ‘years of education’ and ‘race’, aiming to study their importance in the transmission of parental income. The education variable represents the actual grade of school completed, ranging 1–17 where a code value of 17 indicates that the individual completed at least some postgraduate work. In the case of race, we transform the categorical variable ‘race of head’ into a dummy variable that takes the value 1 when the race of the son is white and zero otherwise. Using a dummy for white race, we implicitly assimilate black to the other non-white races. Please see the Online Appendix for a discussion on the use of educational categories instead of years and of a black race dummy instead of a white race dummy. Overall, results do not change significantly.

4 Intergenerational Income Elasticity results

In the first part of this section we present the results of our pooled data regression. In particular, using the entire 1980–2010 sample, we show the value of IGE at each quantile. We also measure the importance of education and race as channels of intergenerational income transmission. In the second part, we study the evolution of IGE between 1980 and 2010 at different points of the distribution of income and the role of education and race along that period and across the distribution.

4.1 IGE by quantiles: a pooled regression analysis for the 1980-2010 period

The β intergenerational income elasticity estimates obtained from the pooled (1980–2010) sample at the mean and at all conditional ventiles are displayed in Table 2 and Fig. 1.[12] The OLS estimation yields a value of 0.47, which is in line with the literature (see appendix for Table 4).

[12] Given that individuals appear in our sample during several survey waves, our observations can be considered to be ‘clustered’ in individuals, and standard errors must take this into account. For that purpose, we have applied the clustered version of the bootstrap method in the ‘quantreg’ R package, which is based on the proposal of Hagemann (2016). When possible all figures plot a standard error bar centered at the point estimate. We thank an anonimous referee for pointing this out to us.

Table 1 Descriptive statistics

		Son's age		Son's income		Dad's age		Dads's income		Race share (%)		
Year	Obs.	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Whites	Blacks	Other
1980	457	26.79	1.43	10.72	0.73	44.92	6.34	10.94	0.63	61.49	36.98	1.53
1981	551	27.32	1.67	10.66	0.84	44.57	5.99	10.97	0.63	62.25	35.93	1.81
1982	629	27.81	1.93	10.61	0.86	44.59	6.17	10.97	0.63	61.84	36.09	2.07
1983	680	28.43	2.20	10.67	0.86	44.84	6.15	11.00	0.63	62.50	35.15	2.35
1984	776	28.90	2.50	10.70	0.85	44.76	6.11	11.01	0.64	63.14	34.28	2.58
1985	850	29.28	2.80	10.70	0.87	44.80	6.10	11.02	0.64	65.41	33.76	0.35
1986	921	29.73	3.09	10.75	0.83	44.94	6.22	11.03	0.63	65.58	33.66	0.33
1987	993	30.22	3.33	10.76	0.87	44.95	6.17	11.05	0.63	65.86	33.33	0.40
1988	1043	30.82	3.60	10.81	0.83	44.95	6.17	11.05	0.63	65.77	33.37	0.19
1989	1095	31.37	3.84	10.81	0.89	44.83	6.17	11.06	0.64	67.03	32.05	0.27
1990	1158	31.81	4.10	10.80	0.86	44.66	5.98	11.05	0.65	66.67	32.12	0.52
1991	1228	32.37	4.34	10.79	0.88	44.70	6.05	11.04	0.66	65.07	30.62	0.81
1992	1247	33.00	4.68	10.84	0.94	44.60	6.06	11.07	0.65	65.76	30.07	0.64
1993	1326	33.54	4.87	10.82	0.96	44.41	6.00	11.07	0.66	63.20	27.98	0.90
1994	1317	33.99	5.06	10.89	0.89	44.31	5.97	11.09	0.65	67.81	29.46	1.75
1995	1339	34.42	5.40	10.90	0.90	44.28	6.02	11.09	0.65	68.33	28.83	1.87
1996	950	35.11	5.81	11.01	0.83	44.08	5.75	11.20	0.63	76.74	20.84	1.16
1998	1014	35.95	6.59	11.13	0.82	43.77	5.74	11.21	0.62	75.84	21.20	2.76
2000	1077	36.68	7.10	11.13	0.86	43.60	5.80	11.19	0.65	76.04	21.08	2.60
2002	1136	37.40	7.74	11.13	0.80	43.33	5.69	11.20	0.67	75.88	21.74	2.20
2004	1215	37.62	8.40	11.10	0.88	43.18	5.62	11.20	0.68	75.56	23.05	1.32
2006	1293	37.76	9.02	11.06	0.92	43.02	5.36	11.21	0.68	73.86	24.36	1.39
2008	1381	38.09	9.47	11.04	0.92	42.99	5.24	11.21	0.70	73.35	24.76	1.59
2010	1408	38.24	9.91	10.94	0.96	42.95	5.30	11.22	0.73	72.30	25.36	2.06

