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Essays on intergenerational mobility and equality of opportunity

(Ensayos sobre movilidad intergeneracional e igualdad de oportunidades)

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ESSAYS ON INTERGENERATIONAL MOBILITY AND EQUALITY OF OPPORTUNITY

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Abstract

This doctoral dissertation is divided in three chapters. While all of them deal with the measurement and determinants of economic mobility and (in)equality of opportunity, each has a distinct topic and focuses on a special facet of the opportunity and mobility puzzle.

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

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. In the first chapter of this dissertation a large sample of income observations in the 1980-2010 period for the U.S. is built using the PSID database, 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 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.

Channels of inequality of opportunity: the role of education and occupation in Europe

Our second chapter studies the contribution of individual education and occupation to individual opportunity in Europe. Although the differences in inequality of opportunity (IO) among European countries are significant, no systematic approach has yet been proposed to analyse the channels through which different individual circumstances turn into different income levels. Here, we propose a simple two-step method to quantify the contribution to IO of individual education and occupation across Europe in 2004 and 2010. We find that the level

of education channels up to 30% of total IO, with important differences across Europe but no clear patterns of change over time. Moreover, we observe a negative correlation between the share of IO channelled through education and the share of the population with tertiary education. Once education is taken into account, the occupational category of individuals explains less than 5% of total IO in most European countries.

Inheritances and inequality of opportunity in wealth

While the analysis of inequality of opportunity (IO) in income has flourished in the last decade, the study of wealth opportunity has not seen the same development. Recent findings about the historical trends and levels of wealth inequality have not been accompanied by advances in the study of the 'opportunity component' of that inequality. In our third chapter using a unique dataset for Spain that contains information about wealth, income and external circumstances (gender, parental occupation and inheritances), we analyse IO in wealth in 2011 applying a non-parametric regression method. Our results show that inheritances play a different role determining the IO in wealth and in income. While the level of IO in wealth is strongly related to whether the household received inheritance and, especially, to the amount of the inheritance received, this factor does not seem to be an important circumstance in determining the level of IO in income.

Resumen

Esta tesis doctoral se divide en tres capítulos. Si bien todos ellos se ocupan de la medición y los determinantes de la movilidad económica y de la igualdad de oportunidades, cada uno trata un tema distinto y se centra en una faceta especial del rompecabezas de la movilidad y las oportunidades.

Una talla no vale para todos: un análisis por cuantiles de la movilidad intergeneracional de ingresos en Estados Unidos (1980-2010).

La sabiduría popular y la literatura existente sugieren que la movilidad económica es menor en las colas de la distribución de ingresos; sin embargo, los pocos estudios que han estimado la elasticidad intergeneracional de ingresos (IGE) en diferentes puntos de la distribución en los Estados Unidos estaban limitados por muestras pequeñas, llegaban a resultados dispares y no estimaban la tendencia de la elasticidad en el tiempo. En el primer capítulo de esta disertación se construye una gran muestra de observaciones de ingresos en el período 1980-2010 para los Estados Unidos utilizando la base de datos PSID, lo que nos permite obtener estimaciones cuantitativas robustas de la IGE tanto para la muestra conjunta como para cada ola. Para la muestra conjunta, el IGE muestra una relación en forma de U con la distribución del ingreso, con valores más altos en las colas (0,64 en el percentil 10 y 0,48 en el percentil 95) y un valor mínimo -la mayor movilidad- de 0,38 en el percentil setenta. La evolución de la tendencia de la IGE también varía según la distribución del ingreso: en los cuantiles inferiores y medios la movilidad de ingresos aumentó durante los años 80 y 90, pero disminuyó en los años 00, mientras que para los cuantiles más altos se mantuvo relativamente estable durante todo el período. Finalmente, se evalúa el impacto de la educación y la raza en la movilidad. Ambos factores son importantes y aparecen relacionados con la posición en la distribución de ingresos.

Canales de la desigualdad de oportunidades: el papel de la educación y la ocupación en Europa.

Nuestro segundo capítulo estudia la contribución de la educación y la ocupación individuales la desigualdad de oportunidades (IO) en distintos países de Europa. Aunque la literatura muestra que las diferencias en desigualdad de oportunidades entre los países europeos son

significativas, no se ha propuesto ningún enfoque sistemático para analizar los canales a través de los cuales las diferentes circunstancias individuales se convierten en diferentes niveles de ingresos. En este sentido, proponemos un método simple en dos pasos que permite cuantificar la contribución a IO de la educación y ocupación del individuo en toda Europa en 2004 y 2010. Encontramos que el nivel de educación canaliza hasta el 30 % del total de IO, con importantes diferencias en toda Europa, aunque no hay patrones claros de cambio en entre las dos olas. Además, se observa una correlación negativa entre la proporción de IO canalizada a través de la educación y la proporción de la población con educación terciaria. Una vez que se tiene en cuenta la educación, la categoría ocupacional de los individuos explica menos del 5 % del total de IO en la mayoría de los países europeos.

Herencias y desigualdad de oportunidades en riqueza

Mientras que el análisis de desigualdad de oportunidades ("Inequality of opportunity", IO) en ingresos ha florecido en la última década, el estudio de las oportunidades en riqueza no ha visto el mismo nivel de desarrollo. Los recientes hallazgos sobre las tendencias históricas y los niveles de desigualdad en la riqueza no han sido acompañados por avances en el estudio del "componente de oportunidad" de esa desigualdad. En nuestro tercer capítulo, utilizando un conjunto de datos singular que contiene información sobre riqueza, ingresos y circunstancias externas (género, ocupación de los padres y herencias), analizamos IO en riqueza en 2011 en España aplicando un método de regresión no paramétrico. Nuestros resultados muestran que las herencias desempeñan un papel diferente determinando IO en riqueza y en ingresos. Si bien el nivel de IO en riqueza está fuertemente relacionado con el hecho de que el hogar haya recibido herencia y, especialmente, la cantidad de la herencia recibida, este factor no parece ser una circunstancia importante para determinar el nivel de IO en ingresos.

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Introduction

To what extent is the economic performance of individuals conditioned by circumstances beyond their control like socioeconomic background, race and gender? How does this conditioning take place? Which are the main explicative factors? These are the questions that vertebrate this doctoral dissertation, presented in three self-contained chapters which address different aspects of intergenerational mobility and inequality of opportunity.

In the first chapter we investigate the correlation between parental income and individual's income. Using the Panel Study of Income Dynamics (PSID), we analyze how the level of intergenerational immobility (measured by the intergenerational income elasticity (IGE)) changes throughout the income distribution in the United States, from the poorest and 'middle class' to the richest. Recent studies estimating the IGE find the level of intergenerational immobility in the U.S. to be higher than previously thought [Solon (1992)), Zimmerman (1992), (Mazumder (2005))], relatively high compared to other countries with a similar degree of development [Corak (2006), Björklund and Jäntti (2009), Blanden (2013)], and with no clear pattern or trend overtime [Hertz (2007); Aaronson and Mazumder (2008); Lee and Solon (2009)]. Most of these studies, however, estimate the IGE at the mean using an approach based on the ordinary least squares (OLS) and ignore, therefore, the possible variation of the IGE at different points of the income distribution. The few works that have estimated the IGE in the U.S. at different quantiles have not found a clear relation between the IGE and the income distribution, being flawed with relatively small samples [Eide and Showalter (1999); Grawe (2004); Cooper (2011))].

The first chapter of this thesis contributes to the debate about the level and evolution of the IGE in the U.S. in three different ways. First, using a much bigger sample than previous studies, which allows for more accurate estimates specially at the tails of the income distribution, we find that, for the 1980-2010 period as a whole, the IGE estimates progressively change across the income distribution, following a U-shaped pattern, with parental income influence on children's income being greater at the tails of the distribution. This result is robust to the use of both conditional and unconditional quantile regression methods. The second contribution of the chapter is a time series analysis of the IGE at different income percentiles along the 1980-2010 period. We find indeed that the mid and the top quantiles show no clear IGE trend over the period analyzed, while the lower part of the distribution shows a decreasing trend until the early 2000s, when it turns increasing. Finally, we explore the role of sons' education and race as intergenerational transmission channels of parental income. The educational channel seems to be more important at the tails of the distribution and shows no clear trend, while the racial channel appears to be relevant for the IGE only at the bottom of the income distribution and shows an increasing trend in the 00s after having decreased in the 90s.

Our second and third chapters build upon the analysis of inequality of opportunity (IO) in a broader way. While the study of intergenerational income mobility uses the income relationship between two contiguous generations, the IO approach tries to isolate the share of total inequality associated with factors out of individual's control (circumstances) like socioeconomic background, race and gender, among others.

So far, the bulk of the literature on inequality of opportunity has centered in its measurement for income and the corresponding comparison across countries, although little attention has been paid to the channels of transmission. It is essential, however, to understand how different individual initial conditions turn into different future levels of outcome. The level of attained education, which is a key factor in the production function that significantly influences the acquisition of earnings, and the acquired occupation, which is also affected by the functioning of the labor market, are the two main candidates as channels of transmission. Different circumstances in childhood may lead to different levels of education and occupational categories, which in turn contribute to generate different economic outcomes in the adulthood.

The second chapter of this dissertation develops a novel strategy to estimate how much of the IO in income is channeled through the educational level and the occupational category of the individual in Europe (2004 and 2010), using the "ex-ante" approach (Ferreira and Gignoux (2011)) for comparability reasons, although the method can also be applied to the "ex-post" approach (Checchi and Peragine (2010)). In a first step, the method estimates the 'smoothed income distribution' (i.e., the individual income conditioned to individual circumstances) and computes IO in the acquisition of income. In the second stage, the smoothed income distribution is in turn conditioned to the education of the individual, and the residual of this last regression to the occupation of the individual. Finally, we estimate the IO associated to each component, isolating –to the best of our knowledge for the first time in the literature- the shares of IO transmitted through individual education and individual occupation (once controlled for education).

Taking advantage of the two special modules on intergenerational transmission of poverty in the EU-SILC database (waves 2005 and 2011, with data referring to the previous year) the application of our strategy finds the level of education to be a relevant channel of the IO. It mediates more than 15% of IO in ten European countries in both 2004 and 2010, with special importance in Portugal and Luxembourg, where it mediates more than 30% of IO in 2010, finding also that the importance of education as a channel for IO is negatively correlated with the share of the population that attains tertiary levels of education. In addition, we find that the level of education seems to encompass most of the possible influence of the occupational category, for once the education channel has been discounted, the influence of the occupational channel of IO is associated with only between 1% and 5% of IO in most countries and in both waves.

Although the debate about inequality has traditionally focused on the analysis of income, there is a growing interest on the study of wealth, with recent evidence showing that wealth inequality in the United States has been increasing since the late 1970s after having had a decreasing trend since the 1930s(Saez and Zucman (2016)) and that the wealth-income ratio has also began to increase steadily since the 1970s in the U.S., U.K., Germany and France, reaching back the levels of the XVIIIth and XIXth centuries (Piketty and Zucman (2014)). Simultaneously, the impact of wealth on subjective well-being (Hochman and Skopek (2013)), on access to education Johnson (2014) and in the racial gap (Shapiro (2004); Oliver and Shapiro (2006)) are being increasingly acknowledged.

Unfortunately, despite this growing interest, the analysis still lacks objective measures about the 'fairness' of those high inequality levels in wealth. It is relevant to know not only how unequally wealth is distributed, but also to what extent that inequality is the consequence of effort and talent or, on the contrary, it is related to external prior factors that the individual is not responsible for. We believe that the debate could be enriched if the mere analysis of wealth inequality is complemented with an analysis of inequality of opportunity in the acquisition of wealth.

With the intention of providing a first-time approach to inequality of opportunity in wealth, in the third chapter we use a unique dataset collected by the Spanish Central Bank which, in addition to wealth, includes the parental occupational category and the inheritances received by the household. In addition, we apply a general non-parametric smoothing method (Lasso de la Vega et al. (2017)) to calculate the IO in wealth for Spain in 2011.

The results in our third chapter reveal that -even with a limited set of circumstances- IO in wealth in Spain can represent almost half of total wealth, and that an external circumstance like the inheritance received seems to have a particularly strong effect on wealth inequality, significantly higher than it has on income. In particular, we find that -with gender and parental occupation as baseline circumstances- considering whether an individual received or not an inheritance, the IO to total inequality ratio in wealth increases from 27.6% to 33.1%. Furthermore, accounting for the *amount* inherited further boosts the IO ratio in wealth to 49.0%. Compared to our results for IO in income, we find that the IO in wealth to be higher both in absolute and relative terms, where the relative IO in income reaches 33.4%.

In sum, this doctoral dissertation tries to improve the understanding of intergenerational mobility and inequality of opportunity. As we discuss in each of the chapters and the final conclusion, significant questions remain unanswered but it is our hope to have posed new ones that will stimulate future research in these relevant fields.

Chapter 1

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

1.1 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 the last 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 doubts about 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

[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 last 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.

(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 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 indeed that the top quantiles and the mid-bottom quantiles of the distribution seem to have followed different trajectories in the three decades considered.

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. In Section 5 we

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

[5]See Appendix Table 1.A1 for a review of elasticity estimates for the US using OLS in the literature. In Table 1.A2 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.

develop a sensitivity analysis and Section 6 concludes.

1.2 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 $y_{p_{it}}$,

$$\ln y_{s_i} = \alpha + \beta \ln y_{p_i} + \varepsilon_{it} \tag{1.1}$$

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]

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. Finally, when only parental income is included as an explanatory variable, the model in (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.

[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. The value of IGE can thus be influenced by many other variables involved (education quantity, education quality, race, location, social connections, etc.) In fact, our study of education and race discloses part of the influence of these variables on IGE: controlling for race and for the amount of education reduces the our measure of IGE in more than 30% at most quantiles and even more than 60% at the 5th percentile (see Table 1.2).

1.2.1 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:

$$\ln y_{s_{it}} = \alpha + \beta \ln y_{p_i} + \sum_{n=1}^{4} \gamma_n A_i^n + \sum_{n=1}^{4} \delta_n C_{it}^n + \sum_{n=1}^{4} \theta_n [\ln y_{p_i}] C_{it}^n + \varepsilon_{it} \tag{1.2}$$

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:

$$\ln y_{s_{it}} = \alpha_t D_t' + \beta_t [\ln y_{p_{it}} D_t'] + \sum_{n=1}^{4} \gamma_n A_i^n + \sum_{n=1}^{4} \delta_n C_{it}^n + \sum_{n=1}^{4} \theta_n [\ln y_{p_{it}}] C_{it}^n + \varepsilon_{it} \tag{1.3}$$

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. 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.

1.2.2 Quantile regression

We use Quantile Regression to contrast if 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 equation (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 (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 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

[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.

errors of the estimation at those quantiles.

Conditional and unconditional quantile regression

Both OLS and QR estimates are obtained based on the distribution of the outcome variable Y conditional to the distribution of the explanatory set of X variables. The law of iterated expectations permits to obtain an 'unconditional' expectation as the weighted average of the conditional expectations of the distribution. Thus, in general, the OLS estimated coefficients at the mean of the conditional distribution can be used to recover the 'unconditional' distribution. However, this strategy does not apply to quantile regression (Angrist and Pischke (2008)). Obtaining the unconditional quantiles estimates when there is no 'law of iterated quantiles' is a challenging and "work in progress" task for statisticians and econometricians.

So far, the most successful 'unconditional quantile regression' approach among practitioners is the method proposed by (Firpo et al. (2009)). They propose a two-step process which uses the 'influence function' concept to estimate the impact of different X covariates at different unconditional quantiles. [8] Unfortunately, the presence of age controlling variables in our main specification makes this method not directly applicable in our case. These age controlling variables are included in the model to correct for measurement error, control life cycle bias and make all income observations comparable. Therefore, not conditioning the estimation to these controls would give us unreliable estimates of IGE.

Nevertheless, to check the robustness of our results, we will compare in our sensitivity analysis (Section 5) conditional and unconditional estimations of IGE with an age-restricted subsample. We find the results in the conditional and unconditional regressions are overall quite similar.

1.2.3 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

[8] The first step estimates the 'Recentered Influence Functions' (RIF) for observations below and above each unconditional quantile; the second step regresses these RIF values on the X covariates.

and other genetic traits are potential candidates. Unfortunately, the availability of data to test some of these factors is limited.[9]

We focus on two possibly explaining variables that are time-consistent along 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 along the last three decades.

To estimate the impact of education for the entire pool, we first add in equation 1.2 the 'years of education' variable e_{s_i}.

$$\ln y_{s_{it}} = \alpha + \beta \ln y_{p_i} + \lambda e_{s_i} + \sum_{n=1}^{4} \gamma_n A_i^n + \sum_{n=1}^{4} \delta_n C_{it}^n + \sum_{n=1}^{4} \theta_n [\ln y_{p_i}] C_{it}^n + \varepsilon_{it} \tag{1.4}$$

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 1.4. 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 (1.2)) will remain unchanged. On 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 equation (1.4) with the one obtained in equation (1.2) 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 equation 1.5. Variable r_{s_i} is a dummy variable that takes the value 1 for white individuals and is 0 otherwise.

[9] 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. Bowles and Gintis (2002) is a prominent exception, finding the impact of intelligence on income is relatively small, accounting for a 12.5% share of the intergenerational correlation. However, data availability has made scholars focus mainly on variables like education and race (Hertz (2006) ; Torche (2013)).

Then, the impact of race can be calculated comparing the elasticity β from equation (1.5) and the β from (1.4), and relating it with the original baseline beta: $(\beta_{edu} - \beta_{race+edu})/\beta_{baseline}$

$$\ln y_{s_{it}} = \alpha + \beta \ln y_{p_i} + \lambda e_{s_i} + \varphi r_{s_i} + \sum_{n=1}^{4} \gamma_n A_i^n + \sum_{n=1}^{4} \delta_n C_{it}^n + \sum_{n=1}^{4} \theta_n [\ln y_{p_i}] C_{it}^n + \varepsilon_{it} \qquad (1.5)$$

Finally, we have analogously included the variables e_{s_i} and r_{s_i} in our trend estimation (1.3), in order to analyze the influence of son's education and race in the time evolution of IGE.

1.3 Database

To measure intergenerational income mobility, we use 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. Note that income reported refers to the year prior to the interview.[10] To keep the maximum possible number of observations, 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-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,

[10] 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 et al. (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 5^{th} and 95^{th} percentiles.

are supplied by the PSID.[11] 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 ((Solon, 1992, p. 404)) 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. Nevertheless, 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. 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. We carry out a sensitivity analysis of different cut-off income values in Section 5. [12]

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. [13]

[11]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 and therefore, one must be aware that our PSID sample could not reflect the recent changes in the composition of the American population. Also, a recent study finds that attrition in the PSID affects specially the lower part of the distribution, and that IGE might be downward biased at the lower quantiles (Schoeni and Wiemers (2015)). This effect, although less important when -like in our analysis- sampling weights are used, could made the U-shaped Quantile-IGE relation even steeper at the low part of the distribution.

[12]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.

[13] 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.

In principle, income elasticity estimates need the permanent income component of 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)), Mazumder (2005) or Mitnik et al. (2015) 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 (6.24 observations on average). In line with Mazumder's findings, our intergenerational elasticity estimates are sensitive to increasing the number of years averaged from 3 to 7, but do not change when we further increase the number of years averaged to 9 (see Section 5 for a sensitivity analysis on this issue). [14]

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 (Black and Devereux (2011)).[15] 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 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 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. 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.

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

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

In table 1.1 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 times. As discussed in section 1.4.1, we have taken this into account in the computation of standard errors (see Footnote 18).

Besides our 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 addition, to test for possible non-linearities of the effect of education on income we also run our main pool analyisis using a categorical education variable. The results were coincident, with only slight differences in the extreme quantiles of the distribution (see Figures 1.2 and 1.3).[16]

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. We also considered using a black race dummy, thus assimilating white to the other non-black race observations, and did a robustness check with that choice. Given that less than 3% of the observations report races other than black or white each year (see Table 1.1), the results of the impact of race in IGE for the whole pool were quite similar with either choice (see Figures 1.4 and 1.5). Among the non-black and non-white race observations, 19.8% of them were "Spanish-American, Latino Origin", 13.9% "Asian, Pacific Islander", 9,4% "American Indian, Aleut or Skimo" and 56.9% were coded "Other". Given the slight prevalence of the hispanics among

[16]We used the following categories: less than primary (less than 8 years of education completed), primary (8 years), some secondary education completed (more than 8 and less than 12 years), secondary (12 years), post-secondary (more than 12 and less than 16 years), tertiary (16 years) and post tertiary (17 years of education or more). Figures 1.2 and 1.3) show that on the top quantile the impact is higher using categorical variables, where just one more year of education may imply a 'Masters' degree and a greater impact on income than what could be linearly expected. On the other hand, the categorical division might lose some diversity of the data, specially among people who did not finish primary education, where some of them have more years of education than others. That is maybe why in the lowest quantile the impact of education on mobility is higher using "years of education". Taking this into account, and given that the results were in general quite similar using either variable for the greatest part of the income distribution, we decided to stick with the original PSID variable for our trend analysis.

this group, and the fact that hispanic socioeconomic demographics are far more similar to blacks than to whites (Sullivan et al. (2015)), we opted to keep our white race dummy all across our study.[17]

1.4 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.

1.4.1 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 1.2 and Figure 1.1.[18] The OLS estimation yields a value of 0.47, which is in line with the literature (see Table 1.A1). 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

[17] Note that the "Spanish-American" coding in the PSID dissappears from 1985 and only reappears in 1990, while the "Asian, Pacific Islander" and the "American Indian, Aleut or Skimo" codings both appear only from 1985. That explains the high proportion of answers coded "Other". Also remember that we are only using the SRC and Census samples of the PSID, and not the so-called, "Latino Sample".

[18] 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.

at the $90^{th} - 95^{th}$ percentiles.[19]

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 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 1,424 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.[20]

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 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 sons' 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

[19]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.

[20]Recall that our sample consists of 25.084 observations from 3.088 inviduals. See Appendix Table 1.A2 for a summary review of the results of the literature using QR for IGE estimation in the US.

inertia at both ends of the distribution in the U.S., but with more intensity at the bottom than at the top.[21]

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 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*.

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 between generations. Our results –see Table 1.2– show that when education is included in the regression (equation (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.[22] 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 inheritance of income- and increases significantly when approximating to the extremes of

[21] 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.

[22] See table 1.A1 for a review of the most relevant previous literature on this issue.

the distribution (see Table 1.2 and Figure 1.2). 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 can provide to their children.[23]

With respect to race, the OLS regression yields a decrease in the IGE of 10% when we include the dummy variable 'race' as an additional control in equation (1.5). Thus, at the mean, one tenth of the 'inheritance' of parental income can be attributed to the race of the individual (Table 1.2). 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 1.2 and Figure 1.4).

1.4.2 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: 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 (Figure 1.6).[24]

In our OLS estimation at the mean (see Figure 1.6, 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

[23]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). 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 Figure 1.3).

[24]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 all available upon request.

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.[25] With a bigger sample using tax records and the Statistics of Income annual cross sections, Chetty et al. (2014b) 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.[26]

Concerning the trend at different points of the income distribution, our quantile regression estimates show that, for all quantiles below the median, the IGE decreased in the 80s and 90s and increased in the 2000s, which is the same result as the OLS estimation. 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.

Although 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 has generally decreased in 2010, although more observations will be required to confirm this new trend in the IGE series.[27]

[25] 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)

[26] 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.

[27] Using the Wald test, we have tested the hypothesis that all IGE estimates from different years at a given quantile are equal (see Table 1.3). The hypothesis is rejected at the 5% significance level only the 20th, 35th, 55th and 95th percentiles, and cannot be rejected in the rest. Even in these cases, the test only rejects that the coefficients are equal, but does not evaluate the slope or the direction of the possible trend. The relatively small sample for each wave and the relatively high standard errors (especially at the tails of the income distribution) make us be cautious about the statistical signficance of the estimated IGE trends.

Education and race impact on IGE between 1980 and 2010

The share of the IGE captured by the 'Years of education' variable at each year and quantile of interest is displayed in Figure 1.7. At the lower quantiles, the share of the IGE attributed by education shows an increasing pattern in the 80s and 90s, and a stable level in the 2000s. At the mid-low quantiles, median and at the OLS estimation, the role of education remains fairly steady along the whole period, only slightly decreasing in the mid 90s, and increasing again from the mid 00s. For the mid-high quantiles, the pattern seems to be increasing in the 80s, slightly decreasing in the 90s, and slowly increasing again in the 2000s. At the high quantiles -like in the mid-low and mid-high groups of quantiles- there is a fall in the importance of education in IGE in the late 90s and followed by an increase in the 2000s

The importance of race in the intergenerational transmission of income (Figure 1.8) decreased during the 80s and 90s all across the distribution and at the mean (OLS estimation). At the lower quantiles, where race had a stronger role in the beginning of the 80s, this reduction was more pronounced. In the quantiles around the median (mid-low and mid-high figures) this decreased occurred mainly in the 90s. From the early 2000s, however, this trend was reversed and the impact of race on IGE shows a similarly increasing trend all across the income distribution. Remarkably, this increase offsets a great part of the decrease that took place in the previous two decades.[28]

1.5 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 data treatment. The number of years averaged to measure income, the thresholds used to exclude outliers, the sample choice, the age controlling

[28] The 1991 Civil Rights Act against discrimination may have contributed to this declining importance of race as a conditioning factor in the transmission of parental income, and to the decrease of the income 'white premium'. As with the 'years of education variable' (see Footnote 23), the impact of race on IGE might be encompassing other factors correlated with race. Chetty et al. (2014a) point out that it is demographical segregation and the level of public goods in an area what has a greater impact on mobility. They find mobility seems to be lower for people living in these areas regardless of the actual race of the individual. In any case, we believe the upturn we find in the role of race from the early 2000s makes this topic deserving of a detailed analysis in future research.

variables and the estimation method are decisions that could impact our results. Accordingly, we check the robustness of our main findings under different methodological and data options.

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 our preferred measure of 7 years. Thirdly, we investigate the effect of adopting different thresholds to exclude outlier observations. A fourth check analyzes the stability of the life income trajectories across the period studied and the effect of changing the reference age at which elasticity is measured. Finally, using an age-centered reduced sample, we also check the results using unconditional quantile regressions without age controlling covariates.

Sample choice

For the pooled estimation, using only the SRC sample of the PSID yields an OLS estimate of 0.45 (Table 1.4), which is slightly lower than our OLS estimate of 0.47. Quantile regression estimates of the IGE still present a clear U-shaped relation with the son's position at the income distribution (Figure 1.9) showing very similar estimates.

Outliers

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 baseline 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 1.4). However, quantile estimation is quite robust to the inclusion of these outliers, except at the extreme quantiles, where IGE estimates are slightly higher (Figure 1.10).

Permanent income and life cycle

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 the IGE in this case, due to the effects of transitory shocks that produce an 'attenuation bias' in the estimates. Our sensitivity analysis confirms this prediction, with an OLS value of the IGE of only 0.37 when we average up to 3 years of parental income when the child was between 15 and 17 years old, (a mean of 2.76 years) instead of our choice of up to 7 years when the child was between 13 and 19 years old (mean 6.24 years). Also, when using only 3 years of parental income, QR estimates for the IGE are smaller across the entire income distribution, diverging especially at the top quantiles, where the attenuation bias caused by transitory shocks seems to be higher. When we increase the number of years averaged to up to 9 years in the 12-20 range of the child age (mean 8.12 years), the estimates do not change significantly from our baseline choice (Table 1.4 and Figure 1.11).[29]

Since model 1.3 estimates the age control covariates for the whole pooled sample, there could be an estimation bias in the trend due to changing life income trajectories across cohorts. To analyze this possibility, we have calculated the average income at each age for cohorts born in the 50s, 60s, and 70s and have checked that the life cycle trajectoriy is similar for the three groups of cohorts (Figure 1.12).

Conditional and unconditional quantile regressions

As explained in Section 2, we cannot directly apply the unconditional quantile regression proposed by Firpo et al. (2009), to our main specification (1.2). Nevertheless, we wanted to check whether the estimation at the unconditional quantiles would differ significantly from the conditional quantile regression we apply. In order to compare both methods, we created a subsample of our pooled observations keeping only pairs of observations when both the son and parent were between 35 and 45 years old (note that parental age and income are always measured when the son was 16). This way, we can remove the age control covariates from the model and apply unconditional quantile regression. This subsample still has 4583 observations, not sufficient to undergo yearly estimations –as we have done with the full sample- but enough to estimate IGE and the role of education and race.[30]

[29] Nybom and Stuhler (2016) show that without observations of parent and son incomes over the full lifespan of the individual, the 'true' lifetime IGE might always be underestimated. However, recent studies with large administrative databases find, respectively, that the attenuation bias is greatly reduced after five (Chetty et al. (2014b)) and nine (Mitnik et al. (2015)) years of income are averaged. In our case, the data show almost no change in the estimates when averaging more than 7 years of parental income.

[30] We have used the RIF-OLS function provided by Nicole Fortin (available at http://faculty.arts.ubc.ca/nfortin/datahead.html).

For the unconditional estimates, the results for the IGE are in Table 1.5 and plotted in Figure 1.13. We observe that the results are quite similar to those obtained with the full sample using conditional quantile regression with age controlling variables. Also, these results show that the age controls included in our main analysis are effectively controlling for the life cycle. With respect to the effect of education and the impact of race at different quantiles, unconditional estimation provides again similar measures (Figure 1.14).

1.6 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 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 child's 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's 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 the 'middle class'.

We believe that these findings may contribute to better target 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 son's 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.

About the trend evolution of the IGE, there seem to be also different patterns for 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. The role of education shows no strong trend pattern across the income distribution in the period analyzed, altough it seems to increase slightly in the 00s for all quantiles. The impact 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.

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1.7 Tables and Figures

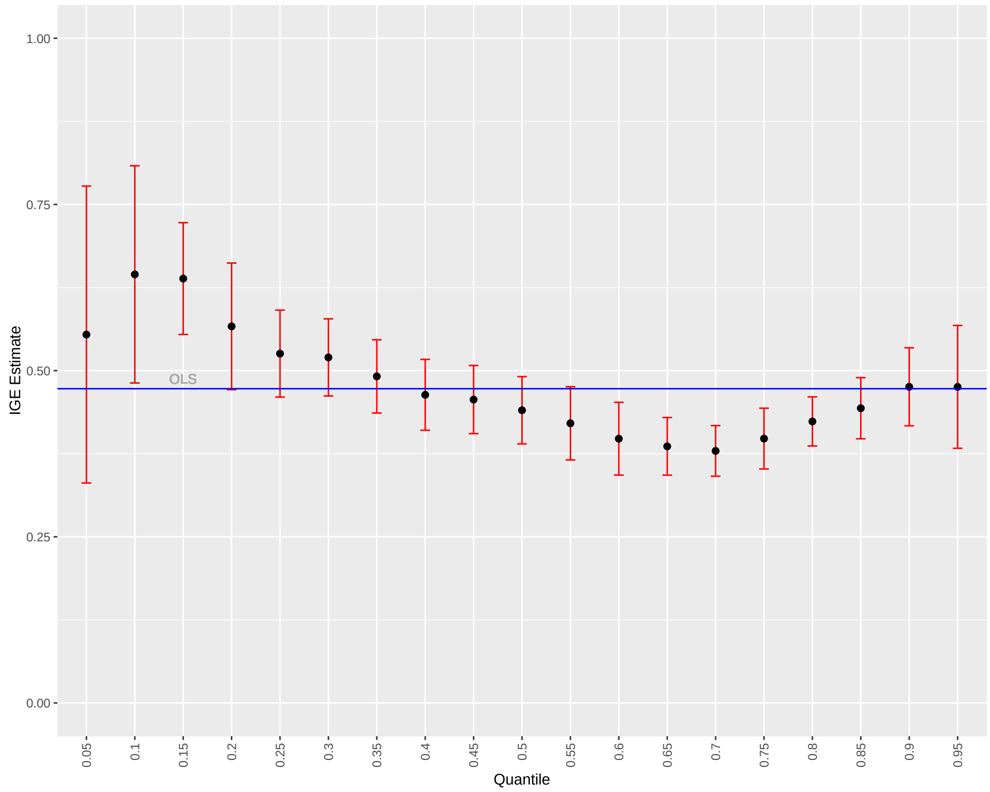

Figure 1.1: IGE pool estimates 1980-2010 period. Baseline model: 25084 observations

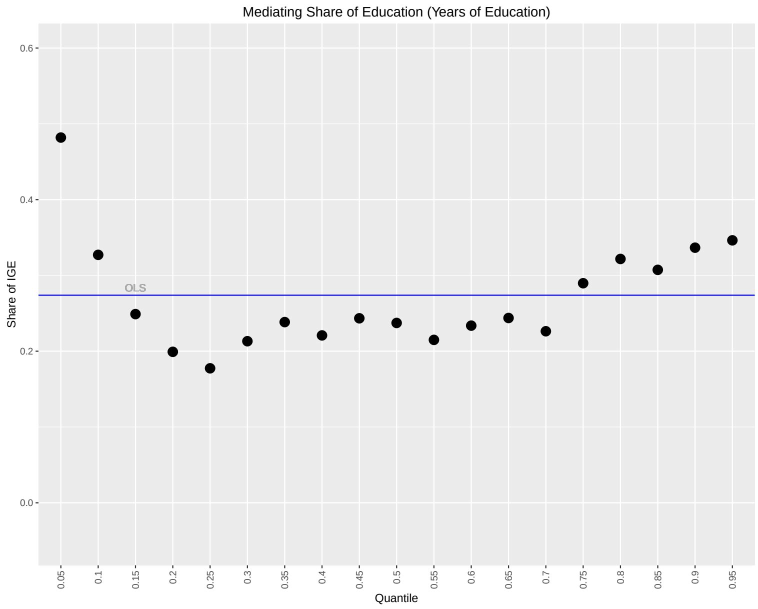

Figure 1.2: Impact of Education on IGE (Years of Education), as a share of IGE. Pooled estimates.

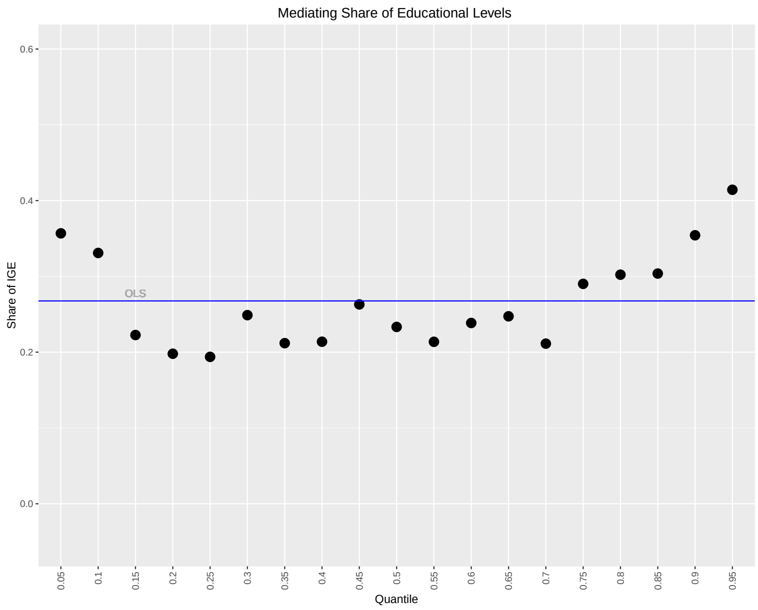

Figure 1.3: Impact of Education on IGE (Educational Categories), as a share of IGE. Pooled estimates.

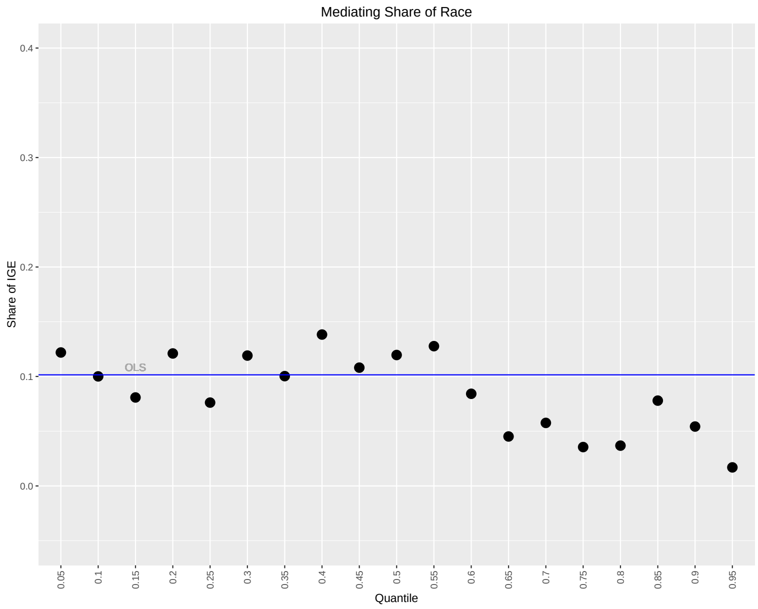

Figure 1.4: Impact of Race on IGE (White Race Dummy), as a share of IGE. Pooled estimates.

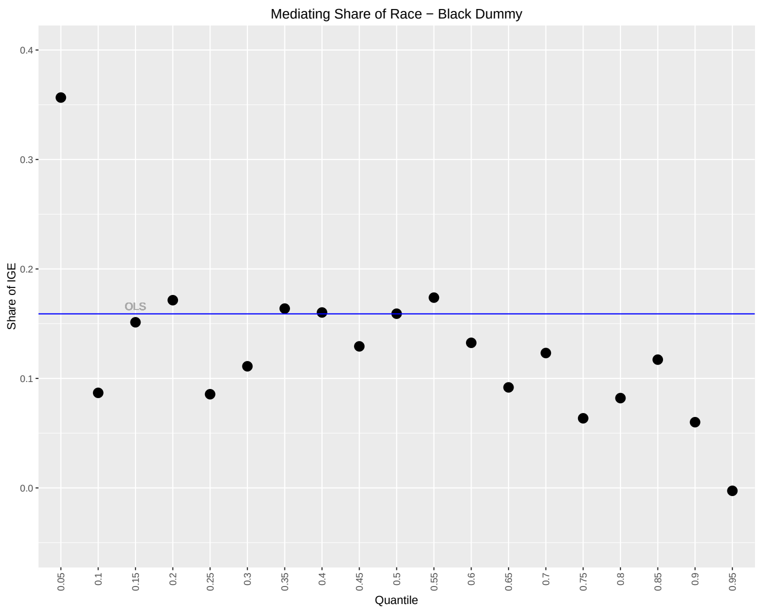

Figure 1.5: Impact of Race on IGE (Black Race dummy), as a share of IGE. Pooled estimates.

