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One size doesn't fit all: A quantile analysis of intergenerational income mobility in the US (1980-2010)*

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Abstract

Using family income from the Panel Study of Income Dynamics (PSID), we apply Quantile Regression to estimate the Intergenerational Income Elasticity (IGE) by percentiles in the U.S. from 1980 to 2010. For the whole period, the IGE shows a Ushape across the income distribution, with maximum values at the tails (0.66 at the 10th percentile and 0.48 at the 90th percentile) and a minimum value –highest mobility- of 0.37 at the 70th percentile. These values contrast with the Ordinary Least Square estimate, which is 0.47. The trend evolution of the IGE varies also across the income distribution. While for all percentiles up to the median (and OLS) the trend of IGE was decreasing in the 80s and 90s and slightly increasing in the 00s, the IGE remained relatively stable for the richer along the whole period. With respect to the channels of intergenerational income transmission, son's education and race were found to be important.

Keywords: Intergenerational Mobility, quantile regression, trend evolution, the United States.

JEL Classification: D31, D63.

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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 opportunities.[1] In the last decades, however, this commonplace perception has been questioned. Studies estimating the Intergenerational Income Elasticity (IGE) as a measure of the level of intergenerational immobility 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 those 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.[3] Most of these studies, however, derived the IGE from a regression-to-the-mean model using ordinary least squares estimation and the few works that have estimated the IGE at different quantiles of the distribution have considered a cross section with relatively small samples (Eide and Showalter (1999); Grawe (2004); Cooper (2011)). With regard to the trend evolution of IGE, research up to date has arrived at disparate results and has never estimated the trend at different quantiles of the distribution.[4]

This paper enriches the debate on the level and evolution of IGE in the US in three different ways. First, the paper improves our understanding of how heritability of household income differs across the income distribution. Using family income data from the Panel Study of Income Dynamics (PSID), we apply Quantile Regression (QR)

[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 1931). In fact, according to the last International Social Survey, (SSP Research Group (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] See Jäntti et al. (2005), Corak (2006) and (2013), Björklund and Jantti (2009) and Blanden (2013).

[4] Aaronson and Mazumder (2008) used decennial Census data and reported a decrease in elasticity from 1950 to 1980, which turned into an increase from 1980 on. In contrast, Hertz (2007) and Lee and Solon (2009) found no significant changes in the trend of intergenerational mobility during the 1980-2000 period. Measuring rank-rank relative mobility instead of IGE, Chetty et al. (2014b) also found a stable trend for cohorts born between 1971 and 1993. Finally, Mayer and Lopoo (2005) found no clear trend for the whole period, but revealed a long period of decreasing IGE between 1984 and 1994 (p. 176).

to estimate the IGE in the US between 1980 and 2010 across the entire child's adult income distribution. For this task, we combine the new advances in QR computation with the model proposed by Lee and Solon (2009), which allows exploiting a greater number of data and controlling for measurement errors and life cycle biases. 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 child's adult income distribution, we develop a time series analysis. Using our up-to-date database, the second contribution of the paper is thus to estimate at different income percentiles the time evolution of IGE in the US for the 1980-2010 period. 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. Finally, as the third contribution of the paper, we explore the role of son's education and race as intergenerational transmission channels of parental income, both across the income distribution and along the time trend.[5]

Three major discussions in the recent literature justify the interest in improving the knowledge about the IGE in the US. The first one considers intergenerational mobility a proxy for equality of opportunity (Roemer (2004), Corak (2013), Brunori et al. (2013)). To the extent that parental income is a major circumstance for which individuals are not responsible, the influence of parental income in the future income of children would reflect a lack of equality in opportunity.[6] A second discussion has highlighted the potential negative effect of inequality on intergenerational mobility –referred as the Great Gatsby Curve (Krueger (2012), Corak (2013), Bishop et al., (2014)). The significant rise of inequality in the US (amplified with the recession) has alerted the American society to a potential undesirable decrease on social mobility in the future. The third debate has focused on the impact of inequality of opportunity on growth. It has been recently proposed that this impact may occur because income inequality is actually a composite measure of at least two different types of inequality –inequality of opportunity and inequality of effort– that show opposite effects on growth, i.e., negative for the former and positive for the latter (World Bank (2005); Bourguignon et al.

[5]See the Appendix for a comparison of the main characteristics and results of our analysis and all previous studies on IGE for the US in the literature.
[6]The literature on equality of opportunity has emphasized the importance of other circumstances (factors over which individuals have no control but affect their final output) such as parental background, race, sex or region of birth (Roemer (1998), Rodríguez (2008), Ferreira and Gignoux (2011), Marrero and Rodríguez (2012)).

(2007); Marrero and Rodríguez (2013).[7] As a result, an increase in intergenerational mobility would not merely be interpreted as a decrease in inequality of opportunity, but also as a positive factor for efficiency and growth.

Being such a relevant measure, we find that the estimation of IGE only at the mean of the distribution gives a very incomplete picture of mobility. In fact, our main finding is that the intergenerational transmission of parental income towards their descendants in the US is strongly connected to the position the adult child occupies at the distribution. Pooling all available data for the 1980-2010 period, we find that the IGE shows an 'almost perfect' U-shaped relationship with the income distribution, with maximum values at the tails of 0.66 at the 10th percentile and 0.48 at the 90th percentile, and a minimum value of 0.37 around the 70th percentile. These values are significantly different from our pooled OLS estimate, 0.47, which highlights the fact that traditional least squared analysis omits too much valuable information by centering only on the average value.

Likewise, we find that the trend evolution of the IGE also depends on the income distribution. While the IGE trend is decreasing in the 80s and 90s and slightly increasing in the 00s at the mean and mid and lower parts of the distribution, it remains relatively stable during the last three decades at the mid-high and top quantiles.[8] Our third set of findings highlights the importance of child's education and race as channels of intergenerational income transmission, not only for the entire pool, but also across the son's income distribution. In particular, we find that the child's 'years of education' represents between 20% and 50% of IGE, being more important at the tails of the distribution. Meanwhile, the child's race can explain up to a quarter of the inheritance of parental income, its importance being highest at the bottom of the income distribution and irrelevant around the 70th percentile.

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. Using OLS and QR, Section 4 presents our main IGE results for the pooled sample, and its trend from 1980

[7] Marrero and Rodríguez (2013) found robust evidence of this hypothesis for the US at the state level between 1970 and 2000. A theoretical model that studies the relationship between inequality of opportunity and inequality of effort on growth is developed in Marrero and Rodríguez (2014).

[8] Using a different dimension, Chetty et al. (2014a) find that geographical placement within the US is relevant to the level of 'mobility', calculated as the probability of reaching the top quintile starting from the bottom quintile in the previous generation.

to 2010. In Section 5 we develop a sensitivity analysis of our results to different data treatments and specifications. Finally, Section 6 concludes.

2. Methodology

The intergenerational income elasticity refers to the influence of parental income in children's adult income.[9] In the canonical Galton (1886) regression of a child's income ($y_{S_{it}}$) on the parent's income (y_{P_i}),[10]

$$\ln y_{S_{it}} = \alpha + \beta \ln y_{P_i} + \varepsilon_{it}, \qquad (1)$$

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 βcoefficient, 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 children's economic achievement. Accordingly, 1-β is a measure of income intergenerational mobility, mobility interpreted as independence from origin. Finally, the error term ε_{it} represents all other influences on the child's adult income not correlated with parental income.[11]

The use of this basic model may present 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). This technique obtains an average estimate of IGE for the whole population, ignoring the possible variation of intergenerational mobility across income quantiles. Finally, since only parental income is included as an explanatory variable, the model in (1) is incapable of analyzing channels of income

[9] To enable a broader set of cross-country comparisons, the literature has typically focused on the incomes of fathers and sons since the changing role of women in the labor force is more difficult to analyze.

[10] Ideally, parental and child incomes should reflect permanent income to avoid life cycle biases. Alternatively, age controls should be incorporated to the equation. Below we explain in detail our approach to tackle this problem.

[11] See Mulligan (1999) for a detailed description of this model.

transmission between parents and children. Next, we explain the main strategies we have adopted to overcome these limitations.

2.1. Pooled OLS estimates

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:

$$\ln y_{S_{it}} = \alpha + \beta \ln y_{P_i} + \sum_{n=1}^{4} \gamma_n A^n + \sum_{n=1}^{4} \delta_n C^n + \sum_{n=1}^{4} \theta_n \left[\ln y_{P_i} C^n \right] + \varepsilon_{it} \qquad (2)$$

where $\ln y_{S_{it}}$ is the real household income (in logs) of adult sons from family *i* at year *t* = 1980, 1981, …, 2010;[12] $\ln y_{P_i}$ is the averaged parental household income (in logs) of family *i* when the son was a child between 13 and 19 years old;[13] the rest of terms control for the influence of the life cycle on parental and son's income. Variable A, parameters γ_1 to γ_4, represents the age of the parent in family *i* when the children was 16 years old. Variable C, parameters δ_1 to δ_4 - measures the difference between the age of the son and the age of 40 years old at each year *t* in which income is computed.[14] The third variable $\ln y_{P_i} C^n$, 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 (n goes up to the fourth power) in order to control for different possible functional shapes when time interacts with income.

We estimate (2) for the entire pool, thus obtaining a weighted average of IGE in the US for the entire sample. Later, we estimate the time trend of β between 1980 and 2010

[12]Since the PSID database starts at 1968, we choose 1980 as our initial year in order to have enough pairs of parents and adult sons in the sample.

[13] We discuss this decision in Section 3. The effect of changing the number of years of income averaged in the estimation is analyzed in the section devoted to the sensitivity analysis (Section 5).

[14] If c is the birth cohort of the individual, then we have $C = t - c - 40$. We have also tested the sensitivity of the estimates to the use of a different age reference (45 years old) in Section 5, finding no changes in trend and only a small general increase in the estimates of IGE.

using all available information. For this purpose, we need to modify equation 2 as follows:

$$\ln y_{S_{it}} = \alpha_t D_t^{'} + \beta_t \left[\ln y_{P_i} D_t^{'}\right] + \sum_{n=1}^{4} \gamma_n A^n + \sum_{n=1}^{4} \delta_n C^n + \sum_{n=1}^{4} \theta_n \left[\ln y_{P_i} C^n\right] + \varepsilon_{it} \qquad (3)$$

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, and so on.[15] Thus, estimating (3) gives us a different intercept (α) and slope (β) for t = 1980, 1981… 2010. Note that we assume that the age-controlling variables are time invariant[16].

2.2. Quantile regressions

We use the QR technique to contrast if intergenerational mobility varies across the income distribution.[17] This method offers the possibility of obtaining point estimates at any selected quantile of the son's income distribution (2013).[18] Using the entire pool of data, we run QR for equation (2) and estimate IGE at every fifth percentile (5^{th}, 10^{th} … 95^{th}). Initially, the QR estimates are obtained for the pooled 1980-2010 sample. The large size of this sample allows us to improve the accuracy of QR estimates. Later, we estimate the QR version of (3) and characterize the time trend evolution of IGE at different percentiles for the 1980 – 2010 period. Despite that these estimations are slightly less accurate because the sample must be split, they permit 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 around the average of the distribution, QR minimizes absolute errors at any particular quantile of the distribution (Koenker 2005). Suppose that we want to calculate the QR estimate

[15] We actually add a time dummy for each PSID wave because the PSID is biannual since 1996.

[16] If this assumption does not hold and the life income trajectories are not actually stable overtime or across the income distribution, the elasticity estimates might be biased (Nybom and Stuhler (2011)). Our sample, however, seems to have a fairly unchanging shape for the averaged life cycle across cohorts from different decades (see Section 5). As for differences across the income distribution, the quantile regression estimates implicitly assume different life cycles at each quantile.

[17] A few studies have applied QR to estimate IGE, most notably, Eide and Showalter (1999) and Grawe (2004). These studies, however, usually suffer from a shortage of observations to obtain good estimates at the tails of the distribution.