More importantly, if we enrich the picture with the conditional QR estimations, we observe a U-shaped relationship. The intergenerational income elasticity is highest at the lower percentiles of the distribution –reaching a value of around 0.6 at the 5^{th}–20^{th} percentiles. Then, it declines steadily, reaching a minimum around 0.38 at the 70^{th}percentile. At the top part of the distribution, the IGE increases again, reaching a value of almost 0.5 at the 90^{th}–95^{th} percentiles.[13]

These results indicate that the 'inheritance' of family income in the US varies when we move along the conditional income distribution of adult sons. For example, a hypothetical shift in one dollar of parental income would shift average son's income in 0.47 dollars (our OLS estimate), while the 10^{th} quantile of the conditional income distribution would shift

[13]Our target variable is total family income, which is computed after transfers but before taxes, and is not directly affected by differential taxation overtime (we ignore here possible behavioral effects). Although (Mitnik et al. 2015, p. 71) do not find a significant difference between using pre-tax and post-tax income in the measurement of the IGE, our total family income might be affected by different transfer policies overtime. Transfers could be specially relevant for the lower part of the distribution and could downward bias the IGE estimates at the lowest quantiles.

Table 2 Pooled regression estimates

	Baseline		Model w/ Education		Model w/ Edu + Race		Impact on IGE (Share of Baseline)		
Quantile	IGE	(SE)	IGE	(SE)	IGE	(SE)	Edu	Race	Edu + Race
OLS	0.473	0.018	0.343	0.017	0.295	0.017	0.274	0.101	0.375
0.05	0.554	0.223	0.287	0.286	0.220	0.233	0.482	0.122	0.604
0.1	0.645	0.163	0.434	0.129	0.369	0.165	0.327	0.100	0.427
0.15	0.639	0.084	0.480	0.055	0.428	0.132	0.249	0.081	0.330
0.2	0.567	0.095	0.454	0.086	0.385	0.097	0.199	0.121	0.320
0.25	0.526	0.065	0.432	0.051	0.392	0.048	0.177	0.076	0.254
0.3	0.520	0.058	0.409	0.057	0.347	0.062	0.213	0.119	0.332
0.35	0.491	0.055	0.374	0.078	0.325	0.050	0.238	0.100	0.339
0.4	0.464	0.053	0.361	0.071	0.297	0.054	0.221	0.138	0.359
0.45	0.456	0.051	0.345	0.056	0.296	0.073	0.243	0.108	0.352
0.5	0.440	0.051	0.336	0.024	0.283	0.049	0.237	0.120	0.357
0.55	0.421	0.055	0.330	0.045	0.277	0.038	0.215	0.128	0.343
0.6	0.398	0.055	0.305	0.025	0.271	0.051	0.234	0.084	0.318
0.65	0.386	0.043	0.292	0.042	0.274	0.053	0.244	0.045	0.289
0.7	0.379	0.038	0.293	0.051	0.272	0.033	0.226	0.058	0.284
0.75	0.398	0.046	0.283	0.052	0.268	0.039	0.290	0.036	0.325
0.8	0.424	0.037	0.287	0.038	0.272	0.041	0.322	0.037	0.359
0.85	0.443	0.046	0.307	0.039	0.273	0.047	0.307	0.078	0.385
0.9	0.476	0.059	0.316	0.044	0.290	0.058	0.337	0.054	0.391
0.95	0.476	0.092	0.311	0.104	0.303	0.074	0.346	0.017	0.363