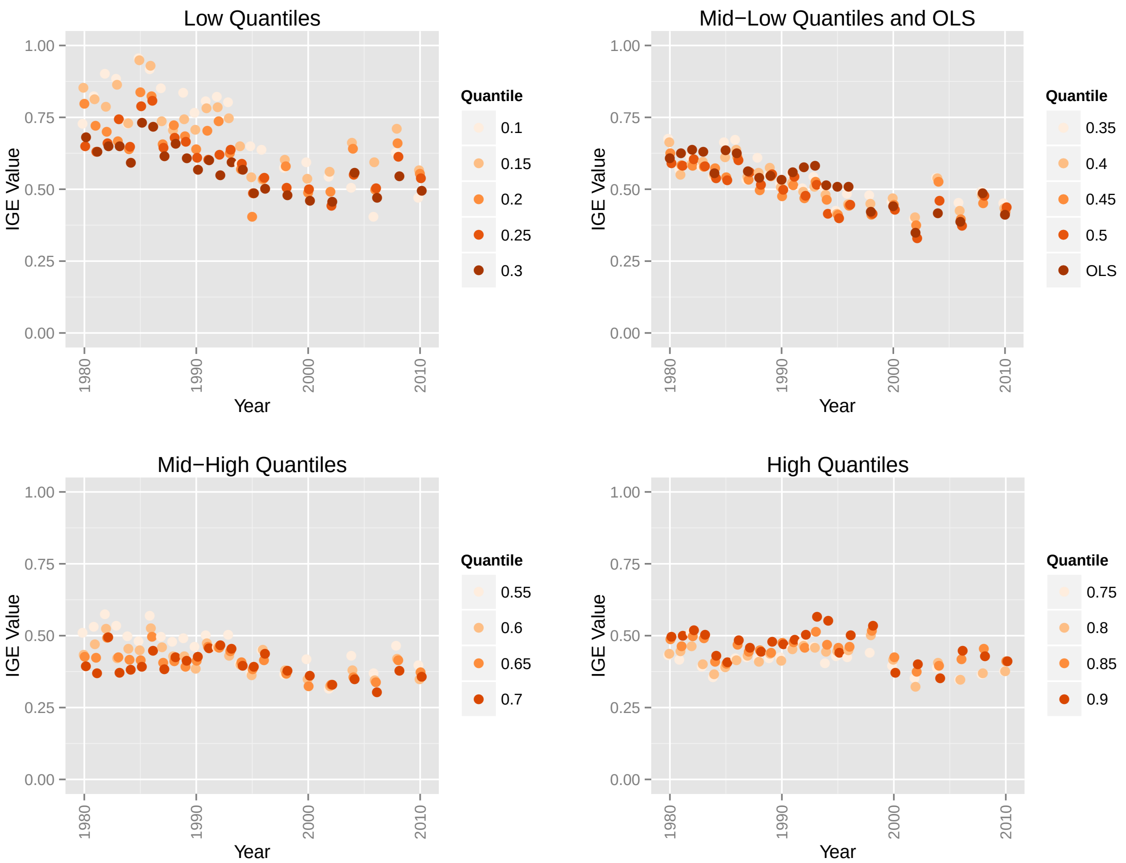

Figure 1.6: IGE Trend 1980-2010

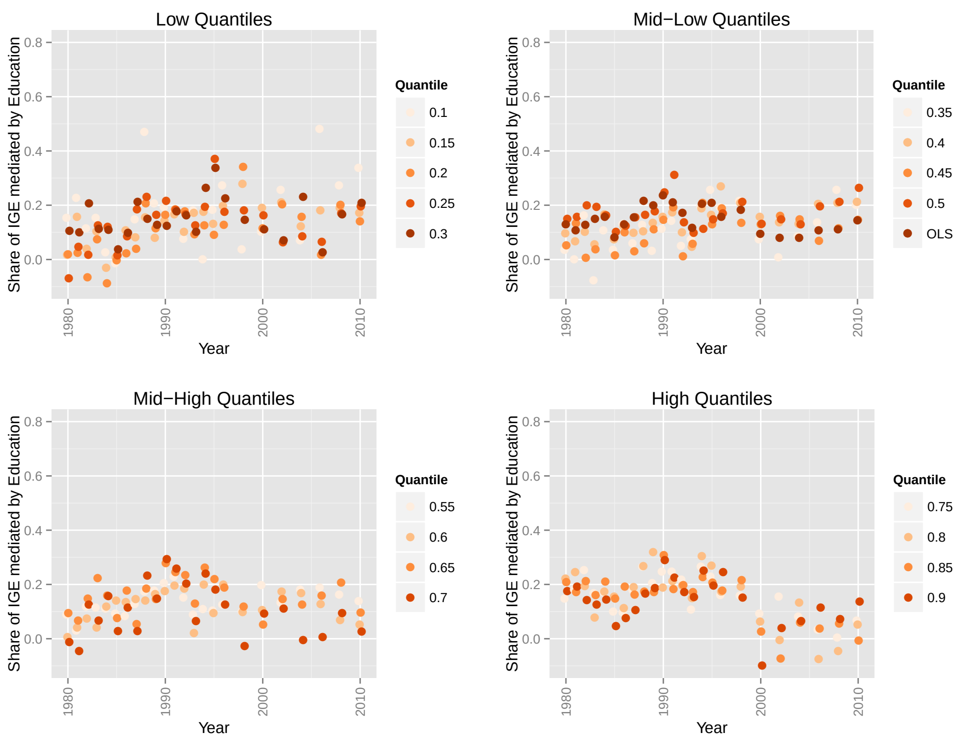

Figure 1.7: Share of IGE decrease when controlling for Education (years), by groups of quantiles. Trend 1980-2010

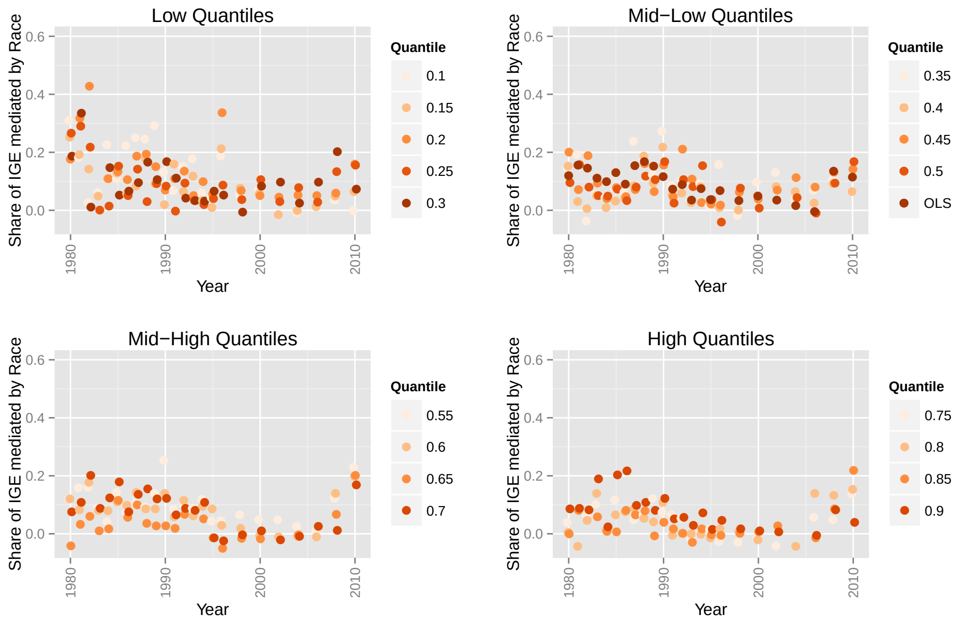

Figure 1.8: Share of IGE decrease when controlling for Race (white race dummy), by groups of quantiles. Trend 1980-2010

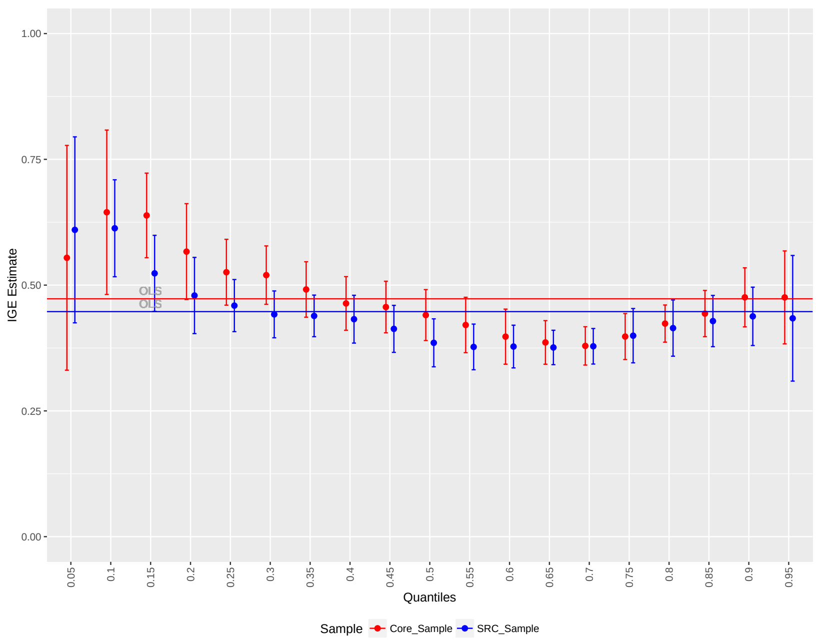

Figure 1.9: Sensitivity of pooled IGE estimates to PSID sample used. Baseline choice: 25084 observations. SRC sample: 16239 observations

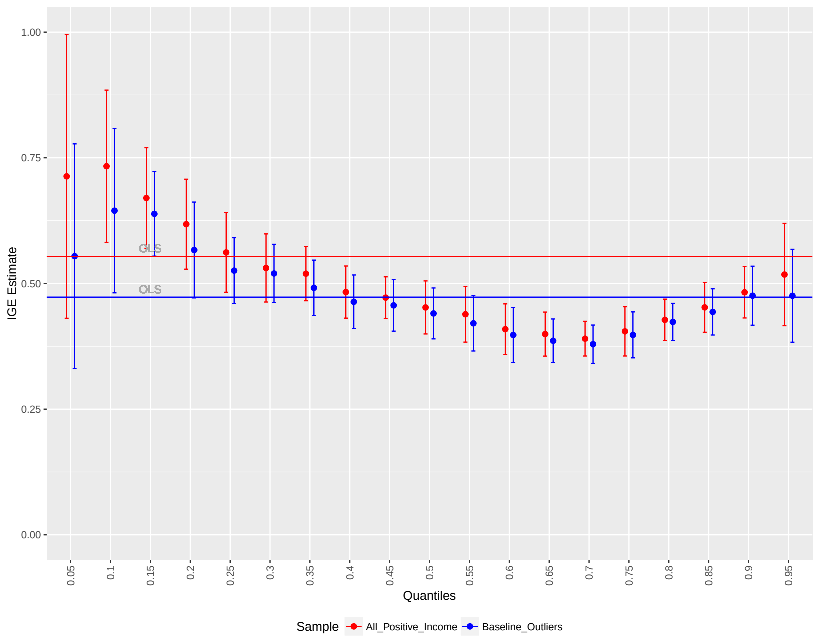

Figure 1.10: Sensitivity of pooled IGE estimates to the outlier thresholds. Baseline choice (excluiding income under 100 and over 150000 USD dollars of 1967): 25084 observations; Excluding only negative income: 25271 observations

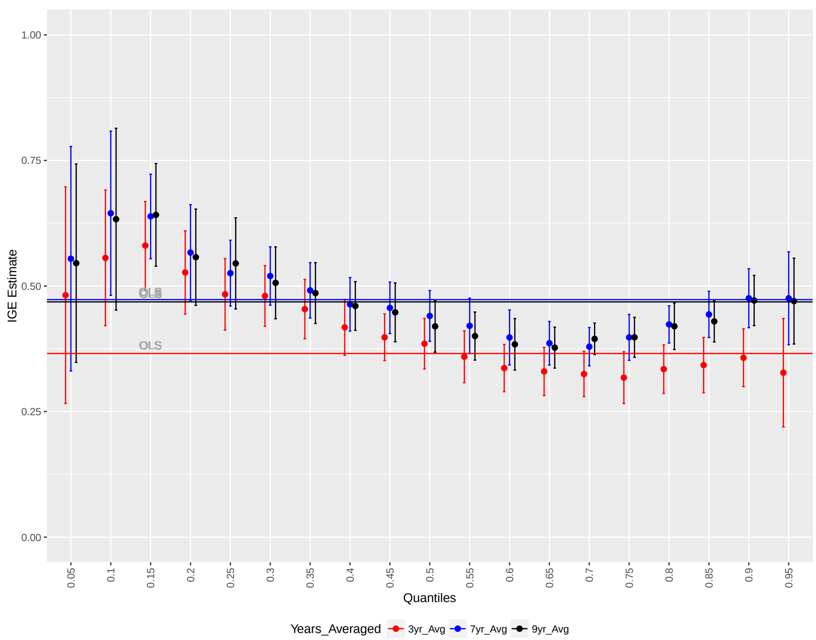

Figure 1.11: Sensitivity of pooled IGE estimates to the number of years of parental income averaged. 25245 observations when averaging up to 3 years of parental income (mean 2.76 years). 25084 observations when averaging up to 7 years income (mean 6.24 years) and 23577 observations when averaging up to 9 years of parental income (mean 8.13 years)

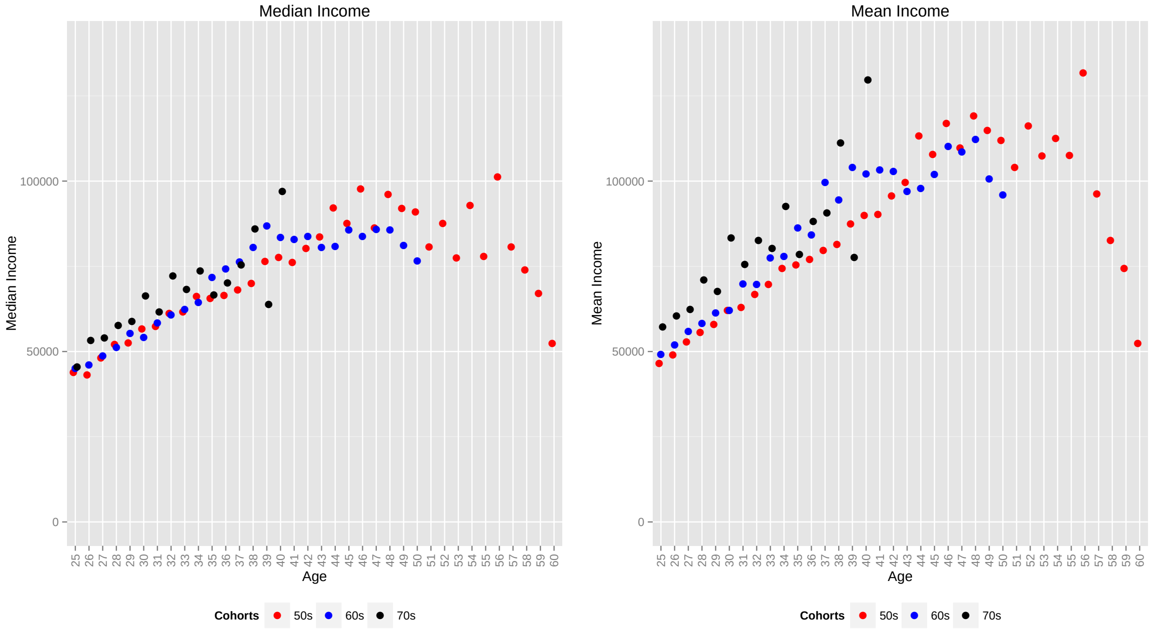

Figure 1.12: Life cycle trajectories for cohorts by decades

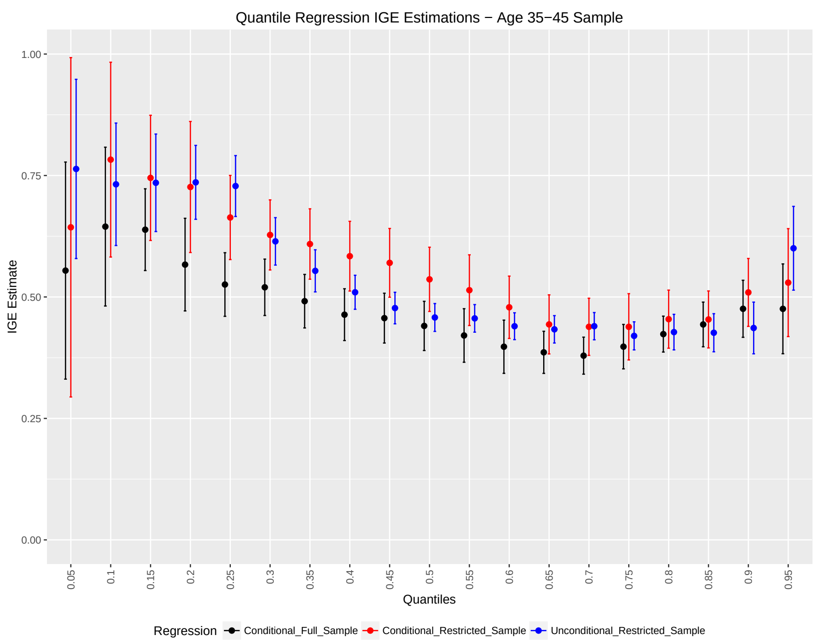

Figure 1.13: Conditional and Unconditional Estimates of IGE. Baseline model: 25084 observations of individuals between 25 and 65 years old, with age controls in the specification. Age restricted model: 4583 observations of individuals only between 35 and 45 years of age, no age controls in the specification

		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

Table 1.1: Descriptive Statistics

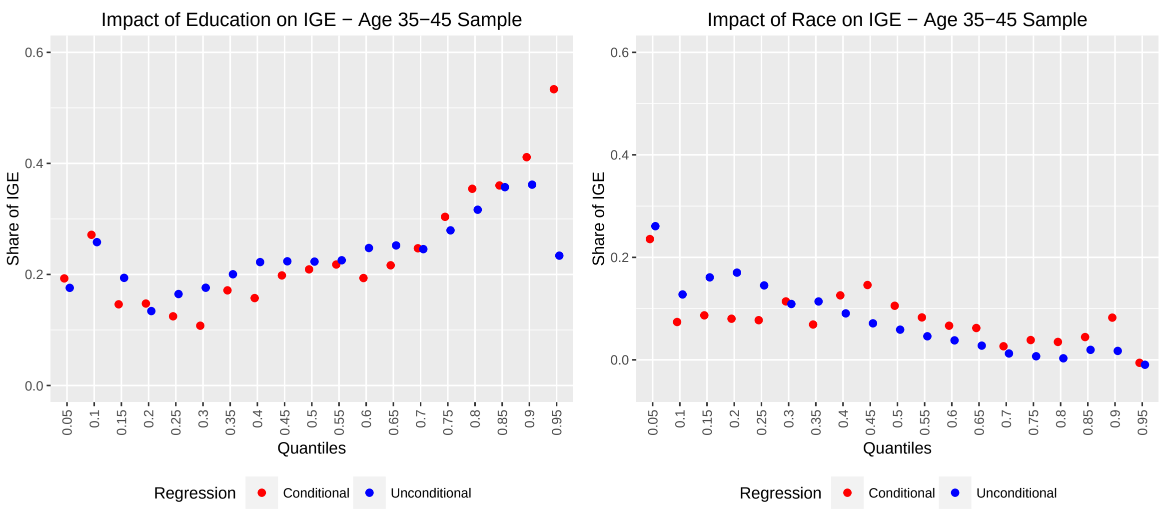

Figure 1.14: Conditional and Unconditional Estimates of Education and Race impact on IGE. Age restricted model: 4583 observations of individuals only between 35 and 45 years of age, no age controls in the specification

	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

Table 1.2: Pooled Regression Estimates for the pooled sample

Quantile	Wald Statistic	P-Value
0.05	34.943	0.053
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
0.95	43.225	0.007

Table 1.3: Wald statistics for equality of IGE coefficients across the 1980-2010 period at each quantile

	Baseline Estimates		SRC Sample		3 yr. Avg		9 yr. Avg		Exclude Neg. Income	
Quantile	IGE	(SE)	IGE	(SE)	IGE	(SE)	IGE	(SE)	IGE	(SE)
OLS	0.473	0.018	0.447	0.021	0.366	0.015	0.468	0.019	0.554	0.019
0.05	0.554	0.223	0.610	0.185	0.482	0.216	0.545	0.197	0.713	0.282
0.1	0.645	0.163	0.613	0.096	0.556	0.135	0.633	0.181	0.733	0.151
0.15	0.639	0.084	0.523	0.076	0.581	0.088	0.642	0.102	0.670	0.100
0.2	0.567	0.095	0.479	0.076	0.527	0.083	0.557	0.096	0.618	0.089
0.25	0.526	0.065	0.459	0.052	0.483	0.071	0.545	0.091	0.562	0.079
0.3	0.520	0.058	0.442	0.047	0.480	0.060	0.506	0.071	0.531	0.068
0.35	0.491	0.055	0.439	0.041	0.454	0.059	0.486	0.061	0.520	0.054
0.4	0.464	0.053	0.432	0.048	0.418	0.056	0.460	0.048	0.483	0.052
0.45	0.456	0.051	0.413	0.047	0.398	0.046	0.448	0.059	0.472	0.041
0.5	0.440	0.051	0.385	0.048	0.385	0.050	0.420	0.051	0.452	0.053
0.55	0.421	0.055	0.377	0.045	0.359	0.052	0.400	0.048	0.439	0.055
0.6	0.398	0.055	0.378	0.042	0.337	0.047	0.384	0.051	0.409	0.050
0.65	0.386	0.043	0.376	0.034	0.330	0.048	0.377	0.041	0.399	0.044
0.7	0.379	0.038	0.378	0.035	0.325	0.045	0.395	0.031	0.390	0.035
0.75	0.398	0.046	0.399	0.054	0.318	0.052	0.398	0.040	0.405	0.049
0.8	0.424	0.037	0.415	0.056	0.335	0.048	0.420	0.046	0.428	0.041
0.85	0.443	0.046	0.429	0.051	0.343	0.055	0.429	0.041	0.452	0.049
0.9	0.476	0.059	0.438	0.058	0.357	0.058	0.471	0.050	0.482	0.051
0.95	0.476	0.092	0.434	0.125	0.328	0.108	0.470	0.085	0.518	0.102

Table 1.4: Sensitivity Analysis: IGE estimates for different data options. Baseline options has 25084 observations; SRC Sample option has 16239 observations; Up to 3 years averaged for parental income has 25245 observations; Up to 9 years averaged has 23577 observations ; The option of outliers excluding only negative observations has 25271 observations.

	Conditional Regression		Unconditional Regression	
Quantile	IGE Estimate	IGE SE	IGE Estimate	IGE SE
0.05	0.643	0.349	0.764	0.184
0.1	0.783	0.200	0.732	0.126
0.15	0.745	0.129	0.735	0.100
0.2	0.726	0.135	0.736	0.076
0.25	0.664	0.087	0.728	0.063
0.3	0.628	0.072	0.614	0.049
0.35	0.609	0.072	0.554	0.043
0.4	0.584	0.072	0.510	0.035
0.45	0.570	0.071	0.477	0.032
0.5	0.536	0.066	0.458	0.029
0.55	0.514	0.073	0.456	0.028
0.6	0.479	0.064	0.440	0.028
0.65	0.444	0.061	0.433	0.028
0.7	0.439	0.059	0.440	0.028
0.75	0.439	0.068	0.420	0.029
0.8	0.454	0.060	0.428	0.037
0.85	0.454	0.059	0.426	0.039
0.9	0.509	0.070	0.436	0.053
0.95	0.530	0.111	0.600	0.086

Table 1.5: Conditional and Unconditional Estimates. Baseline (Age Restricted) Model. The age restricted model does not include age controls in the specification, and includes only indivuals between 35 and 45 years old. Total sample of 4583 observartions

1.8 Appendix Tables and Figures

	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%	
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 (2015)	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 1.A1: Review of OLS IGE estimates for the U.S. 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 (2015)	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

Table 1.A2: Review of Quantile Regression IGE estimates for the US in the literature

Chapter 2

Channels of inequality of opportunity: the role of education and occupation in Europe

2.1 Introduction

There seems to be a social and academic consensus in considering inequality caused by initial socioeconomic factors as unfair, for it is thought to be out of the responsability sphere of the individual. In line with this perception -and led by the pioneering interdisciplinary work of Roemer (1993)- economists have started in the last two decades to shift the focus from overall inequality to the so-called 'inequality of opportunity' (IO), trying precisely to measure the extent of that 'unfair' inequality. The concept of (in)equality of opportunity has come to play a central role not only in the academic context but also in the political debate.

In one of its most common formal definitions, equality of opportunity demands that individual characteristics or 'circumstances', upon which the individual has no control (such as family background, race or place of birth) do not affect the outcome (income, welfare, health) obtained by the individual [Rawls (1971), Sen (1980), Roemer (1993), Fleurbaey (2008)]. If this does not hold, the existing IO would be unjust, and public intervention should help to 'level the playing field' [Roemer et al. (2003)].[1]

So far, most of the existing literature on equality -or inequality- of opportunity has endeavoured in the development of different approaches to measure IO and its comparison across countries.[2] Albeit crucial for any ulterior analysis, these works have limited interest for any applied policy decision, since they provide little information about the mechanisms that channel IO, i.e., the factors that make the initial conditions relevant for future income.

Then, which -and how important- are these mechanisms? How do different individual initial conditions turn into different future levels of income? A priori, one would think of two main channels, namely, the education system and the allocation in the labor market. On the one hand, education has widely been recognised as a key element in the economic production function going back to the works of Becker (1964) and Lucas (1988), and its effect on the acquisition and distribution of earnings has also been established in the literature [Psacharopoulos (1994), Card (1999), Trostel et al. (2002) or Lemieux (2006)]. On the other hand, the connec-

[1] In addition, recent findings point out that IO would be also inefficient and negative for economic growth, as it favors the misallocation of talent and human capital [Marrero and Rodríguez (2013 and 2016); Bradbury and Triest (2016)]

[2] See, for example, Lefranc et al. (2008), Rodríguez (2008), Checchi and Peragine (2010), Ferreira and Gignoux (2011), Marrero and Rodríguez (2012), Li Donni et al. (2015) or Brzezinski (2015).

tion between the individual educational enrolment or attainment and parental background has been widely analysed in the educational opportunity literature [Gamboa and Waltenberg (2012), Brunori et al. (2012) or Ferreira and Gignoux (2014)], and there is also evidence that the educational level mediates a relevant share of the intergenerational income persistence [Eide and Showalter (1999), Palomino et al. (2014) and Chetty et al. (2014)]. As for the occupational category - which could proxy industry specific human capital- it has also been shown to impact the economic achievement [Sullivan (2010)] and is in turn connected with the family background. Circumstances like parental connections when looking for a job and nepotism -which limit the scope of labor market competition- could be relevant to explain the final allocation for a particular position [Pérez-González (2006)].

It seems then that the education and occupation of the individual are tied to both ends of (in)equality of opportunity: the initial conditions and the final outcome. Different circumstances in childhood may lead to different levels of education and different occupational categories, which in turn contribute to generate different economic outcomes in the adulthood. Data on these potentially important mediators the level of education and the occupational category- are frequently included in databases and could be exploited.

The analysis of these two possible channels of IO, however, is not straightforward. First, both channels are closely linked, and the education system is expected to strongly condition the final allocation in the labor market. Second, some of the possible educational and occupational variables are subtle and hard to analyse, like school quality, job connections or access to social networks. The first problem can be tackled if the analysis method follows the natural order of both factors in the life cyle, thus considering education as a prior mediator that influences occupation, and assuming that -generally- formal education is not influenced by the occupational category.[3] As for the second problem, even though the absence of a complete set of education and occupation variables should make us concious of the impossibility of measuring their full channeling role, it should not prevent us from attempting the analysis.

Acknowledging these shortcomings, this paper develops a strategy to estimate how much of the IO in income is channelled through the educational level and the occupational category

[3]As explained in Section 2 below, in our proposed methodology the channeling role of occupation is measured controlling for education first.

of the individual in Europe.[4] In a first stage, without loss of generality, we apply the ex-ante approach to estimate the 'smoothed income distribution' (i.e., the income conditioned to individual circumstances) and compute IO in the acquisition of income, following Ferreira and Gignoux (2011) and Checchi and Peragine (2010). We have used the ex-ante approach for comparability reasons with recent studies estimating IO for EU countries [Marrero and Rodríguez (2012), Brzezinski (2015), Checchi et al. (2016)], but the methodology can be also applied to the ex-post approach [Checchi and Peragine (2010)]. In the second stage, using again the ex-ante approach, we condition the smoothed income distribution to the education of the individual, and the residual of this last regression to the occupation of the individual; finally, we estimate the IO associated to each component, isolating in this way the shares of IO transmitted through individual education, occupation (once controlled for education) and the final residual component.

Exploiting the two special modules on intergenerational transmission of poverty in the EU-SILC database (waves 2005 and 2011), we apply our methodology for 26 European countries in both waves. Even though only the level of education is used to analyse the role of the education system (there is no information on school quality or school socioeconomic status), we find education to be a relevant channel of IO. First, the level of education mediates the 15% of IO or more in ten European countries in 2004 and 2010 (more than 30% of IO in Portugal and Luxembourg in 2010). Second, there is no clear geographical pattern. For example, the range of the educational channel of IO in Central Europe goes from 8.4% (Germany) to 31.0% (Luxembourg) in 2010, while, for the same year, ranges from 7.9% (Estonia) to 24.0% (Hungary) in Eastern Europe. Third, there is not a general tendency in the variation of the educational share of IO between 2004 and 2010: 9 out of 26 European countries experience an increase of their educational share of IO, 11 remain stable and 6 decrease. In addition, we find that the importance of education as a channel for IO is negatively correlated with the share of the population that attains tertiary levels of education. This result points at a potential social externality of expanding access to education: the provision of opportunities. It seems that, in countries where a greater part of the population can access higher levels of education, the connection between background circumstances, levels of education and adult

[4] This method can be applied to other outcome variables, not necessarily income.

income is weaker.

The level of education seems to include most of the possible influence of the occupational category, for once the education channel has been discounted, the influence of the occupational channel of IO is associated with only between 1% and 5% of IO in most countries and in both waves. Still, the range across countries is relatively large, with Netherlands in 2004 (0.93%) and Cyprus in 2010 (8.24%) as the countries where occupation mediates less and most, respectively. The geographical pattern of this channel in Europe is not clear and the variation between 2004 and 2010 does not have a well-defined tendency.

The rest of the paper is structured as follows. In Section 2, we present the methodology to measure the channels of IO. Section 3 details our choices and treatment of the EU-SILC database and comments on the results of our primary regressions. Section 4 presents our estimates of overall inequality and IO across Europe in 2004 and 2010, while section 5 displays our findings for the educational and occupational channels. In Section 6, we discuss the implications of the correlation between the educational IO channel and the levels of attained education. Finally, Section 7 concludes.

2.2 Methodology

We present a two-step procedure to estimate the importance of the educational and occupational channels in determining IO. Among the existing approaches to estimate IO, we adopt the ex-ante parametric approach [Checchi and Peragine (2010), Ferreira and Gignoux (2011)] in the first step, for it allows us to compare our IO estimates with existing estimations of IO for Europe. In the second step, we use the smoothed income distribution, that incorporates all differences in individual income attributed to observed circumstances, and decompose it to estimate the shares of IO that are associated with the education attained and the occupational category of individuals.

2.2.1 Step 1: Computing inequality of opportunity

The alternative methods to estimate IO are classified into two main approaches, the ex-post and the ex-ante [Fleurbaey (2008)]. The ex-post approach states that there is equality of opportunity if all individuals who exert the same degree of effort obtain the same outcome, while the ex-ante refers to equality of opportunity if all individuals face the same set of opportunities regardless of their circumstances. The results from using one of the other are not always totally consistent, and the formal compatibility and different practical implications of these approaches have been discussed in Fleurbaey and Peragine (2013) and Ramos and Van de Gaer (2012). As mentioned above, for comparability reasons we focus here on the ex-ante approach; however, our method could be applied to the ex-post approach as we outline in the Appendix.

Assume that the income y_i of the individual $i \in \{1, ..., N\}$ is a function of her effort e_i and her set of circumstances C_i, so that $y_i = f(C_i, e_i)$. Circumstances are assumed to be exogenous by definition. Effort however is likely to be influenced, among other factors, by personal circumstances. Accordingly, individual income may also be written as $y_i = f(C_i, e_i(C_i))$. Suppose the population is partitioned into T mutually exclusive and exhaustive types denoted by $\epsilon = J_1, ..., J_T$, where all individuals of a given type t share the same circumstances. Then, within each type, and assuming all circumstances have been accounted for, only effort e_i would determine the income of each individual i. Equality of opportunity, then, is achieved when the individual's income is independent of her circumstances. Strictly speaking, this would demand that the following condition holds true:

$$F^t(y) = F^m(y), \forall t, m, \tag{2.1}$$

where $F^t(y)$ denotes the income distribution for individuals of type t. In this case, no set of circumstances offers a better opportunity set of incomes than any other, thus abiding the condition for ex-ante equality of opportunity (what Lefranc et al. (2008) call 'strong equality of opportunity'). On the contrary, if one distribution dominates the other, this would offer unambiguous evidence against equality of opportunity. Unfortunately, relying on stochastic dominance is generally not guaranteed to rule one way or the other. Distributions can be significantly different and yet cross each other, in which case it is unclear whether one type is better off than the other [Atkinson (1970)].

To break potential ties, a practical alternative is to use an inequality index able to decompose income inequality into inequality *within* types and inequality *between* types, focusing for that purpose on a specific moment of each type distribution, i.e., the mean or a parametric estimate of income conditioned to circumstances. Differences in income within types cannot be attributed to circumstances, while inequality between types can be used as a measure of IO.[5]

Among all the possible inequality indices that fulfill the basic principles found in the literature on inequality (progressive transfers, symmetry, scale invariance and replication of the population), only those of the Generalized Entropy class are additively decomposable into a between-group and a within-group component [Bourguignon (1979) and Shorrocks (1980)].[6] We use the Mean Logarithmic Deviation (MLD) because it belongs to the Generalized Entropy class, has a path-independent decomposition [Foster and Shneyerov (2000)], and uses weights based on the groups' population shares. For an income distribution y, with mean $\overline{y}$, the MLD is defined as:

$$I_{MLD}(y) = \frac{1}{n}\sum_{i=1}^{n}\ln(\frac{\overline{y}}{y_i}). \tag{2.2}$$

The decomposition of this index into between-group and within-group inequality components solves:

$$I_{MLD}(y) = \sum_{t=1}^{T} p_t \ln(\frac{\overline{y}}{\overline{y}_t}) + \sum_{t=1}^{T} p_t I_{MLD}(y^t), \tag{2.3}$$

where p_t is the population share of each group t, $\overline{y}$ is the overall population mean and $\overline{y}_t$ is the mean value for each group t. The first term of Eq. (2.3) represents inequality between groups of the population (types) while the second component represents inequality within those groups. [7]

[5]Since it is impossible to observe all individual circumstances in practice, this estimate of IO is interpreted as a lower bound. Between-types inequality can only increase if the number of observed circumstances increases and the population is partitioned into more types. This problem is pervasive in the literature on inequality of opportunity. For a different approach, where types are seen as latent classes, see Li Donni et al. (2015).

[6]The broadly used Gini coefficient is not additively decomposable. In the case that type income ranges overlap, which occurs in our case, this measure is decomposable in three terms: a between-group component, a within-group component and a residual. The problem here is how to assign the last term to the between-group and within-group components.

[7]See, for example, Jenkins (1995) for an application of this decomposition to inequality in the UK in the 70s and 80s.

In an equivalent expression, the 'between' component of inequality can be obtained as the inequality of a 'smoothed distribution' μ in which all individuals from each group t have the same circumstances and the same value of $y_i^t = y_i \mid C_i^t$, while the within component is the inequality of a 'standardized distribution' (ϕ) in which all differences across groups have been eliminated and only differences within groups remain [Ferreira and Gignoux (2011), Checchi and Peragine (2010)]:

$$I_{MLD}(y) = I_{MLD}(\mu) + I_{MLD}(\phi). \tag{2.4}$$

In this framework, a non-parametric approach would estimate the income means for each predefined type without any assumption on the relation of income and circumstances. However, when the number of circumstances is high, the number of observations in some of the types may become too low to obtain accurate non-parametric estimates.[8] A parametric approach, on the other hand, assumes a log-linear relationship between circumstances and income and orthogonality of circumstances and the error term, but it allows to estimate the income conditioned to circumstances for all types even when the number of observations per type is relatively low [Bourguignon et al. (2007); Ferreira and Gignoux (2011)]. Given the size of our sample and the relatively high number of circumstances that we have in the database (see Section 3.3), we adopt the parametric approach and estimate the following log-linearized equation:

$$\ln y_i = C_i \psi + \varepsilon_i. \tag{2.5}$$

The estimated OLS coefficients $\hat{\psi}$ are then used to obtain the smoothed income distribution in which all individuals belonging to the same type (i.e., sharing the same set of circumstances C_i) are assigned the same income as follows:

$$\tilde{\mu}_i = \exp[C_i \hat{\psi}], \tag{2.6}$$

[8]The non-parametric approach has been used, nevertheless, in methods that focus on ordinal methods of IO measurement using dominance criteria [Lefranc et al. (2008); Rodríguez (2008)].

where $\tilde{\mu}_i$ is the income predicted for all individuals i conditioning on their set of circumstances. Accordingly, IO -inequality *between* types- is computed by applying I_{MLD} to the 'smoothed distribution':

$$IO = I_{MLD}(\tilde{\mu}). \tag{2.7}$$

The *within* component can, in a parametric framework, be expressed as the inequality of the standardized distribution ϕ, which is obtained by assigning all individuals the same average level of the conditioning variables $\overline{C_i}$, plus the individual variability not captured by circumstances [Ferreira and Gignoux (2011)]:

$$\tilde{\phi}_i = \exp[\overline{C_i}\hat{\psi} + \hat{\varepsilon}_i], \tag{2.8}$$

This distribution $\tilde{\phi}$ eliminates all differences attributed to circumstances, but keeps within-type variability through the term $\hat{\varepsilon}_i$. Inequality in this distribution can be expressed as:

$$IR = I_{MLD}(\tilde{\phi}). \tag{2.9}$$

where IR thus represents the residual or complementary share of overall inequality not explained by the observed set of circumstances.[9] Overall inequality I, then, can be decomposed in IO and IR, in a version of equation (2.4) that uses the parametric estimates of the distributions:

$$\underbrace{I_{MLD}(y)}_{I} = \underbrace{I_{MLD}(\tilde{\mu})}_{IO} + \underbrace{I_{MLD}(\tilde{\phi})}_{IR}, \tag{2.10}$$

[9]Note that $\tilde{\phi}^i = \exp[\overline{C_i}\hat{\psi} + \hat{\varepsilon}_i]$ is equivalent to: $\exp[\overline{C_i}\hat{\psi}] \cdot \exp[\hat{\varepsilon}_i]$. Applying MLD to this last expression, and given that $\exp[\overline{C_i}\hat{\psi}]$ is constant, it is true -recall that the MLD index is scale invariant- that $I_{MLD}(\tilde{\phi}) = I_{MLD}(exp[\hat{\varepsilon}_i])$. Thus, in a parametric framework using the MLD inequality measure, the within inequality component boils down to the MLD of the distribution of the residual term from the parametric regression.