[18] Contrary to OLS, the QR estimates cannot be obtained with matrix algebra and need to be estimated with a linear programming solving method, such as the simplex or the interior points method. We use the 'Barrodale and Roberts' algorithm included in the 'Quantreg' package for R, programmed by Koenker (2013).

of the quantile τ. Then, those absolute errors corresponding to observations below the quantile τ are weighted with the weight 1-τ, while the absolute errors for those observations above the quantile $\tau$are weighted (asymmetrically) with τ. For example, the QR estimate at the 10th percentile (τ= *0.1)* weights the absolute errors for those observations below the 10th percentile with the weight 1-τ = 0.9, and absolute errors for observations above the 10th percentile with the weight 0.1.At the 10th percentile, 10% of the data –observations below the estimator- are weighted 90% in the estimation. 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, when using QR it is important to have a large sample of observations.

2.3. Channels of intergenerational income transmission

In this kind of analysis, it is a challenging issue to understand the main channels through which income is transmitted 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 channels is limited.[19] We focus on two mediating variables that are time-consistent along the PSID panel: son's 'years of education' and 'race'. We firstly attempt to measure the strength of these channels across quantiles of the children's income distribution for the entire pool of data, and then at each PSID wave along the last three decades.

To estimate the impact of education or race for the entire pool, we add in model (2) the variable 'years of education' of the son, e_{S_i}, or the variable 'race', r_{S_i}, which is a dummy variable taking value of 1 for adult sons who declared 'white race' in the survey and 0 otherwise. In addition, when e_{S_i} is included in the model (4a) we add a quartic variable to control for the possible joint interaction of this variable and the age of the individual on income, $F = e_{S_i}C$

[19] For example, it is hard to find micro data on standardized intelligence test results for parents and children. For this reason, studies of this transmission channel are rare (Bowles and Gintis (2002) is a prominent exception) and scholars have focused mainly on variables like education and race (Hertz (2006) and Torche (2013)).

$$\ln y_{S_{it}} = \alpha + \beta \ln y_{P_i} + \lambda_e x_{S_i} + \sum_{n=1}^{4} \gamma_n A^n + \sum_{n=1}^{4} \delta_n C^n + \sum_{n=1}^{4} \theta_n \left[\ln y_{P_i} C^n \right] + \sum_{n=1}^{4} \phi_n F^n + \varepsilon_{it} \tag{4a}$$

$$\ln y_{S_{it}} = \alpha + \beta \ln y_{P_i} + \lambda_r x_{S_i} + \sum_{n=1}^{4} \gamma_n A^n + \sum_{n=1}^{4} \delta_n C^n + \sum_{n=1}^{4} \theta_n \left[\ln y_{P_i} C^n \right] + \varepsilon_{it} \tag{4b}$$

where x is either e (4a) or r (4b), and λ is the partial direct impact of the variable x on son's income, given parental income and all other controls in 4. How can we interpret a possible change in the β coefficient after the inclusion of the variable x? Let us consider an extreme situation in which the education or race variable x is uncorrelated with parental income. In this case, even when the variable x 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 (2)) will remain unchanged. On the other extreme, if the variable x is strongly correlated with parental income, the new β will significantly drop when the variable x is included in the regression. Hence, we can interpret that the smaller the change in β when we include the variable x in the regression, the weaker the role of this variable as a transmission channel.

Finally, we have also included the variables e_{it} and r_{it} in equation (3) to analyze the mediating role of son's education and race in the time evolution of IGE and their own direct impact on child's adult income.

3. Database

To measure intergenerational income mobility, we use the Panel Survey of Income Dynamics (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.[20] To keep the maximum number of observations possible, we use the core sample of the PSID, conformed by two independent probability samples: the first one is an equal probability sample of households based on a stratified multistage selection of the civilian non-

[20] The quality of the PSID database has often been assessed by comparing different distributions from this database with their equivalent in other sources. For instance, Gouskova and Schoeni (2010) have compared estimates of family income between the PSID and the March Current Population Survey (CPS) for the entire history of the PSID (1968-2007). They find that the distributions are in close agreement throughout the 39-year history of the PSID, above all in the range between the 5th and 95th percentiles.

institutional population of the U.S. (drawn by the Survey Research Center, SRC); the second one is a national sample of low-income households (drawn by the Survey of Economic Opportunity, SEO). The combination of both is also a probability sample, but selection probabilities are unequal and, therefore, population weighting is needed in the estimation of intergenerational income elasticity. These weights, designed to compensate for unequal selection probabilities and differential attrition, are supplied by the PSID.[21] Despite the fact that some studies have previously considered only the SRC sample (Solon (1992); Lee and Solon (2009)) it is interesting to note that Solon (1992, p. 404) has found that his results were comparable when using the full core sample with weights and that Hertz (2007) has shown that –in terms of the evolution of the variance of family income– the combination of the SEO and the SRC samples resembles the much larger Current Population Survey (CPS) more than each of the samples alone. In Section 5, we check the sensitivity of our estimates carrying out our main analysis only for the SCR sample and find that our main results do not change significantly.

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 is consistently included in the PSID since its creation. 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.[22]

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.[23]

In principle, income elasticity estimates need the permanent income component of

[21] On the construction and revision of the PSID weights for the whole core sample see Gouskova et al. (2008). A representative sample of 2,043 Latino (Mexican, Cuban, and Puerto Rican) households was added to the PSID data in 1990. However, this sample missed out Asians, and because of this crucial shortcoming, and a lack of sufficient funding, the Latino sample was dropped after 1995. To avoid longitudinal inconsistencies, we have not considered this Latino sample.

[22] For comparability, we follow Lee and Solon (2009) and exclude observations for which income is less than \$100 or more than \$150,000 in 1967 dollars as measured by the CPI. In total, 190 observations (0.75% of the sample) were eliminated. For a sensitivity analysis of different cut-off income values see Section 5.

[23] 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) and the structural change in women's access to the labor market occurred in the decades analyzed. In this respect, note also that race data for wives is only available from 1984.

parents and children. Unfortunately, it is usually not possible to have income data over the whole life cycle of individuals, so typically there is a bias in IGE estimation due to the life cycle bias and transitory shocks. Solon (1992), Zimmerman (1992) and Mazumder (2005) have proposed to average several years of parental income to proxy 'permanent' income and to reduce the effect of transitory shocks. For this task, 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.[24] In line with Mazumder's (2005) findings, our intergenerational elasticity estimates are sensitive to the number of years of parental income averaged (see section 5).

The life cycle bias also applies to the observed income of children. When the observations of children income are made at early ages, a downward 'life cycle' bias arises in the estimation. Previous works on intergenerational elasticity have concluded that observing income at the middle of the life cycle is the best proxy of permanent income.[25] 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).[26] 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 age-dependent covariates in the regression to control for the different age at which family income is observed. For consistency, we control in the regressions also for parental age in order to tackle the potential parental life cycle bias.

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. Note that 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, a total of

[24] Lee and Solon (2009) averaged yearly parental family income when the child was between 15 and 17 years old (three years).

[25] For a review of these studies see Black and Devereaux (2011). Usually income is reported at an age between 30 and 40 years old(see, for example, Mayer and Lopoo (2005).

[26] Previous studies such as Chadwick and Solon (2002) and Eberharter (2008) also control for age in their intergenerational elasticity regressions.

25,258 observations. In addition, we include the mean and standard deviation of (parental and son) age and (parental and son) real family income in logs.

Besides our main total family income variable, we also consider from the PSID the variables *years of education* and *race of the individual*, aiming to study their importance in the inheritance of income (see Table 1). 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 discrete variable *race of head* into a dummy variable that takes the value 1 when the race of the son is white and zero otherwise.[27]

4. Intergenerational Income Elasticity results

In the first part of this section we present the results of our pooled data regression. In particular, we show the value of IGE at each quantile for the 1980 – 2010 period as a whole. In addition, we 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 mediating 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 percentiles are displayed in Table 2. The OLS estimation yields a value of 0.47, which is in line with the literature.[28] More importantly, if we enrich the picture with the QR estimations, we observe a clear U-shaped relationship (Figure 1). The intergenerational 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 0.4 at the upper-middle part of

[27] On average, whites represent approximately the 70% of the sample, blacks are the 29%, and the remaining 1% has other racial origins.

[28] Most estimates of the IGE generated from the PSID fall in the range of 0.4 to 0.51. See Appendix for a survey of IGE estimates for the U.S. in the literature.

the distribution (percentiles 60th to 75th).[29] Finally, at the top part of the distribution, IGE increases again, reaching a value of almost 0.5 at the 90th-95th percentiles.[30]

Thus, we can conclude that the inheritance of family income in the US varies when we move along the income distribution of adult's sons. For example, for sons around the 10th percentile, if their parental income increased (or decreased) in 1,000 dollars, their expected current income would increase (or decrease) in 660 dollars. Yet, the same 1,000 dollars change in parental income would only imply an expected change of 370 dollars for sons at the 70th percentile. Children at the upper middle class show the smallest degree of intergenerational persistence, while top incomes and, above all, low incomes are very much conditioned by their childhood economic circumstances, represented here by parental income.

Previous studies estimating IGE at different quantiles have relied on much smaller samples and have found disparate results. 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 1,424 observations found a continuous –almost linear– decrease in IGE from the 5th percentile to the 95th percentile. According to these authors there is not a significant increase in IGE at the upper part of the distribution (see Table 3).

In addition to our bigger sample, there exists another reason that could explain why these previous studies do not find an increase of the IGE from the 70th percentile onwards. While we use parents and sons' household taxable income, Eide and Showalter (1999) regress son's earnings on parental income and Cooper (2011) measures intergenerational elasticity for sons' 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. If so, values of intergenerational elasticity of

[29] Households in these percentiles received on average an annual pre-tax income of 75.000-100.000 US dollars of 2010.

[30] Standard errors are calculated by bootstrapping. For the quantile estimates, we follow Koenker (1994)'s suggestion and apply the '*xy*' bootstrap method with 50 repetitions. This resampling method replaces 'xy' pairs and it has been proved to perform very well in Monte-Carlo simulations for quantile regression.

earnings would underestimate actual intergenerational elasticity of income at the top quantiles.[31]

Next, we focus on the role of education and race as channels of income transmission between generations.[32] Our results –see Table 4– show that when education is included in the regression (equation (3)), the estimated IGE decreases 27.4% at the mean (OLS estimation) and between 18% and 47% depending on the percentile.[33] This influence is lower in the range of the 20th-70th percentiles -around 20% of the inheritance of income- and increases significantly when approximating to the extremes of the distribution (see Table 4 and Figure 2b). Thus, even though we cannot control for the quality of the schools, between one fifth and half of intergenerational income transmission is explained by the different amount of education –measured in years– that parents provide to their children.[34]

Besides, the direct positive effect of education on children's income, measured by the coefficient e_{S_i} in equation 4, is significant and greater at the bottom of the distribution (Table 4). One additional year of education represents an increase of 0.09 logs of income at the middle of the distribution, 0.12 at the top of the distribution, and 0.16 at the lowest percentile.[35] Hence, both the mediating role of education in the inheritance of income and the direct effect of education on children's income are important and higher at the tails of the distribution.

With respect to race, the OLS regression yields a decrease in IGE of 10% when we include the dummy variable 'race' as an additional control in equation 4. At the mean,

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[31]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 derivated from it- is concentrated at the top percentiles of the distribution. In fact, the lowest 50% of the household income distribution possess only 1% of the net worth in the US (2012).

[32] We analyze each transmission channel independently. However, if being white is connected with the amount of time that a child goes to school, both effects could be mixed. We tested this effect by including both variables in our baseline model, and found as in Hertz (2006) that there are no significant crossed effects.

[33] Compared to the existing literature, our OLS result is in line with most of the previous research, which finds approximately a 30% mediating role of education in the persistence of income across generations. Nevertheless, some works (Torche (2013); Blanden (2014)) find an even higher explaining role of education (around 50%).

