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## MEASURING THE LINK BETWEEN INTERGENERATIONAL OCCUPATIONAL MOBILITY AND EARNINGS: EVIDENCE FROM 8 EUROPEAN COUNTRIES

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# Measuring the link between intergenerational occupational mobility and earnings: Evidence from eight European countries

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**Abstract**
This paper investigates the relationship between family background and earnings using relative social mobility to decompose residual background correlations, namely the effect of background on earnings left after controlling for background-related intervening factors. Using the European Union Survey on Income and Living Conditions for 8 countries, we first show that country differences in terms of intergenerational inequality concern residual background correlations and then decompose these correlations using changes in relative social positions. In immobile countries, we find that significant residual correlations are mainly driven by penalisation of upward mobility in the UK (glass ceiling) and by an insurance against downward mobility in Spain and Italy (parachute). In mobile countries, insignificant residual correlations mask heterogeneous returns to social mobility. While our findings for Southern countries hardly concur with human capital theory, the widespread emergence of glass ceiling effects appears to be consistent with this theory.

**JEL Classification:** D31, J62, J24, J31

**Keywords:** intergenerational inequality, returns to intergenerational occupational mobility, international comparison, relative social positions.

## 1. Introduction

A primary objective of the empirical literature on intergenerational inequality and social mobility is to understand the mechanisms that generate income persistency. Most of the studies attempt to distinguish the roles played by nature and nurture in the transmission process (e.g. Bjorklund et al. 2005 and 2007, Sacerdote 2007, Holmlund et al. 2011), while fewer works decompose the impact of family background on children's earnings into two major intervening factors, i.e., educational and occupational attainments (e.g., Ganzeboom and Treiman 2007, Blanden et al. 2007 and 2011). Such decompositions are crucial to assess the institutional factors that drive intergenerational inequality and to shape judgements on the fairness of the process of inequality transmission. By way of example, the effect of family background on earnings could be more acceptable when it is mediated by differences in abilities and values leading to effort-intensive outcomes, i.e., educational attainment (Jencks and Tach 2006). Likewise, as the dependence of occupational attainment on family ties increases, the process of inequality transmission becomes less acceptable (Ganzeboom and Treiman 2007).

Along the lines of decomposition studies, two recent works have shown that a sizeable residual correlation between family background and children's earnings persists even after considering several intervening factors (Bowles and Gintis 2002) and that, within the EU, this correlation is significantly higher in countries characterised by a higher intergenerational inequality (Raitano and Vona 2013a). A related strand of literature interprets this direct effect of family background on earnings univocally as a measure of individual abilities (Lam and Schoeni 1993, Agnarsson and Carlin 2002). While this interpretation is coherent with the fact that better parents positively affect children's abilities through several channels besides formal educational attainment (e.g., selecting better schools)[1], it neglects the influence of family background on labour market outcomes (Hudson and Sessions 2011), such as on the probability of finding a good job.

The aim of this paper is to unpack the black box of this residual background correlation (RBC henceforth)[2]. The main idea is to use intergenerational occupational mobility to distinguish between two types of RBC. A standard type emerges because in higher occupations, the well-off child should have a better endowment of human capital (*a glass ceiling effect*). In contrast, the second type is associated with insurance for the children of the well-off ending up in lower occupations (*a parachute effect*). To implement this idea, we use the 2005 module on intergenerational mobility of

[1] Also the transfer of soft skills and cultural tastes can be seen as part of the human capital endowment above formal schooling. See, e.g., Osborne Groves (2005), Goldthorpe and Jackson (2008), Dohmen et al. (2012), Duncan and Murnane (2011).

[2] Note that the concept of RBC is different from the one of intergenerational income elasticity, i.e. the estimated relationship between parental and child income, as RBC is estimated conditioning on children characteristics and intervening factors such as education and occupation.

the EUSILC dataset and examine these two effects in eight EU countries characterised by different levels of intergenerational inequality and belonging to different welfare regimes. Our empirical analysis is motivated by the theoretical claim that returns to upward and downward social mobility could arguably stem from different sources. A glass ceiling of upward mobility is likely to depend on both network effects and unobservable skills that are positively correlated with family background. Conversely, it is hard to believe that the parachute effect can be associated with better unobservable skills; hence, in this case, family networks should be of paramount importance.