by 0.64 dollars and the 70^{th} quantile by just 0.38. Children at the upper middle part of the conditional distribution show the smallest degree of intergenerational persistence, while top incomes and, specially, low incomes are very much conditioned by their childhood economic circumstances, represented here by parental income. Previous studies estimating the IGE at different quantiles have relied on much smaller samples and have found disparate results. For example, Grawe (2004), using a sample of only 354 observations, found that intergenerational elasticity is higher at the median than at the tails, i.e., an inverse U-shaped. Eide and Showalter (1999) using a sample of 612 observations, and Cooper (2011) with a sample of 1424 observations found a continuous –almost linear– decrease in the IGE as we go up the income distribution. According to these authors there is not a significant increase in the IGE at the upper part of the distribution.[14]

Besides the much bigger sample used in our research, there exists another reason that could explain why these previous studies do not find an increase of the IGE in the US

[14]Recall that our sample consists of 25.084 observations from 3.088 inviduals. See appendix Table 5 for a summary review of the results of the literature using QR for IGE estimation in the US.

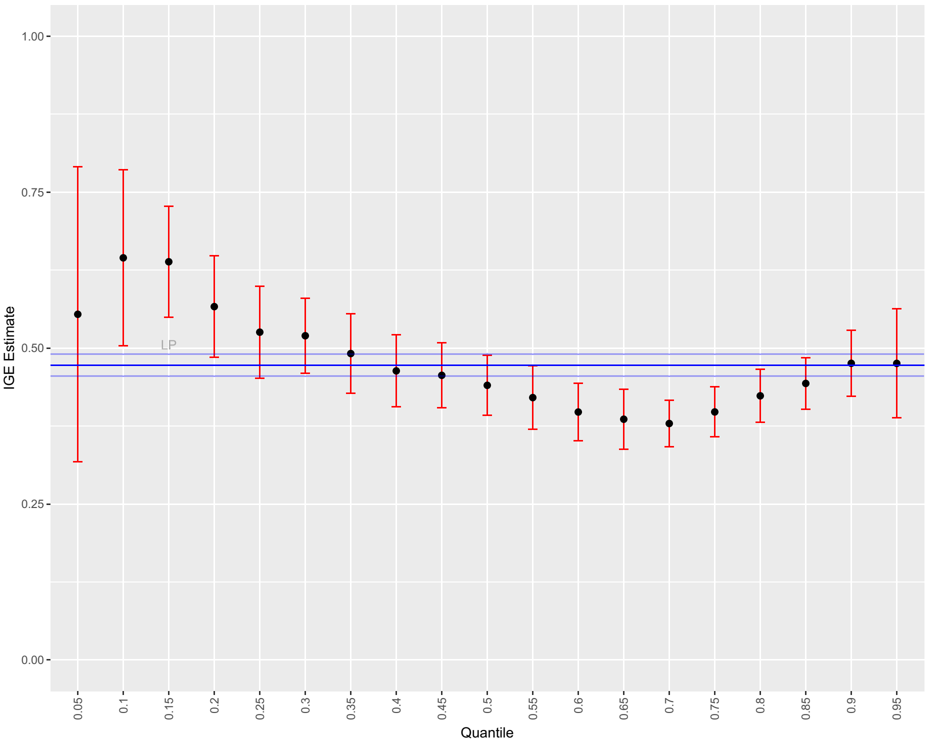

Fig. 1 IGE pool estimates for the baseline model (25084 observations). Confidence intervals plotted in red for contidional quantile estimates obtained with QR estimation and in blue for the linear proyection estimates (LP) obtained with OLS estimation