[34] Recently, Chetty et al. (2014a) have found that the quality of public schools is one key variable to explain intergenerational mobility (measured as the rank-rank correlation between parental and children incomes). The other two important variables would be the segregation in the area of residence and the social public goods provided in the area.

[35]Eide and Showalter (1999) found similar results, while Cooper (2011) found a greater effect for the highest percentile than for the lowest one. In the latter case, the use of labor earnings instead of total taxable income could again explain this discrepancy.

one tenth of the inheritance of parental income can be attributed to the race of the individual (Table 4). Looking at the quantiles, 25% of inherited income is attributed to race at the bottom 5^{th}, it remains around 10% from the 10^{th} to 60^{th} percentiles, and then shows a bumpy shape at the upper segment of the income distribution (Figure 2b). The direct effect of the 'white race' dummy in our OLS regression is 0.36, very similar to previous estimates of the impact of race on income. All else equal, this result implies in terms of 2010 dollars a 36% reduction in estimated income for black and other racial origin sons compared to whites at the mean of the distribution.[36] By quantiles, the direct effect of race on income is monotonically decreasing. Thus, the 'white premium' in terms of expected income is stronger at the bottom of the distribution and fades away for high-income percentiles (See Table 4; tenth column).

A final comment on this issue is worth noting. Controlling for 'years of education' wipes out the difference in IGE for the upper part of the distribution almost completely from the 60^{th} percentile upwards, with similar estimates for IGE along that segment of the income distribution. This finding supports the role of education: if it were not for the different amount of education received, all individuals would have lower levels of parental income dependence, and –for 60^{th} percentile and up- this level of determinism would be almost the same. At lower percentiles, however, the value of IGE still shows a negative relation with the position at the income distribution, even if we control also for race. It seems that there must be other factors related with lower income –but unrelated to race and to the amount of education- that increase intergenerational income transmission and reduce mobility.

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

For the period 1980-2010 as a whole, high-income quantiles and, above all, low-income quantiles showed greater IGE than middle-income quantiles. But, how was the evolution of IGE for the entire distribution and by quantiles during this period? For illustrative purposes, in addition to the OLS estimates, we present the results averaged in five groups: the low-income group (10^{th}, 15^{th} and 20^{th} percentiles); the mid-low income group (percentiles 25^{th}, 30^{th} and 35^{th}); the middle-income group (percentiles

[36]Hertz (2006) estimates a 33% reduction in income for black sons compared to whites. Cooper (2011) and Torche (2013) estimate a 32% and a 34% decrease respectively.

40th, 45th, 50th, 55th and 60th); the mid-high income group (percentiles 65th, 70th and 75th); and the high-income group (80th, 85th and 90th percentiles).[37]

Before presenting our results by groups of percentiles, we briefly comment on the OLS estimates of IGE (Table 5). Intergenerational elasticity shows a clear decreasing trend from 1980 to 2002, followed by an important increasing trend until 2008. In 2010, IGE decreases to 0.42. This result contrasts with Aaronson and Mazumder (2008) who found an increase in IGE over the period 1980-2000, 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 IGE for the period 1984-94.[38]

In addition to covering a longer period of time (the last decade, 2000-2010), we also enrich the debate by estimating the IGE trend by quantiles. The results show basically two distinct patterns in the trend of IGE depending on the part of the distribution considered (Table 5 and Figure 3). The low-income, mid-low and middle-income groups experienced a decreasing trend in IGE during the first two decades studied: IGE was in the 0.8 to 0.5 range in the early 80s reaching its minimum around 0.4 in 2002. From 2002 to 2008 the trend reversed and elasticities for these groups increased. Later on, IGE estimates decreased again. It is worth noting that the IGE of the low-income group has always been the highest, this group consistently suffering from lower mobility than the rest of income groups.

In what concerns the upper part of the distribution, both the mid-high and the high-income groups maintained a steady value of IGE along the three decades analyzed. The mid-high group, always with the lowest IGE of all groups, showed a quite stable value of IGE around 0.4. Likewise, the IGE value of the high-income group remained at a slightly higher level than the mid-high income group along the whole period.

Despite of these differences, the change of century seems to be a turning point in the trend of IGE for all groups. Elasticity raised in all income groups since 2002, above all with the Great Recession (2007-2009), although the strength of this increase diverged among the quantiles analyzed. After the Great Recession, and regardless of the income

[37] As we explained in Section 2.2, quantile regressions are very sensitive to the size of the sample when estimating at the tails of the distribution. This was not a problem in our pooled analysis, but once we computed different estimates for each PSID wave, the 5th and 95th IGE estimates became not significant and we have therefore excluded them from our income groups averages. Estimates for all other percentiles remained significant at the 95% confidence level.

[38] Although they analyze the trend by cohorts, those are the years in which the cohorts are 30 years old, the age at which they estimate IGE in their rolling groups regression (p. 176).

group, intergenerational elasticity has decreased significantly, although at least one more observation will be required to confirm this new trend in the IGE series.

As in the previous section, we focus now on the mediating role of education and race. The OLS results show that years of education explain approximately 25%-35% of IGE for most of the years analyzed (Table 6), showing no clear trend. By income groups the trend of the mediating role of education presents two different patterns. The low and mid-low income groups showed an increasing trend in the mediating role of education for the whole period analyzed, while the middle, mid-high and high income groups showed a slightly increasing trend until 2002, followed by a slight decrease since then (Table 6 and Figure 4). It seems that since 2000 the number of years in the education system has lost importance as a way of 'inheriting' parental income for middle and high incomes, while the opposite is true at the low part of the distribution. For low-income earners, the number of years at school is getting more important to explain income immobility, although we would need more observations to confirm this trend. With respect to the direct effect of education on income our trend analysis shows that its value remains stable for all income groups (and OLS estimates) during the whole 30-years period (Table 6). In accordance with the results above, the average coefficients for the low income groups are the largest.[39]

According to our OLS estimates, race explained approximately 15% of IGE until 1992, and then its mediating role reduced drastically until 2006, when a minimum of 0% was reached. Since then, the importance of race in the inheritance of income has increased, reaching an 11% in 2010 (Table 7). Analysis by income groups presents a similar pattern: the explicative power of race decreased slowly during the 1980-2006 period, and increased afterwards (Table 7 and Figure 5). Consistent with our pool regression results, the mediating role of race is lower for the high and mid-high income groups, although values at different groups tend to converge overtime. With respect to the direct effect of race on income we observe in Table 7 that there is a decreasing pattern until

[39]Naturally, the fact that the 'years of education' have gained importance in explaining IGE at the lower tail of the distribution does not imply that education 'per se' contributes to immobility of the poorer. On the contrary, the direct effect of education on income is positive and higher at this part of the income distribution. It is the *smaller amount* of education that the poorer receive what explains part of their immobility.

2006 with a regain in importance afterwards. The magnitude of this direct effect is higher at the low quantiles.[40]

5. Sensitivity analysis

As argued above, our data and methodology choices in Sections 2 and 3 were devised to improve the accuracy of estimations while reducing measurement errors. However, the estimation of the IGE can be sensitive to the data treatment chosen by the researcher. The number of years averaged to measure income, the thresholds used to exclude outliers, the sample choice and the age control methods are possibly the decisions that could most significantly impact our results. Accordingly, we check the robustness of our main findings under different data treatment choices. For simplicity, our sensitivity analysis is developed for the mean (OLS) and median when considering results about the trend.

First, to control for the database adopted, we consider only the SRC sample instead of the whole 'core' sample. Second, to analyze the importance of the permanent income concept for our results, we shorten the number of years taken for the calculus of parental 'permanent' income, using 3 years of parental income instead of 7 years. Thirdly, we investigate the effect of adopting different thresholds to exclude outlier observations. Lastly, we check the stability of the life income trajectories across the period analyzed and the effect of changing the reference age at which elasticity is measured.

For the pooled estimation, using only the SRC sample of the PSID yields an OLS estimate of 0.49 (Table 8), which is very close to our preferred estimate of 0.47.[41] Quantile regression estimates of the IGE still present a clear U-shape relation with the son's position at the income distribution. In this case, the intergenerational elasticity is highest at the lowest percentile of the distribution –reaching a value of around 0.7 at the 5^{th} percentile (Figure 6). The trend of the IGE when using only the SRC sample and OLS regression is similar to our original trend, perhaps slightly steadier (Table 9 and Figure 7). When comparing QR estimations at the median, the time trend using only the

[40] The 1991 Civil Rights Act against discrimination is a legislative landmark that could have contributed to this declining importance of race on income in the 90s. However, the upturn of the mediating role of race and its direct effect on income at the end of the 2000s makes this topic deserving of a detailed analysis that is beyond the scope of this paper.
[41] Note that SRC estimations are not weighted and, therefore, are only valid for the sample and not for the whole US population. The PSID only provides weights for the whole core sample (SRC + SEO samples).

SRC sample remains steady in the 90s and 00s, diverging from our preferred estimation (Table 9 and Figure 8).

As explained by Mazumder (2005) a shorter averaged period of parental income is a worse proxy of permanent income and one should expect a lower value of IGE in this case. Our sensitivity analysis confirms this prediction, with an OLS value of IGE of 0.37 when we average 3 years of parental income instead of 7 years (Table 8). QR estimates for the IGE are also smaller across the entire income distribution, especially at the top quantiles, converting the U-shape curve in an almost downward line (Figure 6).The shape of the time trend is not much affected either in the OLS estimation or the QR estimation at the median, although it shifts downwards (Table 9 and Figures 7 and 8).

To test the sensitivity of the estimates to the choice of outliers, we have changed the data selection choice and kept all valid income observations except for negative values, instead of our preferred criteria for outliers proposed by Lee and Solon (2009). As expected, the inclusion of more extreme values affects significantly the OLS estimation, which for the whole pooled sample rises from 0.47 to 0.55 (Table 8). The OLS trend of IGE shifts up in a similar proportion for the whole 1980-2010 period, while the QR estimates at the median remain almost unchanged, showing their robustness to the potential influence of outliers.

Finally, concerned about the possibility of an estimation bias due to changing life income trajectories across cohorts (Nybom and Stuhler 2011), we calculated the average income at each age for cohorts born in the 50s, 60s, and 70s. Although for the younger cohorts it is still too early to analyze the full life cycle, the results do not show a significant change in the life cycle shape at the ages in which they can be compared (Figures 9 and 10). This, together with the extensive number of years we use to estimate parental income, leads us to believe that there is no significant influence of the life cycle bias in our estimates. Also, our results confirm that changing the reference age in the regression controls from 40 to 45 years old only produces a slight increase in the estimates, but does not change the trend pattern (Figures 11 and 12).

6. Conclusion

Despite the extensive literature on the magnitude of Intergenerational Income Elasticity in the US and –more recently- on its trend overtime, most studies measure it around the mean of the income distribution using OLS. The few studies that estimate the IGE at different quantiles work with small samples, since they consider only a cross-section of individuals at a small age range. Trying to overcome these limitations, we use up-to-date family income data from the PSID, exploiting 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 son's education and race as potential intergenerational transmission channels of parental family income.

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's adult income distribution. The IGE shows a U-shaped relationship with the son's income rank, with maximum values at the tails of the distribution (0.66 at the 10th percentile and 0.48 at the 90th percentile) and a minimum value of 0.37 at the 70th percentile.

We also find that, for our pooled data, son's education represents between 20% and 50% of IGE, being more important at the tails of the distribution. Meanwhile, race can explain up to a quarter of the inheritance of parental income, its importance being highest at the very bottom of the income distribution and irrelevant around the 70th percentile. After controlling for education and race, IGE values are lower and the U-shape relation between IGE and the income position is less pronounced.

Our QR results also contribute to the debate about the trend evolution of the IGE in the 1980-2010 period, for there seem to be different patterns for different parts of the income distribution. We find that, for all percentiles up to the median (and OLS), the trend of IGE decreased in the 80s and 90s and slightly increased in the 00s, while for higher-income percentiles the IGE remained relatively stable all along.