2.2.2 Step 2. The educational and occupational channels

From the smoothed distribution calculated in the previous step, we know that the part of total income for individual i belonging to type t that is explained by her observed circumstances C_i, ${y_i}^C$, is given by:

$$ {y_i}^C = y_i \mid C_i = \tilde{\mu}_i. \tag{2.11} $$

However, in general, circumstances do not directly convert into future income. There exists a set Z of intermediate variables, like the education or the job category attained by the individual, which are conditioned by individual circumstances and that, in turn, are the factors affecting the income of the individual. Accordingly, the component of income explained by observed circumstances can then be expressed as:

$$ y_i^C = f(Z_i, \nu_i), \tag{2.12} $$

where Z_i is the set of the observed intermediate variables, and ν_i a term that includes all the unobserved mediating variables and the random component of income of individual i.[10]

First, we consider that the set of intermediate variables consists in the levels of individual education (E), i.e., $Z_i = E_i$. Then, in accordance with Eq. (2.12) we can assume:

$$ \ln y_i^C = E_i \eta + \nu_i. \tag{2.13} $$

The OLS estimated coefficients of this regression can be applied to the values of E_i to obtain the distribution of expected income -conditioned to circumstances- predicted by personal

[10] Analogously, it could be argued that effort, or at least part of it, would be transformed into income through other mediating factors H. Education, for example, could also be a mediator between effort and income (people who exert more effort achieve a higher level of education that will increase their income). We could express the component of income *not* explained by observed circumstances (from Eq. (2.5)) as $y_i^{\overline{C}} = \exp[\varepsilon_i] = f(H_i, \Omega_i)$, where H_i collects observed mediators between effort and income, and Ω_i includes the effect on income of unobserved mediators and a random component. Unfortunately, although our term IR is sometimes called 'inequality of effort' in the literature and could be considered an upper bound of such inequality, we must not forget that ε_i includes both the effect of effort *and* of unobserved circumstances. We are then unable to isolate the effect of effort, which prevents us from going further into the analysis of the residual component of income.

education; i.e., $y_i^{C,EDU} = exp[E_i\hat{\eta}]$, where the estimates of η include not only the direct effect of education E on income conditioned to circumstances y^C, but also the indirect effect.

In Section 2.1., we obtained IO as the inequality *between* types, using the smoothed distribution. In this step, we will in turn decompose $I_{MLD}(y^C)$ into its own 'between' and 'within' components, the groups being now formed by people with the same amount of individual education. While y_i^C has the same value for all individuals with the same set of circumstances C_i, now ${y_i}^{C,EDU}$ has the same value for all individuals with the same education (and the same circumstances). Inequality in this 'oversmoothed' distribution is the income inequality 'between' the groups of people with different education, conditioning to their circumstances. In other words, it is the inequality of opportunity 'channelled' by the level of individual education.

The inequality of the residual $y_i^{C,\overline{EDU}}$ is then interpreted as the inequality of y_i^C 'within' the groups of people with the same amount of education. Inequality in the distribution of the residual income $y_i^{C,\overline{EDU}} = exp[\hat{\nu}_i]$ is equivalent to a standardized distribution obtained by applying $\hat{\eta}$ to a constant average level educational level $\overline{E}$ and adding the residual term. Both distributions differ only in a change of scale and would have the same level of inequality using MLD, since $I_{MLD}(exp[\overline{E}_i\hat{\eta}_i + \hat{\nu}_i]) = I_{MLD}(exp[\hat{\nu}_i])$. Thus, the decomposition is:

$$\underbrace{I_{MLD}(y^C)}_{IO} = \underbrace{I_{MLD}(y^{C,EDU})}_{IO_{EDU}} + \underbrace{I_{MLD}(y^{C,\overline{EDU}})}_{IO_{\overline{EDU}}}, \tag{2.14}$$

where IO_{EDU} represents the part of IO that is channelled through the educational level, and the residual term $IO_{\overline{EDU}}$ measures the amount *not* mediated by education. For instance, if the individual educational level predicts the income vector y^C perfectly, we will have that $y_i^{C,EDU} = y_i^C$ for all i, and all the IO in income would be mediated by the attained education, i.e., $IO = IO_{EDU}$, and $IO_{\overline{EDU}}$ would be zero. The inverse would occur if all variability in y^C was captured by the error term ν in Eq.(2.13) and nothing by the estimated $E\hat{\eta}$.

The relative share of IO mediated by the level of education (including both the direct and potential indirect effects), denoted by IO^R_{EDU} is given by:

$$IO^R_{EDU} = \frac{I_{MLD}({y_i}^{C,EDU})}{I_{MLD}({y_i}^{C})} = \frac{IO_{EDU}}{IO}. \tag{2.15}$$

where $0 \leq IO^R_{EDU} \leq 1$ by construction.[11]

However, the educational level is not the only possible channel of IO. The component of ${y_i}^C$ not channelled by education, denoted by $y_i^{C,\overline{EDU}}$ could be transmitted by other variables. In particular, the occupational category of the individual is another reasonable candidate -also available in our database for Europe- that could channel IO. Different occupational categories may be related to circumstances (e.g. parental occupation) and may also be related to different salaries or economic advantages. Then,

$$\ln y_i^{C,\overline{EDU}} = O_i\kappa + \xi_i, \tag{2.16}$$

where O represents the occupational category of the individual and ξ represents the remaining part of the circumstance-conditioned income y^Cnot explained by the educational level nor the occupational category. By using only the part of y_i^C not attributed to the level of education ($y_i^{C,\overline{EDU}}$) we measure the channelling role of the other possible mediating variables -i.e. occupation- *free* of the interaction with the education channel, and IO_{OCC} will be net of the influence of education. Formally, this does prevent IO_{EDU} from including the joint effect of education and the variable analysed (occupation) if they were correlated. However, the fact that the attained educational level temporarily precedes the occupational category of the individual discards that possibility. In other words, the order of the IO decomposition follows the natural order in which these variables generally transmit opportunities: first education, then occupation.

We can thus obtain the distribution of ${y_i}^C$ predicted by occupation, once the educational channel has been accounted for, ${y_i}^{C,OCC} = \exp\left[O_i\hat{\kappa}\right]$ and the residual ${y_i}^{C,OTH} = \exp[\hat{\xi}_i]$, which represents the part of ${y_i}^C$ channelled through variables other than education and occupation.

[11] Note that our strategy could be applied to the version of the ex-post approach proposed by Checchi and Peragine (2010). See Appendix I.

Finally, the relative share of IO mediated by the level of occupation (net of the educational channel), denoted by IO^R_{OCC}, is given by:

$$IO^R_{OCC} = \frac{I_{MLD}({y_i}^{C,OCC})}{I_{MLD}({y_i}^{C})} = \frac{IO_{OCC}}{IO}, \tag{2.17}$$

where $0 \leq IO^R_{OCC} \leq 1$ by construction.

Using y_i^C from Eq.(2.5), Eq.(2.6) and Eq.(2.11), and applying Eq.(2.13) and Eq.(2.16), the steps in the decomposition of IO could be recapitulated in:

$$\underbrace{C_i\hat{\psi}_i}_{\ln y_i^C} = \underbrace{E_i\hat{\eta}}_{\ln y_i^{C,EDU}} + \overbrace{\underbrace{O_i\hat{\kappa}}_{\ln y_i^{C,OCC}} + \underbrace{\hat{\xi}_i}_{\ln y_i^{C,OTH}}}^{\hat{\nu}_i} \tag{2.18}$$

and that, as show above:[12]

$$I_{MLD}(y^C) = I_{MLD}(y^{C,EDU}) + I_{MLD}(y^{C,OCC}) + I_{MLD}(y^{C,OTH}), \tag{2.19}$$

where $I_{MLD}(y^{C,OTH})$ is the inequality of opportunity not associated with education nor with occupation. Finally, dividing the above expression by $I_{MLD}(y^C) = IO$ we obtain,

$$1 = IO^R_{EDU} + IO^R_{OCC} + IO^R_{OTH}, \tag{2.20}$$

where IO^R_{EDU} is the share of IO channelled by the educational level, IO^R_{OCC} the share of IO channelled by the occupational category (net of education) and IO^R_{OTH} the share of IO not channelled by either of the two variables considered.

This sequential decomposition process could continue and be applied to as many channels as we have information about, as long as the decomposition follows the order in which these channels come into play in the life of the individual. Although it requires the use of the decomposable MLD index, our method achieves a complete decomposition of IO in the considered

[12]Note that, being a logarithmic addition, Eq.(2.18) is equivalent to $y_i^C = y_i^{C,EDU} \cdot y_i^{C,OCC} \cdot y_i^{C,OTH}$.

channels and the residual 'unchannelled' IO.

In the following sections we describe how we use information about the individual level of education and the occupational category to apply our strategy and measure their IO channeling role for 26 European countries in 2004 and 2010.

2.3 Database and primary regressions

We use data from the European Statistics of Income and Living Conditions database (EU-SILC), which encompasses homogeneous surveys on living conditions implemented by the national institutes of statistics under the coordination of Eurostat. Collected data contains information on a wide range of items, including income, education and occupation of all individuals in each household. Some variables are also collected or aggregated at the household level.

In its 2005 and 2011 waves, the living conditions survey included an additional questionnaire aimed to gather information about the economic and social background of the respondents. Thus, the "Intergenerational Transmission of Poverty" module in 2005 and the "Intergenerational Transmission of Disadvantages" module in 2011 include questions about parental education and occupation, and about the financial situation of the household during the respondents' childhood. These items upon which the individual has no control are circumstances, which makes them suitable for an IO analysis [Roemer (2009)].

Our particular set of circumstances, which is very similar to the one used in Marrero and Rodríguez (2012) for comparability reasons, comprises the highest level of parental education attained from both father and mother, father's occupational category (since mother's occupation is missing in several countries, we dropped it from the set of circumstances) and the perceived financial struggle in the household when the respondent was about 14 years old.

The educational level of the father is coded slightly differently in each wave.[13] In order to have the most homogenous set of circumstances possible, we have recoded the 2005 parental educational levels into the 2011 equivalents, coding 'less than primary' as 'No education', grouping the ISCED levels 1 and 2 (primary and secondary) into 'Low Education', and levels 3 and 4 into 'Middle Education'. The occupational circumstances of the father correspond to the broad one-digit groups from the International Standard Classification of Occupation (ISCO-88).[14]

The question referring to the financial difficulties perceived by the respondent during childhood was slightly changed in the 2011 module. In 2005, the question referred to 'how often did the household have financial difficulties', where in 2011 two different questions address the difficulty to 'make ends meet' and the 'financial situation of the household'. Again for the sake of homogeneity across waves, we have chosen to include only the latter question and have also recoded the answers in five categories instead of six like in the 2005 questionnaire.[15] Finally, we complete our set of circumstances with two other individual variables from the main survey questionnaire: gender of the individual and the country of birth (local, from another EU country or from another country outside the EU).

We use "equivalent disposable household income" as the proxy for the economic advantage of the individual; income from 2010 (2011 wave) has been converted to 2004 (2005 wave) terms using the Harmonised Consumer Price Index published by Eurostat. Our sample is restricted to only household heads, the head being the person of the household with the

[13]In the 2005 module, there were 5 different categories: less than primary, which includes no education and education below the primary level (1997 International Standard Classification of Education (ISCED) level 0); primary education (ISCED 1), lower secondary education (ISCED 2), upper secondary education (ISCED 3), post-secondary non-tertiary education (ISCED 4), and first stage and second stage of tertiary education (ISCED 5 and 6). In 2011, however, the parental questionnaire only has four educational levels: 'No education', 'Low education' (ISCED levels 0, 1 and 2), 'Middle Education' (ISCED levels 3 and 4) and 'High Education' (ISCED levels 5 and 6). Parental education from both father and mother is provided for all individuals in all countries in the sample.

[14]Categories include: managerial, professional, technician, clerical, sales, skilled agricultural, craft trade, machine operation, elementary occupation and armed/military occupation. Father's occupation is available for all countries except for Sweden, where that information is missing for around 75% of the sample used in both waves. Note that we have also included 'unemployed' as occupational category for those individuals who were unemployed, not disabled to work nor retired, and for which the occupational category was not coded.

[15]In the 2011 module, the perceived financial situation could be considered very bad, bad, moderately bad, moderately good, good and very good. We have chosen to melt the two middle categories in one single 'moderate' category, in order to have the same number of categories in both waves. The analogous answers to the 2005 question about how often did the household had financial difficulties were: 'most of the time', 'often', 'occasionally', 'rarely' and 'never'. Also note that, while in 2011 this item appears in all countries' questionnaires, in 2005 this question was not included in Austria, Germany, Greece, France and Portugal.

highest individual labour income.[16] In order to exclude incomes obtained at the tails of the life-income cycle, and to include cohorts with the highest proportion of employed individuals [Ferreira and Gignoux (2011)], only household heads within the 30-50 years of age range are kept. We have also removed extreme outlier observations of equivalent income; specifically, those placed more than three quartiles below or above the adjusted interquartile range.[17] Descriptive statitistics for income and all parental and individual variables in each country and wave are presented in Appendix Tables 2.A1 and 2.A2.

In general, our descriptive statistics find differences in average equivalent income similar in rank to the ones found in national accounts statistics (i.e. using GDP per capita), with Luxembourg and Norway on top of the list. Nordic and central countries, in general, show higher shares of parents with higher level of education, a pattern that also occurs when we consider the educational level of the individual. Note also that, in all countries, the share of individuals with higher education is greater than the share of parents (either fathers or mothers) with higher education; the opposite occurs when we look at the shares of the individuals with the lowest educational levels. Also, nordic and central countries tend to show higher shares of parents and individuals with professional, managerial or technical occupational categories.

The results from regressing income on circumstances for each country and wave in order to obtain the ${y_i}^C$ smoothed distribution (Eq. (2.5)) are shown in Appendix Tables 2.A3.A to 2.A3.E. In general, higher levels of parental education, both for father and mother, have positive coefficents (the omited category is 'low education'), and are significant in most of the countries. Occupational categories of the father such as "Professional" or "Managerial" generally have positive coefficients and are significant in most of the cases; other categories are not always significant and have ambiguous coefficients (the omitted category is 'skilled agricultural'). Regarding the financial situation of the household during childhood, the category

[16]The equivalence scale used by Eurostat is $1 + 0.5 * (HM_{14} - 1) + 0.3 * HM_{13}$, where HM_{14} refers to the individuals in the house who are fourteen or older, while HM_{13} refers to the individuals in the house who are thirteen or younger. Although we considered using individual labour income as the proxy variable of the economic advantage -and not just to determine the household head- we found impossible to obtain that variable homogeneously among countries -some countries provide only gross income while others provide only the net measure- and therefore discarded that option. Also please note than in our tables and figures we refer to the years when the income reported was obtained: 2004 and 2010.

[17]We have calculated the adjusted boxplot for each country and wave, accounting for skewedness, and using the parameter 3 to exclude extreme outliers see [Hubert and Vandervieren (2008)].

"Difficulties most of the time" has the expected negative coefficient (the omitted category is "Difficulties rarely") and is significant in most of the countries. The female-gender dummy has a negative coefficient and is also significant in most cases. Finally, being a citizen from a non-EU country has a negative and significant coefficient for most of the contries analysed (here the ommited category is being a national citizen).

Tables 2.A4.A to 2.A4.E in the Appendix show the estimated coefficients in the 'second step' regressions for each educational level and each occupational category (Eq. [2.13) and Eq. (2.16)] for all countries and waves.[18] The coefficient for 'tertiary education' tends to be positive and significant in both waves in most countries, while the opposite happens with the coefficients for 'primary' and 'pre-primary' levels of education. Among the professional categories, the 'elementary occupation' category shows in general a negative and significant coefficient, while both 'professional' and 'managerial' categories tend to have positive and significant coefficients in most countries.

2.4 Inequality and Inequality of opportunity in Europe in 2004 and 2010

The period analysed, 2004 and 2010, includes the end of a high economic growth era and the first impact of a deep economic slowdown. For the 28 European Union countries as a whole, real GDP growth rates changed from around 3% in the years before 2008, to an average growth rate in the 2008-2013 period of around 0% per year.[19] Although the effects of the 'Great Recession' on the variables we analyse were probably longer in time and higher in magnitude, changes between the 2004 and the 2010 waves could partially represent the impact of the first part of the recession.

In this section, we first have a look at the results for total income inequality between the two waves and compare them with the IO performance, while the association of IO with individual education and occupation will be analysed in Section 2.5. The inequality indices

[18]Unlike parental education, the respondent's education is categorised in ISCED levels for both waves. The occupation, on the other hand, is coded using the same one-digit groups from the ISCO-88. Note the omitted categories in these regressions are 'Upper Secondary (ISCED 3)' for education, and 'Skilled Agricultural' for occupation

[19]See http://ec.europa.eu/eurostat/web/products-datasets/-/tec00115.

and standard errors for the equivalent household income of individuals in our sample are calculated for the 26 countries analysed in the 2004 and 2010 wave, and presented in the first four columns of Table 2.1. The IO estimates and standard errors are shown in the last four columns of Table 2.1. Figures 2.1 and 2.2 show the inequality and IO values, respectively, for 2004 in the X-axis and for 2010 in the Y-axis.[20]

As shown in Figure 2.1, total inequality did not suffer radical changes in most countries. It increased slightly in Iceland, Germany, Italy and Spain, while it decreased in Austria, Lithuania and, especially, in Portugal and Poland. Nordic countries are consistently at the bottom of the inequality ranking in both waves, with the exception of Iceland in 2010, that shows a higher level of inequality than its Nordic neighbours, probably influenced by the stronger impact of the recession in that country that, as we will see, could also affect its IO levels. The Baltic republics, Poland and the Mediterranean countries show the highest degree of inequality in both waves, while the western-central Europe countries (Netherlands, Belgium, France, Austria, Germany and Luxembourg) and some of the former communist countries (Slovenia, Slovakia, Hungary or the Czech Republic) have inequality levels just above those of the Nordic countries. Ireland and the United Kingdom are placed -in terms of inequality- between the Mediterranean and the central European countries, while Cyprus is an exception, with lower levels of inequality than its Mediterranean counterparts.[21]

In terms of IO, our homogeneous set of circumstances for all countries in both waves allows for a cross-country comparison of the results (Figure 2.2). Going from the bottom to the top in the most recent wave, we see Nordic countries are placed at the lower end of the IO ranking, as they were in the inequality measure. Iceland is, again, a 'Nordic outlier' in 2010. Among the Central European countries (we include here Ireland and the UK for simplicity), Germany and Netherlands have lower IO levels (comparable to those of the Nordic countries) while France, Austria and the UK have higher IO ranking positions, just above Slovenia, Slovakia and the Czech Republic in 2010. Next, we find a mixed group that includes

[20]Standard errors for the inequality indexes have been calculated by bootstrapping with 1000 replicates.

[21]Our ranking for the 2004 wave -both for total inequality and for inequality of opportunity- is consistent with Marrero and Rodríguez (2012), with minor differences in the values of particular countries due to different database decisions. Our 2010 results are also in line with Brzezinski (2015), who reproduces the work of Marrero and Rodríguez (2012) for both waves. Again, some minor discrepancies with our estimations can be attributed to different data choices. Also note that -compared to these previous works on IO in Europe- we add Cyprus, Iceland and Luxembourg to the sample of countries.

Belgium, Ireland, Italy and most of the other East European countries (Estonia, Hungary, Poland, Latvia and Lithuania), while Spain and Cyprus are at the higher end of this group; finally, Luxembourg, Greece and Portugal occupy the top of the IO ranking in 2010. The comparison between inequality and IO rankings shows that the Baltic republics rank better in terms of IO than in terms of sheer inequality, while the opposite occurs for Belgium and, specially, for Luxembourg.

As for the dynamics of IO over this period, only Portugal, Poland, Latvia and Lithuania show a significant decrease in IO, with Italy and Sweden presenting also minor decreases. Portugal is still among the countries with the highest levels of IO, but its situation has relatively improved compared to 2004, when its IO was far above all other European countries analized. Most of all other countries are along the 45^o line (Norway, Finland, Czech Republic and the UK) or slightly above it, showing a small increase (Denmark, Germany, Slovenia, France, Austria, Ireland, Spain and Cyprus). Finally, Hungary and Estonia show a moderate increment, and it is Slovakia, Iceland, Belgium and Greece who show the highest increase in inequality of opportunity between 2004 and 2010.

2.5 The mediating role of education and occupation

Although the results presented in Section 3.1 are certainly relevant, we believe, as discussed in the introduction, that an analysis of the possible channels of these levels of inequality of opportunity could be of great interest. Thus, we turn now to results obtained by applying our proposed method -presented in Section 3.2- to our sample of 26 European countries in 2004 and 2010.

Table 2.2 shows the percentage of IO associated with individual education and occupation, while Table 2.3 presents the absolute values of IO_{EDU} and IO_{OCC} for each country and wave. First of all, results still reveal a relevant role of the level of education as a channel of IO. Relative to the total estimate of IO in each country and wave, we find (see Figure 2.5) that the level of education attained by the individual can mediate about one third of IO in Portugal and Luxembourg, almost one quarter in Greece and Hungary, and more than 20% in Italy and Poland. Most of the other countries are in the 8% - 20% range, with the Nordic countries -except Norway- showing the lowest share of IO channelled through education[22]

The change in the channelling importance of the educational level between the two waves shows an important increase in Greece, with Germany, Norway, Luxembourg, Slovakia, Belgium and Austria also having moderate increments. There is a marked decrease in Sweden, Finland and Iceland, while Spain, Ireland, Slovenia and Cyprus present a moderate decrease. The rest of the countries remain close to the 45^{o} line and show no significant changes between the two waves.

The other potential candidate to channel IO present in the EU-SILC database is the occupational category of the individual, since it is related both to income and circumstances. However, once we control for education, the share of IO channelled by the occupational category is relatively small in most countries, amounting only to between 1% and 5% in most countries and to around 8% in Cyprus and Austria in the most recent wave (Figure 2.8). These two countries are also the only ones in which this share shows a clear increase between the two waves. On the other hand, Norway, Germany, Finland, Hungary and Ireland show a decrease in the share of IO, with Greece, Latvia and the Czech Republic showing a smaller decrease. The rest of countries channel similar shares of IO through occupation in both waves. In general, we observe a greater degree of dispersion in the change overtime of the share of IO channelled through occupation than in the share channelled by education. However, no clear trend or geographical pattern is observed in either case.[23]

Combined, the occupational category and the educational level explain up to 35% of IO (Portugal and Luxembourg; less in the rest of the countries). Although it represents an important share of IO -and it could explain part of the unfortunate lead that Portugal, Greece and Luxembourg had in inequality of opportunity in 2010- we must not forget there is still an important part of IO not associated with either of these factors. According to our estimates, more than 70% of IO is mediated by unoserved factors other the educational level and the educational category. As pointed out by other studies, school quality or parental connections

[22]The level of education also seems to account for a similar share of the intergenerational income elasticity (IGE). Eide and Showalter (1999) and Palomino et al. (2014) find that controlling for education the value of IGE decreases by around 30% using OLS, while Blanden et al. (2014) finds a decrease close to 50%

[23]When we plot the absolute levels of IO instead of the relative shares, the rankings of countries and evolution overtime of the education and occupation channels do not change significantly (see Figures 2.9 and 2.10).

could be some of the most relevant mediators channeling that share of IO unexplained by our limited set of mediators. Chetty et al. (2014) find for the U.S., in that line, that rank intergenerational mobility is related to the quality of the schools in different geographical areas. But there could be many more and less obvious channels. Neumann et al. (2009), for example, point at another source of earnings and that, in our context, could be a potential IO mediator: job congruence, (i.e., the similarity between job interests and the actual job). It could be the case that some circumstances should favour a more free or informed career choice and, therefore, a higher income. As richer databases become available, we believe our strategy should be applied to the exploration of more potentially important mediators.

2.6 The educational IO channel and the expansion of higher education

We focus next on analysing the different share of IO channelled by education in different European countries and the possible relation with different national variables, carrying out a simple but illustrative exercise. The intuition of the channelling role of education on income opportunities is simple: people with more favourable circumstances achieve higher educational levels, which, in turn, enable them to obtain more income through increased productivity. In line with this theoretical relation, our results provide an objective measure of how much of the circumstance-conditioned income is obtained through different levels of education. We find that, even though we cannot account for the possible variation in quality within the same level of schooling, the share is still relevant, implying that acting on the educational channel of transmission could potentially reduce the measure of IO in up to one third in some countries.

Thus, the relevance of the educational level achieved by the individual as a channel of IO raises another question: which factors are associated with the role of education in the transmission of opportunities? Clear candidates can be found in the own average levels of education attained at each country. Having a relatively big sample of 26 countries at two different points in time, we have performed a descriptive cross-correlation analysis, comparing the access to different levels of education of the population and the channelling role of education (Table 2.4). Figure 2.11 shows that EU countries with a bigger share of population with higher (tertiary) education seem to have a smaller share of IO channelled through education. On the contrary, that correlation turns positive with the percentage of the population attaining only the lowest levels of education (Figure 2.12). This correlation also occurs when we take into account the absolute level of the educational channel of IO instead of the share it represents over total inequality of opportunity (Appendix Figures 2.A1 and 2.A2). As suggested by Roemer and Ünveren (2016) in a dynamic equality of opportunity intergenerational model, the public educational investment can equalise opportunities in the steady state as long as private investment in education fails to maintain an edge in human capital for the children of more advantaged parents. In practice, countries where tertiary education is spread among wider shares of the population- such as nordic countries- also tend to have a higher share of public funding in tertiary education (see OECD (2016), Indicator B3).

As could be expected, given that the occupational channel is measured net of the educational level, the share of IO channelled through the occupational category and the share of the population with high level (or low level) of studies show no clear correlation (Figures 2.13, 2.14 and 2.A3 and 2.A4 in the Appendix).

Indirectly, the role of education in channelling IO might shed some light on the debate about the effect of educational investment on economic growth. This effect has traditionally been attributed to direct increases in skills (and productivity) and to positive social externalities of education [Angrist and Krueger (1991), Card (1999) or Krueger and Lindahl (2001)]. Since IO has recently been found to be negative for growth [Marrero and Rodríguez (2013) and (2016), Marrero et al. (2016) and Bradbury and Triest (2016)], our results add a third possible connection between education and growth, the one that takes place via a decrease in IO. However, we leave the exploration of this avenue for future research.

2.7 Concluding Remarks

In this paper we try to go beyond the beaten path of IO measurement and cross-country comparisons and disentangle the channels through which different circumstances turn into different incomes. Using data from the EU-SILC survey, we present a simple new strategy to decompose ex-ante measures of inequality of opportunity in their educational and occupational channels. Nonetheless, this method could be extended to the ex-post approach and to different transmission channels (e.g. education quality or work connections) if appropriate data were available.

In short, our proposed methodology obtains the circumstance-determined income (the smoothed distribution) and successively decomposes it –using log-linear regression- by orthogonal mediating factors, following the natural order in which these mediators come into play (first education and then occupation). Finally, using the decomposable MLD index, the inequality of the smoothed distribution is partitioned into the different shares of inequality of opportunity explained by each considered factor.

Applying this methodology to data from 26 European countries in 2004 and 2010, we find that a relevant share of IO is channelled through the different levels of education. In 2010, this share accounts to around one third of IO in Portugal and Luxembourg, almost one quarter in Greece and Hungary, and more than one fifth in Italy and Poland. Most of the other countries are in the 8% - 20% range. Once the educational channel is taken into account, the importance of the occupational channel is relatively small, channelling less than 5% of IO in most countries. On the other hand, although particular countries have suffered significant changes, we find no general pattern of change in the shares of IO channelled by education and occupation in the two waves of data analysed.

We believe that our findings, although limited to only the level of education and the occupational category, may be relevant for practitioners and policymakers concerned about inequality of opportunity. We provide some evidence of what before was only an intuition: that a significant share of inequality of opportunity derives from the different level of education that people with different circumstances can achieve. In addition, we find the occupational category to have limited importance once the education channel has been taken into account.

Also, trying to explore the factors that explain the differential importance of the educational channel across countries, we have detected a positive (negative) correlation between the share of IO channelled by education and the share of the population with low education (tertiary education). It seems that when more people can achieve levels of education above lower education and tertiary education is more broadly accessible to the population, the IO channelled through this variable decreases (both in absolute and relative terms).

Finally, and notwithstanding the importance of the educational level, the relevant share of

IO still unexplained by our set of variables remains a challenge for future research. In that line, we believe our method provides a simple useful strategy for the prospective analysis of other potential channels (e.g., education quality, social connections) when the necessary data are available.

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2.8 Tables and Figures

Table 2.1: Inequality and Inequality of Opportunity Europe - 2004 and 2010.

	Inequality				Inequality of Opportunity			
	2004		2010		2004		2010	
Country	Index	SD	Index	SD	Index	SD	Index	SD
AT	0.1192	0.008	0.1024	0.004	0.0096	0.0004	0.0136	0.0005
BE	0.0913	0.004	0.1000	0.005	0.0088	0.0004	0.0197	0.0010
CY	0.1129	0.004	0.1284	0.006	0.0227	0.0009	0.0268	0.0013
CZ	0.1125	0.006	0.1076	0.004	0.0114	0.0005	0.0108	0.0004
DE	0.1033	0.003	0.1308	0.004	0.0026	0.0001	0.0060	0.0001
DK	0.0584	0.004	0.0738	0.004	0.0021	0.0002	0.0064	0.0003
EE	0.1893	0.009	0.1891	0.010	0.0174	0.0006	0.0236	0.0011
EL	0.1771	0.007	0.1734	0.010	0.0221	0.0009	0.0335	0.0014
ES	0.1897	0.005	0.2136	0.007	0.0229	0.0005	0.0267	0.0009
FI	0.0845	0.003	0.0896	0.005	0.0044	0.0003	0.0033	0.0002
FR	0.1051	0.003	0.1101	0.003	0.0098	0.0003	0.0121	0.0004
HU	0.1191	0.004	0.1228	0.003	0.0156	0.0006	0.0215	0.0005
IE	0.1382	0.006	0.1463	0.007	0.0189	0.0008	0.0224	0.0009
IS	0.0882	0.009	0.1156	0.021	0.0060	0.0005	0.0138	0.0028
IT	0.1526	0.004	0.1692	0.005	0.0245	0.0006	0.0208	0.0005
LT	0.2326	0.010	0.2168	0.017	0.0332	0.0015	0.0211	0.0022
LU	0.1198	0.008	0.1235	0.006	0.0282	0.0016	0.0334	0.0012
LV	0.2269	0.011	0.2386	0.009	0.0297	0.0011	0.0209	0.0006
NL	0.0937	0.005	0.0950	0.004	0.0041	0.0002	0.0047	0.0003
NO	0.0602	0.003	0.0694	0.004	0.0033	0.0002	0.0037	0.0002
PL	0.2462	0.005	0.1637	0.004	0.0285	0.0005	0.0197	0.0004
PT	0.2110	0.009	0.1744	0.007	0.0451	0.0024	0.0347	0.0014
SE	0.0660	0.003	0.0735	0.006	0.0045	0.0003	0.0016	0.0001
SI	0.0869	0.004	0.0972	0.005	0.0077	0.0002	0.0101	0.0004
SK	0.1053	0.003	0.1154	0.006	0.0034	0.0001	0.0118	0.0004
UK	0.1613	0.008	0.1603	0.006	0.0170	0.0005	0.0145	0.0005

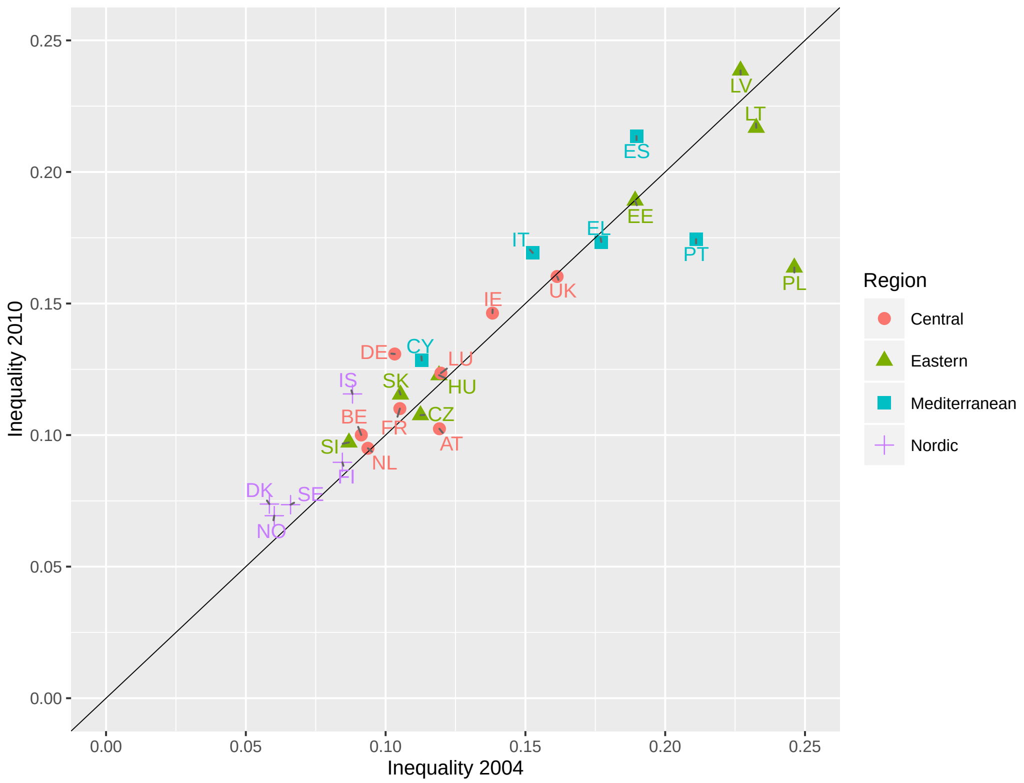

Figure 2.1: Inequality in Europe - 2004 and 2010

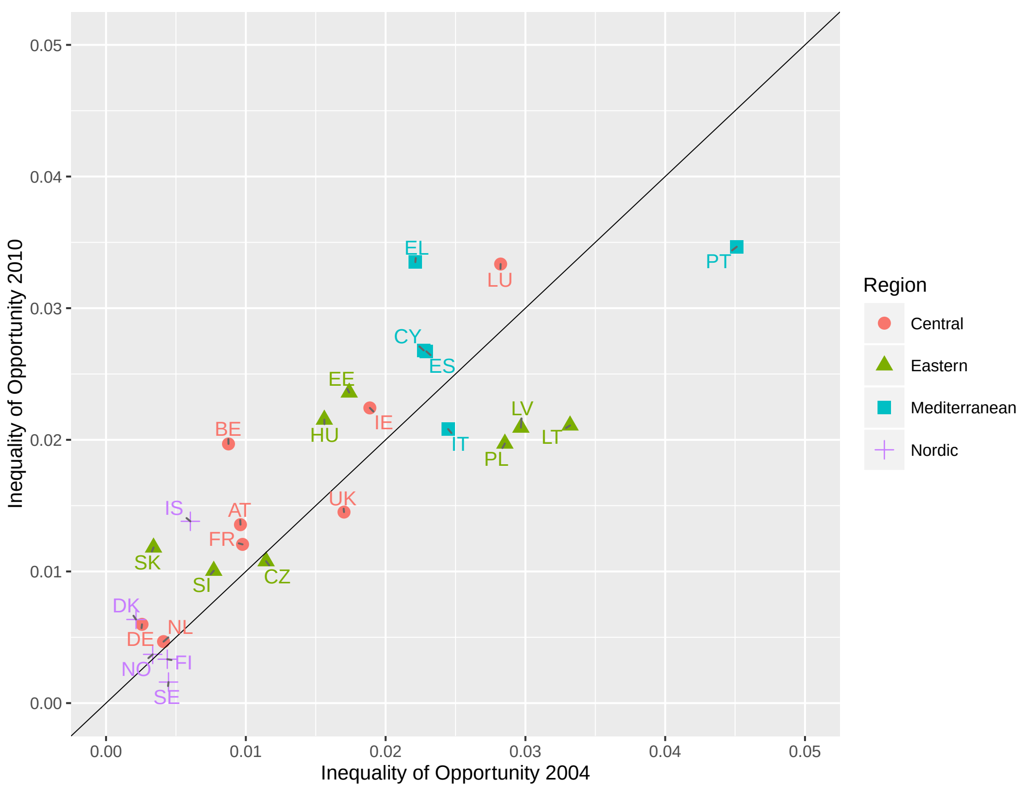

Figure 2.2: Inequality of Opportunity in Europe - 2004 and 2010.

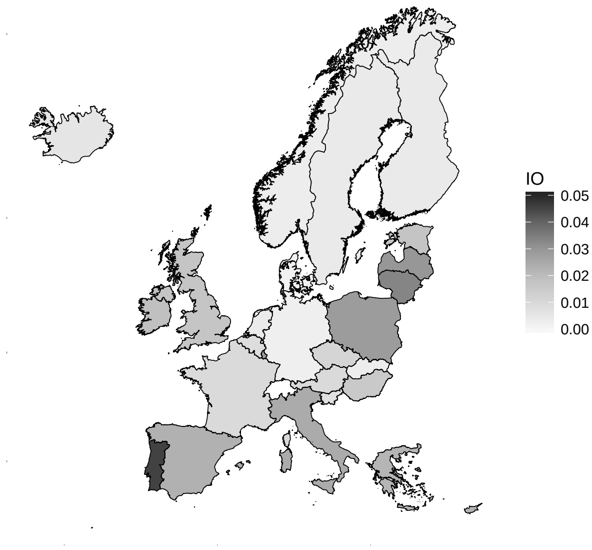

Figure 2.3: Inequality of opportunity 2004

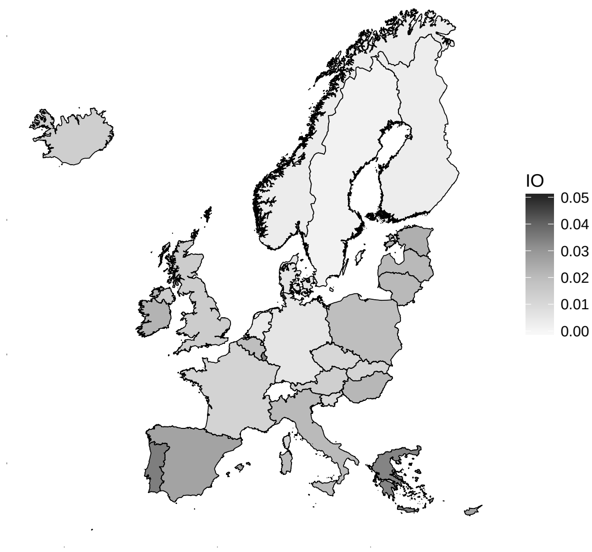

Figure 2.4: Inequality of opportunity 2010

Table 2.2: Share (%) of Inequality of Opportunity channelled through Education and Occupation - 2004 and 2010.