from the 70^{th} percentile onwards. While we use parents and sons' total household income, Eide and Showalter (1999) regress son's *earnings* on parental earnings/income, and Cooper (2011) measures intergenerational elasticity for child and parents labor earnings. A great deal of the correlation between parental and children incomes at the upper part of the distribution could occur through capital income, which is included in the total household income variable. If so, values of intergenerational elasticity of sons' earnings would underestimate actual intergenerational elasticity of income at the top quantiles. In this sense, Jantti et al. (2006), using transition matrices to measure intergenerational mobility also of earnings, find higher inertia at both ends of the distribution in the U.S., but with more intensity at the bottom than at the top.[15]

[15]Bowles and Gintis (2002) find that wealth explains 0.12 out of a 0.32 correlation between parental and children income, more than a third of the value. Wealth –and therefore the capital income derived from it- is concentrated at the top percentiles of the distribution. Levine (2012) reports that in 2010 the top 1% of the households ordered by wealth had a share of 34.5% of the net worth in the U.S. while the bottom 50% possessed only 1%. Fräßdorf et al. (2011) show that the share of inequality in household income explained by capital income is increasing in the U.S. Outside the US, Lucas and Kerr (2013) have also found -using a nested model- that intergenerational transmission of income is significantly greater than intergenerational transmission of earnings in Finland.

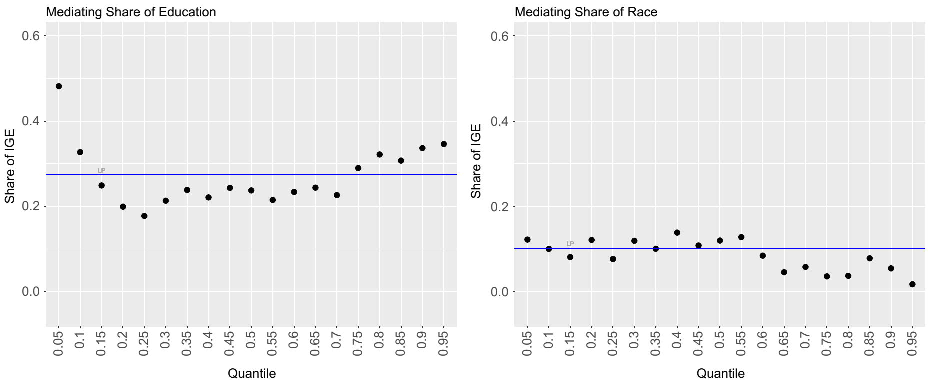

Fig. 2 Impact of Education and Race as a share of IGE. Pooled estimates

Studies measuring intergenerational elasticity applying QR in other countries are scarce, but seem to concide in finding less mobility at the bottom of the income distribution. In line with our results, (Tejada et al. 2015), in their estimation of intergenerational elasticity of income for the 1982 born cohort in the city of Pelotas (Brasil), find higher values of the IGE at both ends of the income distribution. On the other hand, Bratberg et al. (2007) apply QR for earnings data from Norway cohorts born in 1950–1960, and find the relation between the IGE and the position at the earnings distribution to be decreasing, with higher IGE at the bottom tail, but more mobility (lower IGE) at the top of the earnings distribution. Again, the distinction between income and earnings discussed above could explain that at the top of the *earnings* distribution mobility is higher than at the middle, while the opposite happens when we consider *income*.