For this high part of the distribution, we also find that the mediating role of son's education showed no trend in the 80s, a weak increasing trend in the late 90s (reaching a peak in 2002), followed by a mild decreasing trend in the rest of the 00s. For mid percentiles, this role is quite stable over the whole period, while it shows a growing trend for the mid-low percentiles since the mid 90s. As for race, the trend pattern of its mediating importance is similar for all percentiles: decreasing in the 80s and 90s but regaining it from the mid 2000s.

We believe that our findings call for at least two important lines of future research. First, what is the relationship between the dispersion of a country's income distribution and its IGE across quintiles? Do countries with less income dispersion have a flatter IGE-quantile curve? Extending this analysis to other regions could help to scrutiny this issue. Second, whether caused by the 'Great Recession' or by structural change, both the upturn in the trend of IGE during the 2000s -for the mid and low parts of the income distribution- and the recent general increase in the mediating role of race in economic persistence could be a cause of future political and social concern that deserve further study.

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Table 1. Descriptive Statistics *

Year	*Number of observations*	*Average age of sons*	*Standard deviation of age*	*Average of log of sons' real family income*	*Standard deviation of log of sons' real family income*	*Average age of head parent (children at age 16)*	*Standard deviation of age of head parent (children at age 16)*	*Average of log of real parental avg. fam. income*	*Standard deviation of log of real parental avg. fam. income*	*Average years of education (sons)*	*% of whites in the sample*	*% of blacks in the sample*	*% of other races in the sample*
1980	458	26.79	1.43	10.72	0.73	44.84	6.54	10.94	0.63	12.70	61.57	36.90	1.53
1981	551	27.32	1.67	10.66	0.84	44.57	5.99	10.97	0.63	12.66	62.25	35.93	1.81
1982	631	27.81	1.93	10.62	0.86	44.52	6.29	10.96	0.63	12.61	61.81	36.13	2.06
1983	684	28.42	2.21	10.67	0.86	44.76	6.53	10.99	0.63	12.77	62.43	35.23	2.34
1984	780	28.89	2.50	10.70	0.85	44.70	6.36	11.00	0.64	12.78	63.08	34.36	2.56
1985	853	29.27	2.80	10.70	0.87	44.78	6.26	11.02	0.64	13.14	65.72	34.00	0.35
1986	927	29.73	3.08	10.75	0.83	44.83	6.54	11.03	0.63	13.08	65.66	34.06	0.33
1987	1001	30.23	3.33	10.76	0.86	44.77	6.68	11.04	0.63	13.10	66.00	33.67	0.40
1988	1049	30.82	3.60	10.81	0.83	44.83	6.57	11.05	0.63	13.13	66.03	33.78	0.19
1989	1097	31.37	3.83	10.81	0.89	44.79	6.24	11.05	0.64	13.17	67.43	32.29	0.28
1990	1164	31.82	4.10	10.80	0.86	44.51	6.34	11.05	0.65	13.11	66.96	32.30	0.52
1991	1237	32.38	4.35	10.79	0.89	44.49	6.56	11.03	0.67	13.08	67.31	31.85	0.84
1992	1252	33.01	4.68	10.84	0.94	44.53	6.37	11.07	0.65	13.19	68.05	30.19	0.66
1993	1333	33.54	4.87	10.82	0.96	44.29	6.37	11.06	0.66	13.16	68.49	30.54	0.98
1994	1325	33.98	5.06	10.89	0.89	44.18	6.37	11.08	0.65	13.16	68.45	29.80	1.75
1995	1345	34.43	5.40	10.89	0.90	44.23	6.23	11.09	0.65	13.17	68.99	29.13	1.88
1996	951	35.10	5.81	11.01	0.83	44.05	5.85	11.20	0.63	13.47	77.64	21.19	1.17
1998	1021	35.93	6.58	11.13	0.82	43.57	6.27	11.20	0.63	13.50	75.66	21.59	2.75
2000	1085	36.72	7.10	11.13	0.86	43.40	6.22	11.19	0.65	13.44	75.88	21.53	2.59
2002	1151	37.40	7.76	11.13	0.80	42.99	6.44	11.20	0.67	13.53	75.81	21.93	2.26
2004	1229	37.66	8.39	11.10	0.88	42.85	6.40	11.19	0.68	13.56	74.92	23.76	1.30
2006	1305	37.73	9.02	11.06	0.92	42.76	6.00	11.21	0.68	13.60	74.15	24.46	1.38
2008	1401	38.05	9.46	11.02	0.93	42.60	6.16	11.20	0.70	13.65	73.37	24.98	1.57
2010	1428	38.22	9.94	10.94	0.96	42.57	6.20	11.21	0.73	13.67	72.05	25.84	2.04
Total/Average for the pooled sample	25258	33.54	6.89	10.89	0.89	43.98	6.37	11.10	0.66	13.24	69.50	29.10	1.37

* To achieve cost savings, in 1997 the PSID sample was reduced and the survey made biannual (Gouskova et al. 2008).

Table 2. Intergenerational Elasticity. Quantile Regression.

Percentile	*Beta (IGE) Model2*	*Bootstrapped Standard Error **	*Lower CI*	*Upper CI*
5	0.55	0.07	0.41	0.68
10	0.66	0.06	0.54	0.78
15	0.65	0.04	0.56	0.73
20	0.56	0.04	0.49	0.64
25	0.53	0.03	0.47	0.60
30	0.51	0.03	0.46	0.57
35	0.49	0.03	0.44	0.54
40	0.46	0.02	0.41	0.51
45	0.46	0.02	0.41	0.50
50	0.44	0.02	0.40	0.48
55	0.42	0.03	0.37	0.47
60	0.40	0.02	0.35	0.44
65	0.38	0.02	0.34	0.42
70	0.37	0.02	0.34	0.41
75	0.40	0.02	0.36	0.44
80	0.42	0.02	0.39	0.46
85	0.44	0.02	0.40	0.49
90	0.48	0.02	0.43	0.52
95	0.47	0.05	0.38	0.57
OLS	0.47	0.02	0.44	0.51

* We use the 'xy' bootstrap method (Koenker 1994)

Figure 1

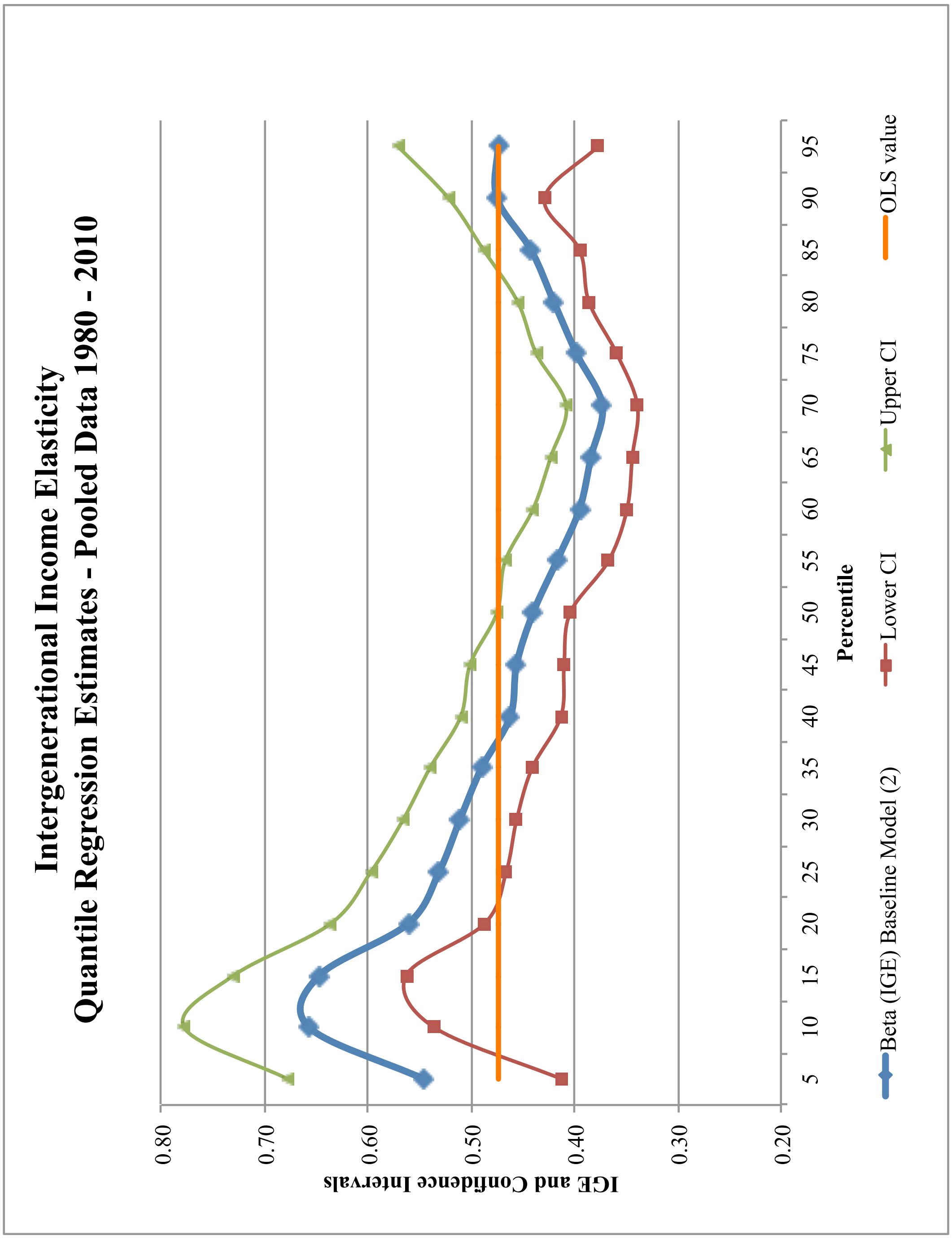

Intergenerational Income Elasticity
Quantile Regression Estimates - Pooled Data 1980 - 2010
IGE and Confidence Intervals
0.80
0.70
0.60
0.50
0.40
0.30
0.20
5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95
Percentile
Beta (IGE) Baseline Model (2)
Lower CI
Upper CI
OLS value

Table 3. IGE estimates compared..

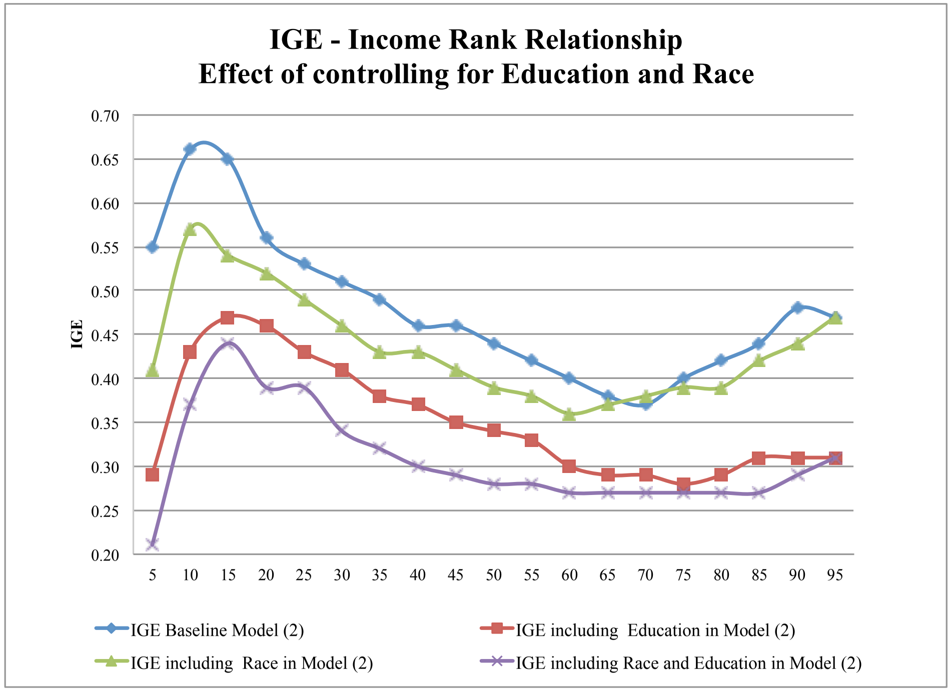
			Cooper (2011) (1)		*Eide and Showalter (1999) (2)*		*Grawe (2004) (3)*	
Percentile	*Beta*	*Standard Error (Boot-strapped)*	*Beta*	*Standard Error (Boot-straped)*	*Beta*	*Standard Error (Boot-strapped)*	*Beta*	*Standard Error*
5	0.55	0.07	0.63	0.14	0.77	0.13		
10	0.66	0.06	0.52	0.08	0.47	0.19	0.35	0.17
15	0.65	0.04						
20	0.56	0.04						
25	0.53	0.03	0.49	0.05	0.35	0.08	0.49	0.1
30	0.51	0.03						
35	0.49	0.03						
40	0.46	0.02						
45	0.46	0.02						
50	0.44	0.02	0.45	0.04	0.37	0.05	0.53	0.07
55	0.42	0.03						
60	0.40	0.02						
65	0.38	0.02						
70	0.37	0.02						
75	0.40	0.02	0.41	0.04	0.35	0.06	0.46	0.08
80	0.42	0.02						
85	0.44	0.02						
90	0.48	0.02	0.38	0.08	0.17	0.03	0.40	0.22
95	0.47	0.05	0.24	0.08	0.19	0.06		
Number of Obs.		25258		1424		612		354