	Education Share (%)		Occupation Share (%)	
Country	2004	2010	2004	2010
AT	13.06	16.77	5.79	7.69
BE	10.99	15.19	3.19	3.65
CY	19.96	14.40	5.52	8.24
CZ	15.14	18.04	3.28	2.37
DE	1.99	8.41	5.40	3.00
DK	5.39	6.36	2.94	3.27
EE	5.94	7.89	4.65	3.85
EL	14.24	24.02	4.87	3.68
ES	19.91	16.15	3.51	4.34
FI	6.95	0.12	5.30	3.51
FR	14.75	14.05	2.33	2.93
HU	23.81	23.98	2.99	1.21
IE	19.15	14.99	4.01	2.16
IS	7.93	0.07	2.06	2.70
IT	20.41	20.35	3.26	3.16
LT	11.75	10.14	2.90	2.61
LU	26.20	31.01	4.37	3.81
LV	10.76	8.86	2.90	1.48
NL	9.56	12.06	0.93	1.78
NO	4.93	11.39	6.04	1.48
PL	21.48	21.90	4.97	5.39
PT	32.85	32.50	0.98	1.46
SE	7.20	1.26	1.71	1.92
SI	19.19	14.67	3.83	4.33
SK	8.09	12.19	2.10	1.60
UK	9.44	10.12	4.09	4.94

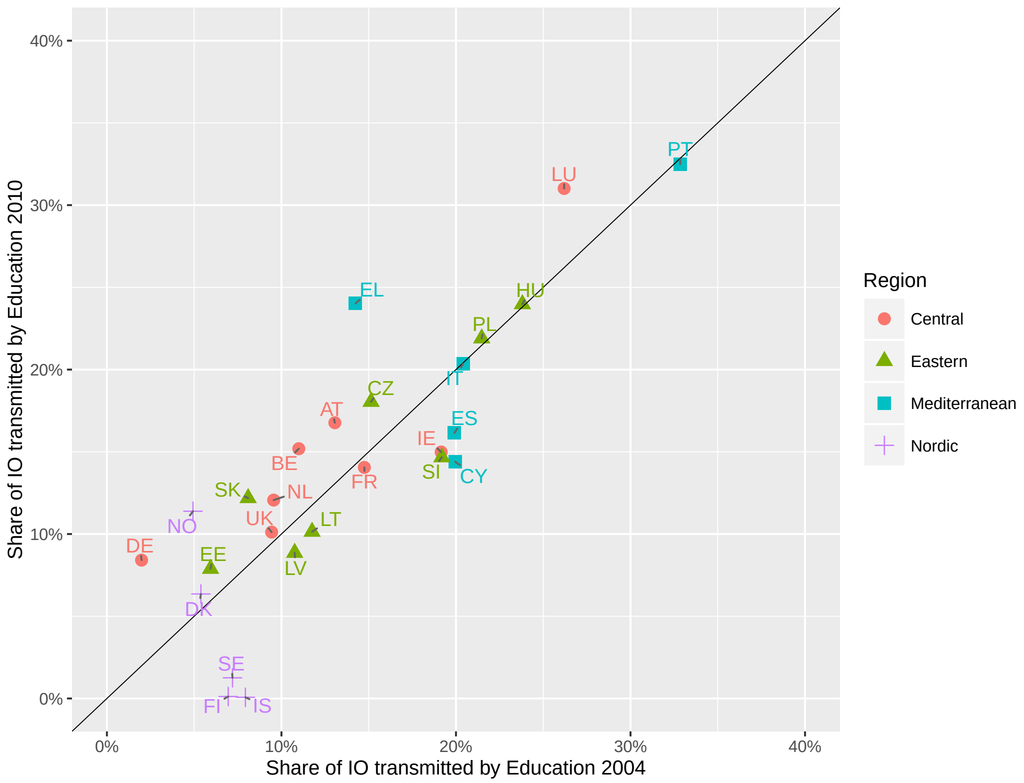

Figure 2.5: Share of Inequality of Opportunity channelled through Education in Europe - 2004 and 2010.

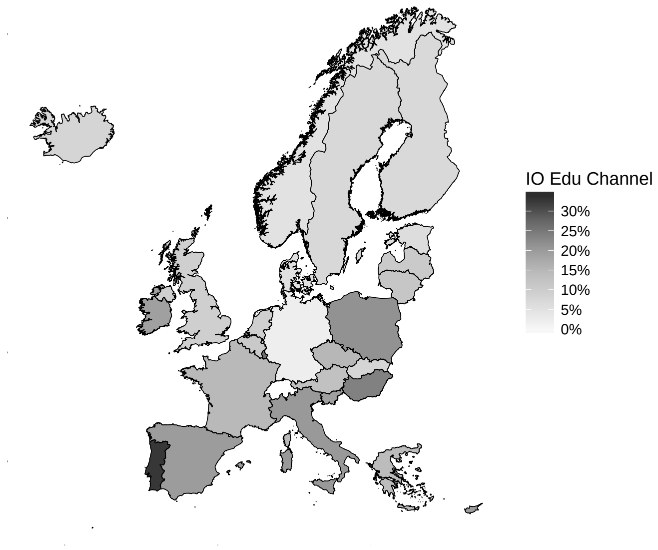

Figure 2.6: Education IO Channel 2004

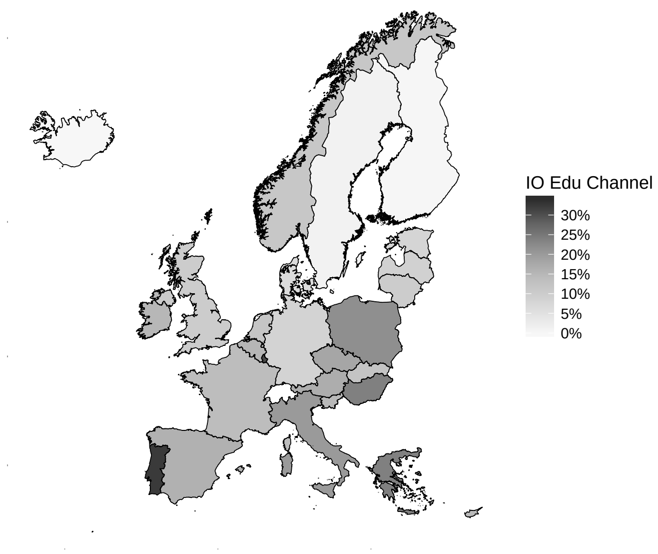

Figure 2.7: Education IO Channel 2010

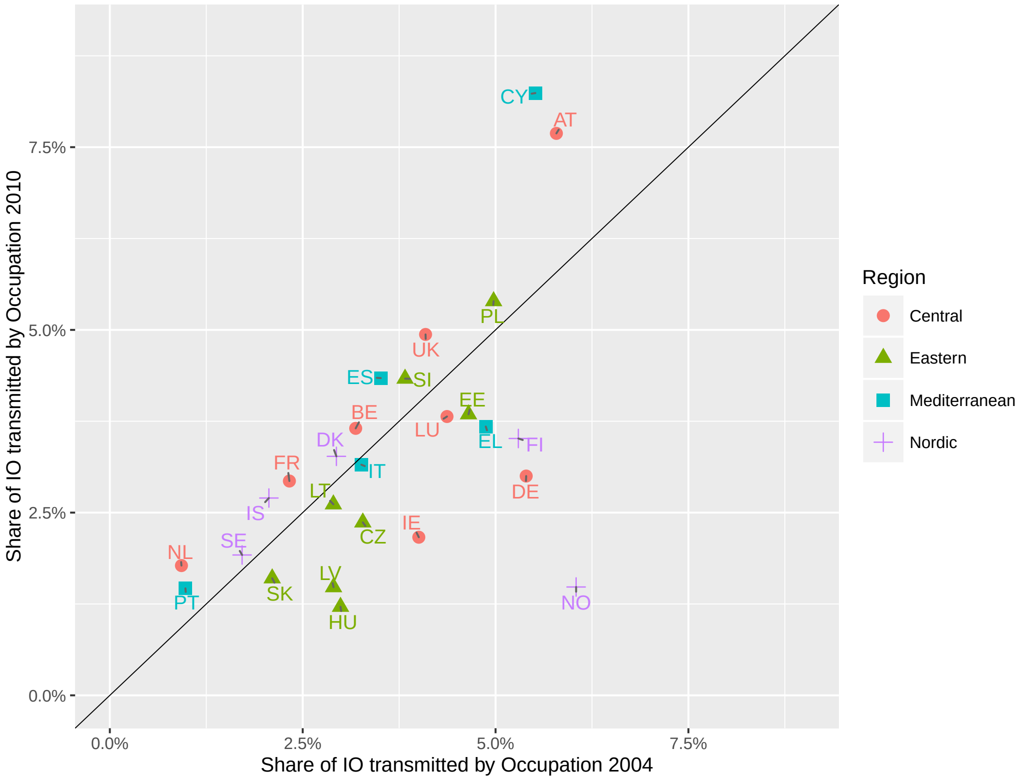

Figure 2.8: Share of Inequality of Opportunity channelled through Occupation in Europe - 2004 and 2010.

Table 2.3: Inequality of Opportunity channelled through Education and Occupation - 2004 and 2010.

	IO Educational Channel				IO Occupational Channel			
	2004		2010		2004		2010	
Country	Index	SD	Index	SD	Index	SD	Index	SD
AT	0.0013	0.0003	0.0023	0.0005	0.0006	0.0002	0.0010	0.0002
BE	0.0010	0.0003	0.0030	0.0007	0.0003	0.0001	0.0007	0.0003
CY	0.0045	0.0007	0.0039	0.0010	0.0013	0.0003	0.0022	0.0006
CZ	0.0017	0.0005	0.0019	0.0004	0.0004	0.0002	0.0003	0.0001
DE	0.0001	0.0000	0.0005	0.0001	0.0001	0.0001	0.0002	0.0001
DK	0.0001	0.0001	0.0004	0.0003	0.0001	0.0001	0.0002	0.0002
EE	0.0010	0.0004	0.0019	0.0009	0.0008	0.0004	0.0009	0.0005
EL	0.0032	0.0008	0.0080	0.0015	0.0011	0.0003	0.0012	0.0004
ES	0.0046	0.0007	0.0043	0.0007	0.0008	0.0002	0.0012	0.0003
FI	0.0003	0.0001	0.0000	0.0001	0.0002	0.0001	0.0001	0.0002
FR	0.0014	0.0003	0.0017	0.0003	0.0002	0.0001	0.0004	0.0001
HU	0.0037	0.0006	0.0052	0.0006	0.0005	0.0001	0.0003	0.0001
IE	0.0036	0.0009	0.0034	0.0010	0.0008	0.0003	0.0005	0.0003
IS	0.0005	0.0003	0.0000	0.0002	0.0001	0.0002	0.0004	0.0006
IT	0.0050	0.0006	0.0042	0.0005	0.0008	0.0002	0.0007	0.0001
LT	0.0039	0.0010	0.0021	0.0011	0.0010	0.0004	0.0006	0.0007
LU	0.0074	0.0015	0.0103	0.0015	0.0012	0.0006	0.0013	0.0004
LV	0.0032	0.0011	0.0019	0.0006	0.0009	0.0005	0.0003	0.0002
NL	0.0004	0.0002	0.0006	0.0003	0.0000	0.0000	0.0001	0.0001
NO	0.0002	0.0001	0.0004	0.0002	0.0002	0.0001	0.0001	0.0001
PL	0.0061	0.0007	0.0043	0.0006	0.0014	0.0002	0.0011	0.0002
PT	0.0148	0.0024	0.0113	0.0019	0.0004	0.0002	0.0005	0.0002
SE	0.0003	0.0002	0.0000	0.0000	0.0001	0.0000	0.0000	0.0001
SI	0.0015	0.0004	0.0015	0.0004	0.0003	0.0001	0.0004	0.0001
SK	0.0003	0.0001	0.0014	0.0004	0.0001	0.0000	0.0002	0.0001
UK	0.0016	0.0004	0.0015	0.0005	0.0007	0.0003	0.0007	0.0002

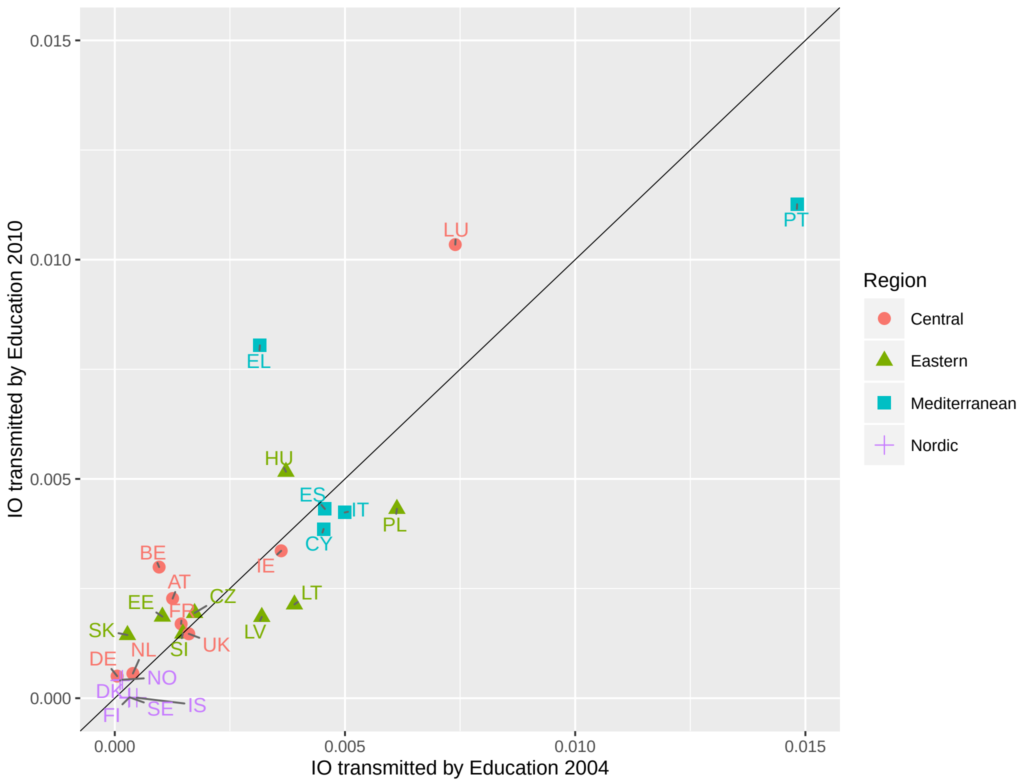

Figure 2.9: Inequality of Opportunity channelled through Education in Europe - 2004 and 2010.

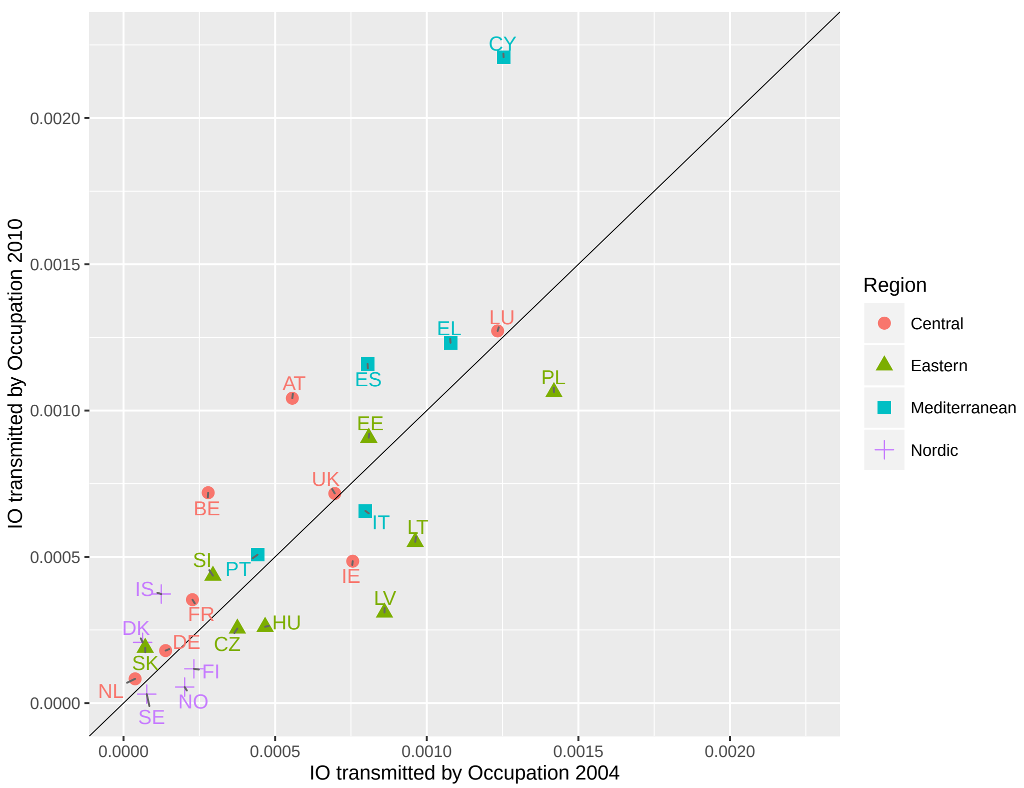

Figure 2.10: Inequality of Opportunity channelled through Occupation in Europe - 2004 and 2010.

Table 2.4: Shares of the sample population with low and high education levels.

	Share with low Education (ISCED 0, 1 and 2)(%)		Share with high education (ISCED 5 and 6)(%)	
Country	2004	2010	2004	2010
AT	11.96	10.30	21.30	24.53
BE	21.06	15.30	40.94	48.60
CY	26.32	20.71	30.88	36.37
CZ	6.66	3.95	15.87	18.86
DE	4.01	3.70	45.44	46.00
DK	16.15	10.05	35.78	44.71
EE	8.07	9.75	28.29	33.42
EL	37.41	26.32	23.32	29.09
ES	44.69	39.28	31.03	36.47
FI	10.89	6.30	42.98	49.40
FR	21.77	13.72	29.76	38.76
HU	20.88	14.86	16.31	23.98
IE	31.56	19.67	34.50	50.25
IS	22.97	18.35	29.28	38.92
IT	40.50	34.10	13.94	18.92
LT	4.42	6.48	26.96	34.06
LU	32.63	33.25	31.63	31.61
LV	10.40	12.54	22.84	31.62
NL	16.13	11.28	40.23	45.27
NO	4.45	10.61	39.90	48.73
PL	11.24	7.41	15.91	23.39
PT	72.48	64.15	13.24	16.78
SE	8.34	3.59	33.97	45.08
SI	18.05	11.75	14.23	30.86
SK	4.84	2.83	18.45	25.18
UK	9.25	7.33	45.17	46.00

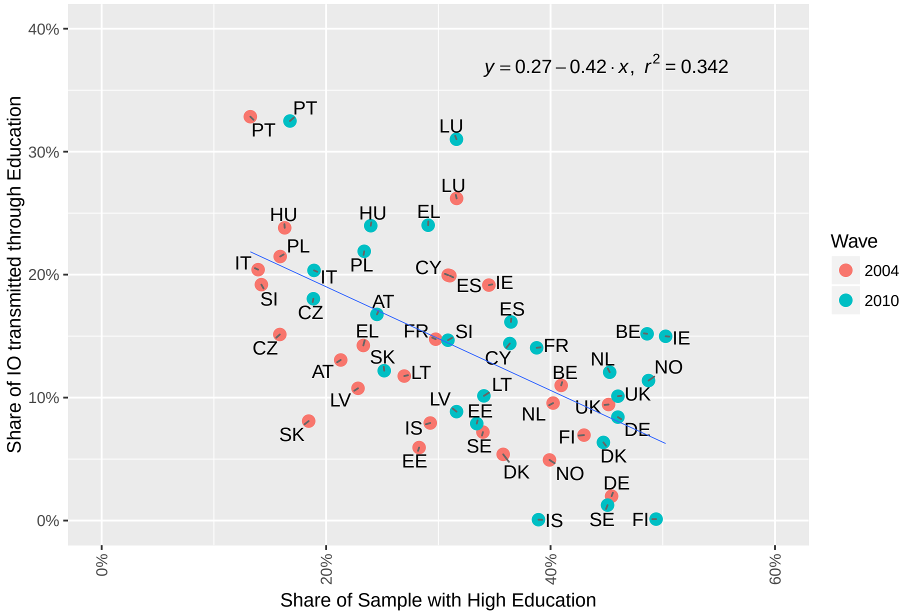

Figure 2.11: Share of population with high education and share of IO channelled through education.

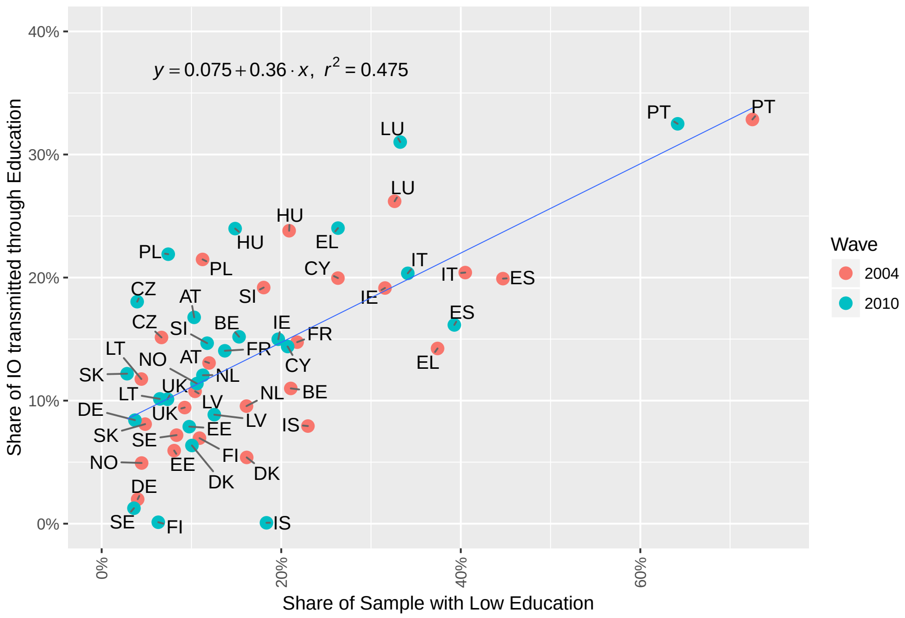

Figure 2.12: Share of population with low education and share of IO channelled through education.

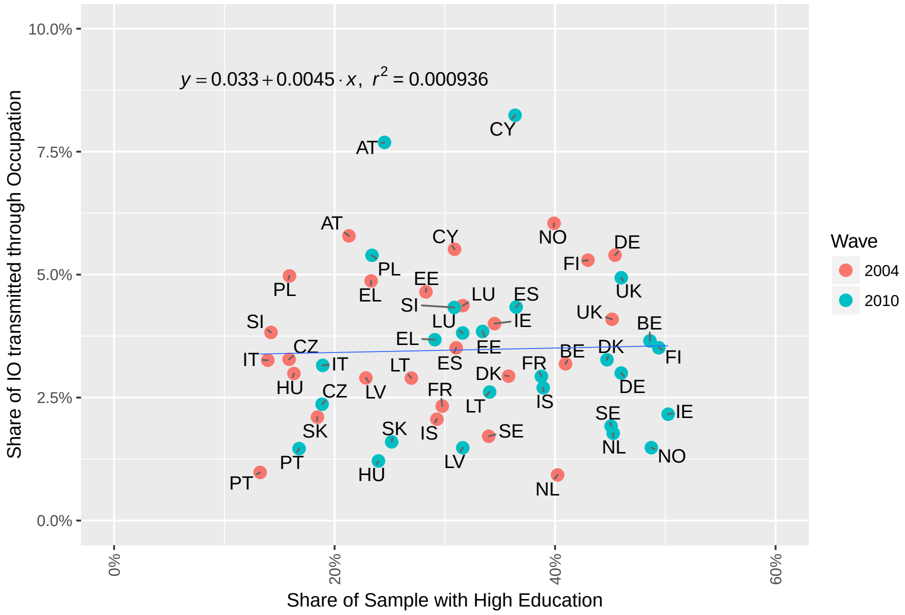

Figure 2.13: Share of population with high education and share of IO channelled through occupation.

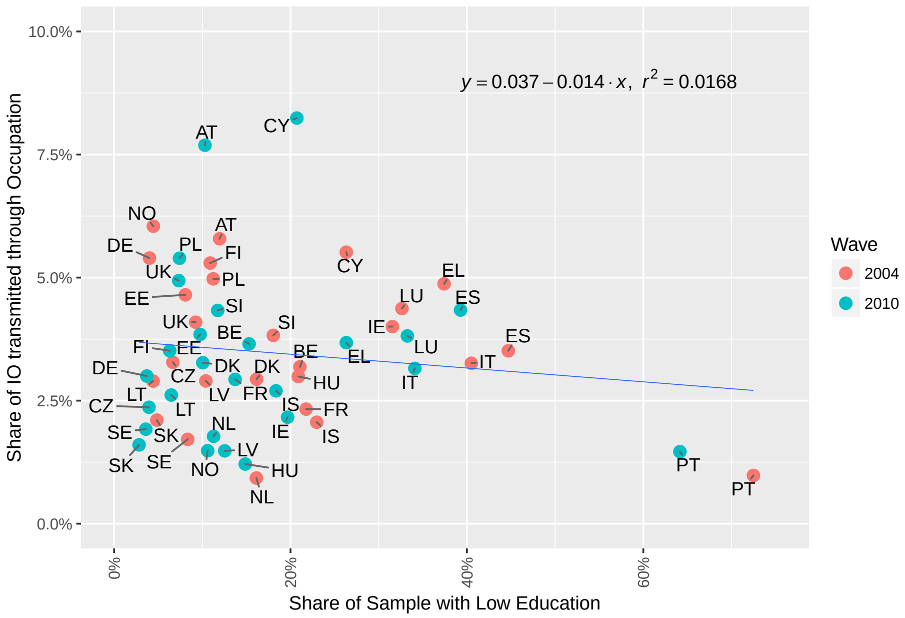

Figure 2.14: Share of population with low education and share of IO channelled through occupation.

2.9 Appendix I: Decomposing ex-post IO channels

2.9.1 The hybrid *ex post-ex ante* method

Our strategy could potentially be applied to the version of the ex-post approach proposed by Checchi and Peragine (2010). This approach partitions the population in p tranches (groups of people belonging to different types but exerting the same level of effort), and then re-scales each tranche distribution in such a way that all tranches have the same mean as the overall distribution (see Checchi and Peragine (2010, p.436):

$$y_i^W = y_i^p \frac{\overline{Y}}{\overline{y}^p}, \forall i, p, \tag{2.21}$$

where y_i^W is the re-scaled income of individual i belonging to tranche p. $\overline{Y}$ and $\overline{y}^p$ are the overall mean and the p tranche mean, respectively. The complete re-scaled distribution y^W thus eliminates all differences between tranches (effort) and retains only differences due to circumstances, which makes it equivalent to our smoothed distribution and $y^W = y^C$.[24]

Based on that distribution, the second step of our methodology could be applied, and the role of the channeling variables could be measured just as described in section 2.2. This would formally be a hybrid method in which $y^C = y \mid C$ is estimated ex-post (i.e. assuming that people with the same level of effort belonging to different types should have the same mean income), but the channeling role of the education (or other mediating factors) is estimated ex-ante, ie., assuming groups of people with different levels of education should have the same mean 'circumstance conditioned income' and measuring the educational IO channel as the deviation from that assumption.

2.9.2 The ex-post decomposition

Alternatively, the above mentioned ex-post method could be adapted and used again to partition y^W in tranches using the individual education level information. A tranche f would

[24]Note that, in the absence of any objective measure of effort (as is usually the case) estimates are obtained under the assumption that all individuals in the same income quantile at different types have exerted the same level of effort and belong to the same tranche.

in this case be a group of people having different levels of education but exerting the same level of effort (proxied again by the division in deciles, percentiles, etc.). Each tranche distribution would then be re-scaled again so all tranches have the same overall mean (implying that all effort differences have been equalized and that differences can only be attributed to the different level of education).

$$y_i^{W-EDU} = y_i^{Wf} \frac{\overline{Y^W}}{\overline{y^W}^f}, \forall i, f, \tag{2.22}$$

where y_i^{W-EDU} is the re-scaled circumstance condition income ${y_i}^C = {y_i}^W$ of individual i belonging to tranche f. $\overline{Y^W}$ and $\overline{y^W}^f$ are the overall mean and the f tranche mean, respectively. Thus, the inequality of this twice re-scaled distribution would be the part of IO channelled by education.

If we intend to analyse the channeling role of a second variable once education has been taken into account, we will use the re-scaled distribution y^W that retained only differences due to circumstances, and will transform it in such a way that all types (made according to the levels of *the first* channel considered) belonging to the same tranche have the same mean. This way we eliminate the differences attributable to the first channel (e.g. education). Secondly, we would proceed to re-scale once again this very new distribution in the way described in the paragraph above, using in this case the new channeling variable (eg. occupation). The inequality of this last distribution would be the component of IO channelled by occupation once education has been accounted for.

2.10 Appendix II: Data and Figures

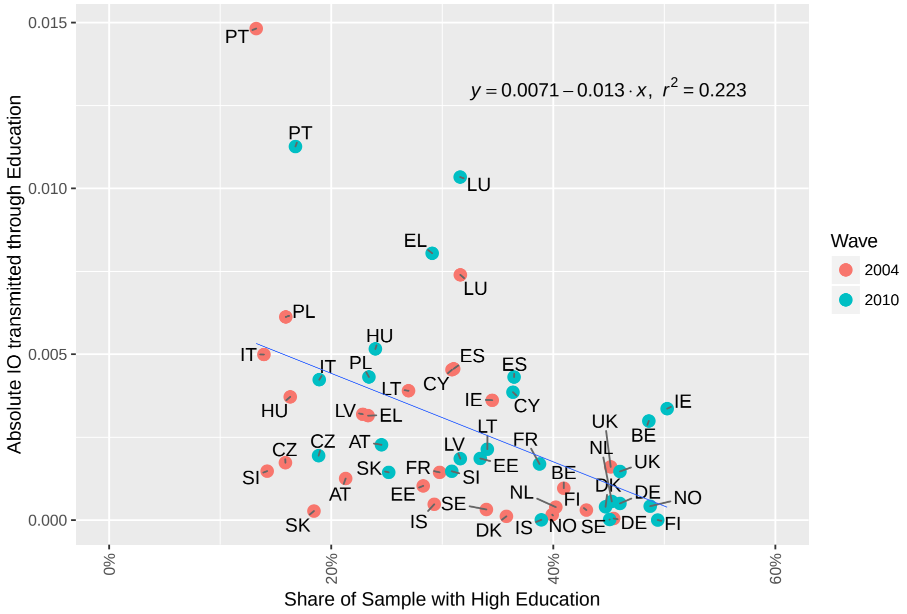

Figure 2.A1: Share of population with high education and level of IO channelled through education.

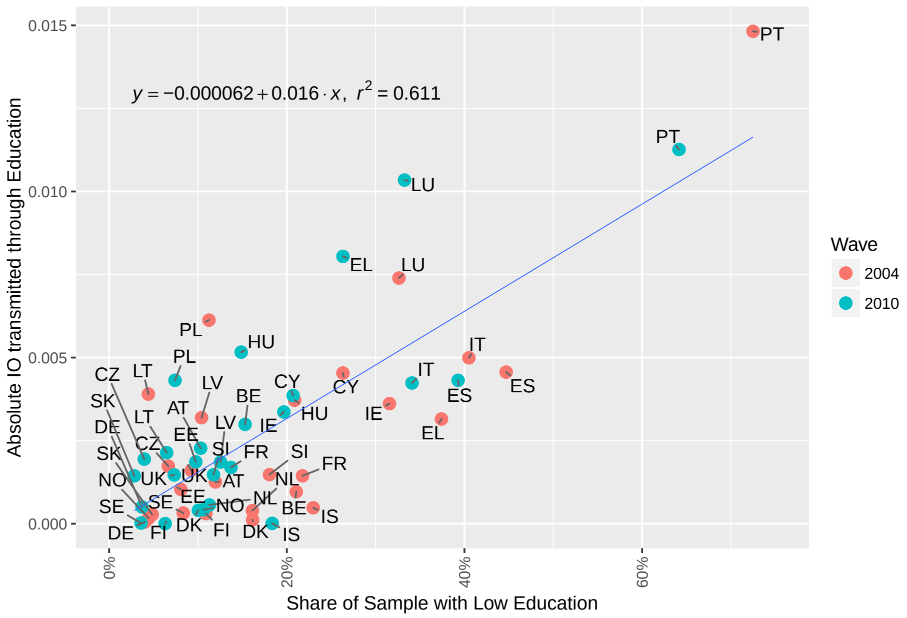

Figure 2.A2: Share of population with low education and level of IO channelled through education.

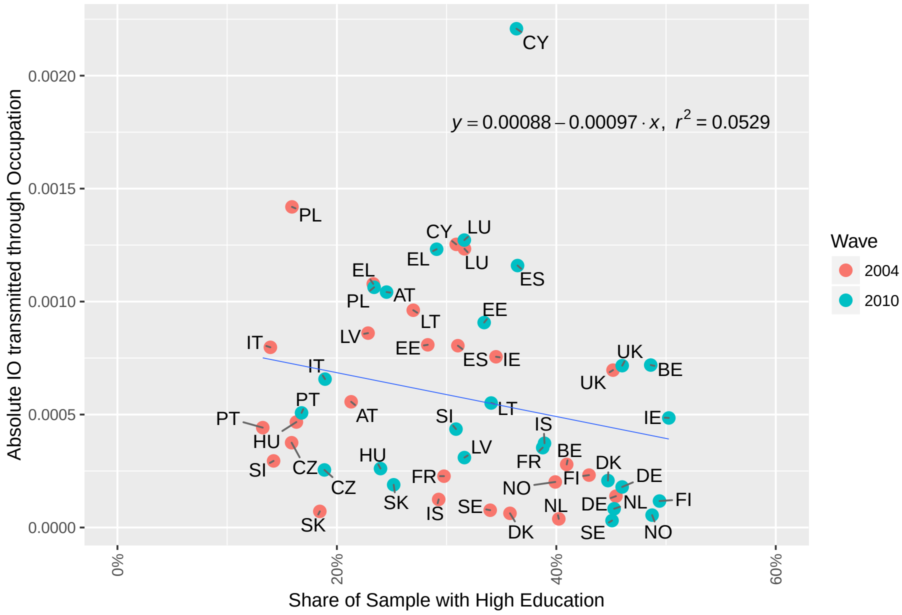

Figure 2.A3: Share of population with high education and level of IO channelled through occupation.