4.1.1 Education and race impact on elasticity in the pool

Next, we focus on the role of education and race as possible channels of income transmission across generations. Our results –see Table 2– show that when education is included in the regression (3), the estimated the IGE decreases a share of 0.274 (27.4%) at the mean (OLS estimation). This OLS result is similar to Eide and Showalter (1999) or Cooper (2011) who find approximately a 30% mediating role of education in the persistence of income across generations at the mean in the distribution; other works (Torche 2013; Blanden et al. 2014) find an even higher explaining role of education.[16] Our QR results find a share of the IGE mediated by education between 20% and 48% depending on the quantile. This share is lower in the range of the 20th-70th percentiles –representing around 20% of the IGE- and increases significantly when approaching the extremes of the distribution (see Table 2 and Fig. 2a). Thus, even though we cannot control for factors like the quality of the schools or the peer-effects, between one fifth and half of intergenerational income transmission is

[16]See appendix Table 4 for a review of the most relevant previous literature on this issue.

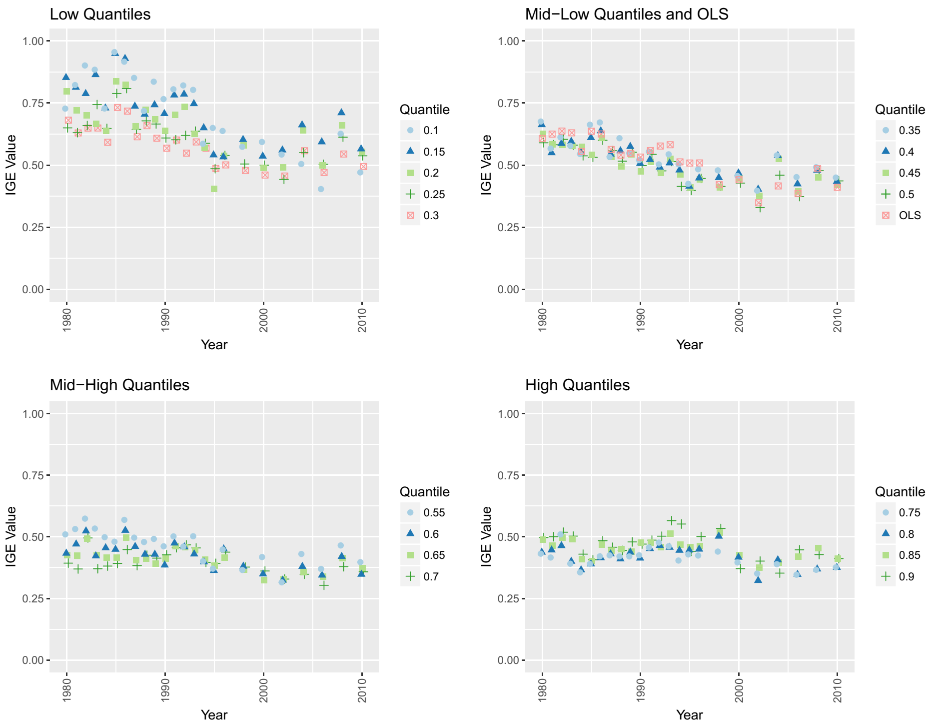

Fig. 3 IGE Trend 1980-2010

explained just by the different amount of education –measured in years– that parents can provide to their children.[17]

With respect to race, the OLS regression yields an additional decrease in the IGE of 10% when we include the dummy variable 'race' as an additional control in Eq. 5. Thus, at the mean, one tenth of the 'inheritance' of parental income can be attributed to the race of the individual (Table 2), controlling by the years of education. Looking at the impact of race on the IGE across the income distribution -which, to the best of our knowledge, has never before been studied in the literarature- we find it to be of around 10% at the bottom half percentiles, the influence being much smaller (about 5%) from the 60^{th} percentile upwards (Table 2 and Fig. 2b).

The role of education shows no strong trend pattern across the income distribution in the period analyzed—see Online Appendix—altough it seems to increase slightly in the 00s

[17] Needless to say, the years of education mediating role could englobe other factors cross-correlated with the number of years of schooling, parental income and son's income (e.g. parental motivation). Also note that, for robustness, we have also run the analysis using educational levels instead of years of education, finding a similar impact on the IGE (see Figs. 2a and A5a).