(1) Cooper uses a sample of 1424 observations. He estimates a pool of male heads, using labor income from the years 1967 to 2007, with ages ranging from to 35-50 and using only individuals that report at least 5 years of income.
(2) Eide and Showalter average two years of father's income (1967-69) and regress it on the average of the son income during the years 1984-91. They use family income from both the SRC and the SEO samples from the PSID. Their sample has 612 observations.
(3) Grawe uses a PSID sample of only 354 observations, observing parental income during the years 1967-71 and children income during the year 1978 – 81.

Table 4. Model Including Mediating Variable/s

Percentile	*IGE Baseline Model 2*	*IGE Model 2 w/ Edu*	*IGE Model 2 w/ Race*	*IGE Model 2 w/ Edu and Race*	*% Decrease in IGE when controlling for Education*	*% Decrease in IGE when controlling for Race*	*% Decrease in IGE controlling for Education and Race*	*Coefficient 'Years Edu' in Model 2 w/ Edu*	*Coefficient 'White Race' in Model 2 w/ Race*	*Coefficient 'Years Edu' in Model 2 w/ Edu and Race*	*Coefficient 'White Race' in Model 2 w/ Edu and Race*
5	0.55	0.29	0.41	0.21	46.97	24.77	60.73	0.16	0.81	0.16	0.76
10	0.66	0.43	0.57	0.37	35.31	13.39	43.99	0.14	0.50	0.14	0.49
15	0.65	0.47	0.54	0.44	27.20	16.07	32.15	0.12	0.39	0.12	0.36
20	0.56	0.46	0.52	0.39	18.89	7.66	30.84	0.11	0.37	0.11	0.31
25	0.53	0.43	0.49	0.39	18.64	8.29	27.50	0.11	0.34	0.11	0.29
30	0.51	0.41	0.46	0.34	20.55	9.78	32.68	0.10	0.32	0.10	0.31
35	0.49	0.38	0.43	0.32	22.45	11.43	35.31	0.10	0.29	0.10	0.31
40	0.46	0.37	0.43	0.30	20.56	7.58	35.50	0.09	0.28	0.10	0.30
45	0.46	0.35	0.41	0.29	24.34	9.65	35.75	0.09	0.26	0.10	0.27
50	0.44	0.34	0.39	0.28	22.95	10.91	35.68	0.09	0.25	0.09	0.26
55	0.42	0.33	0.38	0.28	20.38	7.91	34.05	0.09	0.21	0.09	0.26
60	0.40	0.30	0.36	0.27	23.29	7.85	31.39	0.09	0.21	0.09	0.24
65	0.38	0.29	0.37	0.27	23.70	4.17	29.17	0.09	0.19	0.09	0.20
70	0.37	0.29	0.38	0.27	22.79	-0.80	28.69	0.09	0.15	0.09	0.18
75	0.40	0.28	0.39	0.27	29.90	3.27	33.42	0.09	0.15	0.09	0.17
80	0.42	0.29	0.39	0.27	31.90	6.43	35.95	0.10	0.13	0.10	0.15
85	0.44	0.31	0.42	0.27	30.54	6.11	38.69	0.10	0.13	0.10	0.11
90	0.48	0.31	0.44	0.29	34.74	7.37	39.16	0.10	0.12	0.10	0.13
95	0.47	0.31	0.47	0.31	34.18	0.21	33.97	0.12	0.10	0.12	0.16
OLS	0.47	0.34	0.43	0.29	27.43	10.02	37.89	0.12	0.36	0.11	0.30

Figure 2a and Figure 2b



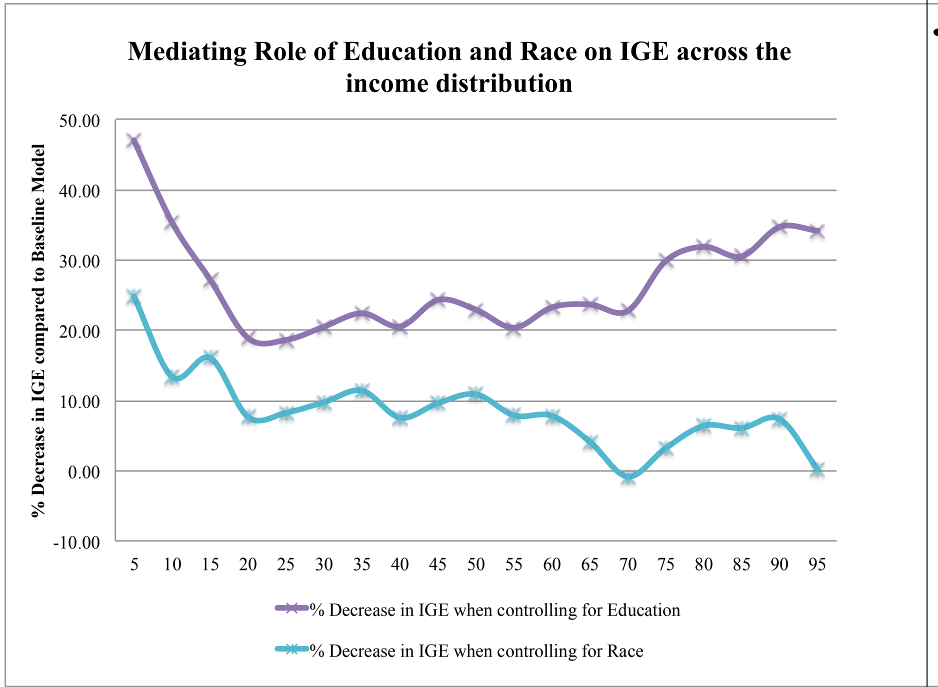


Table 5. Average QR Trend of IGE and Standard Errors at each group of percentiles and OLS trend.

	OLS		*Low Income*		*Mid-Low Income*		*Mid Income*		*Mid-High Income*		*High Income*	
	IGE Estimate	*Standard Error*	*IGE Estimate*	*Standard Error*	*IGE Estimate*	*Standard Error*	*IGE Estimate*	*Standard Error*	*IGE Estimate*	*Standard Error*	*IGE Estimate*	*Standard Error*
1980	0.60	0.08	0.79	0.16	0.69	0.13	0.56	0.10	0.41	0.06	0.47	0.07
1981	0.62	0.08	0.78	0.16	0.60	0.14	0.53	0.09	0.40	0.08	0.47	0.10
1982	0.63	0.07	0.79	0.14	0.63	0.14	0.56	0.10	0.48	0.06	0.48	0.07
1983	0.63	0.07	0.86	0.16	0.66	0.10	0.54	0.07	0.40	0.07	0.47	0.06
1984	0.55	0.07	0.70	0.14	0.57	0.08	0.52	0.06	0.38	0.07	0.41	0.07
1985	0.63	0.06	0.91	0.14	0.71	0.10	0.51	0.07	0.39	0.06	0.40	0.06
1986	0.62	0.06	0.89	0.15	0.72	0.08	0.58	0.06	0.45	0.06	0.46	0.05
1987	0.56	0.06	0.74	0.11	0.56	0.09	0.51	0.07	0.40	0.06	0.44	0.06
1988	0.54	0.05	0.70	0.14	0.63	0.08	0.49	0.06	0.42	0.06	0.43	0.06
1989	0.54	0.05	0.75	0.11	0.60	0.08	0.52	0.07	0.41	0.05	0.45	0.05
1990	0.53	0.05	0.69	0.13	0.56	0.07	0.46	0.06	0.42	0.05	0.45	0.06
1991	0.56	0.04	0.75	0.10	0.58	0.06	0.51	0.06	0.45	0.06	0.47	0.05
1992	0.58	0.05	0.77	0.14	0.55	0.06	0.47	0.05	0.47	0.06	0.48	0.06
1993	0.58	0.04	0.71	0.15	0.59	0.07	0.50	0.05	0.46	0.05	0.51	0.06
1994	0.51	0.04	0.60	0.10	0.56	0.07	0.43	0.05	0.40	0.05	0.49	0.06
1995	0.51	0.04	0.53	0.12	0.46	0.06	0.39	0.05	0.40	0.06	0.45	0.06
1996	0.51	0.04	0.57	0.13	0.49	0.10	0.45	0.05	0.42	0.07	0.46	0.07
1998	0.42	0.04	0.57	0.15	0.49	0.07	0.40	0.05	0.40	0.06	0.52	0.11
2000	0.44	0.04	0.54	0.12	0.46	0.07	0.41	0.07	0.36	0.06	0.41	0.09
2002	0.35	0.04	0.52	0.11	0.43	0.08	0.35	0.06	0.33	0.05	0.36	0.09
2004	0.41	0.04	0.61	0.12	0.54	0.10	0.46	0.07	0.35	0.06	0.38	0.08
2006	0.39	0.04	0.51	0.15	0.47	0.08	0.39	0.07	0.33	0.07	0.41	0.07
2008	0.50	0.04	0.68	0.12	0.56	0.08	0.46	0.06	0.38	0.05	0.42	0.04
2010	0.42	0.03	0.52	0.12	0.50	0.09	0.41	0.05	0.37	0.04	0.40	0.06

Figure 3. Average QR Trend of IGE at each group of percentiles and OLS trend.

Table 6. Percentage decrease in IGE averaged for each group of quantiles when including the 'Years of Education' and direct effect of education.