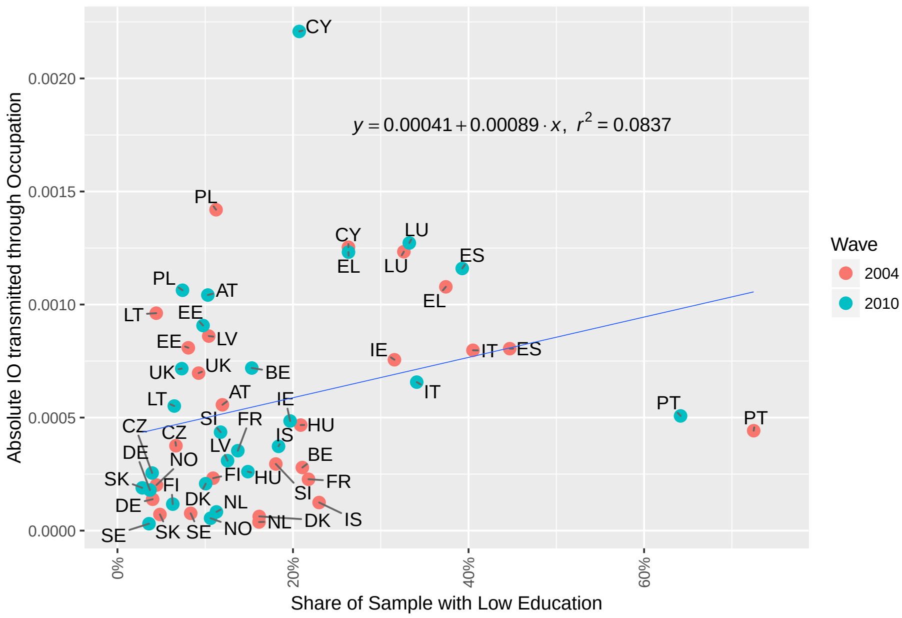

Figure 2.A4: Share of population with low education and level of IO channelled through occupation

Table 2.A1: Descriptive values of variables and shares of each category (in percentage) - 2005

	AT	BE	CY	CZ	DE	DK	EE	EL	ES
Observations	1831	2032	1995	1726	5238	1814	1796	2582	6417
Income Mean	19722.89	19043.57	15323.20	4898.51	20127.62	25831.25	3490.09	11528.29	12746.60
Income Standard Deviation	9287.79	7884.80	7662.01	2299.47	9669.37	7723.85	2132.86	7351.99	7797.20
Father Education Level									
Less than Primary Education (ISCED 0)		13.39	29.22				0.89	26.92	22.83
Low Education (ISCED 1 or 2) (*)	57.56	47.83	48.27	16.74	13.40	39.47	45.66	59.22	62.09
Middle Education (ISCED 3 or 4)	38.67	22.83	15.59	74.57	53.04	43.77	39.20	8.09	5.75
High Education (ISCED 5 or 6)	3.77	15.94	6.92	8.69	33.56	16.76	14.25	5.77	9.33
Mother's Education Level									
Less than Primary Education (ISCED 0)		14.71	38.80				1.34	32.49	26.04
Low Education (ISCED 1 or 2) (*)	74.17	55.22	45.81	35.23	35.59	59.76	45.60	57.71	65.78
Middle Education (ISCED 3 or 4)	23.21	19.93	11.78	60.72	53.13	26.90	37.69	7.01	4.25
High Education (ISCED 5 or 6)	2.62	10.14	3.61	4.06	11.28	13.34	15.37	2.79	3.93
Father Occupational Category									
Managerial	4.26	10.33	0.85	4.46	6.68	8.54	9.35	10.50	6.40
Professional	3.06	9.94	5.11	5.85	14.87	12.13	7.35	4.26	3.85
Technical	11.52	6.15	4.81	15.12	11.42	9.70	4.96	1.98	4.64
Clerical	5.52	9.84	4.16	3.01	7.37	4.91	1.17	5.38	5.33
Sales	10.60	5.36	11.98	3.59	2.98	5.18	1.06	4.26	7.36
Skilled Agricultural (*)	12.89	4.53	18.40	5.74	5.61	13.29	3.23	37.10	15.04
Craft Trade	27.69	23.57	23.86	35.86	30.95	22.71	29.12	17.78	24.40
Machine operation	7.65	7.78	10.88	18.02	10.88	7.99	31.90	7.47	11.10
Elementary	16.49	10.09	19.10	6.78	5.15	12.62	9.91	9.80	19.71
Armed/Military	0.05	2.26	0.35	1.33	1.15	0.83	1.73	1.16	1.85
Unemployed	0.27	10.14	0.50	0.23	2.94	2.09	0.22	0.31	0.31
Economic difficulties in childhood									
Very often		3.84	5.96	4.63		2.54	3.17		8.73
Often		5.91	16.99	9.50		4.80	12.69		9.30
Occasionally		12.84	40.05	28.10		14.83	36.14		20.29
Rarely (*)		11.71	29.87	25.26		18.14	22.49		20.65
Never		65.40	7.12	32.21		59.21	25.50		39.58
Gender									
Woman	38.83	40.40	38.65	41.89	48.42	51.16	47.55	36.64	37.35
Man (*)	61.17	59.60	61.35	58.11	51.58	48.84	52.45	63.36	62.65
Country of birth									
Local (*)	88.09	89.91	85.21	97.10	95.42	97.52	87.92	91.29	94.00
Other EU	2.57	4.92	4.86	1.91		0.72		1.90	1.29
Other	9.28	4.82	9.92	0.98	4.58	1.76	12.08	6.82	4.71
Adult Child Education Level									
Pre-primary (ISCED 0)		0.64	0.50						
Primary (ISCED 1)	0.16	6.94	14.59	0.06	0.40	0.06	0.45	25.41	20.76
Low secondary (ISCED 2)	11.80	13.48	11.23	6.60	3.61	16.10	7.63	12.01	23.94
High Secondary (ISCED 3) (*)	55.54	35.58	40.50	76.01	41.35	48.07	53.51	34.90	22.38
Post Secondary non-tertiary (ISCED 4)	11.20	2.41	2.31	1.45	9.20		10.13	4.38	1.90
Tertiary (ISCED 5 and 6)	21.30	40.94	30.88	15.87	45.44	35.78	28.29	23.32	31.03
Adult Child Occupational Category									
Managerial	5.52	9.65	2.06	6.03	4.26	6.67	12.92	7.67	5.33
Professional	8.25	16.98	13.08	10.25	21.67	17.36	11.75	13.83	12.31
Technical	16.00	12.89	14.84	22.19	28.22	25.63	11.47	8.56	9.88
Clerical	15.02	20.08	11.43	7.82	16.25	10.58	3.62	11.54	10.88
Sales	20.04	9.01	17.14	11.94	8.72	13.23	11.19	13.09	14.54
Skilled Agricultural (*)	2.46	0.98	1.25	2.03	1.34	1.82	3.90	11.15	3.43
Craft Trade	15.95	13.63	16.84	21.90	10.46	11.74	17.37	17.62	17.67
Machine operation	5.63	6.59	6.07	11.18	4.22	5.24	19.04	8.06	8.29
Elementary	10.60	10.19	15.79	6.26	4.60	7.17	8.30	7.51	16.86
Armed/Military	0.55		1.50	0.41	0.27	0.55	0.45	0.97	0.81

Table 2.A1.A Descriptive values of variables and shares of each category (in percentage) - 2005

	FI	FR	HU	IE	IS	IT	LT	LU	LV
Observations	3020	4052	2888	2139	888	10373	2014	1799	1471
Income Mean	21670.10	18471.30	3812.88	23211.82	26021.48	17355.22	2622.03	32487.55	2737.68
Income Standard Deviation	9720.17	8996.01	1824.00	12595.40	9933.90	9183.99	1777.92	16962.61	1926.07
Father Education Level									
Less than Primary Education (ISCED 0)	0.23	5.77	1.18	2.38	2.59	14.16	5.81	6.34	1.50
Low Education (ISCED 1 or 2) (*)	64.93	62.59	45.39	78.78	34.46	70.78	60.72	52.14	52.01
Middle Education (ISCED 3 or 4)	17.98	22.95	45.33	10.38	50.45	11.59	24.53	27.85	33.85
High Education (ISCED 5 or 6)	16.85	8.69	8.10	8.46	12.50	3.47	8.94	13.67	12.64
Mother's Education Level									
Less than Primary Education (ISCED 0)	0.17	6.89	1.56	1.96	2.59	18.47	7.45	8.28	2.24
Low Education (ISCED 1 or 2) (*)	67.68	70.95	60.94	77.09	66.44	71.77	58.39	65.54	48.81
Middle Education (ISCED 3 or 4)	20.53	16.16	33.21	14.03	25.23	8.58	25.77	18.07	37.87
High Education (ISCED 5 or 6)	11.62	6.00	4.29	6.92	5.74	1.18	8.39	8.12	11.08
Father Occupational Category									
Managerial	9.21	7.97	5.47	25.06	19.71	8.51	4.87	8.45	6.12
Professional	5.50	8.93	5.64	8.23	10.70	3.51	7.40	9.78	8.23
Technical	10.43	8.02	5.30	2.95	9.80	7.06	3.28	12.90	5.64
Clerical	1.66	5.26	3.50	5.66	1.58	5.50	2.04	4.78	1.56
Sales	3.68	3.01	3.15	5.28	5.97	4.02	1.74	3.17	2.31
Skilled Agricultural (*)	23.87	12.83	11.70	1.36	19.93	12.42	6.06	11.06	2.45
Craft Trade	19.87	24.43	34.28	18.61	21.51	26.91	26.07	21.85	27.60
Machine operation	15.76	18.51	16.45	10.19	6.19	14.02	23.93	22.40	28.82
Elementary	3.11	7.38	11.39	17.06	3.60	11.96	22.79	4.34	14.28
Armed/Military	0.66	3.41	1.87	1.73	0.11	1.77	0.94	1.06	2.11
Unemployed	6.26	0.25	1.25	3.88	0.90	4.32	0.89	0.22	0.88
Economic difficulties in childhood									
Very often	5.86		10.80	7.90	2.93	14.39	8.39	6.61	5.71
Often	8.38		17.38	8.51	4.17	21.06	17.68	10.56	12.85
Occasionally	25.43		15.51	22.44	14.53	30.36	29.00	19.79	26.78
Rarely (*)	23.08		32.86	23.00	14.41	19.04	18.67	16.23	17.54
Never	35.30		22.75	37.68	63.29	15.15	25.87	45.53	35.83
Gender									
Woman	48.21	42.92	45.64	59.19	49.10	37.48	51.79	37.52	50.44
Man (*)	51.79	57.08	54.36	40.81	50.90	62.52	48.21	62.48	49.56
Country of birth									
Local (*)	98.81	87.88	97.54	87.52	95.27	93.38	93.74	49.31	85.32
Other EU	0.66	3.87	0.35	9.35	2.48	1.37	0.40	42.47	
Other	0.43	8.24	2.11	3.13	2.25	5.13	5.86	8.06	14.68
Adult Child Education Level									
Pre-primary (ISCED 0)		0.89	0.14			0.52			0.14
Primary (ISCED 1)		6.10	0.93	12.25	0.45	7.29	0.15	22.68	7.14
Low secondary (ISCED 2)	10.89	14.78	19.81	19.31	22.52	32.69	4.27	9.95	3.13
High Secondary (ISCED 3) (*)	45.79	48.47	62.81	23.00	38.29	38.42	35.65	33.07	54.11
Post Secondary non-tertiary (ISCED 4)	0.33			10.94	9.46	7.14	32.97	2.67	12.64
Tertiary (ISCED 5 and 6)	42.98	29.76	16.31	34.50	29.28	13.94	26.96	31.63	22.84
Adult Child Occupational Category									
Managerial	15.46	8.12	9.38	16.27	15.32	7.16	8.44	6.61	10.20
Professional	17.28	13.52	9.73	18.61	18.13	8.47	18.02	19.01	11.28
Technical	15.56	18.07	10.84	5.61	17.57	21.10	8.44	21.68	12.85
Clerical	6.52	12.49	8.17	14.31	9.23	11.94	3.87	13.29	5.57
Sales	12.52	10.88	11.95	17.16	12.39	10.52	10.58	9.45	11.76
Skilled Agricultural (*)	10.17	3.80	3.39	0.42	6.53	2.18	6.70	2.83	3.40
Craft Trade	10.50	11.50	22.09	7.95	12.84	17.43	21.55	10.89	16.86
Machine operation	6.36	10.61	11.70	7.15	3.15	10.49	11.42	6.39	14.41
Elementary	4.93	9.58	11.84	12.11	4.84	9.33	10.82	9.56	13.19
Armed/Military	0.70	1.43	0.90	0.42		1.37	0.15	0.28	0.48

Table 2.A1.B Descriptive values of variables and shares of each category (in percentage) - 2005 (cont.)

	NL	NO	PL	PT	SE	SI	SK	UK
Observations	2573	1664	7796	1948	1822	2333	2624	1687
Income Mean	20102.14	30139.73	2958.35	9474.34	20144.79	10138.65	3082.21	26498.48
Income Standard Deviation	8007.64	10598.06	2108.33	6836.42	7452.32	4129.92	1371.77	15915.52
Father Education Level								
Less than Primary Education (ISCED 0)			13.24	35.88	1.32	4.20		49.02
Low Education (ISCED 1 or 2) (*)	62.22	30.11	43.02	58.32	71.19	50.02	34.95	12.45
Middle Education (ISCED 3 or 4)	19.08	46.63	38.85	2.82	12.79	42.26	55.75	23.00
High Education (ISCED 5 or 6)	18.69	23.26	4.89	2.98	14.71	3.51	9.30	15.53
Mother's Education Level								
Less than Primary Education (ISCED 0)			15.06	46.61	2.03	5.87		55.96
Low Education (ISCED 1 or 2) (*)	78.78	36.06	47.88	48.77	73.05	63.14	51.07	17.96
Middle Education (ISCED 3 or 4)	13.99	35.88	33.79	1.59	13.56	29.66	45.08	9.66
High Education (ISCED 5 or 6)	7.23	28.06	3.27	3.03	11.36	1.33	3.85	16.42
Father Occupational Category								
Managerial	22.50	12.02	2.94	6.31	1.32	3.77	7.66	5.93
Professional	10.73	8.65	3.85	2.10	2.69	4.46	6.75	9.90
Technical	13.41	17.97	5.84	3.39	2.74	9.86	9.79	7.47
Clerical	6.30	4.39	2.95	5.60	1.48	4.89	2.90	18.97
Sales	3.93	4.81	2.10	5.95	1.37	5.36	2.82	22.47
Skilled Agricultural (*)	1.98	10.52	27.41	23.82	1.87	15.00	3.16	0.59
Craft Trade	20.44	23.74	27.64	27.36	7.85	27.05	27.06	1.54
Machine operation	9.52	14.60	15.41	11.04	3.29	21.95	21.57	10.20
Elementary	4.12	0.96	9.04	13.04	0.27	6.09	15.59	19.15
Armed/Military	1.48	1.14	1.56	1.33	0.44	0.90		
Unemployed	5.60	1.20	1.26	0.05	1.81	0.69	2.71	3.79
Economic difficulties in childhood								
Very often	2.68	1.74	8.80		3.73	11.96	21.76	7.65
Often	7.00	4.21	15.74		5.87	22.12	27.21	9.25
Occasionally	14.61	11.96	30.52		13.01	32.62	33.08	22.05
Rarely (*)	18.23	26.62	15.03		20.75	17.49	14.25	18.26
Never	54.06	54.21	27.95		54.50	15.52	3.43	36.16
Gender								
Woman	52.74	47.54	45.82	40.61	50.77	51.69	43.75	51.33
Man (*)	47.26	52.46	54.18	59.39	49.23	48.31	56.25	48.67
Country of birth								
Local (*)	95.61	93.99	99.73	97.07	87.16	89.50	98.29	92.59
Other EU	1.32	2.94	0.06	1.28	5.21		1.33	0.47
Other	3.07	2.94	0.21	1.64	7.63	10.50	0.38	6.94
Adult Child Education Level								
Pre-primary (ISCED 0)		0.06	0.36			0.04		
Primary (ISCED 1)	2.10	0.18	10.88	57.29	0.60	15.77		
Low secondary (ISCED 2)	14.03	4.21		15.20	7.74	2.23	4.84	9.25
High Secondary (ISCED 3) (*)	40.26	51.20	69.00	14.12	47.20	60.01	76.71	42.15
Post Secondary non-tertiary (ISCED 4)	3.38	4.45	3.86	0.15	10.48	7.72		3.44
Tertiary (ISCED 5 and 6)	40.23	39.90	15.91	13.24	33.97	14.23	18.45	45.17
Adult Child Occupational Category								
Managerial	11.43	11.30	4.46	6.31	4.67	3.94	7.70	18.08
Professional	23.28	16.29	13.33	7.80	22.61	12.52	13.19	16.00
Technical	23.36	27.76	10.34	9.39	21.41	18.05	17.99	14.64
Clerical	13.99	5.89	6.49	9.86	8.62	10.07	6.67	14.58
Sales	11.08	18.03	10.57	13.14	17.45	11.92	10.82	15.23
Skilled Agricultural (*)	0.93	2.70	11.90	4.88	1.15	2.19	1.33	0.71
Craft Trade	7.35	9.07	21.83	25.62	9.93	13.50	19.70	7.11
Machine operation	4.39	6.01	10.40	9.96	10.70	19.03	14.94	6.82
Elementary	3.85	2.76	9.88	12.06	3.18	8.32	7.66	6.82
Armed/Military	0.35	0.18	0.80	0.98	0.27	0.47		

Table 2.A1.C Descriptive values of variables and shares of each category (in percentage) - 2005 (cont.)

Table 2.A2: Descriptive values of variables and shares of each category (in percentage) - 2011

	AT	BE	CY	CZ	DE	DK	EE	EL	ES
Observations	2699	2078	1878	3011	4374	1313	1876	2059	5975
Income Mean	22212.72	20671.17	17432.12	7464.02	21280.40	29207.95	5004.36	10476.10	12907.89
Income Standard Deviation	10431.38	8922.71	8854.89	3463.65	10381.66	10171.59	2929.11	6059.35	7794.01
Father Education Level									
No Education	0.37	1.92	4.53	0.17	0.25			4.61	3.78
Low Education (ISCED 0,1, or 2) (*)	36.94	49.86	67.09	64.50	8.96	28.41	37.15	72.17	79.46
Middle Education (ISCED 3 or 4)	47.28	25.51	18.85	25.34	59.35	46.46	44.72	14.86	7.15
High Education (ISCED 5 or 6)	15.41	22.71	9.53	10.00	31.44	25.13	18.12	8.35	9.61
Mother's Education Level									
No Education	1.33	3.32	8.25	0.23	0.66		0.05	6.65	5.96
Low Education (ISCED 0,1, or 2) (*)	54.72	55.25	69.44	64.20	23.34	46.69	32.36	74.60	84.27
Middle Education (ISCED 3 or 4)	38.68	24.69	17.25	30.79	63.85	32.98	46.32	14.13	5.31
High Education (ISCED 5 or 6)	5.26	16.75	5.06	4.78	12.14	20.34	21.27	4.61	4.47
Father Occupational Category									
Managerial	4.41	7.36	1.33	3.59	5.42	12.41	7.57	7.63	6.31
Professional	5.63	16.17	6.92	7.21	14.95	14.55	9.38	5.15	5.44
Technical	7.85	11.65	8.20	14.02	17.83	7.69	6.56	2.67	8.57
Clerical	6.52	9.82	3.46	3.85	5.92	4.65	1.39	8.98	5.84
Sales	15.49	5.87	9.64	3.72	6.24	11.73	1.44	4.37	9.24
Skilled Agricultural (*)	13.71	5.39	15.55	3.82	4.55	12.64	4.42	32.10	13.36
Craft Trade	29.08	22.23	25.24	33.64	26.73	28.26	24.52	20.54	19.83
Machine operation	6.74	12.90	12.89	22.62	13.35	5.41	35.18	11.02	12.57
Elementary	7.74	4.19	14.32	4.95	2.99	0.84	6.34	5.10	14.76
Armed/Military	0.93		0.64	1.33			1.01	1.60	1.41
Unemployed	1.89	4.43	1.81	1.26	2.01	1.83	2.19	0.83	2.68
Perceived financial situation in childhood									
Very bad	5.63	2.31	11.08	1.36	2.22	1.68	0.53	4.47	2.68
Bad	9.48	5.58	13.05	4.05	5.62	3.96	3.68	9.96	8.08
Moderate	54.13	40.09	45.85	59.25	49.89	44.33	70.79	60.08	56.64
Good (*)	23.82	42.40	24.81	32.18	33.24	36.02	22.65	19.82	30.33
Very Good	6.93	9.62	5.22	3.16	9.03	14.01	2.35	5.68	2.28
Gender									
Woman	39.87	43.41	46.01	53.70	43.39	51.87	45.52	41.04	41.87
Man (*)	60.13	56.59	53.99	46.30	56.61	48.13	54.48	58.96	58.13
Country of birth									
Local (*)	84.77	84.36	77.58	96.45	94.51	93.91	91.84	89.36	89.81
Other EU	5.34	6.50	9.16	2.62		1.83		2.09	3.05
Other	9.89	9.14	13.26	0.93	5.49	4.27	8.16	8.55	7.15
Adult Child Education Level									
Pre-primary (ISCED 0)	0.33	0.72	0.80					0.58	
Primary (ISCED 1)		3.46	9.80	0.03	0.41	0.15	0.43	13.60	12.05
Low secondary (ISCED 2)	9.97	11.12	10.12	3.92	3.29	9.90	9.33	12.14	27.23
High Secondary (ISCED 3) (*)	53.39	32.82	40.47	75.66	40.05	45.24	53.09	37.74	23.00
Post Secondary non-tertiary (ISCED 4)	11.78	3.27	2.45	1.53	10.24		3.73	6.85	1.26
Tertiary (ISCED 5 and 6)	24.53	48.60	36.37	18.86	46.00	44.71	33.42	29.09	36.47
Adult Child Occupational Category									
Managerial	8.82	9.72	1.81	5.51	6.31	6.55	13.38	7.72	5.91
Professional	14.64	18.19	17.41	10.89	18.91	22.62	14.18	15.15	13.89
Technical	19.12	19.49	12.89	24.54	26.20	35.26	11.51	7.53	9.14
Clerical	11.52	15.11	12.25	9.10	15.89	9.29	5.12	13.50	12.40
Sales	13.56	10.01	14.27	13.25	8.78	3.20	10.50	14.42	15.26
Skilled Agricultural (*)	1.93	0.43	1.65	1.69	1.01	2.06	3.73	10.34	2.64
Craft Trade	12.93	11.12	14.91	16.14	8.44	10.97	16.42	13.40	13.89
Machine operation	6.30	7.51	7.56	12.26	9.79	4.49	17.70	7.19	11.18
Elementary	10.97	8.42	15.44	6.18	4.69	5.41	6.72	8.84	15.00
Armed/Military	0.22		1.81	0.43		0.15	0.75	1.89	0.69

Table 2.A2.A Descriptive values of variables and shares of each category (in percentage) - 2011

	FI	FR	HU	IE	IS	IT	LT	LU	LV
Observations	1174	4061	5059	1576	948	8546	1791	2869	2280
Income Mean	24117.49	20646.93	3868.11	22969.11	13229.31	16942.67	3627.96	31502.75	3565.00
Income Standard Deviation	10775.89	10223.05	2097.67	12756.74	4899.98	9019.30	2233.40	17132.12	2463.83
Father Education Level									
No Education	0.85	3.74	1.96	1.08	0.11	2.20	1.17	4.39	0.18
Low Education (ISCED 0,1, or 2) (*)	49.83	74.74	59.74	55.65	34.07	75.77	59.30	50.12	45.00
Middle Education (ISCED 3 or 4)	28.53	8.99	27.61	29.70	49.79	17.14	29.15	31.40	42.24
High Education (ISCED 5 or 6)	20.78	12.53	10.69	13.58	16.03	4.89	10.39	14.08	12.59
Mother's Education Level									
No Education	1.11	5.74	2.85	1.02	0.11	3.05	1.06	6.94	0.22
Low Education (ISCED 0,1, or 2) (*)	46.17	74.74	61.26	50.44	61.81	79.79	50.59	58.84	37.81
Middle Education (ISCED 3 or 4)	31.94	10.00	29.29	37.06	28.80	14.09	36.68	25.34	47.32
High Education (ISCED 5 or 6)	20.78	9.53	6.60	11.48	9.28	3.07	11.67	8.89	14.65
Father Occupational Category									
Managerial	3.83	9.31	3.68	12.56	12.03	6.38	5.97	7.49	4.08
Professional	12.86	8.42	7.23	10.28	13.71	5.39	8.77	10.18	10.39
Technical	11.24	12.76	5.44	5.33	6.96	9.13	3.41	12.65	5.26
Clerical	1.53	7.83	1.66	2.28	2.00	6.81	1.56	5.26	1.01
Sales	6.56	4.19	5.14	8.06	9.39	7.48	3.07	3.38	2.28
Skilled Agricultural (*)	19.59	9.78	8.08	13.90	18.78	9.17	7.76	10.32	6.62
Craft Trade	16.10	15.81	30.07	16.56	21.94	26.01	26.47	24.75	26.93
Machine operation	16.61	5.86	22.04	6.35	9.60	11.99	21.11	18.89	30.31
Elementary	4.09	21.94	13.03	13.77	4.11	11.60	20.04	3.83	9.34
Armed/Military	1.02	1.40	1.46	2.35	0.11	1.42	0.73	1.12	1.80
Unemployed	6.56	2.71	2.17	8.57	1.37	4.62	1.12	2.13	1.97
Perceived financial situation in childhood									
Very bad	0.85	3.00	2.45	3.68	3.27	2.84	1.17	3.69	1.14
Bad	3.83	6.99	7.14	7.61	5.70	6.17	6.48	7.81	3.46
Moderate	58.09	59.37	66.08	54.44	60.97	67.95	59.24	49.77	60.00
Good (*)	31.60	25.81	21.92	27.47	20.99	20.99	30.04	32.24	29.17
Very Good	5.62	4.83	2.41	6.79	9.07	2.05	3.07	6.48	6.23
Gender									
Woman	45.57	43.98	45.42	57.23	52.64	40.62	54.16	38.90	53.86
Man (*)	54.43	56.02	54.58	42.77	47.36	59.38	45.84	61.10	46.14
Country of birth									
Local (*)	94.04	90.47	98.99	78.93	89.45	90.84	95.25	46.43	90.83
Other EU	2.81	2.86	0.75	14.78	6.43	3.07	0.50	43.26	
Other	3.15	6.67	0.26	6.28	4.11	6.10	4.24	10.32	9.17
Adult Child Education Level									
Pre-primary (ISCED 0)		0.34				0.25	0.06		0.04
Primary (ISCED 1)		5.20	1.64	5.71	0.21	2.80	0.67	23.18	0.31
Low secondary (ISCED 2)	6.30	8.18	13.22	13.96	18.14	31.06	5.75	10.07	12.19
High Secondary (ISCED 3) (*)	43.02	47.11	56.63	21.32	32.38	43.27	32.27	33.11	48.68
Post Secondary non-tertiary (ISCED 4)	1.28	0.42	4.53	8.76	10.34	3.71	27.19	2.02	7.15
Tertiary (ISCED 5 and 6)	49.40	38.76	23.98	50.25	38.92	18.92	34.06	31.61	31.62
Adult Child Occupational Category									
Managerial	10.48	8.52	4.57	8.25	11.71	8.51	9.83	6.45	8.51
Professional	21.12	15.74	15.04	19.29	30.17	12.46	19.21	19.10	18.99
Technical	16.01	19.50	11.80	12.69	12.13	16.62	9.32	19.21	12.46
Clerical	4.94	10.79	7.47	13.26	6.43	14.15	4.80	10.81	6.14
Sales	16.87	10.32	11.33	12.25	17.19	10.81	11.95	9.79	12.54
Skilled Agricultural (*)	8.94	3.13	2.63	7.93	5.17	1.95	4.91	2.89	2.63
Craft Trade	10.39	10.88	18.13	8.12	8.33	15.45	16.47	13.07	13.73
Machine operation	7.33	9.63	13.72	7.49	2.64	8.54	12.34	6.76	10.66
Elementary	3.49	10.22	14.09	10.72	6.22	10.20	10.94	11.85	14.21
Armed/Military	0.43	1.28	1.23			1.31	0.22	0.07	0.13

Table 2.A2.B Descriptive values of variables and shares of each category (in percentage) - 2011 (cont.)

	NL	NO	PL	PT	SE	SI	SK	UK
Observations	2980	1574	5288	2229	1280	2758	2546	2565
Income Mean	23565.42	36954.13	4854.86	9320.42	22766.68	11709.01	6225.33	19194.33
Income Standard Deviation	9717.66	13440.66	2886.16	5910.61	8205.95	4786.54	2661.38	11564.46
Father Education Level								
No Education	0.34	0.38	0.28	18.21		0.11	0.04	2.53
Low Education (ISCED 0,1, or 2) (*)	39.60	26.37	43.44	75.41	39.69	69.00	31.46	52.32
Middle Education (ISCED 3 or 4)	35.03	39.83	49.30	2.87	39.77	19.98	58.72	27.10
High Education (ISCED 5 or 6)	25.03	33.42	6.98	3.50	20.55	10.91	9.78	18.05
Mother's Education Level								
No Education	0.37	0.95	0.28	25.39		0.18	0.04	3.24
Low Education (ISCED 0,1, or 2) (*)	51.21	28.08	48.07	68.60	34.30	73.24	38.88	68.85
Middle Education (ISCED 3 or 4)	36.98	47.52	45.73	2.38	39.69	18.75	55.89	12.20
High Education (ISCED 5 or 6)	11.44	23.44	5.92	3.63	26.02	7.83	5.18	15.71
Father Occupational Category								
Managerial	10.67	12.77	3.97	5.29	1.02	2.90	4.87	10.88
Professional	15.77	13.47	4.61	3.59	3.98	7.29	7.46	16.34
Technical	17.85	18.93	5.88	6.10	1.80	12.11	10.64	9.20
Clerical	5.50	3.18	2.31	3.95	0.70	4.31	3.06	3.63
Sales	6.88	5.46	4.27	10.09	2.34	5.69	4.05	7.21
Skilled Agricultural (*)	8.09	9.02	23.52	19.43	1.88	7.32	2.16	3.00
Craft Trade	20.47	21.73	26.76	27.82	6.25	27.92	33.62	23.39
Machine operation	6.64	9.40	18.06	12.52	3.20	9.86	22.90	12.71
Elementary	2.65	2.54	7.68	8.39	0.47	17.40	9.15	6.98
Armed/Military	1.71	2.03	1.02		0.23	0.40	0.90	1.48
Unemployed	3.76	1.46	1.91	2.83	1.17	4.79	1.18	5.19
Perceived financiancial situation in childhood								
Very bad	0.81	0.76	1.55	9.11	2.27	5.33	1.45	3.12
Bad	2.95	3.05	6.86	15.16	5.16	10.88	4.60	5.65
Moderate	36.48	44.03	56.30	60.30	37.42	65.95	56.60	55.95
Good (*)	50.07	44.22	32.15	14.36	42.34	13.56	32.52	28.50
Very good	9.70	7.94	3.14	1.08	12.81	4.28	4.83	6.78
Gender								
Woman	52.48	46.12	46.41	46.43	51.33	53.44	46.86	49.51
Man (*)	47.52	53.88	53.59	53.57	48.67	46.56	53.14	50.49
Country of birth								
Local (*)	94.90	92.38	99.91	91.34	94.30	89.45	98.94	88.15
Other EU	1.44	3.49	0.02	2.33	2.34		0.94	3.16
Other	3.66	4.13	0.08	6.33	3.36	10.55	0.12	8.69
Adult Child Education Level								
Pre-primary (ISCED 0)	0.17	0.06	0.09					
Primary (ISCED 1)	0.91	0.13	7.32	42.17		0.98		
Low secondary (ISCED 2)	10.20	10.42		21.98	3.59	10.77	2.83	7.33
High Secondary (ISCED 3) (*)	40.20	36.91	64.58	18.71	43.05	57.40	69.76	46.51
Post Secondary non-tertiary (ISCED 4)	3.26	3.75	4.61	0.36	8.28		2.24	0.16
Tertiary (ISCED 5 and 6)	45.27	48.73	23.39	16.78	45.08	30.86	25.18	46.00
Adult Child Occupational Category								
Managerial	11.71	10.67	5.77	5.16	6.88	4.86	6.36	19.42
Professional	27.89	18.93	15.20	10.54	26.33	18.89	12.18	15.98
Technical	24.03	30.94	11.04	10.36	25.16	19.83	23.02	15.05
Clerical	11.74	6.29	5.64	9.02	5.16	9.43	8.44	10.99
Sales	9.66	14.99	11.59	16.20	15.47	12.87	13.75	14.74
Skilled Agricultural (*)	0.94	1.97	10.61	4.76	1.48	1.63	0.82	0.78
Craft Trade	6.41	9.21	18.87	19.11	8.91	10.91	16.38	7.41
Machine operation	4.03	4.89	11.63	10.23	8.05	11.97	12.88	5.69
Elementary	3.36	2.03	9.02	14.40	2.03	8.56	5.50	9.94
Armed/Military	0.23	0.06	0.62	0.22	0.55	1.05	0.67	

Table 2.A2.C Descriptive values of variables and shares of each category (in percentage) - 2011 (cont.)

Table 2.A3: Regression coefficients of circumstances on income. The omitted categories are Low Level Education, Skilled Agricultural occupation, Difficulties Rarely, Local Citizen and Man.

	AT		BE		CY		CZ		DE		DK	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	9.783***	9.862***	9.748***	9.795***	9.589***	9.670***	8.303***	8.787***	9.737***	9.831***	10.035***	10.057***
	(0.038)	(0.031)	(0.054)	(0.046)	(0.033)	(0.040)	(0.054)	(0.046)	(0.032)	(0.050)	(0.030)	(0.037)
No Education (F)		-0.016	-0.023	0.026	-0.031	-0.017		0.154		-0.022		
		(0.119)	(0.047)	(0.102)	(0.029)	(0.063)		(0.211)		(0.177)		
Medium Level Education (F)	0.004	-0.025	0.013	0.045*	0.108***	0.017	0.126***	0.091***	0.044**	0.059*	-0.021	0.030
	(0.040)	(0.023)	(0.027)	(0.027)	(0.036)	(0.035)	(0.037)	(0.026)	(0.022)	(0.033)	(0.024)	(0.027)
High Level Education (F)	0.306**	0.055	0.007	0.140***	0.147**	0.026	0.190***	0.087**	-0.001	0.130***	-0.018	-0.007
	(0.156)	(0.034)	(0.040)	(0.039)	(0.065)	(0.058)	(0.065)	(0.044)	(0.026)	(0.037)	(0.038)	(0.040)
No Education (M)		0.000	-0.053	-0.121	-0.051*	-0.165***		-0.648***		-0.040		
		(0.073)	(0.046)	(0.082)	(0.027)	(0.048)		(0.162)		(0.107)		
Medium Level Education (M)	0.125***	0.087***	0.032	0.084***	0.108***	0.067*	0.053**	0.104***	0.018	0.033	0.019	0.084***
	(0.032)	(0.021)	(0.028)	(0.026)	(0.038)	(0.035)	(0.027)	(0.020)	(0.015)	(0.022)	(0.020)	(0.026)
High Level Education (M)	0.101	0.144***	0.067*	0.095***	0.186***	0.137**	0.083	0.258***	-0.002	0.038	0.037	-0.009
	(0.075)	(0.047)	(0.039)	(0.034)	(0.063)	(0.058)	(0.064)	(0.043)	(0.024)	(0.032)	(0.029)	(0.032)
Managerial (F)	0.018	0.142***	0.087	0.048	0.080	0.523***	0.046	0.063	0.116***	0.017	0.062	0.163***
	(0.079)	(0.049)	(0.058)	(0.060)	(0.112)	(0.101)	(0.074)	(0.065)	(0.039)	(0.055)	(0.041)	(0.045)
Professional (F)	-0.312*	0.059	0.064	0.077	0.134*	0.328***	0.038	0.094	0.088**	-0.025	0.060	0.231***
	(0.173)	(0.052)	(0.061)	(0.058)	(0.069)	(0.067)	(0.075)	(0.060)	(0.035)	(0.049)	(0.047)	(0.050)
Technical (F)	0.126**	0.130***	0.021	0.134**	0.143***	0.180***	0.039	0.048	0.066*	-0.050	0.076*	0.173***
	(0.061)	(0.042)	(0.062)	(0.055)	(0.055)	(0.053)	(0.056)	(0.051)	(0.035)	(0.046)	(0.040)	(0.050)
Clerical (F)	0.098	0.164***	0.111*	0.139**	0.216***	0.150**	0.209**	0.024	0.066*	0.025	0.069	0.286***
	(0.073)	(0.044)	(0.057)	(0.056)	(0.058)	(0.068)	(0.082)	(0.063)	(0.037)	(0.054)	(0.045)	(0.061)
Sales (F)	-0.015	0.084**	0.039	0.011	0.022	0.153***	-0.077	-0.039	0.107**	-0.028	0.037	0.088**
	(0.053)	(0.034)	(0.063)	(0.061)	(0.039)	(0.048)	(0.074)	(0.061)	(0.048)	(0.053)	(0.045)	(0.045)
Craft Trade (F)	-0.017	0.021	-0.016	0.086*	0.077**	0.064*	-0.050	0.005	0.015	-0.117***	0.019	0.080**
	(0.046)	(0.030)	(0.050)	(0.049)	(0.032)	(0.038)	(0.050)	(0.045)	(0.031)	(0.044)	(0.034)	(0.035)
Machine opperation (F)	-0.009	0.015	-0.001	0.023	0.015	0.078*	-0.084	-0.052	0.011	-0.135***	-0.049	0.047
	(0.059)	(0.041)	(0.057)	(0.052)	(0.039)	(0.044)	(0.052)	(0.046)	(0.034)	(0.047)	(0.037)	(0.051)
Elementary Occ. (F)	-0.064	-0.035	-0.004	0.050	0.019	-0.061	-0.229***	-0.113**	0.086**	-0.054	-0.024	0.412***
	(0.049)	(0.039)	(0.055)	(0.063)	(0.033)	(0.042)	(0.063)	(0.057)	(0.040)	(0.062)	(0.033)	(0.135)
Armed/Military (F)	0.285	-0.044	0.086	-0.001	-0.079	0.035	0.003	-0.039	0.149**		0.103	
	(0.641)	(0.086)	(0.080)	(0.064)	(0.157)	(0.157)	(0.111)	(0.083)	(0.068)		(0.092)	
Unemployed (F)	-0.399*	-0.037	-0.056		0.031	0.099	-0.195	0.070	-0.050	-0.073	-0.149**	-0.034
	(0.227)	(0.062)	(0.056)		(0.142)	(0.085)	(0.220)	(0.088)	(0.046)	(0.072)	(0.058)	(0.076)
Difficulties most of the time		-0.059	-0.155***	-0.128*	-0.236***	-0.151***	-0.103*	-0.013		-0.089	-0.113**	-0.043
		(0.040)	(0.057)	(0.073)	(0.047)	(0.042)	(0.057)	(0.074)		(0.058)	(0.051)	(0.091)
Difficulties often		-0.046	-0.051	-0.190***	-0.188***	-0.160***	-0.030	-0.155***		-0.020	-0.079*	-0.130**
		(0.033)	(0.048)	(0.046)	(0.031)	(0.040)	(0.043)	(0.044)		(0.039)	(0.044)	(0.054)
Difficulties occasionally		0.030	0.002	-0.051**	-0.058**	-0.041	0.010	-0.002		0.046**	0.005	-0.029
		(0.022)	(0.038)	(0.022)	(0.024)	(0.028)	(0.031)	(0.018)		(0.019)	(0.029)	(0.024)
Difficulties never		0.007	0.074**	-0.053	0.061	-0.048	0.057*	-0.014		-0.064**	0.002	-0.043
		(0.037)	(0.030)	(0.036)	(0.041)	(0.050)	(0.030)	(0.048)		(0.031)	(0.022)	(0.033)
Other European Union	0.061	-0.219***	0.040	0.007	-0.085*	-0.191***	0.105	-0.022			0.103	-0.177**
	(0.078)	(0.036)	(0.045)	(0.040)	(0.045)	(0.037)	(0.080)	(0.052)			(0.100)	(0.075)
Other outside EU	-0.280***	-0.338***	-0.334***	-0.518***	-0.410***	-0.461***	-0.319***	-0.001	-0.140***	-0.174***	-0.165***	-0.150***
	(0.041)	(0.028)	(0.048)	(0.037)	(0.034)	(0.037)	(0.096)	(0.075)	(0.031)	(0.038)	(0.058)	(0.052)
Woman	-0.007	-0.026	-0.063***	-0.060***	-0.022	0.014	-0.096***	-0.062***	-0.090***	-0.107***	-0.004	-0.055***
	(0.026)	(0.018)	(0.020)	(0.020)	(0.021)	(0.023)	(0.023)	(0.017)	(0.013)	(0.017)	(0.017)	(0.021)
R-Squared	0.065	0.125	0.093	0.180	0.194	0.200	0.100	0.095	0.024	0.039	0.035	0.083