Table 3 Wald statistics for equality of IGE coefficients across the 1980-2010 period for each quantile and for the linear projection

Quantile	Wald statistic	P-value
OLS	78.449	0.000
0.1	24.418	0.381
0.15	29.747	0.157
0.2	56.663	0.000
0.25	31.562	0.110
0.3	22.796	0.473
0.35	39.172	0.019
0.4	24.231	0.391
0.45	30.784	0.128
0.5	31.960	0.101
0.55	40.646	0.013
0.6	22.881	0.468
0.65	18.219	0.746
0.7	28.760	0.188
0.75	21.712	0.538
0.8	34.355	0.060
0.85	18.144	0.750
0.9	23.005	0.460

for all quantiles. The importance of race in the IGE shows a similar pattern at all quantiles analyzed: decreasing in the 80s and –especially- in the 90s, but regaining importance from the mid 2000s.

4.2 Evolution of the IGE in the US between 1980 and 2010

As seen above, for the period 1980–2010 as a whole, high-income quantiles and, above all, low-income quantiles show greater elasticity than middle-income quantiles. But, how was the evolution of the IGE for the entire distribution and by quantiles during this period? For illustrative purposes, we present the results graphically by groups of quantiles and excluding the two extreme ventiles: the low-income group (10^{th} to 30^{th} percentiles); the mid-low income group (percentiles 35^{th} to 50^{th}); the mid-high income group (percentiles 55^{th} to 70^{th}); and the high-income group (percentiles 75th to 90th). The estimation at the mean (OLS) is plotted with the mid-low income group that includes the median (Fig. 3).[18]

We must caution the reader about the statistical significance of the trends of IGE at the different quantiles. Using the Wald test, we have tested the hypothesis that all IGE estimates from different years at a given quantile are equal (see Table 3). The hypothesis can be rejected at the 5% significance level only for the 20th, 35th and 55th percentiles and for the

[18]For space reasons, the tables with the estimations of the IGE at each ventile for each PSID wave have not been included. Neither have the tables with the trend estimates for the IGE controlling for education and race. They are available upon request.

linear projection estimated with OLS. Also note that the test only statistically rejects that the coefficients are equal, but does not evaluate the slope or the direction of the possible trend.

Our OLS estimation at the mean (see Fig. 3, top-right), the intergenerational elasticity shows a decreasing trend in the first two decades analyzed, followed by an increase in the 2000s. This result contrasts with Aaronson and Mazumder (2008), who found an increase in the IGE over the 1980-2000 period, and with Hertz (2007) and Lee and Solon (2009) who found no trend for that same period. Mayer and Lopoo (2005), on the other hand, found a decreasing trend of the IGE for the period 1984–94.[19] With a bigger sample using tax records and the Statistics of Income annual cross sections, Chetty et al. (2014) estimate rank-rank relative intergenerational mobility for cohorts born after 1971, measuring son's family income when the son is 29-30 years old. For cohorts born in the 70s –which would correspond to our estimates in the 2000s decade- they find a stable trend in relative mobility, which would be consistent with our OLS estimation of an increasing trend in IGE for that period, given that inequality in the United States increased during that decade.[20]

Concerning the trend at different points of the income distribution, our estimates show that, for the linear projection and for all the quantiles below the median, the IGE decreased in the 80s and 90s and increased in the 2000s. This pattern is more pronounced at the lowest quantiles. At the upper part of the distribution, however, both the mid-high and the high-income quantiles maintained a steady value of the IGE along the three decades analyzed, and show only a very mild decreasing pattern in the 90s that turns increasing in the 2000s. It is worth noting that the IGE at the low-income quantiles has always been the highest, this group consistently suffering from lower mobility than the rest of income groups.