	% DECREASE IN IGE WHEN INCLUDING 'YEARS OF EDU'						DIRECT EFFECT OF 'YEARS OF EDUCATION ON INCOME'					
	OLS	***Low***	***Mid-Low***	***Mid***	***Mid-High***	***High***	***OLS***	***Low***	***Mid-Low***	***Mid***	***Mid-High***	***High***
1980	28.57	22.36	22.17	24.17	20.74	42.75	0.11	0.17	0.09	0.08	0.09	0.13
1981	27.35	30.63	21.08	22.60	20.78	41.75	0.11	0.17	0.09	0.06	0.09	0.13
1982	27.03	25.87	26.15	20.76	38.87	35.13	0.11	0.17	0.08	0.08	0.11	0.15
1983	27.39	21.39	18.70	21.56	28.57	37.69	0.09	0.13	0.07	0.06	0.09	0.12
1984	32.36	27.78	20.90	26.62	33.14	41.63	0.11	0.14	0.08	0.08	0.11	0.13
1985	21.37	15.78	7.00	15.83	25.48	35.64	0.07	0.11	0.02	0.03	0.08	0.11
1986	26.05	20.10	18.91	21.59	27.98	32.46	0.10	0.15	0.07	0.07	0.09	0.12
1987	30.22	30.50	18.48	25.35	28.49	34.00	0.10	0.14	0.07	0.07	0.10	0.13
1988	31.21	35.06	16.56	18.91	28.55	36.55	0.10	0.16	0.06	0.05	0.09	0.13
1989	31.68	19.45	14.04	20.43	32.46	46.49	0.10	0.14	0.06	0.06	0.10	0.14
1990	33.65	25.97	19.89	26.90	35.38	39.17	0.11	0.16	0.06	0.07	0.10	0.14
1991	34.95	28.76	17.09	31.52	43.73	43.66	0.12	0.17	0.09	0.08	0.12	0.14
1992	29.86	21.86	20.91	17.96	40.30	40.35	0.12	0.16	0.08	0.06	0.11	0.15
1993	30.65	28.78	20.62	22.33	31.72	42.74	0.13	0.16	0.08	0.07	0.11	0.15
1994	32.03	24.53	27.77	23.39	38.33	45.93	0.11	0.15	0.08	0.06	0.10	0.14
1995	29.13	19.00	34.11	20.53	33.31	40.47	0.09	0.14	0.08	0.06	0.09	0.14
1996	30.77	36.20	16.76	25.89	27.44	45.08	0.11	0.15	0.07	0.06	0.09	0.13
1998	36.17	26.36	20.87	30.14	38.71	50.79	0.12	0.15	0.07	0.06	0.11	0.15
2000	33.79	36.64	25.24	29.53	37.74	40.47	0.12	0.15	0.09	0.08	0.10	0.14
2002	38.97	53.91	21.39	38.25	39.26	47.73	0.10	0.14	0.07	0.06	0.09	0.13
2004	32.20	45.08	21.28	31.41	33.85	45.38	0.10	0.15	0.08	0.07	0.09	0.12
2006	35.81	60.44	21.85	31.25	26.92	30.30	0.10	0.15	0.07	0.06	0.09	0.13
2008	31.08	41.85	26.72	27.03	27.08	37.16	0.09	0.16	0.09	0.07	0.10	0.13
2010	34.45	45.70	29.60	22.51	31.30	34.94	0.11	0.16	0.11	0.07	0.10	0.13

Figure 4. Mediating Role of ‘Years of Education’. OLS and QR results averaged by groups of income, in %.

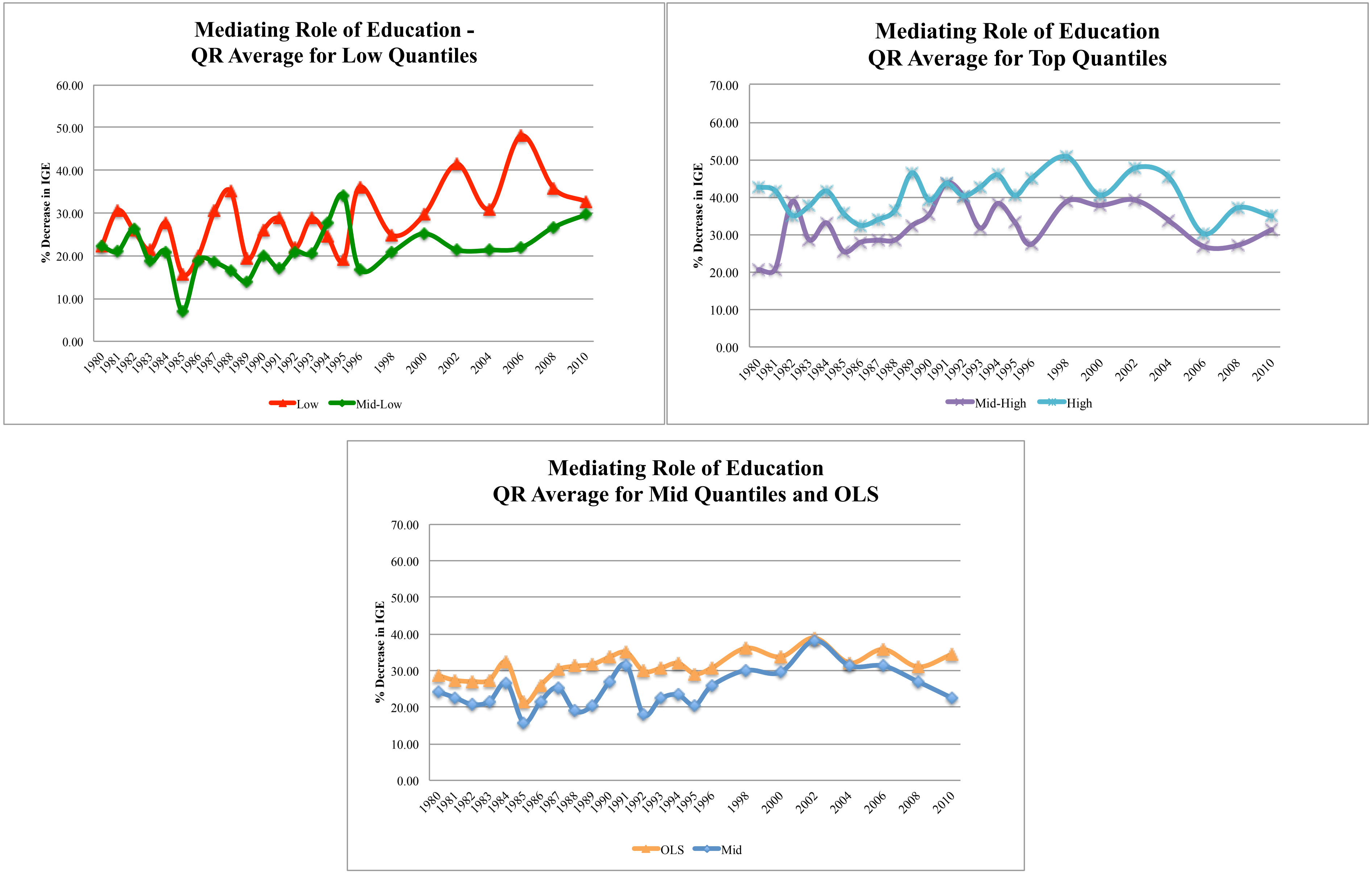


Table 7. Percentage decrease in IGE averaged for each group of quantiles when including “white race” dummy variable and direct effect of race.

	% DECREASE IN IGE WHEN INCLUDING 'WHITE RACE DUMMY'						DIRECT EFFECT OF 'WHITE RACE DUMMY' ON LOG OF REAL INCOME					
	OLS	***Low***	***Mid-Low***	***Mid***	***Mid-High***	***High***	***OLS***	***Low***	***Mid-Low***	***Mid***	***Mid-High***	***High***
1980	12.13	17.34	13.93	13.36	2.97	5.46	0.30	0.40	0.38	0.35	0.21	0.07
1981	16.50	25.69	26.62	7.17	2.07	9.22	0.45	0.77	0.54	0.30	0.18	0.14
1982	18.28	20.23	19.54	16.78	5.97	11.27	0.57	0.92	0.79	0.43	0.27	0.27
1983	12.42	9.57	1.63	4.00	11.34	10.36	0.45	0.62	0.55	0.30	0.30	0.19
1984	12.07	7.46	13.21	7.16	2.35	5.05	0.37	0.51	0.34	0.17	0.13	0.21
1985	12.76	10.11	10.33	7.07	12.70	10.30	0.43	0.59	0.41	0.36	0.29	0.32
1986	9.39	8.58	7.74	7.17	3.02	8.84	0.30	0.40	0.18	0.22	0.19	0.21
1987	14.75	16.32	12.50	9.48	4.68	7.13	0.42	0.69	0.36	0.35	0.24	0.21
1988	17.76	22.85	16.23	11.34	4.42	5.19	0.49	0.84	0.46	0.36	0.27	0.24
1989	16.57	17.52	13.40	12.34	6.47	12.96	0.49	0.82	0.48	0.30	0.27	0.30
1990	12.36	5.36	9.88	13.75	11.13	7.11	0.36	0.40	0.27	0.32	0.34	0.26
1991	13.33	10.14	11.69	12.08	9.55	9.15	0.38	0.52	0.42	0.30	0.29	0.27
1992	14.06	7.30	10.18	9.99	16.75	11.44	0.47	0.75	0.48	0.31	0.33	0.29
1993	10.45	10.33	8.92	10.54	6.33	8.09	0.37	0.53	0.25	0.27	0.28	0.28
1994	10.16	3.02	5.88	6.90	3.85	5.51	0.33	0.47	0.29	0.19	0.16	0.18
1995	5.31	5.54	6.62	1.29	-2.21	2.71	0.19	0.34	0.15	0.07	0.03	0.11
1996	9.66	17.71	21.84	3.48	-0.37	0.55	0.34	0.61	0.35	0.26	0.07	0.04
1998	3.78	12.55	3.39	1.00	1.56	2.73	0.14	0.39	0.11	0.11	0.05	-0.06
2000	4.57	3.26	4.41	4.07	-1.12	2.15	0.17	0.33	0.20	0.13	0.04	0.03
2002	3.15	0.14	7.24	5.96	-4.36	2.76	0.09	0.15	0.21	0.17	-0.01	-0.05
2004	0.00	5.01	5.64	5.31	-7.55	-6.39	0.04	0.17	0.18	0.11	-0.05	-0.14
2006	0.00	-1.14	2.16	1.58	-2.93	1.17	0.03	0.06	0.15	0.02	0.03	0.02
2008	10.96	6.91	10.10	10.25	3.86	10.48	0.33	0.34	0.37	0.31	0.19	0.19
2010	11.00	2.37	9.31	9.38	19.61	16.75	0.26	0.27	0.27	0.27	0.29	0.26

Figure 5. Mediating Role of Race (‘White Race Dummy’). OLS and QR results averaged by groups of income, in %.