Table 2.A3 A

	EE		EL		ES		FI		FR		HU	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	7.771***	8.279***	9.146***	9.072***	9.220***	9.224***	9.784***	9.891***	9.660***	9.778***	7.958***	7.984***
	(0.105)	(0.090)	(0.027)	(0.044)	(0.029)	(0.033)	(0.024)	(0.043)	(0.021)	(0.028)	(0.031)	(0.028)
No Education (F)	-0.189		-0.118***	0.109	-0.087***	-0.111*	-0.251	-0.026	-0.075**	-0.098**	0.004	-0.046
	(0.174)		(0.038)	(0.093)	(0.027)	(0.060)	(0.237)	(0.166)	(0.037)	(0.045)	(0.103)	(0.053)
Medium Level Education (F)	0.084**	0.047	0.112**	0.151***	0.069*	0.084**	0.009	0.038	0.057***	0.049*	0.108***	0.027
	(0.038)	(0.040)	(0.051)	(0.044)	(0.038)	(0.039)	(0.021)	(0.033)	(0.018)	(0.027)	(0.024)	(0.018)
High Level Education (F)	0.145**	0.067	0.116	0.128*	0.149***	0.134***	0.080***	0.005	0.076**	0.115***	0.171***	0.178***
	(0.064)	(0.060)	(0.079)	(0.065)	(0.039)	(0.045)	(0.030)	(0.046)	(0.035)	(0.030)	(0.055)	(0.037)
No Education (M)	0.018	-1.421	-0.054	-0.170**	-0.147***	-0.109**	-0.433*	0.020	-0.108***	-0.056	-0.526***	-0.134***
	(0.141)	(1.270)	(0.035)	(0.077)	(0.026)	(0.050)	(0.227)	(0.138)	(0.037)	(0.039)	(0.086)	(0.045)
Medium Level Education (M)	0.113***	0.124***	0.142***	0.130***	0.118***	0.080*	0.037*	0.016	0.085***	0.055**	0.070***	0.159***
	(0.037)	(0.040)	(0.054)	(0.046)	(0.041)	(0.044)	(0.020)	(0.031)	(0.021)	(0.026)	(0.023)	(0.017)
High Level Education (M)	0.211***	0.241***	0.307***	0.212***	0.118***	0.207***	0.105***	0.029	0.046	0.003	0.216***	0.229***
	(0.050)	(0.051)	(0.082)	(0.072)	(0.045)	(0.048)	(0.027)	(0.040)	(0.035)	(0.029)	(0.050)	(0.032)
Managerial (F)	0.330***	0.265***	0.232***	0.161***	0.177***	0.084*	0.070*	0.090	0.177***	0.162***	0.235***	0.262***
	(0.113)	(0.099)	(0.043)	(0.058)	(0.042)	(0.048)	(0.036)	(0.069)	(0.033)	(0.034)	(0.053)	(0.045)
Professional (F)	0.296**	0.244**	-0.013	0.328***	0.202***	0.303***	0.153***	0.067	0.166***	0.149***	0.123*	0.255***
	(0.118)	(0.098)	(0.084)	(0.078)	(0.057)	(0.060)	(0.042)	(0.058)	(0.037)	(0.041)	(0.065)	(0.045)
Technical (F)	0.342***	0.126	0.326***	0.082	0.319***	0.212***	0.069**	0.113**	0.161***	0.140***	0.228***	0.219***
	(0.121)	(0.099)	(0.080)	(0.081)	(0.044)	(0.042)	(0.031)	(0.055)	(0.033)	(0.032)	(0.049)	(0.038)
Clerical (F)	0.340*	0.137	0.241***	0.185***	0.301***	0.208***	0.059	0.195*	0.114***	0.106***	0.242***	0.193***
	(0.174)	(0.140)	(0.057)	(0.054)	(0.043)	(0.047)	(0.054)	(0.107)	(0.037)	(0.035)	(0.055)	(0.058)
Sales (F)	0.191	0.189	0.051	0.243***	0.172***	0.133***	0.054	0.037	-0.007	0.029	0.150**	0.152***
	(0.172)	(0.141)	(0.060)	(0.068)	(0.037)	(0.041)	(0.043)	(0.063)	(0.045)	(0.042)	(0.059)	(0.036)
Craft Trade (F)	0.221**	0.110	0.114***	0.110***	0.136***	0.113***	0.040*	0.104**	0.051**	0.027	0.081**	0.159***
	(0.103)	(0.086)	(0.035)	(0.040)	(0.028)	(0.034)	(0.024)	(0.047)	(0.024)	(0.030)	(0.033)	(0.026)
Machine opperation (F)	0.196*	0.088	0.086*	0.041	0.198***	0.166***	0.050*	0.100**	0.006	0.007	0.109***	0.104***
	(0.103)	(0.085)	(0.048)	(0.049)	(0.033)	(0.037)	(0.026)	(0.047)	(0.025)	(0.038)	(0.034)	(0.027)
Elementary Occ. (F)	0.188*	-0.273***	0.059	-0.075	0.031	-0.018	0.044	-0.003	-0.044	-0.059**	0.023	-0.009
	(0.112)	(0.106)	(0.045)	(0.065)	(0.029)	(0.037)	(0.045)	(0.068)	(0.032)	(0.028)	(0.038)	(0.030)
Armed/Military (F)	0.034	-0.097	0.109	0.031	0.226***	0.347***	0.274***	0.267**	0.172***	0.223***	0.073	0.166***
	(0.149)	(0.147)	(0.115)	(0.104)	(0.066)	(0.089)	(0.083)	(0.130)	(0.044)	(0.066)	(0.072)	(0.060)
Unemployed (F)	-0.093	-0.294**	0.046	-0.046	0.317***	0.122**	-0.042	0.137**	0.176	-0.049	0.246***	0.117**
	(0.478)	(0.134)	(0.211)	(0.158)	(0.122)	(0.060)	(0.033)	(0.060)	(0.133)	(0.049)	(0.082)	(0.049)
Difficulties most of the time	-0.252**	0.237		-0.288***	0.008	-0.215***	0.015	0.120		0.009	-0.092***	-0.289***
	(0.100)	(0.197)		(0.075)	(0.033)	(0.062)	(0.036)	(0.144)		(0.046)	(0.032)	(0.044)
Difficulties often	-0.112**	-0.253***		-0.118**	0.003	-0.192***	-0.024	0.088		-0.022	-0.068**	-0.144***
	(0.055)	(0.082)		(0.057)	(0.032)	(0.038)	(0.030)	(0.075)		(0.032)	(0.027)	(0.029)
Difficulties occasionally	0.021	-0.087**		-0.081**	-0.040	-0.020	0.012	0.016		0.038**	-0.059**	-0.019
	(0.040)	(0.035)		(0.035)	(0.025)	(0.022)	(0.022)	(0.029)		(0.017)	(0.027)	(0.016)
Difficulties never	-0.015	0.252**		-0.016	0.066***	-0.009	-0.006	0.127**		0.009	-0.003	-0.119***
	(0.042)	(0.105)		(0.060)	(0.022)	(0.066)	(0.020)	(0.058)		(0.036)	(0.024)	(0.043)
Other European Union			0.031	0.021	-0.118*	-0.332***	-0.078	-0.031	-0.044	0.055	0.062	0.310***
			(0.086)	(0.088)	(0.064)	(0.044)	(0.091)	(0.080)	(0.035)	(0.042)	(0.135)	(0.073)
Other outside EU	-0.026	-0.167***	-0.462***	-0.455***	-0.342***	-0.435***	-0.184	-0.260***	-0.219***	-0.313***	-0.029	-0.578***
	(0.042)	(0.051)	(0.047)	(0.049)	(0.038)	(0.030)	(0.112)	(0.076)	(0.029)	(0.031)	(0.059)	(0.129)
Woman	-0.153***	-0.088***	0.046*	0.015	-0.041**	-0.006	-0.007	-0.048*	-0.024*	-0.069***	0.043**	-0.023*
	(0.030)	(0.030)	(0.025)	(0.028)	(0.017)	(0.019)	(0.015)	(0.026)	(0.014)	(0.014)	(0.018)	(0.013)
R-Squared	0.082	0.105	0.109	0.158	0.098	0.096	0.048	0.035	0.094	0.108	0.127	0.169

Table 2.A3.B

	IE		IS		IT		LT		LU		LV	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	9.853***	9.951***	9.925***	9.420***	9.647***	9.444***	7.496***	7.925***	10.314***	10.260***	7.560***	7.583***
	(0.094)	(0.048)	(0.055)	(0.074)	(0.021)	(0.029)	(0.074)	(0.071)	(0.041)	(0.032)	(0.115)	(0.070)
No Education (F)	-0.208*	-0.144	-0.092	-0.418	-0.161***	-0.158***	-0.159**	0.009	-0.134**	-0.162***	-0.157	0.488
	(0.108)	(0.167)	(0.100)	(0.413)	(0.019)	(0.049)	(0.077)	(0.176)	(0.060)	(0.051)	(0.172)	(0.583)
Medium Level Education (F)	0.095**	0.062*	0.020	0.128**	0.139***	0.137***	0.077*	0.101**	0.177***	0.118***	0.142***	0.167***
	(0.043)	(0.036)	(0.041)	(0.052)	(0.020)	(0.023)	(0.046)	(0.048)	(0.028)	(0.023)	(0.049)	(0.040)
High Level Education (F)	0.043	-0.007	0.137*	0.150*	0.200***	0.122**	0.400***	0.090	0.265***	0.216***	0.119	0.171**
	(0.060)	(0.058)	(0.070)	(0.086)	(0.039)	(0.048)	(0.085)	(0.088)	(0.055)	(0.039)	(0.092)	(0.070)
No Education (M)	0.119	-0.202	-0.012	-2.134***	-0.160***	-0.210***	-0.158**	-0.023	-0.119**	-0.011	-0.354**	-0.285
	(0.122)	(0.166)	(0.104)	(0.424)	(0.017)	(0.043)	(0.069)	(0.159)	(0.050)	(0.039)	(0.141)	(0.535)
Medium Level Education (M)	0.171***	-0.005	0.045	-0.178***	0.078***	0.149***	0.138***	0.003	0.068**	0.093***	0.194***	0.096**
	(0.040)	(0.033)	(0.038)	(0.047)	(0.023)	(0.024)	(0.045)	(0.046)	(0.031)	(0.023)	(0.046)	(0.039)
High Level Education (M)	0.165***	0.079	-0.079	-0.017	0.193***	0.251***	0.230***	0.205***	0.125**	0.163***	0.364***	0.294***
	(0.055)	(0.053)	(0.068)	(0.077)	(0.054)	(0.049)	(0.073)	(0.074)	(0.051)	(0.038)	(0.074)	(0.057)
Managerial (F)	0.109	0.272***	0.099*	-0.108	0.120***	0.158***	0.191*	0.157	0.011	0.202***	0.128	0.356***
	(0.094)	(0.056)	(0.053)	(0.079)	(0.026)	(0.039)	(0.105)	(0.104)	(0.051)	(0.043)	(0.133)	(0.103)
Professional (F)	0.227**	0.295***	0.149**	-0.175*	0.031	0.206***	0.126	0.157	-0.020	0.267***	0.196	0.298***
	(0.105)	(0.066)	(0.075)	(0.095)	(0.041)	(0.047)	(0.095)	(0.099)	(0.066)	(0.045)	(0.140)	(0.089)
Technical (F)	0.198*	0.120*	0.077	-0.116	0.120***	0.194***	0.262**	0.257**	0.060	0.165***	0.199	0.180*
	(0.114)	(0.070)	(0.064)	(0.095)	(0.028)	(0.035)	(0.109)	(0.115)	(0.045)	(0.038)	(0.131)	(0.094)
Clerical (F)	0.142	0.058	-0.330***	-0.044	0.106***	0.177***	0.441***	0.294**	0.100*	0.159***	0.124	0.251
	(0.103)	(0.098)	(0.122)	(0.151)	(0.029)	(0.037)	(0.130)	(0.139)	(0.058)	(0.046)	(0.189)	(0.169)
Sales (F)	0.112	-0.052	0.134*	-0.071	0.006	0.044	0.522***	0.020	-0.075	-0.088*	0.117	0.015
	(0.104)	(0.060)	(0.078)	(0.084)	(0.032)	(0.035)	(0.128)	(0.122)	(0.063)	(0.049)	(0.162)	(0.121)
Craft Trade (F)	0.123	-0.058	0.052	-0.047	0.043**	0.076***	0.163**	0.060	-0.063	0.027	0.028	0.210***
	(0.095)	(0.050)	(0.053)	(0.068)	(0.019)	(0.027)	(0.073)	(0.070)	(0.039)	(0.031)	(0.109)	(0.069)
Machine opperation (F)	0.131	-0.155**	0.002	0.042	0.073***	0.068**	0.088	-0.026	-0.041	0.002	0.087	0.180***
	(0.098)	(0.063)	(0.069)	(0.084)	(0.022)	(0.031)	(0.072)	(0.071)	(0.038)	(0.033)	(0.109)	(0.068)
Elementary Occ. (F)	-0.005	-0.203***	0.098	-0.180	-0.088***	-0.048	0.127*	0.045	0.008	-0.028	0.019	0.127
	(0.095)	(0.052)	(0.087)	(0.110)	(0.022)	(0.031)	(0.073)	(0.073)	(0.062)	(0.048)	(0.116)	(0.080)
Armed/Military (F)	0.092	-0.086	-0.400	-0.485	0.240***	0.201***	0.091	-0.426*	0.149	0.095	0.360**	0.086
	(0.126)	(0.098)	(0.499)	(0.428)	(0.045)	(0.062)	(0.186)	(0.240)	(0.125)	(0.081)	(0.170)	(0.133)
Unemployed (F)	0.032	-0.274***	0.146	0.057	0.025	-0.081**	0.259	0.274	0.038	0.017	0.049	0.011
	(0.106)	(0.061)	(0.175)	(0.189)	(0.029)	(0.039)	(0.167)	(0.202)	(0.272)	(0.069)	(0.226)	(0.129)
Difficulties most of the time	-0.147***	-0.137*	0.063	-0.106	-0.163***	-0.094**	-0.173***	-1.167***	-0.216***	-0.073	-0.130	0.357**
	(0.046)	(0.080)	(0.102)	(0.122)	(0.020)	(0.044)	(0.066)	(0.142)	(0.053)	(0.052)	(0.089)	(0.146)
Difficulties often	-0.139***	0.048	-0.014	-0.156	-0.106***	-0.078**	-0.088*	-0.091	-0.029	-0.116***	-0.001	0.021
	(0.046)	(0.058)	(0.086)	(0.099)	(0.018)	(0.032)	(0.053)	(0.075)	(0.041)	(0.036)	(0.066)	(0.087)
Difficulties occasionally	-0.008	0.028	0.043	-0.057	-0.074***	0.012	-0.053	-0.050	-0.018	-0.037*	-0.027	0.064*
	(0.033)	(0.033)	(0.057)	(0.053)	(0.016)	(0.018)	(0.046)	(0.039)	(0.034)	(0.019)	(0.055)	(0.036)
Difficulties never	0.092***	0.016	0.073	-0.387***	0.044**	-0.195***	-0.034	-0.040	0.078***	-0.095**	-0.026	-0.081
	(0.029)	(0.057)	(0.046)	(0.081)	(0.019)	(0.052)	(0.046)	(0.105)	(0.029)	(0.037)	(0.052)	(0.067)
Other European Union	-0.087**	-0.119***	-0.204**	-0.002	-0.104**	-0.213***	0.057	0.225	-0.112***	-0.168***		
	(0.037)	(0.040)	(0.093)	(0.080)	(0.052)	(0.034)	(0.275)	(0.347)	(0.025)	(0.019)		
Other outside EU	-0.081	-0.160***	-0.052	0.105	-0.235***	-0.224***	-0.010	-0.098	-0.390***	-0.380***	0.003	-0.090
	(0.065)	(0.055)	(0.105)	(0.109)	(0.021)	(0.026)	(0.067)	(0.083)	(0.044)	(0.029)	(0.053)	(0.055)
Woman	-0.147***	-0.071**	0.001	0.063	0.036***	0.013	-0.035	-0.076**	-0.132***	-0.090***	-0.117***	-0.029
	(0.023)	(0.028)	(0.032)	(0.041)	(0.012)	(0.015)	(0.031)	(0.035)	(0.023)	(0.017)	(0.036)	(0.031)
R-Squared	0.127	0.136	0.057	0.078	0.138	0.091	0.117	0.082	0.233	0.256	0.112	0.071

Table 2.A3.C

	NE		NO		PL		PT		SE		SI	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	9.645***	9.821***	10.231***	10.392***	7.591***	8.118***	8.892***	9.013***	9.807***	9.945***	9.053***	9.071***
	(0.071)	(0.032)	(0.034)	(0.038)	(0.027)	(0.024)	(0.039)	(0.046)	(0.020)	(0.030)	(0.033)	(0.042)
No Education (F)		-0.088		-0.060	-0.046	0.107	-0.162***	-0.103***	0.058		-0.062	-0.132
		(0.115)		(0.197)	(0.042)	(0.295)	(0.037)	(0.039)	(0.126)		(0.056)	(0.413)
Medium Level Education (F)	0.056**	0.028	0.027	-0.033	0.044*	0.058**	0.194**	0.109	0.078***	0.040	0.092***	0.014
	(0.025)	(0.021)	(0.021)	(0.027)	(0.026)	(0.025)	(0.096)	(0.073)	(0.028)	(0.028)	(0.023)	(0.026)
High Level Education (F)	0.078**	-0.001	0.096***	0.026	0.105*	0.109**	0.178	0.335***	0.116***	0.043	0.146**	-0.067
	(0.031)	(0.027)	(0.031)	(0.035)	(0.059)	(0.047)	(0.133)	(0.087)	(0.029)	(0.037)	(0.058)	(0.051)
No Education (M)		0.125		-0.020	-0.058	-0.073	-0.125***	-0.229***	-0.252**		0.025	-0.394*
		(0.088)		(0.108)	(0.040)	(0.302)	(0.034)	(0.033)	(0.108)		(0.047)	(0.213)
Medium Level Education (M)	0.038	0.051***	-0.015	0.021	0.176***	0.122***	0.111	0.108	-0.012	-0.033	0.043*	0.096***
	(0.028)	(0.019)	(0.021)	(0.025)	(0.025)	(0.024)	(0.117)	(0.074)	(0.027)	(0.029)	(0.023)	(0.025)
High Level Education (M)	0.002	0.117***	-0.043*	0.075**	0.371***	0.253***	0.315***	0.137*	0.046	-0.002	0.020	0.128***
	(0.037)	(0.029)	(0.024)	(0.031)	(0.053)	(0.042)	(0.094)	(0.072)	(0.031)	(0.034)	(0.071)	(0.035)
Managerial (F)	0.143**	0.148***	0.032	0.072*	0.237***	0.290***	0.361***	0.198***	0.052	-0.065	0.161***	0.268***
	(0.072)	(0.041)	(0.037)	(0.043)	(0.053)	(0.046)	(0.063)	(0.060)	(0.074)	(0.117)	(0.055)	(0.068)
Professional (F)	0.156**	0.105***	0.100**	0.056	0.310***	0.342***	0.495***	0.094	-0.075	-0.075	0.155***	0.288***
	(0.077)	(0.040)	(0.044)	(0.047)	(0.063)	(0.048)	(0.141)	(0.083)	(0.052)	(0.062)	(0.055)	(0.065)
Technical (F)	0.234***	0.089**	0.033	0.020	0.255***	0.297***	0.527***	0.218***	-0.011	0.047	0.072*	0.010
	(0.074)	(0.036)	(0.035)	(0.041)	(0.040)	(0.038)	(0.088)	(0.057)	(0.051)	(0.090)	(0.039)	(0.046)
Clerical (F)	0.211***	0.095**	0.037	0.047	0.209***	0.260***	0.275***	0.319***	-0.016	-0.033	0.084*	0.133**
	(0.078)	(0.046)	(0.049)	(0.062)	(0.052)	(0.051)	(0.069)	(0.065)	(0.074)	(0.133)	(0.045)	(0.056)
Sales (F)	-0.014	0.133***	0.019	-0.032	0.130**	0.211***	0.276***	0.189***	0.058	0.085	0.075*	0.071
	(0.083)	(0.042)	(0.046)	(0.051)	(0.060)	(0.043)	(0.066)	(0.050)	(0.074)	(0.073)	(0.045)	(0.050)
Craft Trade (F)	0.119*	0.024	0.010	-0.046	0.136***	0.180***	0.092**	-0.026	-0.038	0.016	-0.056*	0.022
	(0.072)	(0.034)	(0.032)	(0.037)	(0.025)	(0.024)	(0.041)	(0.037)	(0.033)	(0.051)	(0.031)	(0.038)
Machine opperation (F)	0.118	0.041	0.000	0.002	0.152***	0.180***	0.068	0.022	0.014	0.013	-0.005	0.011
	(0.075)	(0.042)	(0.034)	(0.044)	(0.028)	(0.026)	(0.051)	(0.044)	(0.048)	(0.071)	(0.030)	(0.043)
Elementary Occ. (F)	0.105	0.004	0.053	0.030	0.016	0.061*	0.108**	0.124**	0.230	0.053	-0.032	-0.087**
	(0.081)	(0.055)	(0.093)	(0.070)	(0.033)	(0.034)	(0.050)	(0.052)	(0.174)	(0.195)	(0.044)	(0.040)
Armed/Military (F)	0.101	0.101	0.167**	0.106	0.252***	0.389***	0.659***		0.082	0.018	0.005	0.477***
	(0.099)	(0.068)	(0.079)	(0.076)	(0.069)	(0.075)	(0.126)		(0.127)	(0.280)	(0.099)	(0.153)
Unemployed (F)	0.066	-0.015	-0.010	0.030	0.082	0.184***	0.345	-0.071	-0.064	-0.069	0.104	-0.076
	(0.079)	(0.050)	(0.085)	(0.086)	(0.072)	(0.058)	(0.603)	(0.072)	(0.065)	(0.108)	(0.108)	(0.052)
Difficulties most of the time	-0.050	0.110	0.048	-0.038	-0.157***	-0.217***		-0.249***	0.018	-0.047	-0.015	0.049
	(0.059)	(0.078)	(0.068)	(0.113)	(0.035)	(0.069)		(0.057)	(0.047)	(0.081)	(0.033)	(0.044)
Difficulties often	-0.042	-0.152***	-0.056	-0.057	-0.094***	-0.174***		-0.193***	-0.001	-0.086	-0.009	0.105***
	(0.039)	(0.045)	(0.044)	(0.058)	(0.029)	(0.035)		(0.046)	(0.039)	(0.054)	(0.028)	(0.036)
Difficulties occasionally	0.049	0.026	-0.021	-0.022	-0.043*	-0.019		-0.012	0.008	0.011	0.003	0.104***
	(0.030)	(0.018)	(0.029)	(0.021)	(0.025)	(0.018)		(0.034)	(0.029)	(0.026)	(0.025)	(0.025)
Difficulties never	0.034	0.026	0.029	-0.106***	0.024	-0.041		0.122	0.041*	0.022	0.020	0.057
	(0.023)	(0.028)	(0.020)	(0.036)	(0.025)	(0.047)		(0.110)	(0.021)	(0.037)	(0.029)	(0.047)
Other European Union	0.012	-0.061	0.004	0.065	0.117	-0.392	0.004	0.124*	0.000	-0.031		
	(0.078)	(0.058)	(0.052)	(0.056)	(0.346)	(0.589)	(0.118)	(0.071)	(0.039)	(0.081)		
Other outside EU	-0.189***	-0.168***	-0.235***	-0.200***	0.006	-0.143	-0.022	-0.077*	-0.226***	-0.215***	-0.124***	-0.143***
	(0.046)	(0.029)	(0.050)	(0.047)	(0.168)	(0.320)	(0.104)	(0.046)	(0.037)	(0.064)	(0.029)	(0.027)
Woman	-0.017	-0.015	-0.072***	0.003	0.083***	0.036**	0.037	0.026	-0.011	-0.016	0.015	0.064***
	(0.018)	(0.016)	(0.017)	(0.019)	(0.017)	(0.016)	(0.029)	(0.024)	(0.017)	(0.023)	(0.017)	(0.017)
R-Squared	0.039	0.050	0.055	0.050	0.096	0.111	0.179	0.188	0.070	0.019	0.083	0.091

Table 2.A3.D

	SK		UK	
	2004	2010	2004	2010
Constant	7.841***	8.390***	10.281***	9.646***
	(0.058)	(0.072)	(0.186)	(0.070)
No Education (F)		-0.079	-0.055	-0.159*
		(0.559)	(0.049)	(0.093)
Medium Level Education (F)	0.048*	0.018	0.092*	0.019
	(0.027)	(0.030)	(0.050)	(0.028)
High Level Education (F)	0.061	0.181***	0.212***	0.101***
	(0.048)	(0.057)	(0.056)	(0.038)
No Education (M)			-0.176***	-0.010
			(0.044)	(0.083)
Medium Level Education (M)	0.067***	0.134***	-0.193***	0.060
	(0.024)	(0.028)	(0.056)	(0.037)
High Level Education (M)	0.030	0.188***	-0.079	0.137***
	(0.054)	(0.057)	(0.062)	(0.035)
Managerial (F)	0.074	0.186**	-0.051	0.222***
	(0.066)	(0.086)	(0.186)	(0.075)
Professional (F)	0.117*	0.192**	-0.129	0.161**
	(0.070)	(0.084)	(0.189)	(0.074)
Technical (F)	0.107*	0.174**	-0.062	0.089
	(0.063)	(0.077)	(0.187)	(0.076)
Clerical (F)	0.109	0.177*	-0.104	0.176**
	(0.078)	(0.092)	(0.181)	(0.088)
Sales (F)	0.004	0.085	-0.110	0.101
	(0.077)	(0.086)	(0.179)	(0.077)
Craft Trade (F)	0.038	0.133*	-0.287	0.027
	(0.057)	(0.071)	(0.210)	(0.070)
Machine opperation (F)	0.039	0.112	-0.198	-0.102
	(0.057)	(0.072)	(0.182)	(0.073)
Elementary Occ. (F)	0.009	-0.074	-0.239	-0.023
	(0.058)	(0.076)	(0.180)	(0.079)
Armed/Military (F)		0.103		0.084
		(0.129)		(0.111)
Unemployed (F)	0.002	-0.195*	-0.247	-0.094
	(0.078)	(0.116)	(0.192)	(0.082)
Difficulties most of the time	0.001	-0.020	0.006	0.021
	(0.033)	(0.084)	(0.058)	(0.068)
Difficulties often	-0.003	0.063	0.012***	-0.038
	(0.031)	(0.052)	(0.054)	(0.054)
Difficulties occasionally	-0.009	0.026	0.110	0.033
	(0.030)	(0.023)	(0.041)	(0.026)
Difficulties never	0.041	0.041	0.026**	-0.014
	(0.057)	(0.051)	(0.037)	(0.047)
Other European Union	0.038	-0.111	0.407*	0.094
	(0.083)	(0.105)	(0.202)	(0.061)
Other outside EU	-0.381**	-0.133	-0.094***	-0.170***
	(0.150)	(0.230)	(0.055)	(0.040)
Woman	-0.055***	-0.063***	-0.077	-0.077***
	(0.019)	(0.021)	(0.028)	(0.022)
R-Squared	0.029	0.082	0.095	0.085

Table 2.A3.E

Table 2.A4: Top: Regression coefficients of son's educational level on circumstance conditioned distribution. The omitted level is Upper Secondary (ISCED 3); Bottom: Regression coefficients of son's occupational category on the residual of the circumstance smoothed distribution after controlling for education. The ommited category is Skilled Agricultural.

Son's educational level on smoothed (circumstance conditioned) income. Regression coefficients of Equation 2.13

	AT		BE		CY		CZ		DE		DK	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	9.790***	9.864***	9.764***	9.804***	9.544***	9.579***	8.367***	8.802***	9.763***	9.810***	10.054***	10.107***
	(0.006)	(0.004)	(0.006)	(0.007)	(0.007)	(0.009)	(0.004)	(0.003)	(0.001)	(0.002)	(0.003)	(0.005)
Pre-Primary (ISCED 0)		-0.203***	-0.339***	-0.237***	-0.345***	-0.187*						
		(0.046)	(0.043)	(0.043)	(0.068)	(0.096)						
Primary (ISCED 1)	-0.427		-0.110***	-0.071***	-0.130***	-0.036*		-0.265**	-0.071***	-0.062**	-0.206***	-0.021
	(0.280)		(0.014)	(0.023)	(0.015)	(0.020)		(0.105)	(0.012)	(0.026)	(0.041)	(0.127)
Low Secondary (ISCED 2)	-0.146***	-0.149***	0.003	-0.062***	-0.117***	-0.008	-0.176***	-0.066***	-0.026***	-0.065***	-0.023***	-0.022*
	(0.013)	(0.010)	(0.011)	(0.015)	(0.016)	(0.020)	(0.013)	(0.014)	(0.005)	(0.008)	(0.005)	(0.011)
Post Secondary (ISCED 4)	0.042***	0.049***	0.040	0.017	0.014	0.148***	0.092***	0.054**	0.001	0.007		
	(0.014)	(0.010)	(0.026)	(0.024)	(0.030)	(0.038)	(0.028)	(0.022)	(0.003)	(0.005)		
Tertiary (ISCED 5 and 6)	0.060***	0.087***	0.072***	0.074***	0.138***	0.120***	0.103***	0.157***	0.008***	0.049***	0.014***	0.064***
	(0.011)	(0.008)	(0.008)	(0.009)	(0.011)	(0.012)	(0.010)	(0.006)	(0.002)	(0.003)	(0.004)	(0.008)
R-squared	0.108	0.155	0.120	0.178	0.196	0.162	0.175	0.137	0.018	0.078	0.040	0.084

Son's occupational category on the residual of the smoothed income after controlling for education. Regression coefficients of Equation 2.16

	AT		BE		CY		CZ		DE		DK	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	-0.029	0.038**	-0.013	0.057	0.037	0.125***	-0.052**	0.039*	-0.043***	-0.042***	0.012	-0.014
	(0.019)	(0.019)	(0.040)	(0.053)	(0.037)	(0.040)	(0.024)	(0.021)	(0.008)	(0.016)	(0.015)	(0.022)
Managerial	0.078***	0.011	0.083**	-0.029	-0.063	0.008	0.097***	-0.017	0.070***	0.062***	0.039**	0.049*
	(0.023)	(0.022)	(0.041)	(0.055)	(0.047)	(0.051)	(0.028)	(0.024)	(0.010)	(0.017)	(0.018)	(0.025)
Professional	0.084***	0.009	0.022	-0.035	0.005	-0.093**	0.047*	-0.029	0.058***	0.061***	-0.007	0.025
	(0.022)	(0.021)	(0.040)	(0.054)	(0.039)	(0.041)	(0.026)	(0.022)	(0.008)	(0.016)	(0.016)	(0.023)
Technical	0.033	-0.005	0.018	-0.029	-0.012	-0.088**	0.081***	-0.019	0.035***	0.029*	-0.008	0.015
	(0.020)	(0.020)	(0.041)	(0.054)	(0.039)	(0.042)	(0.025)	(0.022)	(0.008)	(0.016)	(0.016)	(0.023)
Clerical	0.072***	0.002	0.016	-0.048	0.000	-0.107**	0.046*	-0.052**	0.026***	0.031*	-0.004	0.010
	(0.021)	(0.021)	(0.040)	(0.054)	(0.039)	(0.042)	(0.028)	(0.023)	(0.009)	(0.016)	(0.016)	(0.024)
Sales	0.032	-0.049**	-0.009	-0.133**	-0.025	-0.144***	0.009	-0.057**	0.026***	0.023	-0.029*	-0.012
	(0.020)	(0.021)	(0.041)	(0.054)	(0.038)	(0.042)	(0.026)	(0.022)	(0.009)	(0.016)	(0.016)	(0.028)
Craftmanship	-0.024	-0.084***	-0.004	-0.025	-0.041	-0.127***	0.075***	-0.022	0.066***	0.072***	-0.018	0.024
	(0.021)	(0.021)	(0.041)	(0.054)	(0.039)	(0.041)	(0.026)	(0.022)	(0.009)	(0.016)	(0.016)	(0.024)
Machinery	-0.006	-0.117***	0.037	-0.054	-0.033	-0.086**	0.054**	-0.060***	0.061***	0.042***	-0.024	-0.003
	(0.023)	(0.022)	(0.042)	(0.055)	(0.041)	(0.044)	(0.026)	(0.022)	(0.009)	(0.016)	(0.017)	(0.026)
Elementary Occ.	-0.017	-0.115***	-0.054	-0.160***	-0.153***	-0.256***	-0.035	-0.100***	0.042***	0.036**	-0.025	-0.035
	(0.021)	(0.021)	(0.041)	(0.055)	(0.039)	(0.042)	(0.028)	(0.023)	(0.009)	(0.017)	(0.016)	(0.025)
Armed Occ.	0.060	0.017			0.033	-0.096*	-0.036	-0.051	0.082***		-0.076	-0.107
	(0.043)	(0.058)			(0.048)	(0.049)	(0.080)	(0.049)	(0.019)		(0.048)	(0.153)
R-squared	0.073	0.068	0.044	0.059	0.067	0.102	0.050	0.054	0.046	0.023	0.025	0.024

Table 2.A4.A

Son's educational level on smoothed (circumstance conditioned) income. Regression coefficients of Equation 2.13

	EE		EL		ES		FI		FR		HU	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	8.025***	8.375***	9.205***	9.083***	9.324***	9.255***	9.840***	9.992***	9.704***	9.791***	8.159***	8.128***
	(0.007)	(0.008)	(0.007)	(0.009)	(0.005)	(0.006)	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
Pre-Primary (ISCED 0)				-0.044					-0.302***	-0.397***	-0.319***	
				(0.102)					(0.025)	(0.034)	(0.066)	
Primary (ISCED 1)	-0.380***	-0.082	-0.091***	-0.216***	-0.165***	-0.133***			-0.111***	-0.137***	-0.428***	-0.168***
	(0.084)	(0.103)	(0.011)	(0.019)	(0.007)	(0.010)			(0.008)	(0.011)	(0.035)	(0.020)
Low Secondary (ISCED 2)	-0.085***	-0.067***	-0.061***	-0.153***	-0.103***	-0.033***	-0.008	-0.014	-0.037***	-0.012	-0.116***	-0.144***
	(0.025)	(0.021)	(0.013)	(0.019)	(0.007)	(0.008)	(0.005)	(0.012)	(0.006)	(0.009)	(0.008)	(0.008)
Post Secondary (ISCED 4)	0.029	-0.041	0.104***	0.093***	0.015	0.033	0.024	0.000		0.007		0.067***
	(0.018)	(0.032)	(0.018)	(0.023)	(0.017)	(0.024)	(0.024)	(0.019)		(0.036)		(0.011)
Tertiary (ISCED 5 and 6)	0.108***	0.157***	0.128***	0.186***	0.094***	0.122***	0.042***	0.003	0.077***	0.087***	0.136***	0.193***
	(0.011)	(0.012)	(0.011)	(0.013)	(0.007)	(0.007)	(0.003)	(0.005)	(0.005)	(0.005)	(0.008)	(0.006)
R-squared	0.073	0.063	0.143	0.219	0.213	0.143	0.069	0.000	0.152	0.150	0.217	0.251

Son's occupational category on the residual of the smoothed income after controlling for education. Regression coefficients of Equation 2.16

	EE		EL		ES		FI		FR		HU	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	-0.061**	-0.115***	-0.046***	-0.014	-0.097***	-0.062***	-0.020**	-0.012	-0.046***	-0.009	-0.087***	-0.053***
	(0.031)	(0.035)	(0.014)	(0.020)	(0.014)	(0.016)	(0.008)	(0.018)	(0.010)	(0.014)	(0.017)	(0.014)
Managerial	0.112***	0.174***	0.122***	0.066**	0.159***	0.039**	0.028***	0.065***	0.081***	0.035**	0.103***	0.074***
	(0.033)	(0.038)	(0.021)	(0.028)	(0.018)	(0.019)	(0.009)	(0.020)	(0.012)	(0.016)	(0.019)	(0.018)
Professional	0.084**	0.120***	0.089***	0.056**	0.151***	0.115***	0.059***	0.038**	0.074***	0.039**	0.105***	0.075***
	(0.033)	(0.037)	(0.018)	(0.024)	(0.016)	(0.017)	(0.009)	(0.019)	(0.012)	(0.015)	(0.019)	(0.016)
Technical	0.059*	0.130***	0.081***	0.030	0.145***	0.139***	0.007	-0.014	0.061***	0.030**	0.110***	0.077***
	(0.034)	(0.037)	(0.019)	(0.027)	(0.016)	(0.018)	(0.009)	(0.019)	(0.011)	(0.015)	(0.019)	(0.016)
Clerical	0.061	0.096**	0.111***	0.034	0.115***	0.107***	0.027***	-0.024	0.038***	-0.022	0.114***	0.068***
	(0.038)	(0.040)	(0.018)	(0.024)	(0.016)	(0.018)	(0.010)	(0.022)	(0.012)	(0.015)	(0.020)	(0.017)
Sales	0.002	0.050	0.057***	0.004	0.071***	0.051***	0.008	0.005	0.033***	-0.018	0.108***	0.049***
	(0.034)	(0.039)	(0.018)	(0.024)	(0.016)	(0.017)	(0.009)	(0.019)	(0.012)	(0.016)	(0.019)	(0.016)
Craftmanship	0.078**	0.168***	-0.008	-0.047*	0.077***	0.016	-0.006	0.010	0.034***	-0.001	0.074***	0.044***
	(0.033)	(0.037)	(0.017)	(0.025)	(0.015)	(0.017)	(0.009)	(0.020)	(0.012)	(0.015)	(0.018)	(0.015)
Machinery	0.058*	0.059	-0.007	0.022	0.109***	0.038**	0.022**	0.007	0.048***	-0.005	0.070***	0.045***
	(0.033)	(0.038)	(0.020)	(0.029)	(0.016)	(0.018)	(0.010)	(0.022)	(0.012)	(0.016)	(0.019)	(0.016)
Elementary Occ.	-0.002	0.050	-0.030	-0.092***	0.036**	0.007	-0.013	-0.023	0.003	-0.028*	0.048**	0.025
	(0.035)	(0.043)	(0.021)	(0.027)	(0.015)	(0.017)	(0.011)	(0.025)	(0.012)	(0.016)	(0.019)	(0.016)
Armed Occ.	0.224***	0.223***	-0.080*	0.122***	0.188***	0.145***	0.127***	0.006	0.091***	0.093***	0.156***	0.061**
	(0.078)	(0.064)	(0.048)	(0.038)	(0.028)	(0.035)	(0.018)	(0.085)	(0.020)	(0.022)	(0.031)	(0.027)
R-squared	0.036	0.045	0.062	0.066	0.052	0.062	0.069	0.052	0.034	0.039	0.028	0.019

Table 2.A4.B

Son's educational level on smoothed (circumstance conditioned) income. Regression coefficients of Equation 2.13

	IE		IS		IT		LT		LU		LV	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	9.867***	9.845***	10.039***	9.317***	9.626***	9.539***	7.633***	7.937***	10.347***	10.238***	7.690***	7.919***
	(0.009)	(0.010)	(0.009)	(0.010)	(0.004)	(0.003)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)	(0.006)
Pre-Primary (ISCED 0)					-0.366***	-0.463***		-0.064			-0.107	-0.188
					(0.025)	(0.032)		(0.149)			(0.152)	(0.184)
Primary (ISCED 1)	-0.099***	-0.095***	-0.116*		-0.224***	-0.171***	0.156	-0.001	-0.263***	-0.227***	-0.061***	-0.174**
	(0.014)	(0.021)	(0.065)		(0.009)	(0.012)	(0.205)	(0.084)	(0.014)	(0.011)	(0.022)	(0.071)
Low Secondary (ISCED 2)	-0.049***	-0.008	-0.013	0.010	-0.118***	-0.092***	-0.099***	-0.043**	-0.092***	-0.051***	-0.036	-0.045***
	(0.012)	(0.016)	(0.015)	(0.017)	(0.005)	(0.005)	(0.025)	(0.020)	(0.018)	(0.015)	(0.027)	(0.013)
Post Secondary (ISCED 4)	0.016	-0.050**	0.075***	-0.028	0.022**	0.069***	-0.011	-0.008	0.031	0.049*	0.049***	0.052***
	(0.015)	(0.021)	(0.020)	(0.019)	(0.009)	(0.011)	(0.014)	(0.013)	(0.026)	(0.027)	(0.018)	(0.018)
Tertiary (ISCED 5 and 6)	0.126***	0.129***	0.085***	0.023*	0.156***	0.132***	0.170***	0.129***	0.121***	0.193***	0.190***	0.136***
	(0.011)	(0.013)	(0.013)	(0.013)	(0.006)	(0.006)	(0.014)	(0.011)	(0.013)	(0.010)	(0.013)	(0.009)
R-squared	0.166	0.149	0.070	0.005	0.208	0.202	0.101	0.063	0.271	0.211	0.144	0.111

Son's occupational category on the residual of the smoothed income after controlling for education. Regression coefficients of Equation 2.16