A central aspect of our empirical strategy consists of using changes in the relative occupational position of the child compared to the parental one to measure intergenerational mobility and separate, at least in some cases, unobservable skills from family networks. For both generations, we construct a refined ranking of social positions using (in hierarchical order) information on occupation, immigrant status, education and other individual characteristics. Using the two surrogate distributions generated by these rankings, we derive measures of intergenerational social mobility[3] as the difference between the relative positions of parents and children.

By way of example, imagine that a child is in the first tercile (low social position) of its distribution but that his father was in the last tercile (high social position). This individual clearly has a good background, but his relative position signals that he has a low ability. In this case, a positive RBC (i.e., a parachute effect) would depend on the family network rather than on unobservable skills related to the child's background. Conversely, it is not easy to infer the true unobservable skills of individuals who maintain their positions and earn more than others while sharing the same occupation but coming from a worse background. Hence, the identification of the glass ceiling effect is more problematic.

Our empirical investigation sheds new light on these effects. We find that a positive and significant RBC is mainly driven by a glass ceiling effect in the UK, while the parachute effect appears important only for Southern countries. The glass ceiling effect also emerges in countries with insignificant RBC, but it is smaller and tends to be offset by penalties to downward mobility.

The remainder of the paper is organised as follows. Section 2 presents the conceptual framework and the empirical strategy. Section 3 describes the index of social mobility used to implement this strategy and the data. Section 4 presents the main results on residual background correlation and returns to changes in relative social positions, whereas section 5 concludes the manuscript.

[3] Being individual relative positions built primarily from occupations, we will use as synonymous the terms occupational and social mobility.

## 2. Conceptual Framework and Empirical Strategy

Economic theory generally studies intergenerational inequality through the lenses of human capital theory (e.g. Solon 2004). The literature acknowledges different channels through which family background affects skill formation, including financial constraints (Becker and Tomes 1979, 1986), peer effects (Benabou 1996), educational policies (Schuetz et al. 2008), soft skills (Bowles and Gintis 2002) and the cumulative effects of educational investments since early childhood (Cunha and Heckman 2007). As a result, family background not only influences the "quantity" of education attained by the child but also its "quality" (Bratsberg et al. 2007). When school quality is highly heterogeneous, wealthier parents are more likely to select better schools or to live in neighbourhoods where those schools are located. Note that heterogeneity in school quality typically increases with the expansion in educational attainment (Shavit et al. 2007). In France and the UK, for instance, recent research shows that well-off children have a higher probability of accessing top schools, which ensures better earnings prospects (Blanden and Machin 2004, Chevalier and Conlon 2003, Gurgand and Maurin 2007).

The human capital view can adequately explain intergenerational inequality in countries where labour markets are competitive and frictions reflect only skill mismatches. Under this assumption, differences in earnings and occupational attainments merely reflect the differences in the observable and unobservable components of human capital. However, family ties may also play a role in determining occupational achievements and earnings, especially in countries belonging to the Southern European "familial" welfare regime (Whelan and Maitre 2010, Checchi et al. 1999, Guell et al. 2007)[4]. Family ties represent a natural network in themselves that will prove all the more extensive and strong proportionately with the height of the family's social position and its capacity to "leverage social relations for economic purposes" (Granovetter 2005, p. 39). Empirically, the direct influence of parental background on child labour market outcomes can occur through membership to social networks (Granovetter 1995, Pellizzari et al. 2011) and the transmission of employers (Corak and Piraino 2011), both of which affect the probability of finding a good job, especially in sectors where competition is lower (Raitano and Vona 2013b)[5].