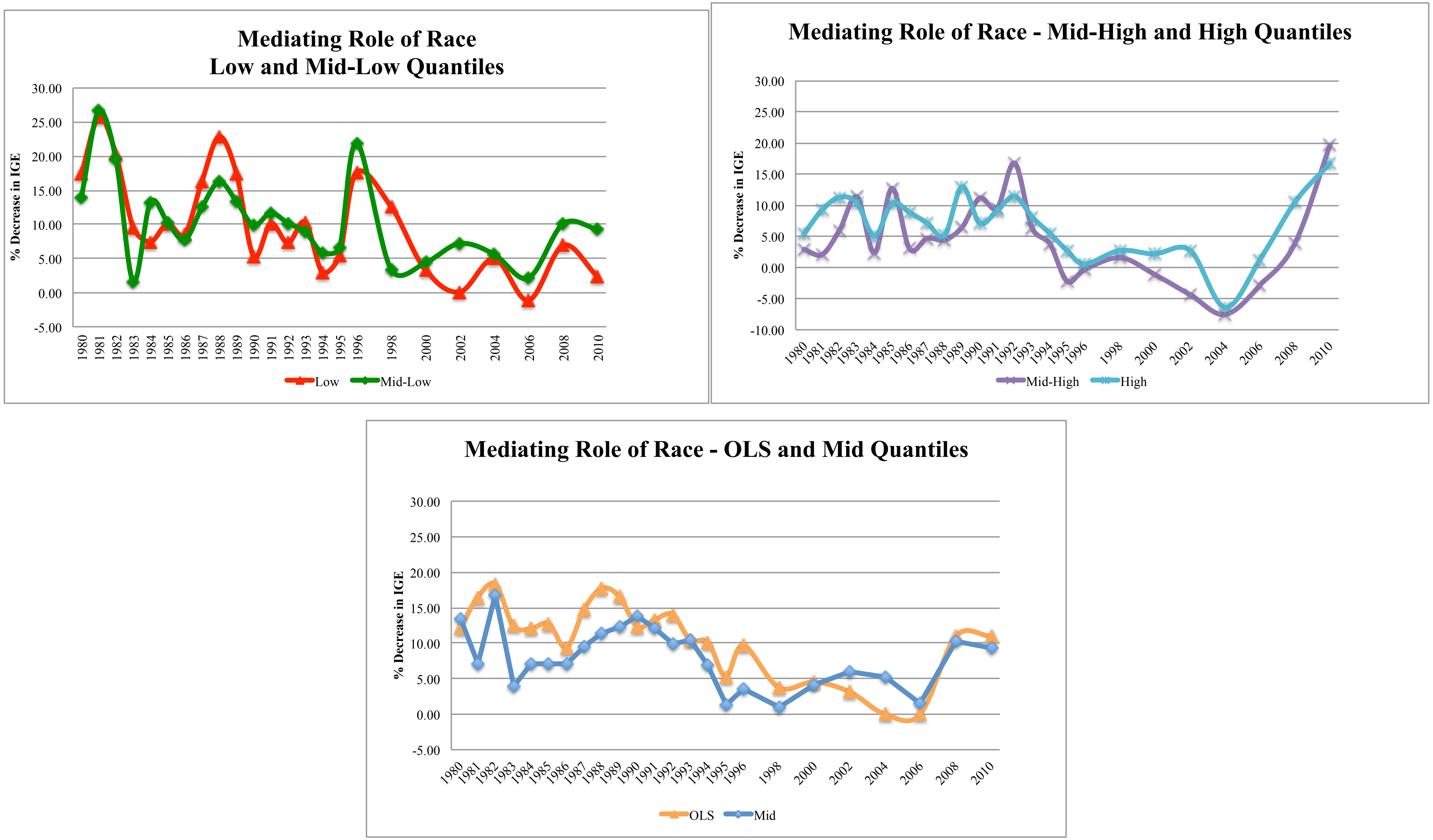
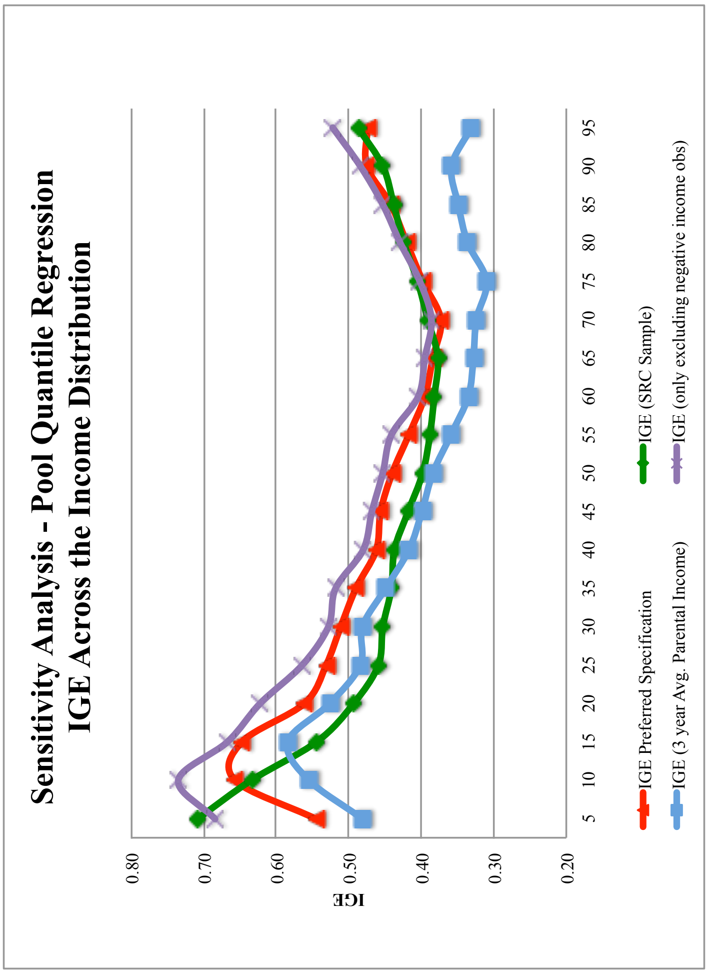


Table 8. Sensitivity Analysis. Pooled Sample.

Percentile	*IGE Preferred Specification*	*IGE (SRC Sample)*	*IGE (3 year Avg. Parental Income)*	*IGE (only excluding negative income obs)*
5	0.55	0.71	0.48	0.68
10	0.66	0.63	0.56	0.74
15	0.65	0.54	0.58	0.67
20	0.56	0.49	0.53	0.62
25	0.53	0.46	0.48	0.56
30	0.51	0.45	0.48	0.53
35	0.49	0.44	0.45	0.52
40	0.46	0.44	0.42	0.48
45	0.46	0.42	0.40	0.47
50	0.44	0.40	0.38	0.45
55	0.42	0.39	0.36	0.44
60	0.40	0.38	0.34	0.40
65	0.38	0.38	0.33	0.40
70	0.37	0.39	0.32	0.39
75	0.40	0.41	0.31	0.40
80	0.42	0.42	0.34	0.43
85	0.44	0.44	0.35	0.45
90	0.48	0.45	0.36	0.48
95	0.47	0.49	0.33	0.52
OLS	0.47	0.49	0.37	0.55
# OBS	25258	16361	25419	25448

Figure 6.

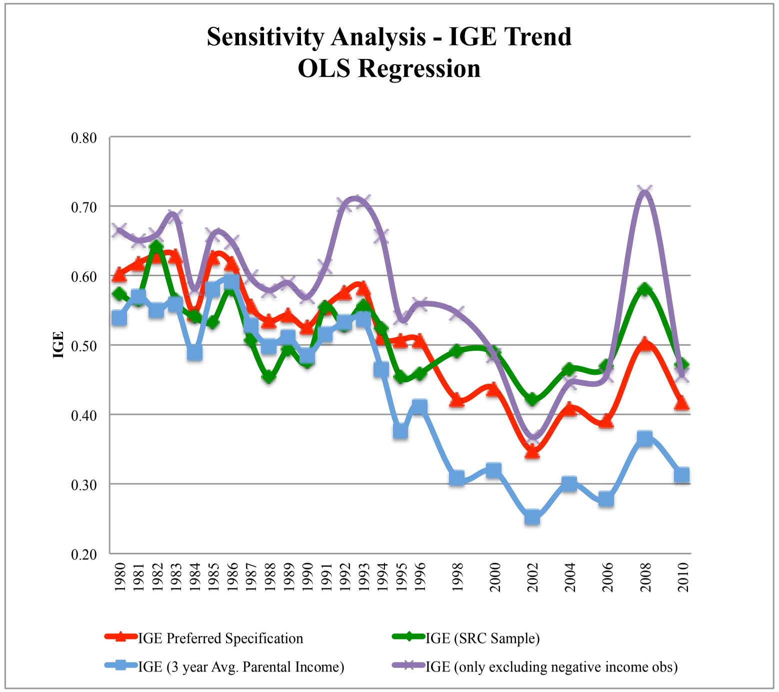


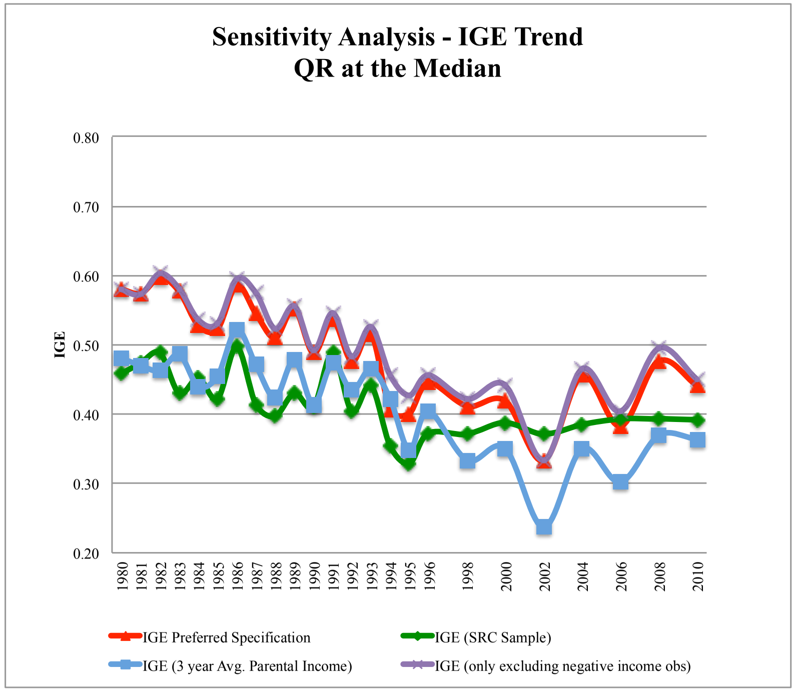
Sensitivity Analysis - Pool Quantile Regression
IGE Across the Income Distribution
IGE
0.80
0.70
0.60
0.50
0.40
0.30
0.20
5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95
IGE Preferred Specification
IGE (SRC Sample)
IGE (3 year Avg. Parental Income)
IGE (only excluding negative income obs)

Table 9. Sensitivity Analysis. Trend of IGE.

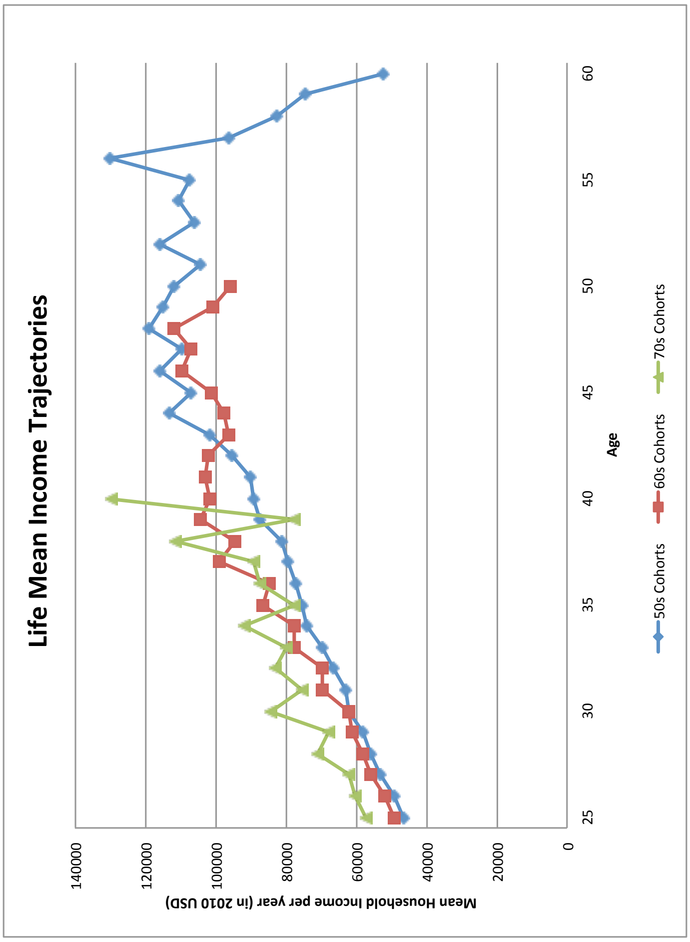
	OLS REGRESSION				50th PERCENTILE QUANTILE REGRESSION			
	IGE Preferred Specification	*IGE (SRC Sample)*	*IGE (3 year Avg. Parental Income)*	*IGE (only excluding negative income obs)*	*IGE Preferred Specification*	*IGE (SRC Sample)*	*IGE (3 year Avg. Parental Income)*	*IGE (only excluding negative income obs)*
1980	0.60	0.58	0.54	0.67	0.58	0.46	0.48	0.58
1981	0.62	0.57	0.57	0.65	0.57	0.47	0.47	0.57
1982	0.63	0.64	0.55	0.66	0.60	0.49	0.46	0.60
1983	0.63	0.57	0.56	0.69	0.58	0.43	0.49	0.58
1984	0.55	0.54	0.49	0.58	0.53	0.45	0.44	0.54
1985	0.63	0.53	0.58	0.66	0.52	0.42	0.46	0.53
1986	0.62	0.58	0.59	0.65	0.59	0.50	0.52	0.60
1987	0.56	0.51	0.53	0.60	0.55	0.41	0.47	0.58
1988	0.54	0.46	0.50	0.58	0.51	0.40	0.42	0.52
1989	0.54	0.49	0.51	0.59	0.55	0.43	0.48	0.56
1990	0.53	0.48	0.49	0.57	0.49	0.41	0.41	0.49
1991	0.56	0.56	0.52	0.61	0.54	0.49	0.47	0.55
1992	0.58	0.53	0.53	0.70	0.48	0.40	0.43	0.48
1993	0.58	0.56	0.54	0.71	0.52	0.44	0.47	0.53
1994	0.51	0.52	0.47	0.66	0.41	0.35	0.42	0.46
1995	0.51	0.46	0.38	0.54	0.40	0.33	0.35	0.43
1996	0.51	0.46	0.41	0.56	0.45	0.37	0.41	0.46
1998	0.42	0.49	0.31	0.55	0.41	0.37	0.33	0.42
2000	0.44	0.49	0.32	0.49	0.42	0.39	0.35	0.44
2002	0.35	0.42	0.25	0.37	0.33	0.37	0.24	0.33
2004	0.41	0.47	0.30	0.45	0.46	0.39	0.35	0.47
2006	0.39	0.47	0.28	0.46	0.38	0.39	0.30	0.40
2008	0.50	0.58	0.37	0.72	0.48	0.39	0.37	0.50
2010	0.42	0.47	0.31	0.46	0.44	0.39	0.36	0.45