	IE		IS		IT		LT		LU		LV	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	0.091	-0.030	-0.003	-0.070**	-0.044***	-0.065***	-0.129***	-0.090***	0.121***	0.052*	-0.084**	-0.070**
	(0.076)	(0.021)	(0.019)	(0.031)	(0.014)	(0.015)	(0.022)	(0.024)	(0.040)	(0.029)	(0.041)	(0.028)
Managerial	-0.037	0.061**	0.033	0.097**	0.078***	0.083***	0.137***	0.164***	-0.031	-0.042	0.105**	0.114***
	(0.077)	(0.028)	(0.023)	(0.040)	(0.016)	(0.017)	(0.029)	(0.029)	(0.045)	(0.033)	(0.046)	(0.031)
Professional	-0.108	0.080***	0.011	0.082**	0.075***	0.100***	0.167***	0.117***	-0.088**	-0.020	0.150***	0.085***
	(0.077)	(0.024)	(0.022)	(0.034)	(0.016)	(0.017)	(0.025)	(0.027)	(0.042)	(0.031)	(0.045)	(0.030)
Technical	-0.041	0.039	-0.004	0.154***	0.081***	0.104***	0.118***	0.092***	-0.091**	0.006	0.094**	0.102***
	(0.078)	(0.026)	(0.022)	(0.038)	(0.014)	(0.016)	(0.028)	(0.029)	(0.042)	(0.031)	(0.045)	(0.030)
Clerical	-0.119	0.025	0.024	0.126***	0.091***	0.100***	0.156***	0.050	-0.104**	-0.033	0.014	0.057*
	(0.077)	(0.025)	(0.025)	(0.047)	(0.015)	(0.017)	(0.033)	(0.035)	(0.042)	(0.032)	(0.051)	(0.032)
Sales	-0.133*	-0.005	0.023	0.024	0.052***	0.035**	0.122***	0.072**	-0.161***	-0.117***	0.022	0.059*
	(0.077)	(0.025)	(0.025)	(0.036)	(0.015)	(0.017)	(0.027)	(0.029)	(0.043)	(0.031)	(0.046)	(0.030)
Craftmanship	-0.043	-0.030	-0.041*	0.008	0.003	0.047***	0.138***	0.114***	-0.191***	-0.054*	0.133***	0.087***
	(0.077)	(0.028)	(0.023)	(0.040)	(0.015)	(0.016)	(0.025)	(0.028)	(0.042)	(0.031)	(0.044)	(0.030)
Machinery	-0.066	0.032	0.029	-0.004	0.034**	0.063***	0.174***	0.022	-0.102**	-0.092***	0.079*	0.029
	(0.078)	(0.030)	(0.041)	(0.049)	(0.015)	(0.017)	(0.027)	(0.028)	(0.045)	(0.032)	(0.044)	(0.031)
Elementary Occ.	-0.113	0.010	-0.040	0.118***	-0.048***	-0.002	0.061**	0.095***	-0.217***	-0.114***	0.010	0.024
	(0.077)	(0.026)	(0.029)	(0.042)	(0.015)	(0.017)	(0.027)	(0.029)	(0.043)	(0.031)	(0.045)	(0.031)
Armed Occ.	0.118				0.033	0.076***	0.479***	0.033	-0.040	0.058	0.398***	0.454***
	(0.097)				(0.023)	(0.024)	(0.113)	(0.095)	(0.076)	(0.122)	(0.101)	(0.124)
R-squared	0.049	0.048	0.029	0.018	0.045	0.043	0.040	0.037	0.060	0.078	0.047	0.020

Table 2.A4.C

Son's educational level on smoothed (circumstance conditioned) income. Regression coefficients of Equation 2.13

	NE		NO		PL		PO		SE		SI	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	9.810***	9.899***	10.225***	10.361***	7.766***	8.328***	9.091***	9.118***	9.825***	9.930***	9.107***	9.201***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.014)	(0.011)	(0.003)		(0.003)	
Pre-Primary (ISCED 0)		-0.087**	0.029		-0.216***	-0.198**						
		(0.041)	(0.049)		(0.047)	(0.086)						(0.004)
Primary (ISCED 1)	-0.054***	-0.078***			-0.122***	-0.098***	-0.270***	-0.260***	-0.283***		-0.060***	-0.091***
	(0.013)	(0.017)			(0.008)	(0.010)	(0.016)	(0.013)	(0.030)	(0.004)	(0.007)	(0.028)
Low Secondary (ISCED 2)	-0.035***	-0.022***	0.001	-0.004			-0.086***	-0.114***	-0.010	-0.017	-0.064***	-0.068***
	(0.006)	(0.005)	(0.015)	(0.008)			(0.020)	(0.015)	(0.008)	(0.012)	(0.019)	(0.010)
Post Secondary (ISCED 4)	0.005	-0.018*	0.016	0.019	0.129***	0.150***	-0.075	0.105	0.028***	-0.005	0.066***	
	(0.012)	(0.010)	(0.013)	(0.016)	(0.012)	(0.011)	(0.116)	(0.073)	(0.008)	(0.008)	(0.010)	
Tertiary (ISCED 5 and 6)	0.032***	0.056***	0.040***	0.065***	0.241	0.177***	0.175***	0.154***	0.038***	-0.003	0.142***	0.102***
	(0.004)	(0.004)	(0.005)	(0.007)	(0.006)	(0.005)	(0.020)	(0.015)	(0.005)	(0.005)	(0.007)	(0.006)
R-squared	0.063	0.155	0.039	0.111	0.204	0.210	0.313	0.283	0.087	0.008	0.198	0.150

Son's occupational category on the residual of the smoothed income after controlling for education. Regression coefficients of Equation 2.16

	NE		NO		PL		PO		SE		SI	
	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010	2004	2010
Constant	-0.028	-0.014	0.034***	0.015	-0.133***	-0.135***	-0.116***	-0.037	0.028	0.007	-0.013	-0.054**
	(0.018)	(0.017)	(0.013)	(0.017)	(0.007)	(0.007)	(0.024)	(0.027)	(0.025)	(0.016)	(0.020)	(0.024)
Managerial	0.035*	0.031*	-0.015	0.025	0.201***	0.165***	0.121***	0.063*	-0.041	0.010	0.051**	0.114***
	(0.018)	(0.018)	(0.014)	(0.018)	(0.013)	(0.012)	(0.030)	(0.034)	(0.028)	(0.017)	(0.023)	(0.027)
Professional	0.045**	0.025	-0.032**	0.000	0.156***	0.156***	0.161***	0.054*	-0.005	-0.006	0.021	0.068***
	(0.018)	(0.017)	(0.013)	(0.018)	(0.010)	(0.009)	(0.030)	(0.031)	(0.025)	(0.016)	(0.021)	(0.025)
Technical	0.022	0.023	-0.043***	-0.023	0.186***	0.168***	0.115***	0.070**	-0.021	0.004	0.032	0.071***
	(0.018)	(0.017)	(0.013)	(0.017)	(0.010)	(0.010)	(0.029)	(0.031)	(0.025)	(0.016)	(0.021)	(0.025)
Clerical	0.020	0.024	-0.037**	-0.058***	0.196***	0.198***	0.211***	0.125***	-0.042	0.004	0.032	0.122***
	(0.018)	(0.018)	(0.015)	(0.019)	(0.012)	(0.012)	(0.029)	(0.031)	(0.026)	(0.019)	(0.021)	(0.025)
Sales	0.030*	-0.026	-0.065***	-0.018	0.177***	0.171***	0.093***	0.003	-0.047*	0.001	-0.005	0.054**
	(0.019)	(0.018)	(0.013)	(0.018)	(0.010)	(0.010)	(0.027)	(0.030)	(0.026)	(0.017)	(0.021)	(0.025)
Craftmanship	0.015	-0.013	-0.011	-0.001	0.099***	0.111***	0.124***	0.021	-0.038	-0.039**	-0.016	-0.017
	(0.019)	(0.018)	(0.014)	(0.018)	(0.009)	(0.009)	(0.026)	(0.029)	(0.026)	(0.017)	(0.021)	(0.025)
Machinery	0.021	0.018	-0.003	-0.020	0.116***	0.138***	0.103***	0.036	-0.027	-0.031*	0.014	0.029
	(0.020)	(0.019)	(0.015)	(0.020)	(0.010)	(0.010)	(0.029)	(0.031)	(0.026)	(0.017)	(0.021)	(0.025)
Elementary Occ.	0.001	-0.004	-0.048***	-0.050**	0.141***	0.123***	0.079***	-0.005	-0.068**	-0.023	-0.011	0.022
	(0.020)	(0.020)	(0.017)	(0.022)	(0.010)	(0.011)	(0.028)	(0.030)	(0.029)	(0.025)	(0.021)	(0.026)
Armed Occ.	-0.006	-0.040		-0.016	0.132***	0.194***	-0.054	0.033	0.058	-0.047	0.067	0.027
	(0.034)	(0.050)		(0.072)	(0.027)	(0.027)	(0.063)	(0.107)	(0.062)	(0.030)	(0.042)	(0.032)
R-squared	0.017	0.031	0.057	0.027	0.070	0.063	0.040	0.017	0.022	0.025	0.029	0.064

Table 2.A4.D

Son's educational level on smoothed (circumstance conditioned) income. Regression coefficients of Equation 2.13

	SK		UK	
	2004	2010	2004	2010
Constant	7.930***	8.591***	10.026***	9.712***
	-(0.002)	-(0.004)	-(0.007)	-(0.005)
Pre-Primary (ISCED 0)				
Primary (ISCED 1)				
Low Secondary (ISCED 2)	-0.048***	-0.122***	-0.124***	-0.144***
	-(0.007)	-(0.018)	-(0.016)	-(0.012)
Post Secondary (ISCED 4)		0.047**	-0.063**	-0.214***
		-(0.022)	-(0.027)	-(0.055)
Tertiary (ISCED 5 and 6)	0.031***	0.118***	0.083***	0.049***
	-(0.004)	-(0.007)	-(0.010)	-(0.006)
R-squared	0.042	0.128	0.109	0.110

Son's occupational category on the residual of the smoothed income after controlling for education. Regression coefficients of Equation 2.16

	SK		UK	
	2004	2010	2004	2010
Constant	-0.009	0.031	0.014	0.067*
	(0.023)	(0.028)	(0.066)	(0.035)
Managerial	0.036	0.005	0.038	-0.016
	(0.024)	(0.031)	(0.067)	(0.036)
Professional	0.015	-0.029	0.032	-0.043
	(0.024)	(0.030)	(0.067)	(0.036)
Technical	0.025	-0.021	-0.008	-0.047
	(0.023)	(0.029)	(0.067)	(0.036)
Clerical	-0.022	-0.025	-0.063	-0.079**
	(0.024)	(0.030)	(0.067)	(0.036)
Sales	-0.012	-0.038	-0.058	-0.130***
	(0.024)	(0.029)	(0.067)	(0.036)
Craftmanship	0.015	-0.031	0.013	-0.068*
	(0.023)	(0.029)	(0.068)	(0.037)
Machinery	0.012	-0.039	-0.028	-0.137***
	(0.024)	(0.029)	(0.068)	(0.037)
Elementary Occ.	-0.037	-0.093***	-0.058	-0.101***
	(0.024)	(0.031)	(0.068)	(0.036)
Armed Occ.		-0.063		
		(0.047)		
R-squared	0.030	0.009	0.045	0.075

Table 2.A4.E

Chapter 3

Inheritances and inequality of opportunity in wealth

3.1 Introduction

The debate about inequality has traditionally focused on the analysis of income. Originally, centered only on the levels and trends of inequality of the income distribution and, more recently, also on the 'unfair' part of income inequality associated with initial circumstances and not with individual decisions or effort, i.e., inequality of opportunity (IO). In contrast, wealth has traditionally played a rather minor role in inequality and IO analysis. Firstly because statistics on income, both at the macro level (from national accounts) and at the micro level (from the relatively abundant income surveys) were more accessible to researchers than those on wealth. And, secondly, because the impact of income on subjective well-being was thought to be far more important than that of wealth.[1]

However, in the last few years, wealth inequality is attracting the attention of researchers and the general public. New administrative datasets including historic data of national wealth have recently begun to be exploited, revealing unsettling findings about wealth inequality and its dynamics. Saez and Zucman (2016) show that wealth inequality in the United States has been increasing since the late 1970s, after having had a decreasing trend since the 1930s, while Piketty and Zucman (2014) find that, in the main western economies (U.S., U.K., Germany and France), the wealth-income ratio has also began to increase steadily since the 1970s, reaching back the levels of the XVIIIth and XIXth centuries. At the same time, the link between wealth and well-being is being revisited, and some advantages derived from a higher wealth level are now being explicitly acknowledged. Hochman and Skopek (2013) show that there is a subjective well-being premium for wealthier individuals, even within rich countries like Germany or Israel. Shapiro (2004) and Oliver and Shapiro (2006) point at the far more important and persistent racial wealth gap between whites and blacks in the U.S. -compared to the income racial gap- linking this gap to access to loans or to education. In this line, Johnson (2014) highlights the importance that family wealth has in the United States educational system, for it can -among other things- provide access to better schools located in more expensive neighborhoods or secure funding for higher education. Finally, global statistics on wealth inequality and on the accumulated share of wealth owned by the

[1] In the classic discussion about the relative or the absolute nature of subjective well-being, economists and sociologists have always used income as the proxy for fulfillment of material needs [Easterlin (1974), Veenhoven (1991), Diener et al. (1993)].

top 1% of the world's population [Davies et al. (2016)] have had a shocking impact on social media (partly due to their diffusion through the Oxfam's report on [Hardoon (2017)) and have put wealth inequality in the spotlight.

Despite recent research showing wealth inequality to be consistently higher than income inequality in countries where data is available (Saez (2017) and World Wealth Income Database at www.wid.world), interest and concern about wealth inequality are still relatively small. One possible reason is the lack of objective measures about the 'fairness' of those high inequality levels. We believe that, similarly to what has happened in the study of income inequality, the public debate could be enriched if the mere analysis of inequality was complemented with the analysis of inequality of opportunity. It is relevant and informative to the academics and to the general public to know not only how unevenly wealth is distributed, but to what extent that inequality is the consequence of effort and talent or, else, is related to external prior factors that the individual is not responsible for. In particular -as our work reveals- a external circumstance like the inheritance received seems to have a particularly strong effect on wealth inequality, and significantly higher than it has on income.[2]

Moreover, in addition to fairness considerations, recent findings point out that income IO could be also inefficient and negative for economic growth, as it implies the misallocation of potential talent and human capital[Marrero and Rodríguez (2013 and 2016); Bradbury and Triest (2016)]. To what extent wealth inequality of opportunity could also be negatively associated with economic growth is yet unknown, but Bagchi and Svejnar (2015) suggest that the relation of wealth inequality with growth could depend on whether wealth accumulation is related with political connections, in which case it this relation would be negative; if it is not, the relation would turn positive.[3]

To the best of our knowledge -surely in part because of the scarcity of joint data of wealth and circumstances- no systematic work has yet analyzed IO in wealth using the IO theoretical framework [Roemer (1993), Fleurbaey (2008), Roemer (2009)] that has already been exten-

[2]In a recent study that estimates inheritances in the historical aggregates series, Alvaredo et al. (2017) find a marked increase in the share of inherited wealth over aggregate wealth in Europe since 1980 and in the US since 1990.

[3]Although it is not an 'inequality of opportunity' analysis (having 'political connections' cannot be considered a circumstance totally external to the individual decisions) the work of Bagchi and Svejnar does point out the fact that overall wealth inequality alone encompases different effects on growth depending on the origin of that wealth.

sively applied to measure IO in income [e.g. Lefranc et al. (2008),Rodríguez (2008), Checchi and Peragine (2010), Ferreira and Gignoux (2011), Marrero and Rodríguez (2012).][4].

Aiming to provide a first-time approach to inequality of opportunity in wealth, in this paper we take advantage of the unique data collected by the Spanish Central Bank in the Spanish Survey of Household Finances (which, in addition to wealth, includes the parental occupational category and the inheritances received by the household) and we apply a non-parametric smoothing method to calculate IO, recently proposed by Lasso de la Vega et al. (2017). This method allows for a more precise measurement of IO compared to the traditional ex-post methodology based on fixed intervals (see Section 3.2).

Our results show that -even with a limited set of circumstances- IO in wealth in Spain can represent almost half of total wealth inequality in our preferred specification. Differences in gender, parental occupation and the amount of inheritances received imply different levels of wealth for any given degree of effort and all of these circumstances matter to inequality of opportunity.[5] In particular, we find that -with gender and parental occupation as baseline circumstances- considering whether and individual received an inheritance increases the ratio between IO and overall inequality in wealth from 27.55% to 33.1%. Furthermore, accounting for the *amount* inherited further boosts that ratio to 48.97% (see Table 3.6).

Our results also suggest that wealth inequality is not only higher than income in overall levels, as already established by the literature, but also in inequality of opportunity levels. Compared to our results for IO in income, we find in fact IO to be higher both in absolute measures (see Tables 3.5 and 3.7) and in the IO ratio. In our preferred specification, the IO ratio for income reaches 33.44% below the 48.97% found for wealth (see Tables 3.6 and 3.8).

These findings are qualitatively robust to different versions of the ex-post IO methodology. Even though we focus on the results obtained by the non-parametric regression method detailed in Section 3.2, we have also run all our estimations using other existing estimation methodologies. In all cases, the IO level and the IO ratio in wealth are significantly higher than for income, and there is a clear increase both when we take into account inheritances

[4] Ferreira et al. (2010) measure inequality of opportunity in Turkey for a composite index of wealth obtained from durable assets owned by the household, but do not have a direct measure of observed or reported wealth.

[5] As we explain in section 3.2, the inequality of opportunity literature proxies the degree of effort by the ranking the individual or household has among others that share *the same* external background circumstances.

and, especially, the amount inherited.

The rest of the paper is structured as follows. In Section 2, we present the non-parametric methodology that we will use to estimate IO. Section 3 describes the properties of our database and our choices in the selection of circumstances and in the aggregation of wealth and income. In Section 4 we show the results of our IO estimations using different choices and methods. Finally, Section 5 concludes.

3.2 Methodology

In essence, inequality of opportunity tries to grasp the part of total inequality of an outcome variable (income, wealth, etc.) that cannot be attributed to individual decissions and falls out of the responsability sphere of the individual. Complete equality of opportunity would then demand that individual characteristics or 'circumstances', upon which the individual has no control (such as family background, race or place of birth) do not affect the outcome (income, welfare, health) obtained by the individual [Rawls (1971), Sen (1980), Roemer (1993), Fleurbaey (2008)]. If this does not hold, the existing IO could be considered 'unfair' and there could be a case for public intervention to help 'level the playing field' [Roemer et al. (2003)].

One of the most widely used formal formulations of the concept of (in)equality of opportunity is the so called 'ex-post' approach, which states that there is equality of opportunity if all individuals who exert the same *degree of effort* obtain the same outcome.[6]

The first task of this approach is precisely to identify individuals who are comparable in terms of their degree of effort. For this purpose, one can classify the population into different 'types' (a subset of the population that shares the same set of circumstances) and then order individuals within their type by the outcome, with the implicit assumption that, among individuals that share the same circumstances (that belong to the same 'type'), only 'effort' determines the relative position in the outcome distribution considered. According to Roemer's pragmatic approach (1993), two people belonging to different types have tried

[6]See Ramos and Van de Gaer (2015) for a complete analytical taxonomy of the different approaches to inequality of opportunity measurement applied in the literature.

equally hard if and only if they are on the same rank of their respective effort distributions.[7]

Therefore, the inequality of the distribution Z of a given outcome Y that is conditioned to the degree of effort E would *not* be associated with the set of known circumstances, and inequality of opportunity (IO) would then be the *remaining* part of total inequality $I(Y)$:

$$IO = I(Y) - I(Z), \tag{3.1}$$

where $Z = Y|E$.

In relative terms, dividing all the expression by $I(Y)$, total inequality can be decomposed into the IE and IO shares:

$$1 = \frac{I(Z)}{I(Y)} + \frac{IO}{I(Y)}, \tag{3.2}$$

Traditionally, in order to estimate $Z = Y|E$, the literature has used the quantile or 'tranches' approach, a tranche being a section of the ordered within-type distribution or the outcome variable (income, wealth, etc.). When applying this method, the choice of the tranche width is an important decision that is usually left to the discretion of the researcher. While the chance of considering individuals with different degrees of effort as comparable close-equals increases with the size of the tranche considered, choosing a narrower tranche range reduces the number of individuals that can be considered close-equals in terms of effort. Ultimately, the tranche can be so small that all individuals could be considered essentially different and, therefore, there will be no close-equals to compare with. To find a satisfactory solution for this problem is not easy, but it seems reasonable to look for a statistical criterion instead of using a discretional division in standard tranches like deciles, ventiles or centiles as it is often the case in the literature.

A second related issue arises from the fact that researchers typically consider the dispersion of outcomes among individuals belonging to the same type and tranche as normative irrelevant

[7] For example, if we consider gender (man or woman), parental occupational class (low, medium or high) and having or not having received inheritance we would have a total of twelve types, and one of them would be, for instance, men whose parental occupational class was medium and who have not received any inheritance. The rank of an individual within this type would be considered his/her degree of effort.

[Checchi and Peragine (2010)]. Thus, the outcomes of observations in the same type and tranche (deciles, in this example) are collapsed to their unweighted mean value in order to obtain Z, as can be visualized in the Z colored in red in Figure 3.1 below. By doing this, however, dispersion among those individuals belonging to the same type and tranche -which implicitly contains potential information- is ignored.

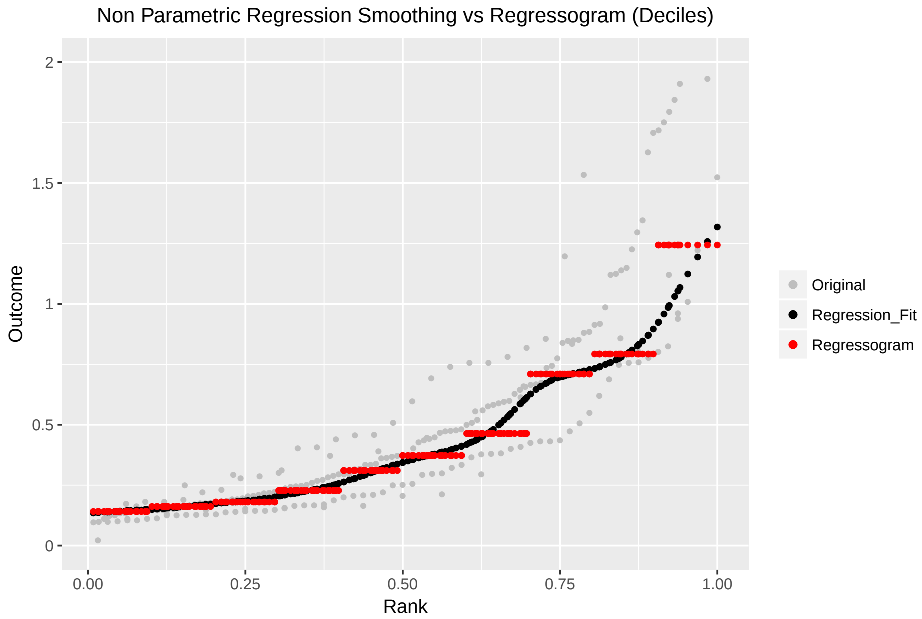

Figure 3.1

To deal with these problems, we will estimate $Z = Y|E$ in our analysis using the non-parametric regression framework proposed by Lasso de la Vega et al. (2017). Instead of discretional width tranches, this approach uses the overlapping optimal bandwidth h to determine which individuals exert a similar degree of effort. Technically, h is chosen to minimize a distance measure like the Mean Integrated Squared Error (MISE) in the non-parametric regression of outcome Y on the degree of effort (rank) E. But, what is the economic rationale behind it? Non-parametric regression takes into account two elements: first, a good fit to the 'true' curve, which means a low bias (the difference between the actual and the expected estimated value); and second, the reduction of the volatility of the estimates (the variance is the standard criterion to measure volatility). These two elements have a conflicting interpretation in terms of equality of opportunity. The smaller the size of the tranches or the bandwidth h, the lower the bias. In this case, as we mentioned above, the probability of considering individuals with similar degrees of effort as different, increases. At the limit, there are no close-equals and if there is any IO, it is due only to the exact equals (if there is any). On the contrary, the larger the size of the tranche, the lower the variance. In this case, the probability of considering individuals with quite different degrees of effort to be similar, increases. At the limit, all individuals are close-equals and the IO is at its maximum. Optimal bandwidth is computed as a balance between both elements. Hence, despite that there is no normatively superior criterion to identify close-equals, using a statistically-optimal based criterion that balances variance and bias seems better than the ad hoc subjective researcher's criterion that is typically applied in the literature.

Also, the fact that the non-parametric regression works with overlapping intervals avoids the paradox that two close observations in terms of effort be considered as having different levels of effort just because they fall at two different sides of the ad-hoc tranche threshold (deciles, centiles, etc.). In the non-parametric regression, the influence of each observation in determining the expected value of the outcome variable for each level of effort only depends on the distance to the estimation point and the kernel function used, and no longer on whether it falls in or out of a discretional tranche division.

Essentially, a non-parametric regression estimates $Z = Y|X$, a vector comprising all the weighted local averages of Y at each point $x \in X$. These averages are obtained using neighboring observations, which are weighted using a smoothing function that relates negatively to the distance (measured in terms of X) that separates them from the evaluated observation. At each point $x \in X$:

$$z(x) = \sum_{i=1}^{n} W_i(x) \cdot Y_i \tag{3.3}$$

Among the possible smoothing functions, we will use the classic Nadaraya–Watson estimator [Nadaraya (1964), Watson (1964)]. The Nadaraya–Watson (NW) weighting estimator is:

$$W_i^{NW}(x) = \frac{K_h(x - x_i)}{\sum_{i=1}^{n} K_h(x - x_i)} \tag{3.4}$$

where K_h is a kernel function K with a bandwidth h and X is, in our context, the degree of effort E, that we proxy by the normalized ranking of the individual within her type. The shape of the kernel weights is determined by K, whereas the size of the estimation is parameterized by h. We will use the NW estimator with a normal or gaussian kernel function and an optimal bandwidth h. To obtain the optimal bandwidth h we minimize the MISE using a normal operator for the kernel weighting, and include also the sampling weights of the survey in the computation.[8]

The inequality of the new estimated distribution $Z = Y|E$ will always be lower than the inequality of the original distribution, that is, $I(Y) \leq I(Z)$. The Nadayara-Watson non-parametric regression smoothing has the desirable property of being a bistocastic transformation: the theoretical outcome distribution $Z = Y|E$ Lorenz-dominates the original Y distribution, avoiding any misinterpretation of the difference in inequality between both distributions [Lasso de la Vega et al. (2017)]. In addition to this ordinal property, a cardinal measure of IO can also be obtained applying any S-convex index of inequality, so that $IO = I(Y) - I(Z)$. In our application we have calculated the Mean Logarithmic Deviation (MLD) or Theil-0 index, the Atkinson (1) index and the Gini index.

The overlapping optimal bandwidth allows the non-parametric regression method to tackle the problem of discretional tranche selection and to account for the dispersion of the effort within types and tranches, while still being able to decompose overall inequality in inequality of effort and inequality of opportunity. In fact, Lasso de la Vega et al. (2017) show that this method generalizes previous standard ex-post decompositions used in the literature, and that the traditional ex-post method could be considered a particular case of non-parametric regression (the regressogram [Tukey (1947)]) in which the weighting function is a constant that gives all observations in the tranche the same importance (thus obtaining the mean value as an estimate) and that considers non-overlapping ad-hoc intervals (deciles, centiles, etc.). A graphical visualization of the difference in the estimation between the non-parametric regression (black line) and the discretional tranches of the regressogram (deciles) can be

[8] We have used the npksum function in the R 'np' package [Hayfield et al. (2008)] in order to obtain the optimal bandwidth using cross-validation and, in the second step, to produce our non-parametric regressions. We are grateful for technical advice to Jean Opsomer and, in particular, to Luc Clair and Jeffrey Racine for their valuable help in programming the optimal bandwidth and regressions computation accounting for the sampling weights.

appreciated in Figure 3.1 above. [9].

3.3 Database

The 2011 Spanish Survey of Household Finances (Encuesta Financiera de las Familias or EFF) is the fourth wave of a series of surveys run by the Spanish Central Bank, which collects detailed information on consumption, income and wealth from a representative sample of the Spanish population. A remarkable feature of this survey is that, thanks to the collaboration of the Tax Office and the National Statistics Institute (INE), the EFF is able to oversample wealthy households on the basis of individual wealth tax records. Since the distribution of wealth is strongly skewed and certain types of assess are held by only a small share of the population, oversampling is crucial for the representativeness of the population and of aggregate wealth [Bover et al. (2014)]. In addition, the Spanish EFF gathers unique information on parental occupation, which is fundamental in the analysis of inequality of opportunity, and, better still, on received inheritances and gifts.[10]

We have included in our sample all households whose head -defined in the survey as the 'reference person' responsible of the economic affairs of the household- is over 30 years old, leaving out younger families who could still not be fully integrated in the labor market. Aiming to gather all possible information about inheritances, we have not established an upper threshold for age. Moreover, since receiving or not an inheritance depends not only on your parental wealth but also on your age, we have replicated our analysis in a subsample of only individuals older than 60, in order to account for the effect of inheritances among

[9] For reference, we have also included in the results section the regressogram estimations together with our non-parametric regression estimates. We have used two ad-hoc tranches divisions: centiles and the optimal bandwidth tranche. Note that the regressogram, even when it uses the optimal bandwidth tranche, misses two key features of the non-parametric regression estimation: accounting for the dispersion of effort via the weighting function, and considering overlapping intervals. Also, in addition to the MLD, we also add the Atkinson (1) and the Gini indices. See Tables 3.5 to 3.8 for the estimations of the non-parametric regression method, Appendix Tables 3.A1 to 3.A4 for the estimation using the regressogram with centiles, and Appendix Tables 3.A5 to 3.A8 for the estimation using fixed tranches with the optimal bandwidth range.

[10] The EFF is included in the European Household Finance and Consumption Survey (HFCS) run by the Eurosystem. Unfortunately, questions about parental occupation have not been included in the core homogeneous questionnaire of the 2011 wave of the European survey and are only available for Spain, Portugal and France (Italy has information about parental education). Among these countries, the Spanish survey includes the most complete questionnaire aobut wealth assets and their source and allows for a thorough and exhaustive measurement of household wealth and its origin.

comparable individuals that are old enough to be very likely to inherit.[11]

Our main target variable is net household wealth, which we compute aggregating wealth from different sources: current market value of real state (including main house and other properties), current value of durable goods (equipment and transportation means), current value of jewelry, businesses and current vuale of financial assets (stocks, shares in funds, public and private bonds, pension plans)[12]. We subtract the pending value of outstanding loans in order to obtain net wealth. For comparison purposes, we have replicated our analysis with income, which we have computed adding different sources of annual income referring to the previous year: labor income (both monetary and in kind), unemployment benefits, income from self-employment, income from retirement benefits or other pensions, interests from accounts, net profits from business managed and participated by household members, and dividends from stocks. In order to better proxy the 'permanent' income and avoid transitory shocks, we have excluded extraordinary sources of income, such as lottery, inheritances, prizes, job-firing compensations or transfers received from third parties or the government that were not included in the concepts stated above. The basic descriptives for the income distribution are in Table 3.3 and the basic descriptives for the net wealth variable in Table 3.2.

We found that equivalizing wealth and income with the squared root scale did not alter significantly our results. Consistently with what Bover (2010) finds for inequality measures, wealth distribution is affected by household structure, but it is not sensitive to considering the *size* of the household. We have therefore used household as the unit of analysis throughout.[13]

Out of the 6106 households in the EFF, 5996 had a head over 30 years old. From that

[11]It can be argued that it may be too late in the life cycle to talk about 'opportunities' when people are over 60 but, even though it is at this age when this circumstance is revealed in the data and can be measured, parental wealth may have been providing opportunities during the previous lifetime of the household individuals.

[12]The 'current value' of assets is self reported by the respondent. The questionnaire, for example, literally asks: 'How much would be the current value of your house? (That is, what you would receive for it if you decided to sell it today)'.

[13]The EFF survey addresses the problem of non-response using the 'multiple imputation' method, that accounts for uncertainty in the imputation by providing five different datasets with different imputed observations in the event of non-response (see Bover et al. (2014) and Barceló (2008)). We have used throughout 'Dataset 1', having previously checked that the differences in the results when using other of the datasets with different imputation values were minimal. As an example, the value of the Theil-O index of inequality of the wealth distribution for our sample of individuals over 30 years old was 0.691 in the first dataset , while it was 0.687 when using the second dataset. The same index was 0.669 and 0.667 respectively for the wealth distribution of individuals 60 years old or over. The differences in the indices for the smoothed distributions obtained through the non-parametric regression were also very small, both for wealth and for income.

sample we also leave out households that had negative wealth or income, which represent 162 observations (2.7% of the sample). This excludes atypic observations of wealth and income in the bottom part of the distribution, and allows us to use inequality indices that only admit positive values (such as the Mean Logarithmic Deviation (MLD) or the Atkinson(1) index). Thus, our main sample will then be formed of 5834 observations, while the subsample of individuals older than 60 will include 3198 observations, that is, 55% of our main sample (see Table 3.1).

The circumstances that we consider are the gender, the highest parental occupational class of any of the parents of the household head or the partner, and the inheritances received by the household. Since having too many values for a certain circumstance would produce a high number of 'types' with a reduced number of observations per type, we obtain three occupational classes collapsing the broad occupational categories of the Spanish Clasificación Nacional de Ocupaciones (CNO).[14] The first group is formed by the categories 1, 2 and 3 of the CNO, that include management, scientific and intellectual technicians and professionals, and support technicians and professionals. The second group includes an ample range of middle occupational class categories: clerical workers, sales workers, skilled agricultural workers, qualified handcraft workers, machine operators, and armed forces. The low occupational class group includes unskilled workers and housekeepers. Considering only gender and parental occupation would result in 6 different types of households (2 genders, 3 occupational classes). The share of the sample belonging to each group of parental occupational level is displayed in Table 3.1.

For the aggregation of inheritances we have included the current value of real state obtained through inheritance or gift, the current value of jewelry inherited, and the historic value of business inherited or received as a donation, as well as the historic value of any other inheritance received.[15] In all cases, the value of partial bequests has only been accounted

[14] The CNO is based on the International Standard of Occupations (ISCO-08). Our aggregation in three occupational groups is similar to the one proposed by Erikson et al. (1979) when collapsing their occupational class schema into three occupational levels.

[15] It is important to value inherited businesses at the moment they were received (information that, fortunately, the survey provides, reported by the respondent). This way we can exclude the possible responsability of the household members in modifying that value. For some assets (real state, jewellery), the survey only provides their current value reported by the respondent. In this case, the possible appreciation or depreciation of their value is to the greatest part not attributable to the household individuals, and using the provided current value is compatible with considering the value of the whole inheritance amount received a 'circumstance', that is, out ot the individual responsability.

for the share received. The reception of inheritances has been categorized first as a binomial variable (which would make a total of 12 types of households according to circumstances: 2 genders, 3 occupational classes, 2 inheritance categories). Trying to capture the difference influence of different amounts of inherited wealth, we alternatively divide the inheritance variable into 5 categories using its quartiles: no inheritance, low quartile, mid-low quartile, mid-high quintile and top quartile. Table 3.4, in addition to the 10th and 90th percentile, displays the quartile thresholds for inheritances (q25, q50 and q75). All this translates into splitting the sample in 30 types: 2 genders, 3 occupational classes, 5 inheritance categories. In the next section, we present our results for each set of circumstances (6, 12 or 30 types) and both for our general sample and the subsample of individuals older than 60.

3.4 Results

With the intention of observing the effect of different sets of circumstances on IO, we have run our analysis for our 6, 12 and 30 types specifications explained in the previous section.

3.4.1 Gender and parental occupation

Although our main finding refers to the effect of inheritances on inequality of opportunity in wealth, a preliminary visualization of our 6-types specification (that only considers gender and parental occupational level) allows us to look at the relation of these two circumstances with the conditional wealth distribution. Figure 3.2 shows the ordered distributions of net wealth for each of the 6 types created using gender and parental occupational level. For a given gender, a higher level of parental occupation implies a higher amount of net wealth, the difference being especially relevant between households whose head has parents with a high-class occupation and those with either mid or low parental occupational class. The relation is similar if we look at the income distribution.

On the other hand, for a given level of parental occupation, households with a male head consistently have a higher amount of wealth (and income) than households with a female head. In fact, the distribution for the type composed by 'men with low-class parental occupation' is even slightly above the type of 'women with mid-class parental occupation' for all 'degrees of effort'. This highlights the importance of the gender circumstance and reveals an wealth and income gap between households depending on the gender of household head.[16]

3.4.2 IO estimates and the role of inheritances

Our estimates first confirm that -as reported in previous research- that total inequality in wealth is higher than total inequality in income. The first three columns in Table 3.5 report the inequality indices for wealth in both samples used, and in all of them the inequality levels are higher than for income (Table 3.7).

To obtain our estimates for inequality of opportunity, in each specification (6, 12 or 30 types) we apply the non-parametric regression methodology described in Section 3.2, regressing wealth and income on each household's rank within its respective type (Equation 3.3). The inequality of each smoothed distribution Z represents the value of 'inequality of effort', and it is included in columns 4-6 of Tables 3.5 and 3.7. These tables also include total inequality of the wealth and income distributions in the first three columns (Mean Logarithmic Deviation (MLD), Atkinson and Gini indices), while the final three columns reflect the inequality of opportunity level (IO) as the difference between overall inequality and the inequality (IE) of the smoothed distribution Z (equation 3.1). Finally, tables 3.6 and 3.8 reflect the IO ratios for wealth and income respectively (Equation 3.2).[17]

As displayed in Table 3.5, the inequality of the smoothed distribution Z (that is, the value of IE) is higher for the 6 types specification than for the 12 and 30 types specification, and therefore IO is lower: as we include more circumstances, the ranking within-type (the degree of effort) tends to explain *less* of the wealth of the household, and more remains explained

[16]We were concerned about the possibility that this gender gap could be caused by the fact that having a female household head might be more likely the case in households where the woman was single or a single mother (recall the head in the survey is chosen as the person responsible for the household finances). If so, the wealth or income gap could be attributed to the household composition (a 'missing' contributing partner) rather than to the gender. However, running the analysis using equivalent net wealth and equivalent regular income (using squared root equivalence scale) yielded practically an identical pattern (see Appendix Figure 3.A1).

[17]Note that for comparability reasons we will refer to the MLD index thoughout the whole analysis of the results, even though all of our findings are qualitatively consistent with the other two inequality indices displayed (Atkinson(1) and Gini). Although our proposed ex-post non-parametric regression methodology can be applied with any S-convex inequality index (Lasso de la Vega et al. (2017)), other inequality of opportunity methods -like the ex-ante method used by Ferreira and Gignoux (2011), Marrero and Rodríguez (2012) or Palomino et al. (2016) among many others- can only be used with an additively decomposable and path independent index like the MLD, which has virtually become a standard in the IO literature.

by the circumstances (by the type the household belongs to), making the IO level go up: for the main sample, the MLD of IO for wealth is 0.15 for the 6 types specification, 0.20 for the 12 types specification and to 0.26 for the 30 types specification. This pattern takes place with all three indices used, and for both samples of the population used (the top part of each table presents the results for the whole sample of households heads of age 30 or older, while the bottom part for the subsample of only heads of age 60 and older (see section 3.3)). For each estimate we include the bootstrapped standard errors below.[18]

The results with our 6 types specification find an IO wealth level of 21.65% of total inequality, and the results for income are similar and even slightly higher (23.59%). When we restrict the sample to households heads over 60 years old, the values for wealth increase slightly, and the share of wealth inequality associated with IO if we only take into account gender and parental occupation is 27.55% (25.90% for income). [19]

How does the IO level change when we include bequests? When we add the binary circumstance of 'obtaining inheritance' and split the population in 12 types, the MLD level of IO wealth increases to 0.20, yielding a relative share of IO in total inequality of 28.94%, which turn into 0.221 and 33.10% when we use our preferred sample of individuals over 60, more likely to receive inheritances. This result contrasts with the level of relative IO income, which barely increases from the 6 types specification, reaching 25.90% in the whole sample and 27.39% in the preferred subsample. In other words, while accounting for gender and parental occupation produced similar IO ratios in income and wealth, the inclusion of inheritances in the circumstances affects significantly IO in wealth, and only slightly IO in income.

However, it is when we account for the amount of the inheritance received when the levels of IO wealth present a sharper increase, and also the greater discrepancy with the IO income levels. In our 30 types specification the IO share goes up to 38.09% in the main sample, and to 48.97% in the subsample of individuals over 60, accounting for almost half of total wealth

[18] We have used random sampling bootstrap with replacement and 1000 replications.