With more intensity for the lower part of the distribution the change of century seems to be a turning point in the trend of the IGE for all groups. Elasticity raised in all income groups since 2002, above all with the Great Recession (2007–2009). After the Great Recession intergenerational elasticity generally decreased in 2010, although more observations will be required to confirm this new trend in the IGE series.

We have also run an analysis of the share of the IGE related to education and race along the 1980-2010 period. The results, which again must be interpreted with caution due to the data limitations when we estimate IGE for each wave separately, are displayed in the Online Appendix (Figs. A8 and A9). They show no clear trend for education at the different quantiles and, for race, they point at an increase in importance in the 2000s after having decreased in the previous two decades.

5 Conclusion

Despite the extensive literature on the subject of measuring the magnitude of the IGE in the US, most of the works estimate it at the mean of the income distribution. The few studies

[19]Mayer and Lopoo analyze trends by cohorts. The period 1984–94 corresponds to the years in which the cohorts are 30 years old, the age at which they estimate the IGE in their rolling groups regression (Mayer and Lopoo 2005, p. 176)

[20]Note that for a certain level of correlation between parent and son's income, IGE regression estimates increase when the inequality ratio between the sons and parents distributions increases. The Gini Index at disposable income in the US rose from 0.357 in 2000 to 0.380 in 2010 as reported by OECD.

that estimate the IGE at different quantiles in the US work with small samples, since they consider only a cross-section of individuals at a small age range. As a result, estimates at the tails are prone to being biased and they have arrived at disparate results. In an attempt to overcome these limitations, we use up-to-date family income data from the PSID to exploit a greater number of data while still controlling for measurement errors and life cycle bias. We apply quantile regression to the estimation of IGE in the US for the 1980–2010 period and explore the role of the child's amount of education and race as potential conditioning factors in the intergenerational transmission of parental family income. To check the robustness of our results, we carry out a large sensitivity analysis that includes the RIF-OLS unconditional quantile regression.

Our main finding reveals that economic persistence is higher at the tails of the distribution. While our OLS estimate of IGE for the entire pool is 0.47, in line with the literature, using QR we find that 'inheritance' of income varies significantly across the child adult income distribution. Moreover, the IGE shows a U-shaped relationship with the son's income rank, with maximum values at the tails of the distribution (0.64 at the 10^{th} percentile and 0.48 at the 95^{th} percentile) and a minimum value -maximum mobility- of 0.37 at the 70^{th} percentile. Children at the top and, more importantly, at the bottom of the distribution have been more conditioned by their parental income than those belonging to the 'middle class'.

We believe that these findings may contribute the better targeting of public policies aiming to promote economic mobility. Moreover, they point to education as a relevant factor that influences economic persistence, especially at both tails of the distribution, and to the additional impact of race in mobility at the mid and lower parts of the distribution. For our pooled data, we find that child education represents between 20% and 50% of the IGE, being particularly important at the tails of the distribution, where a greater share of the intergenerational economic persistence is driven through the different amount of education provided to children. Meanwhile, factors related to race can explain more than 10% of the transmission of parental income, their importance being highest below the 60th percentile of the income distribution.

Finally, and although for most quantiles the hypothesis that all year estimates are equal cannot be statistically rejected at the 5% level - which calls for caution when interpreting these results- there seem to be also different patterns for the IGE evolution at different parts of the distribution. We find that, for all percentiles up to the median (and for the OLS estimate), the trend of IGE decreased in the 80s and 90s and increased slightly in the 00s, while for higher-income percentiles the IGE remained relatively stable all along.