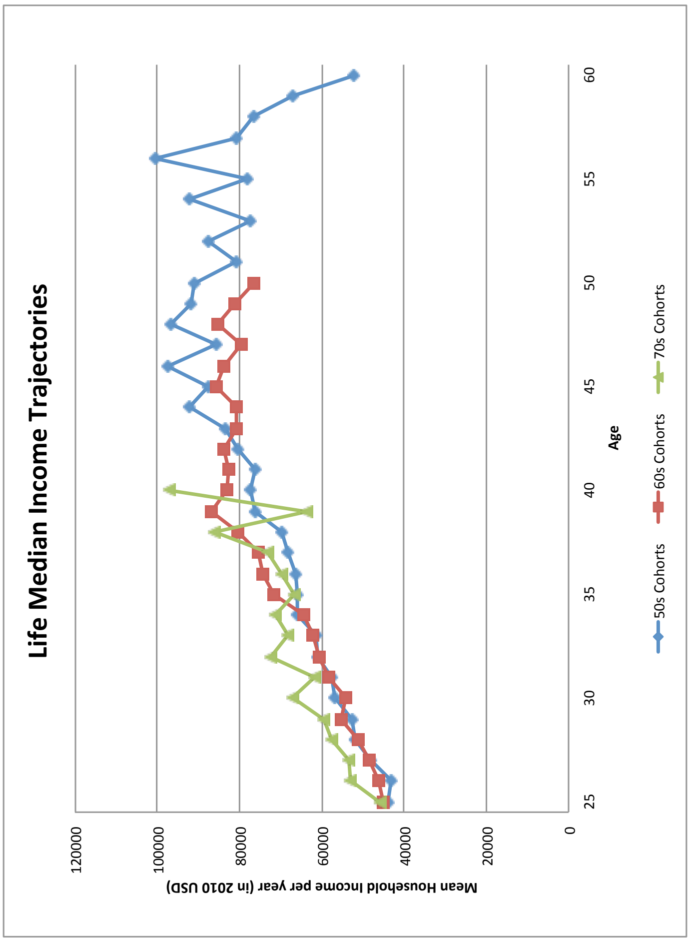
Figures 7 and 8



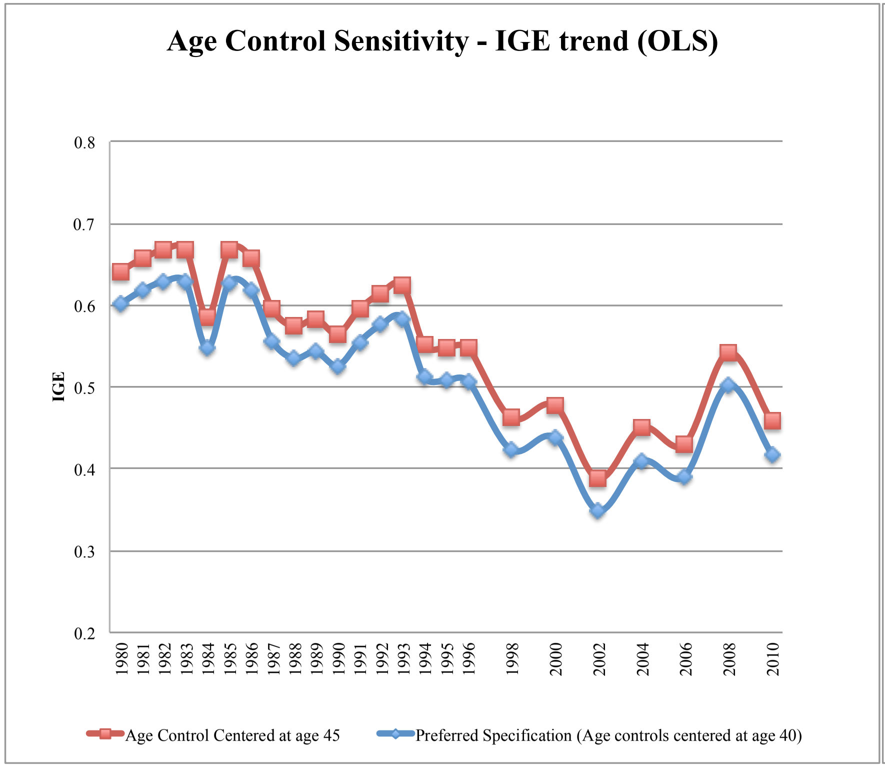


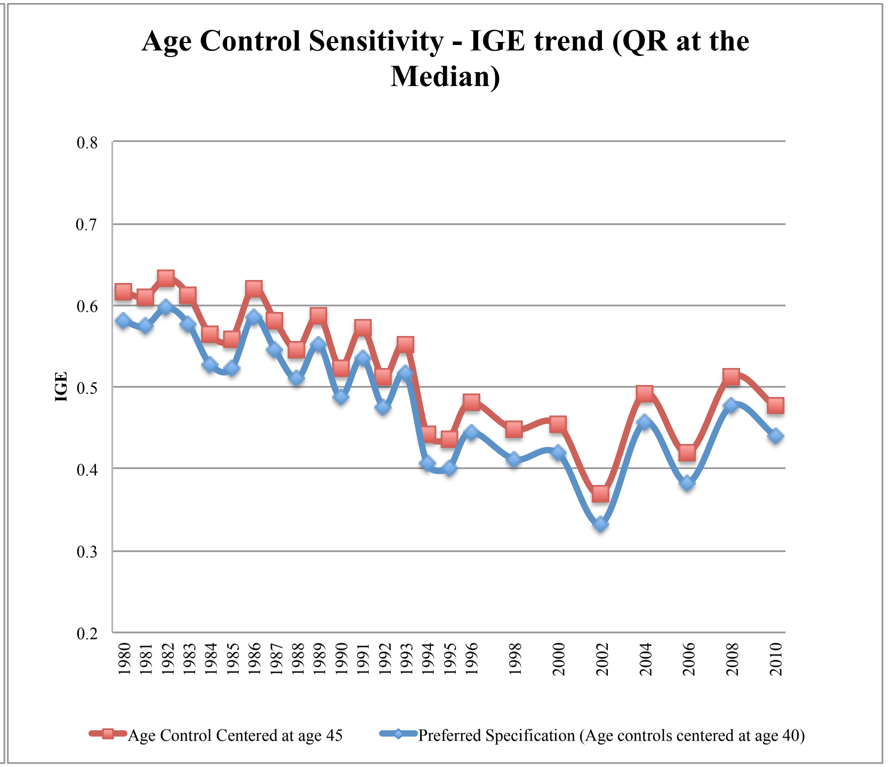
Figures 9 and 10





Figures 11 and 12





Appendix. Table 1.

				ORDINARY LEAST SQUARES U.S. IGE ESTIMATES REVIEW				QUANTILE REGRESSION U.S. IGE ESTIMATES REVIEW			
	DATA	*VARIABLE*	*SAMPLE SIZE (OBS.)*	*VALUE*	*MEDIATING VARIABLES (EDU)*	*MEDIATING VARIABLES (RACE)*	*IGE TREND*	*VALUES (10th, 25th, 50th, 75th and 90th percentiles)*	*MEDIATING VARIABLES (% Decrease controlling for years of education at the 10th, 25th, 50th, 75th and 90th percentiles)*	*MEDIATING VARIABLES (% Decrease controlling for race at the 10th, 25th, 50th, 75th and 90th percentiles)*	*IGE TREND AT DIFFERENT QUANTILES*
Solon (1992)	PSID	Log earnings averaged 5 years for parental income (1967-71) ; year 1984 for sons	290	0.4							
Zimmerman (1992)	NLS	Log earnings	192	Different values for different specifications; values around 0.4 as concluded by the author himself							
Eide and Showalter (1999) [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). Direct effect of 0.11 per year.			0.47; 0.35; 0.37; 0.35; 0.17	30; 26; 35; 34; 12 *		
Eide and Showalter (1999) [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). Direct effect of 0.12 per year.			0.67; 0.49; 0.44; 0.35; 0.26	27; 35; 30; 26; 19 *		
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				0.35; 0.494; 0.54; 0.457; 0.40			
Hertz (2005)	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 (16.7%) Direct effect of 0.33 on average.					
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 15-18).	11,230	Yearly estimations 1978-2000 averaging a value of 0.44			No trend for the 1978-2000 period				

Appendix. Table 1 (cont).

			ORDINARY LEAST SQUARES U.S. IGE ESTIMATES REVIEW					QUANTILE REGRESSION U.S. IGE ESTIMATES REVIEW			
	DATA	*VARIABLE*	*SAMPLE SIZE (OBS.)*	*VALUE*	*MEDIATING VARIABLES (EDU)*	*MEDIATING VARIABLES (RACE)*	*IGE TREND*	*VALUES (10th, 25th, 50th, 75th and 90th percentiles)*	*MEDIATING VARIABLES (%Decrease controlling for years of education at the 10th, 25th, 50th, 75th and 90th percentiles)*	*MEDIATING VARIABLES (%Decrease controlling for race at the 10th, 25th, 50th, 75th and 90th percentiles)*	*IGE TREND AT DIFFERENT QUANTILES*
Cooper (2011)	PSID	A sample of male heads. Average labor income of parents and sons who report at least 3 years of income at age 35-50, from the years 1967 to 2007.	1,424	0.42	OLS Decrease in IGE of 35% (To 0.27). Direct effect of 0.14.	Direct effect of race of -0.32 controlling simultaneously for education, religion and parental weekly work hours		0.52; 0.49; 0.46; 0.41; 0.38	35; 32;31; 33;53 *		
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 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. Direct effect of race -0.34.					
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 child was 10-16 with at least one observation.	647	0.39	48.1% of IGE explained by education (Pathway decomposition method)						
Palomino, Marrero and Rodríguez (2014)	PSID	Log of family income controlling for life cycle on the years 1980-2010 for male children. Parental income averaged for seven years (children aged 13-19).	25,258	0.47	OLS Decrease of IGE of 27.43% (to 0.34)	OLS Decrease of IGE to 0.43 (10.02%). Direct effect of race -0.36.	Slightly decreasing trend for the 1980-2002 period, turned slightly increasing in 2002-2010.	0.66; 0.53; 0.44; 0.40; 0.48	35; 19; 23; 30; 35	13; 8; 11; 3; 7	In the 1980-2010 period, no trend for the mid-high and high percentiles. For the mid and low percentiles, decrease of IGE in the 80s and 90s and slight increase in the 2000s.