[19] Although parental occupation is not a perfect proxy of the individual educational background (and her financial literacy) and acknowledging that our specification uses a different method and also includes gender as a conditionant, this result is not far from Lusardi et al. (2017). They find, using an endogenous model calibrated for the U.S., that (excluding bequests) a 30-40% range of inequality in wealth can be attributed to the financial knowledge of the individual.

inequality. These ratios are far above the ones obtained for income (24.76% and 33.44% respectively) showing that the size of the bequest received has far more impact on wealth than on income inequality of opportunity.

The importance of the amount of the inheritance in the household wealth can be graphically visualized in Figure 3.3, where we plot the distributions of wealth and income for each different inheritance type (by amount received), given the other circumstances (gender and parental level of occupation). The type in the top quartile by the amount of received inheritances clearly shows higher net wealth than any other type at any given degree of effort, both for men and women, and for all parental occupation levels.

In contrast, when we see the graphs for income (Figure 3.4), the results are slightly different. Men with mid-parental occupation and in the top quartile of the inheritance size distribution do seem to have a higher income level at any point of their type distribution, but this does not occur when the parental occupational level is high, where the amount inherited seems to be almost irrelevant for income. As for women, inheriting a higher amount tends to imply higher income levels, but it does not seem to be as determinant as it was for wealth.

3.4.3 Sensitivity analysis: the non-parametric regression estimation vs fixed non-overlapping intervals

As pointed out in the methodology, the non-parametric regression method overcomes the problems of accounting for the dispersion within tranches (and types) and of the discretional classification of effort in ad-hoc tranches. However, despite its qualitative advantages, it remains to see how this methodological changes quantitatively affect the results and measurements of IO compared with the standard ex-post methods. In order to check the robustness of our results we have included the results for the estimation with centile tranches (Tables 3.A1 to 3.A4) and bandwidth length tranches (Tables 3.A5 to 3.A8) in addition to our main non-parametric regression results (Tables 3.5 to 3.8). In order to visualize the difference, a graphical representation of the non-parametric regression (black line) and the regressogram that uses as tranche the non-overlapping optimal bandwidth is available as an example in the Appendix Figure 3.A2, for the 30 types specification and the subsample of household heads over 60 years old.

The levels of IO measured with these other methods are slightly lower, and so are then the IO ratios. This occurs both for wealth and for income and in all types specifications, although the difference is greater as we include more circumstances and split the sample into more types.

Moreover, the main findings are robust and hold in all three different methods: there is a higher level of IO in wealth than of IO in income and inheritances -and the amount inherited- are key circumstances for inequality of opportunity in wealth.

3.5 Concluding Remarks

Recent research finds that wealth inequality is consistently higher than income inequality but, does this apply also to inequality of opportunity? Using unique data for Spain that include wealth, income and circumstances, we measure inequality and inequality of opportunity in wealth and income for Spain in 2011. Our analysis reveals a higher level of IO in wealth than in income, even in terms relative to their respective total inequality (IO ratio). In our preferred specification (excluding younger individuals unlikely to receive potential inheritance, considering the size of the inheritance and using the MLD inequality index) IO in wealth can represent up to half of total wealth inequality (48.97%), compared to a 33.46% IO ratio in income.

This higher level of IO in wealth is to a great extent driven by the effect of inheritances. Without taking them into account (6 types specification) the IO ratios of wealth and income are very similar and the latter is even slightly higher (21.65% and 23.59%). This changes when we include received inheritances as a 'yes/no' binary variable in the IO calculation. In that case, the IO ratio for wealth goes up to 28.94%, while for income it remains almost unchanged at a 23.71%. But it is when we account for the size of the inheritance that IO in wealth shows a marked increase, reaching an IO ratio of 48.97%, which also implies the widest difference with the IO ratio in income 33.44%.

We believe our findings add another relevant ingredient to debate about inequality in the wealth distribution. They show that inequality of opportunity in wealth is significantly higher than in income and that, even with a limited set of circumstances, up to one half of wealth inequality can be considered beyond the responsibility sphere of the individual. Inheritances -especially those of a relatively high amount- represent a key component of inequality of opportunity in wealth.

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3.6 Tables and Figures

Table 3.1: Database Descriptive Statistics

	Sample over 30 years old	Sample over 60 years old
Observations	5834	3198
Share of women heads (%)	39.68	37.52
Share with high parental occupational class (%)	27.37	28.02
Share with mid parental occupational class (%)	62.34	62.07
Share with low parental occupational class (%)	10.28	9.91
Share receiving inheritance (%)	33.77	37.71
Age (Mean)	61.01	72.01
Age (Standard Deviation)	14.26	7.36

Table 3.2: Net Wealth Descriptive Statistics - Euros (rounded to the unit)

	Sample over 30 years old	Sample over 60 years old
Mean	1 317 590	1 560 973
Std. Dev.	4 850 618	4 944 354
q10	56 733	84 893
q25	150 526	186 889
q50	336 457	443 145
q75	883 566	1 118 776
q90	2 193 514	2 770 527

Table 3.3: Regular Income Descriptive Statistics - Euros (rounded to the unit)

	Sample over 30 years old	Sample over 60 years old
Mean	71 336	69 851
Std. Dev.	289 936	297 680
q10	9 234	8 400
q25	16 392	14 000
q50	30 800	27 010
q75	60 071	56 000
q90	119 070	113 278

Table 3.4: Inheritances Descriptive Statistics - Euros (rounded to the unit)

	Sample over 30 years old	Sample over 60 years old
Mean	415 996	262 179
Std. Dev.	2 501 372	924 025
q10	3 543	4 874
q25	17 000	18 030
q50	80 000	90 076
q75	217 450	240 405
q90	510 974	500 000

Table 3.5: Inequality, IE and IO in Wealth - Non Parametric Regression

	Inequality			IE			IO		
	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini
6 Types	0.691	0.499	0.553	0.541	0.418	0.493	0.150	0.081	0.060
S.E.	0.024	0.012	0.008	0.019	0.011	0.008			
12 Types	0.691	0.499	0.553	0.491	0.388	0.487	0.200	0.111	0.066
S.E.	0.024	0.012	0.008	0.017	0.010	0.008			
30 Types	0.691	0.499	0.553	0.428	0.348	0.475	0.263	0.151	0.078
S.E.	0.023	0.012	0.008	0.014	0.009	0.008			
6 Types >60	0.669	0.488	0.555	0.485	0.384	0.482	0.184	0.104	0.073
S.E.	0.031	0.016	0.011	0.023	0.014	0.010			
12 Types >60	0.669	0.488	0.555	0.447	0.361	0.478	0.221	0.127	0.078
S.E.	0.032	0.016	0.011	0.020	0.013	0.010			
30 Types > 60	0.669	0.488	0.555	0.341	0.289	0.446	0.328	0.199	0.109
S.E.	0.033	0.017	0.011	0.015	0.011	0.010			

Table 3.6: IO Share in Wealth (%) - Non Parametric Regression

	MLD	Atkinson (1)	Gini
6 Types	21.65	16.21	10.93
12 Types	28.94	22.23	11.97
30 Types	38.10	30.25	14.17
6 Types >60	27.55	21.26	13.16
12 Types >60	33.10	26.03	13.99
30 Types > 60	48.97	40.71	19.65

Table 3.7: Inequality, IE and IO in Income - Non Parametric Regression

	Inequality			IE			IO		
	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini
6 Types	0.384	0.319	0.458	0.294	0.254	0.408	0.091	0.065	0.050
S.E.	0.018	0.012	0.010	0.010	0.008	0.007			
12 Types	0.384	0.319	0.458	0.293	0.254	0.407	0.091	0.065	0.050
S.E.	0.018	0.012	0.011	0.011	0.008	0.007			
30 Types	0.384	0.319	0.458	0.289	0.251	0.406	0.095	0.068	0.052
S.E.	0.018	0.012	0.011	0.010	0.007	0.007			
6 Types >60	0.432	0.351	0.496	0.320	0.274	0.437	0.112	0.077	0.059
S.E.	0.039	0.025	0.020	0.017	0.012	0.011			
12 Types >60	0.432	0.351	0.496	0.314	0.269	0.432	0.118	0.082	0.064
S.E.	0.038	0.024	0.020	0.017	0.013	0.011			
30 Types > 60	0.432	0.351	0.496	0.287	0.250	0.418	0.144	0.101	0.078
S.E.	0.038	0.024	0.020	0.012	0.009	0.009			

Table 3.8: IO Share in Income (%) - Non Parametric Regression

	MLD	Atkinson (1)	Gini
6 Types	23.59	20.25	10.88
12 Types	23.71	20.36	10.95
30 Types	24.76	21.30	11.29
6 Types >60	25.90	21.91	11.85
12 Types >60	27.39	23.25	12.81
30 Types > 60	33.44	28.77	15.79

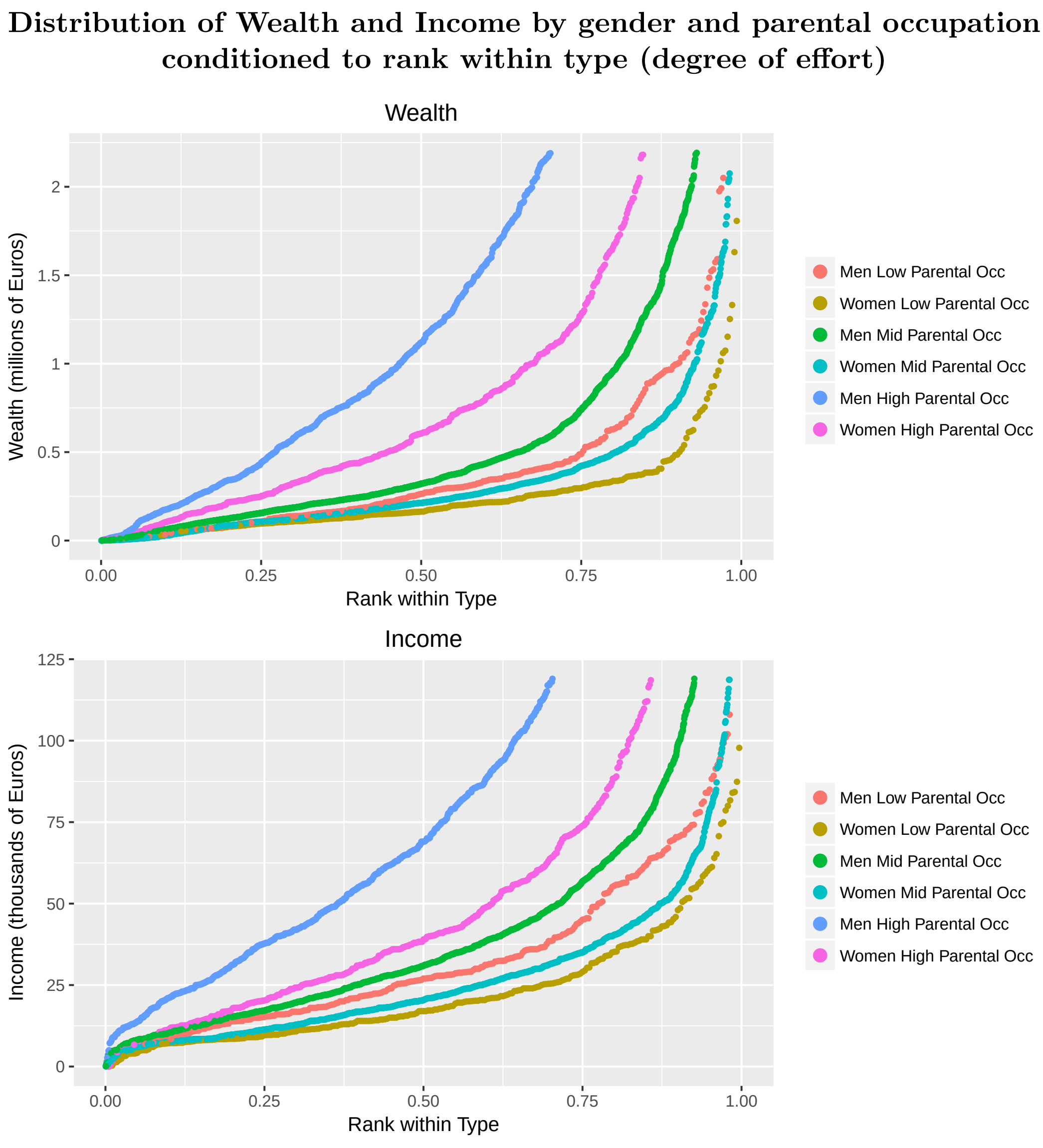

Figure 3.2: Data includes household heads 30 years old or older. We have excluded the 10% higher wealth or income observations in order to 'zoom' the graph and better visualize the differences among types.

Wealth distribution conditioned to rank within type (degree of effort). Types by amount of inheritance, given gender and parental education.

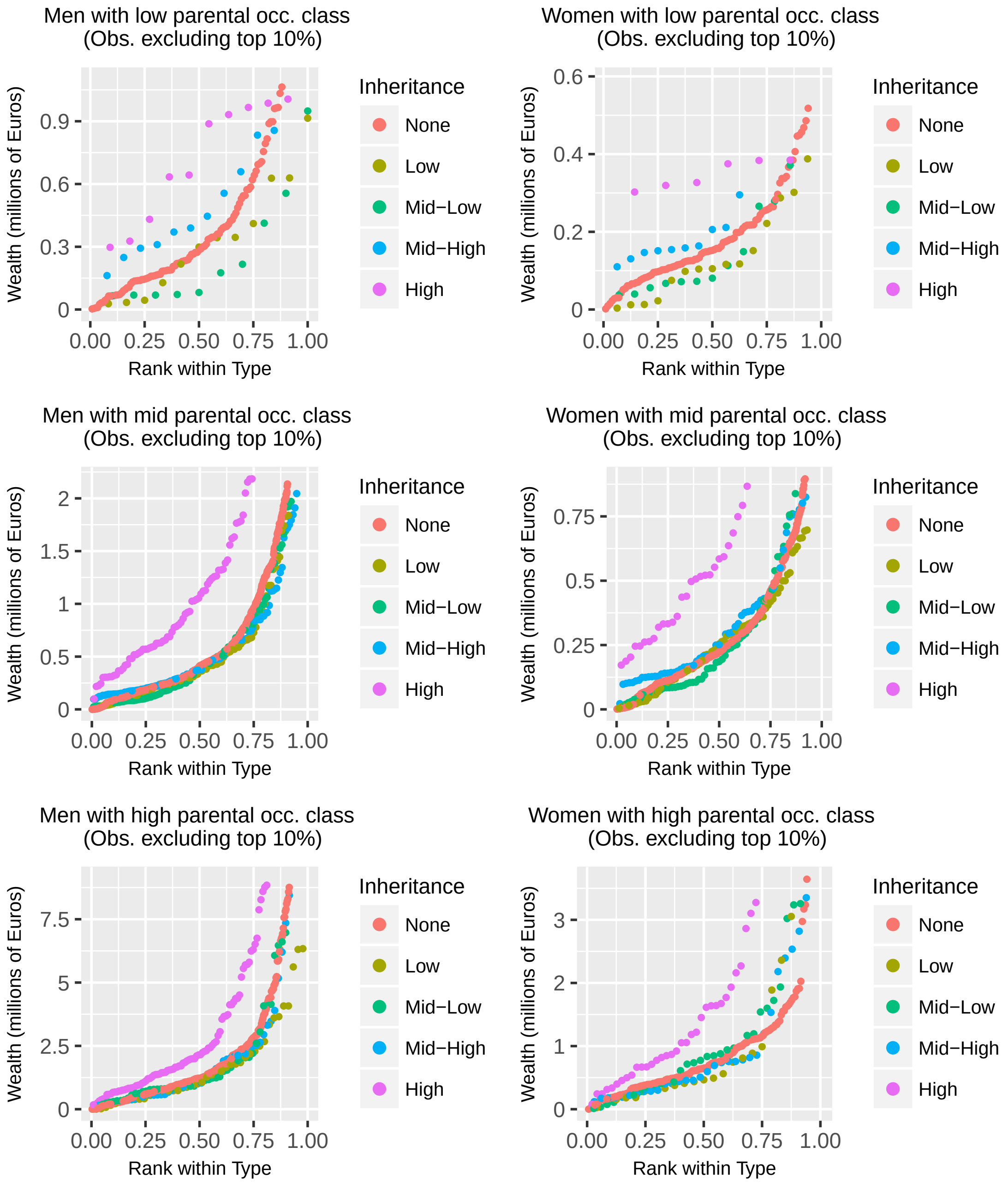

Figure 3.3: Distribution of wealth conditioned to degree of effort for men (left) and women (right) with different levels of parental occupation, for our sample of households heads 60 years or older. The graphs have been 'zoomed', excluding the top 10% of observations to better show the differences for different inheritance thresholds. The inheritance thresholds used to create the 5 inheritance types are the quartiles (q25, q50 and q75) of the inheritances distribution (see Table 3.4).

Income distribution conditioned to rank within type (degree of effort). Types by amount of inheritance, given gender and parental education.

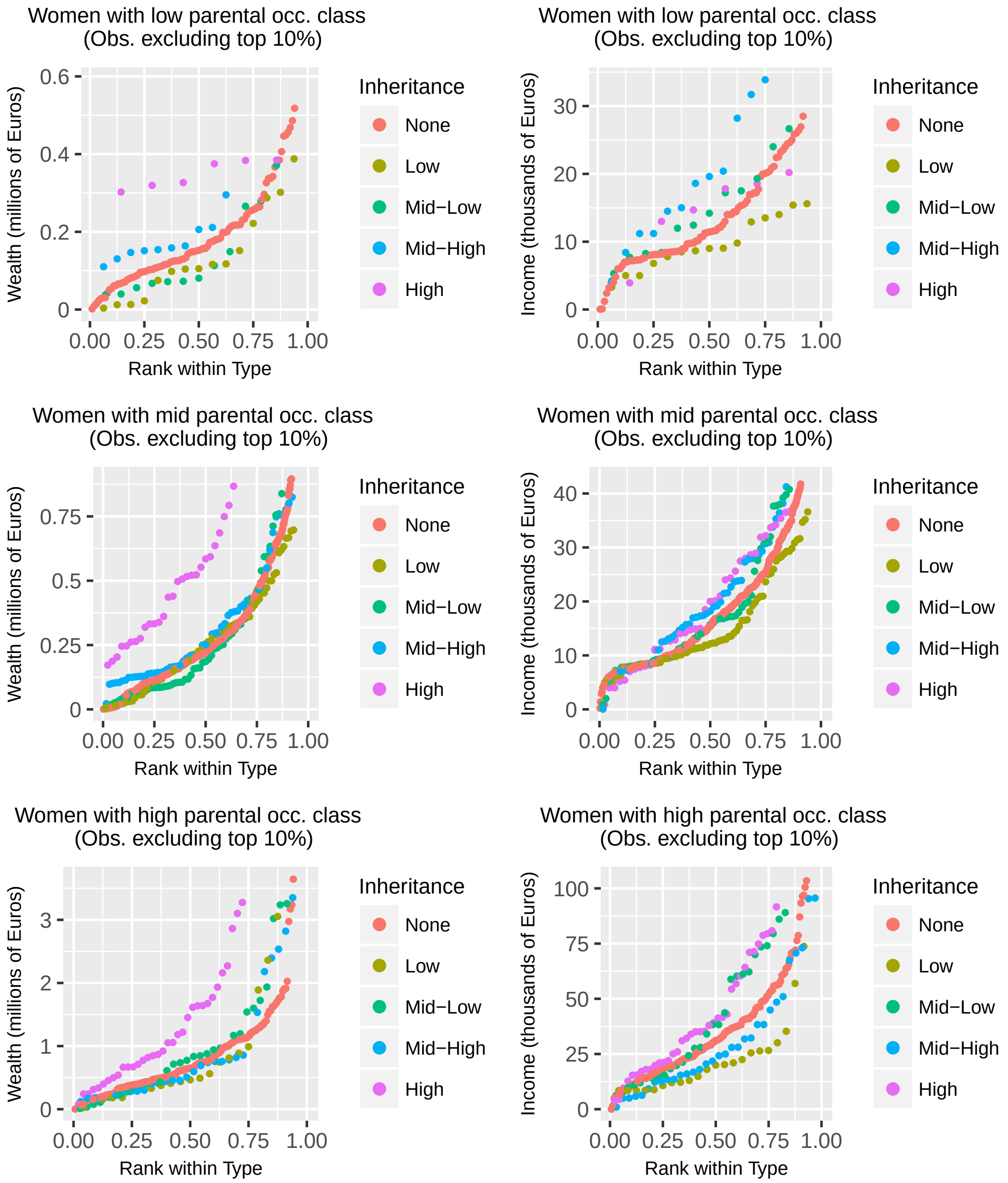

Figure 3.4: Distribution of income conditioned to degree of effort for men (left) and women (right) with different levels of parental occupation, for our sample of households heads 60 years or older. The graphs have been 'zoomed', excluding the top 10% of observations to better show the differences for different inheritance thresholds. The inheritance thresholds used to create the 5 inheritance types are the quartiles (q25, q50 and q75) of the inheritances distribution (see Table 3.4).

3.7 Appendix: Tables and Figures

Distribution of Equivalent Wealth and Income by gender and parental occupation conditioned to rank within type (degree of effort)

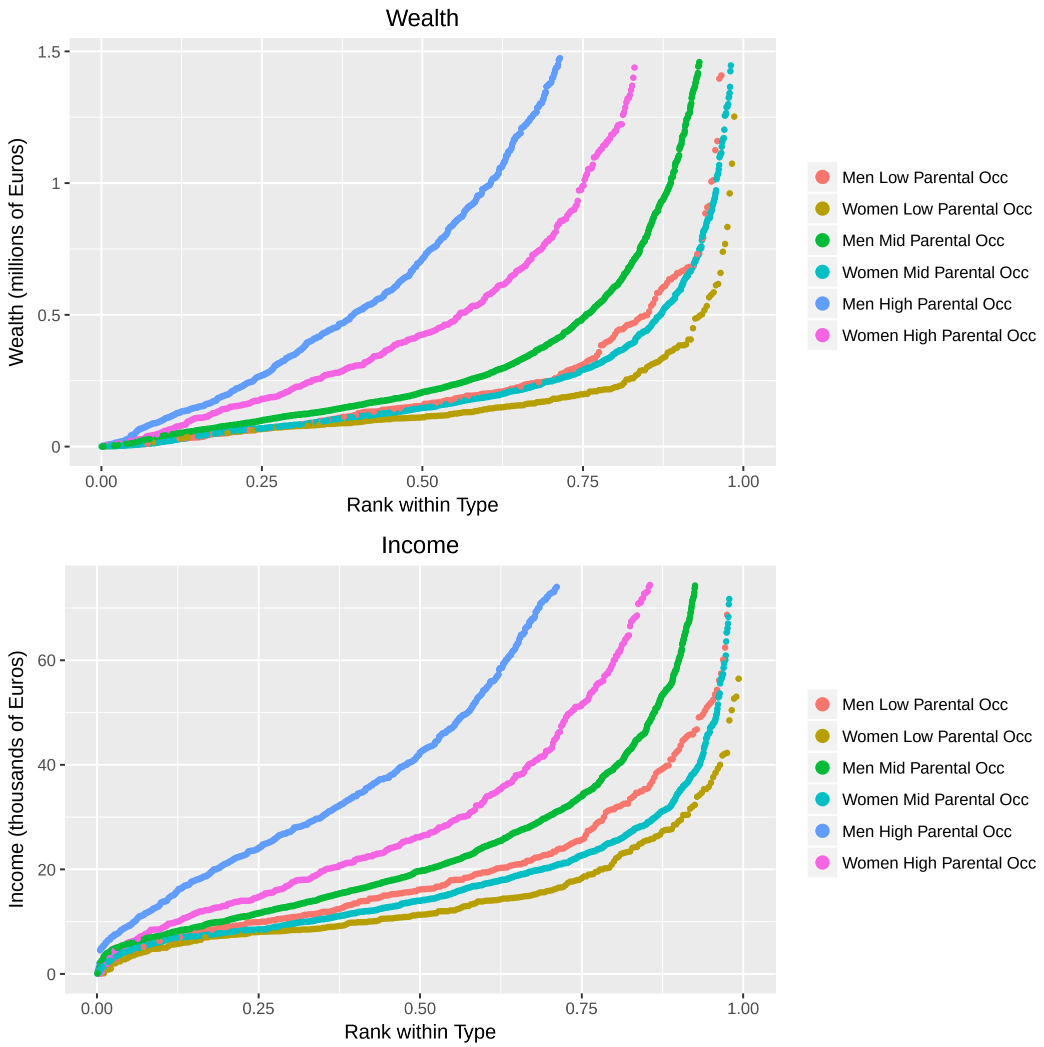

Figure 3.A1: Data includes household heads 30 years old or older. Wealth and income equivalized with the 'squared root' scale. We have excluded the 10% higher equivalent wealth or income observations in order to 'zoom' the graph and better visualize the differences among types.

Table 3.A1: Inequality, IE and IO in Wealth - Regressogram Method - Centiles

	Inequality			IE			IO		
	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini
6 Types	0.691	0.499	0.553	0.551	0.424	0.496	0.140	0.075	0.057
S.E.	0.024	0.012	0.008	0.020	0.012	0.008			
12 Types	0.691	0.499	0.553	0.497	0.392	0.489	0.194	0.107	0.064
S.E.	0.023	0.012	0.008	0.017	0.010	0.008			
30 Types	0.691	0.499	0.553	0.445	0.359	0.481	0.246	0.140	0.073
S.E.	0.024	0.012	0.009	0.015	0.010	0.008			
6 Types >60	0.669	0.488	0.555	0.504	0.396	0.488	0.165	0.092	0.068
S.E.	0.032	0.016	0.011	0.025	0.015	0.010			
12 Types >60	0.669	0.488	0.555	0.471	0.376	0.484	0.198	0.112	0.071
S.E.	0.032	0.017	0.011	0.021	0.013	0.010			
30 Types > 60	0.669	0.488	0.555	0.407	0.334	0.468	0.262	0.153	0.088
S.E.	0.031	0.016	0.011	0.018	0.012	0.010			

Table 3.A2: IO Share in Wealth - Regressogram Method - Centiles

	MLD	Atkinson (1)	Gini
6 Types	20.19	15.04	10.37
12 Types	28.03	21.47	11.57
30 Types	35.58	27.99	13.14
6 Types >60	24.62	18.80	12.19
12 Types >60	29.58	22.98	12.81
30 Types > 60	39.17	31.46	15.80

Table 3.A3: Inequality, IE and IO in Income - Regressogram Method - Centiles

	Inequality			IE			IO		
	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini
6 Types	0.384	0.319	0.458	0.306	0.264	0.414	0.078	0.056	0.044
S.E.	0.018	0.012	0.011	0.011	0.008	0.008			
12 Types	0.384	0.319	0.458	0.305	0.263	0.413	0.080	0.056	0.045
S.E.	0.018	0.012	0.011	0.012	0.009	0.008			
30 Types	0.384	0.319	0.458	0.302	0.260	0.411	0.083	0.059	0.046
S.E.	0.019	0.013	0.011	0.011	0.008	0.007			
6 Types >60	0.432	0.351	0.496	0.337	0.286	0.446	0.095	0.065	0.050
S.E.	0.039	0.025	0.020	0.025	0.018	0.015			
12 Types >60	0.432	0.351	0.496	0.336	0.285	0.445	0.096	0.065	0.051
S.E.	0.039	0.025	0.021	0.026	0.019	0.016			
30 Types > 60	0.432	0.351	0.496	0.301	0.260	0.424	0.131	0.091	0.072
S.E.	0.038	0.025	0.020	0.012	0.009	0.008			

Table 3.A4: IO Share in Income - Regressogram Method - Centiles

	IO Ratio (%)		
	MLD	Atkinson (1)	Gini
6 Types	20.42	17.42	9.61
12 Types	20.72	17.69	9.81
30 Types	21.49	18.37	10.10
6 Types >60	22.05	18.49	10.08
12 Types >60	22.25	18.67	10.27
30 Types > 60	30.33	25.91	14.48

Table 3.A5: Inequality, IE and IO in Wealth - Regressogram Method - Bandwidth Tranche

	Inequality			IE			IO		
	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini
6 Types	0.691	0.499	0.553	0.557	0.427	0.499	0.134	0.072	0.055
S.E.	0.023	0.012	0.008	0.020	0.012	0.008			
12 Types	0.691	0.499	0.553	0.513	0.401	0.494	0.178	0.097	0.060
S.E.	0.024	0.012	0.009	0.018	0.011	0.008			
30 Types	0.691	0.499	0.553	0.439	0.355	0.480	0.252	0.144	0.074
S.E.	0.023	0.011	0.008	0.014	0.009	0.007			
6 Types >60	0.669	0.488	0.555	0.508	0.398	0.490	0.161	0.089	0.066
S.E.	0.031	0.016	0.011	0.025	0.015	0.011			
12 Types >60	0.669	0.488	0.555	0.479	0.381	0.486	0.190	0.107	0.069
S.E.	0.032	0.016	0.011	0.023	0.014	0.011			
30 Types > 60	0.669	0.488	0.555	0.385	0.319	0.462	0.284	0.168	0.093
S.E.	0.032	0.017	0.011	0.018	0.012	0.011			

Table 3.A6: IO Share in Wealth - Regressogram Method - Bandwidth Tranche

	MLD	Atkinson (1)	Gini
6 Types	19.40	14.41	9.88
12 Types	25.71	19.52	10.76
30 Types	36.45	28.77	13.32
6 Types >60	24.06	18.34	11.84
12 Types >60	28.40	21.98	12.50
30 Types > 60	42.51	34.55	16.75

Table 3.A7: Inequality, IE and IO in Income - Regressogram Method - Bandwidth Tranche

	Inequality			IE			IO		
	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini	MLD	Atkinson (1)	Gini
6 Types	0.384	0.319	0.458	0.307	0.264	0.413	0.078	0.055	0.044
S.E.	0.018	0.012	0.010	0.012	0.009	0.008			
12 Types	0.384	0.319	0.458	0.304	0.262	0.412	0.081	0.057	0.046
S.E.	0.018	0.012	0.011	0.012	0.009	0.008			
30 Types	0.384	0.319	0.458	0.299	0.259	0.410	0.085	0.061	0.047
S.E.	0.018	0.012	0.010	0.011	0.008	0.007			
6 Types >60	0.432	0.351	0.496	0.335	0.285	0.446	0.096	0.066	0.050
S.E.	0.039	0.025	0.020	0.025	0.018	0.015			
12 Types >60	0.432	0.351	0.496	0.334	0.284	0.445	0.098	0.067	0.051
S.E.	0.038	0.024	0.020	0.023	0.016	0.014			
30 Types > 60	0.432	0.351	0.496	0.316	0.271	0.434	0.116	0.080	0.062
S.E.	0.038	0.024	0.020	0.019	0.014	0.012			

Table 3.A8: IO Share in Income - Regressogram Method - Bandwidth Tranche

	MLD	Atkinson (1)	Gini
6 Types	20.21	17.23	9.66
12 Types	21.00	17.94	9.98
30 Types	22.16	18.97	10.29
6 Types >60	22.33	18.74	10.14
12 Types >60	22.60	18.98	10.36
30 Types > 60	26.75	22.68	12.52

Non Parametric Regression vs Non Overlapping Tranches (optimal bandwidth)

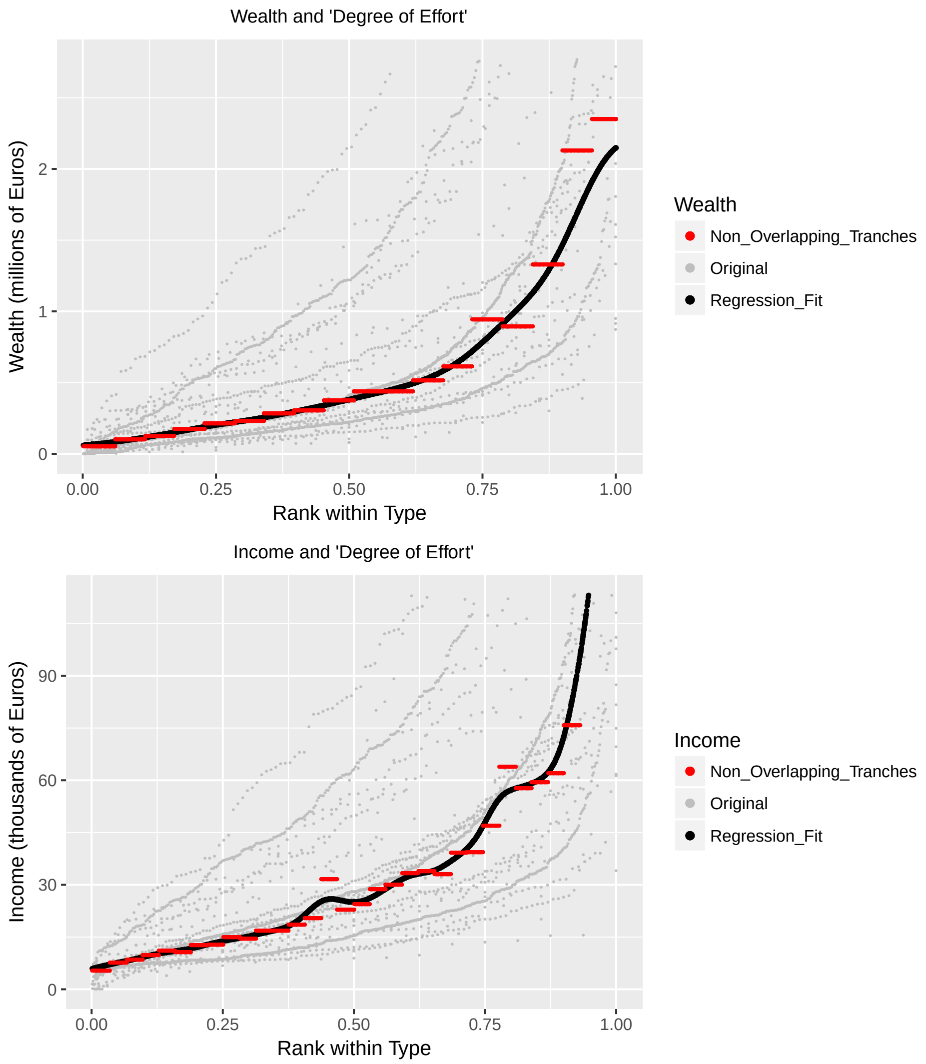

Figure 3.A2: Wealth / Income and degree of effort. Sample age 60 and over. 30 Types. Smoothed fit NW Non-Parametric regression and Non Overlapping Tranches (Bandwidth lenght). Database: Household heads 30 years old or older.We have excluded the 10% higher wealth or income observations in order to 'zoom' the graph and better visualize estimations.

Conclusion

In this section we summarize the main contributions and results of this doctoral dissertation and discuss the possible paths for future research.

In the first chapter, we contribute to the existing literature about intergenerational income mobility in the U.S. measuring the Intergenerational Income Elasticity (IGE) at different points of the income distribution. Using an extensive sample from the Panel Study of Income Dynamics (PSID), we overcome the data size shortcomings of previous research and present more accurate estimates at the tails of the distribution for the IGE in the U.S. during the 1980-2010 period. We then apply conditional quantile regression and check that our results are robust, among other things, to the use of (RIF-OLS) unconditional quantile regression. Our main finding reveals that economic persistence is significantly higher at the tails of the distribution. While our OLS estimate of IGE for the entire pool is 0.47, in line with the existing and recent literature, we find that 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 intensively, at the bottom of the distribution have been significantly more conditioned by their parental income than those at the middle part of the distribution. These findings can contribute to better target public policies aiming to promote economic mobility.

By sources, we find that son's education can represent between 20% and 50% of the IGE, being also 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 explain more than 10% of the transmission of parental income, and their importance is highest below the 60^{th} percentile of the income distribution.

For all percentiles up to the median (and OLS estimates), the trend of the 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. It remains for future research to analyze whether the reversal in the IGE trend for the lower part of the distribution is circumstantial or it represents a structural change.

In the second chapter, using data from the EU-SILC surveys in the 2004 and 2010 waves for 26 European countries, we present a novel strategy to decompose ex-ante measures of Inequality of Opportunity (IO) in their educational and occupational channels. Our methodology obtains the circumstance-conditioned income (the smoothed income distribution) and successively decomposes it by using log-linear regression into orthogonal mediating factors, following the natural order in which these channels come into play (first education and then occupation). Finally, using the decomposable MLD index, the inequality of the smoothed distribution is partitioned into the different shares of inequality of opportunity explained by each considered factor.

We find that a relevant share of IO is channeled through the different levels of education. In 2010, this share accounts to around one third of IO in Portugal and Luxembourg, almost one quarter in Greece and Hungary, and more than one fifth in Italy and Poland. Most of the other countries are in the 8% - 20% range. Once the educational channel is taken into account, the importance of the occupational channel is relatively small, channeling less than 5% of IO in most countries. On the other hand, although particular countries have suffered significant changes, we find no general pattern of change in the shares of IO channeled by education and occupation between the two waves of data analyzed.

Our findings, although limited to only the level of education and the occupational category, may be relevant for practitioners and policymakers concerned about inequality of opportunity, evidencing that a significant share of inequality of opportunity derives from the different level of education that people with different circumstances can achieve.

Also, trying to explore the factors that explain the differential importance of the educational channel across countries, we detect a positive (negative) correlation between the share of IO channeled by education and the share of the population with low education (tertiary education). The higher is the accessibility of individuals to superior education, the lower is the inequality of opportunity channeled through education (both in absolute and relative terms).

Despite that we find a significant channeling importance of the educational level, a relevant share of IO is not explained by our set of variables, which presents an important challenge for future research. We think that our method provides a simple but useful strategy for the prospective analysis of other potential channels (e.g., education quality, social connections) when appropriate data be available.

The third chapter aims to contribute to the literature with an analysis of inequality of opportunity in wealth, with a special focus on the importance of inheritances and its different impact in IO in wealth and in IO in income. Using data from the 2011 Spanish Household Finance and Consumption Survey, our analysis finds that IO is more important when looking at wealth than when measuring IO in income: IO in wealth can represent up to half of total wealth inequality (49%), compared to a 33.4% IO ratio in income.

More importantly, we find that the higher level of IO in wealth is to a great extent driven by the effect of inheritances. Accounting only for the parental occupational level and the gender circumstances, the IO ratios of wealth and income are very similar and the latter is even slightly higher (21.7% and 23.6%, respectively). However, when including 'received inheritances' as a binary circumstance variable (one if receive inheritance, zero otherwise) in the calculation of IO, the IO ratio for wealth goes up to 28.9% while that of IO in income remains almost unchanged at 23.7%. When we additionally account for the size of the inheritance, the importance of IO in wealth increases significantly to a ratio of 49%, reaching the largest difference with the IO ratio in income, which increases only moderately to 33.4%.

The findings of the third chapter show that IO in wealth is significantly higher than in income and that, even with a limited set of circumstances, up to one half of wealth inequality can be considered beyond the responsibility sphere of the individual. Moreover, inheritances -especially those of a relatively high amount- represent a key component of IO in wealth. However, being limited to only Spain and to the 2011 wave, more research in other geographical regions and other waves would be desirable in order to confirm this pattern as a structural feature of inequality of opportunity in wealth. An even more ambitious step would be to develop a theoretical general equilibrium and dynamic framework that could help to understand the distinct formation of inequality of opportunity in income and wealth, and the role of inheritance and other relevant factors in this process.