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Appendix

Table 4 Review of OLS IGE estimates for the U.S. in the literature

	Data	Income variable	Sample size (obs.)	IGE estimate	Impact of education	Impact of race	IGE trend
Solon (1992)	PSID	Log earnings averaged 5 years for parental income (1967–71) ; year 1984 for sons	290	0.41			
Zimmerman (1992)	NLS	Log earnings	192	Circa 0.4			
Eide and Showalter (1999) [parental earnings]	PSID	Log of average of three years of father's earnings (1967–69) and 7 years of son earnings (1984–91)	469	0.34	OLS Decrease in income elasticity of 29.4% (to 0.24)		
Eide and Showalter (1999) [parental income]	PSID	Log of average of three years of father's income (1967–69) and 7 years of son earnings (1984–91)	612	0.45	OLS Decrease in income elasticity of 26.7% (to 0.33)		
Grawe (2004)	PSID	Father earnings observed from 1967 to 1971, averaged if there are at least three observations; children earnings observed from 1978–81, included in the sample if there are at least three observations out of five	354	0.47			
Hertz (2006)	PSID	Log of average family income per person. Children observed in the 1995, 1996, 1997, 1999 and 2001 surveys. Parents averaged in the 1968–72 surveys(4 year average). Mean ages 37 and 38 respectively for parents and children	4,004	0.51		Controlling for race reduces IGE from 0,515 to 0.429. That's a 16.7%	

Table 4 (continued)

	Data	Income variable	Sample size (obs.)	IGE estimate	Impact of education	Impact of race	IGE trend
Lee and Solon (2009)	PSID	Log of son family income controlling for life cycle on the years 1977–2000. Parental income averaged for three years (children aged 15–17)	11,230	0.44 (Avg)			No trend for the 1978–2000 period
Cooper (2011)	PSID	A sample of male heads. Average labor income of parents and sons who report at least 3 years of income at ages 35–50, from the years 1967 to 2007	1,424	0.42	OLS decrease IGE of 35% (to 0.27)		
Torche (2013)	NLSY-79	Log of Family income For adult children, she uses an average of family income over the 1996–2002 period. Parental income is the total household income during 1978, as reported by the parents in the first NLSY79 interview wave	2,178	0.37	OLS decrease of IGE of 54% (to 0.172), controlling for level of education	OLS Decrease of IGE to 0.323 (13.63%) including race and a (non statistically significant) rural area control	
Blanden et al. (2014)	PSID	Log averaged earnings for male children born between 1960 and 1970 measured at ages 30–34, with at least one observation. Parental income is averaged when the children was 10–16 with at least one observation	647	0.38	48.1% of IGE explained by education (pathway decomposition method)		
Palomino, Marrero and Rodríguez (2017)	PSID	Log of family income controlling for life cycle on the years 1978–2000. Parental income averaged for seven years (children age 13–19)	25,084	0.47	OLS decrease of IGE of 27.43% (to 0.34)	Additional OLS decrease of IGE to 0.43 (10.1%)	Decreasing trend 1980–2000 period, turned increasing in 2002–2010

Table 5 Review of quantile regression IGE estimates for the US in the literature

	IGE Estimate (10th, 25th, 50th, 75th and 90th percentiles)	Impact of Education (% decrease controlling for years of education at the 10th, 25th, 50th, 75th and 90th percentiles)	Impact of Race (% decrease controlling for race at the 10th, 25th, 50th, 75th and 90th percentiles)	IGE trend at different quantiles
Eide and Showalter (1999) [parental earnings]	0.47; 0.35;0.37; 0.35; 0.17	30; 26; 35; 34; 12 (*)		
Eide and Showalter (1999) [parental income]	0.67; 0.49; 0.44; 0.35; 0.26	27; 35; 30; 26; 19 (*)		
Grawe (2004)	0.35; 0.494; 0.54; 0.457; 0.40			
Cooper (2011)	0.52; 0.49; 0.46; 0.41; 0.38	35; 32; 31; 33; 53 (*)		
Palomino, Marrero and Rodríguez (2017)	0.64; 0.53; 0.44; 0.40; 0.48	33; 18; 24; 29; 34	12; 8; 12; 4; 1	In the 1980-2010 period, no trend for the mid-high and high percentiles. For the mid and mid low percentiles, decrease of IGE in the 80s and 90s and slight increase in the 2000s

(*) Own calculation using the authors' reported results

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