A theoretical model that connects family background, skill formation and family-related network effects in imperfect labour markets would represent the ideal framework to guide a cross-country empirical analysis of intergenerational inequality. Unfortunately, to the best of our knowledge, neither such a theory exists, nor has cross-country evidence yet documented the

[4] For instance, Unicredit, one of the largest Italian banks, in 2010 gave priority to applicants in the hiring process to the children of workers that were fired according to a collective dismissal procedure (Boeri 2010).

[5] Pellizzari (2010) shows that, given the level of education, family networks affect the probability of a person finding a good job or of being employed in EU countries.

importance of these two channels (quality of human capital vs. network). While our paper primarily contributes to providing new evidence, a stylised theoretical discussion helps us present our empirical strategy in a more rigorous way.

Without a loss of generality, consider the initial endowment $\theta_{ij}$ of each child $i$ from family $j$ as a function of two complementary inputs: a family background input, $b_j$, and idiosyncratic abilities independent from the background, $a_i$. The child goes to school and receives a formal degree, $e$, which is positively correlated with $\theta_{ij}$. He then enters an occupation, $o$, depending on the degree, $e$, received and on $\theta_{ij}$. Because educational and occupational quality is only partially observable, we allow $\theta_{ij}$ to have a direct influence on individual earnings. This residual influence of $\theta_{ij}$ is by definition correlated with family background, and we define "Residual Background Correlation" as the correlation between family background and earnings after controlling for education and occupation. More formally:

$$(1) \qquad w_{ij} = f\left(e\middle|\theta_{ij}\right) * \delta_e + g\left(o\middle|e, \theta_{ij}\right) * \delta_o + \theta_{ij}.$$

Equation (1) states that individual wages depend on the following: 1. The educational attainment $f\left(e\middle|\theta_{ij}\right)$ through its return $\delta_e$; 2. The occupational status or quality $g\left(o\middle|e, \theta_{ij}\right)$ through its return $\delta_o$; 3. $\theta_{ij}$, which is the RBC when we use a proxy of family background to measure $\theta_{ij}$.

In this paper, we are interested in decomposing the RBC-proxy $\theta_{ij}$ into two background-related effects[6]: the quality of human capital (not accounted for by $e$), $h_{ij}$, and the network effect, $n_{ij}$ . Both effects depend on an individual's idiosyncratic abilities, but the correlation between abilities and background differs between them. On the one hand, the effect of high abilities is magnified in a good parental environment, leading to a positive correlation between $a_i$ and $h_{ij}$. On the other hand, family-related networks, if any, matter both for high- and low-ability individuals. The expected signs of the two correlations as a function of ability are then:

i. $E(h_{ij,}a_i) > 0$ only if $a_i > \bar{a}$

ii. $E(n_{ij,}a_i) \geq 0$ for every $a_i$,

where $\bar{a}$ is the threshold level of ability. Using these two conditions and provided that $\bar{a} > 0$[7], we can partially identify our effects of interest. Imagine that we estimate a positive RBC for low-ability individuals. This result reveals the existence of network effects. In turn, a positive RBC for high-ability individuals can either depend on their networks or on unobserved skills related to background.

[6] Dynamic complementarities in the effect of background and abilities make it impossible to identify the effect of $b_j$ and $a_i$ without resorting on sophisticated datasets on siblings types.

[7] Note that all we require is that the two primitive inputs in the production of human capital $a_i$ and $b_j$ are complements (Cunha and Heckman 2007).

As a final remark, a theoretical identification of our effects of interest can be obtained *ad excludendum*, interpreting as dependent on family network those effects that cannot be derived using a simple human capital model. To be precise, assume there are two occupations (high and low), that $\theta_{ij}$ is equal to $a_i \cdot b_j$ with $a_i$ uniformly distributed, and that $b_j$ equals 0 or 1. Moreover, a threshold $\theta_{ij} > \bar{\theta}$ is required to enter the high occupation. Clearly, access to top occupations is easier for the well-off than for the worse-off. In the top occupation, the well-off have on average a higher $\theta_{ij}$ than the worse-off, and hence, they will earn more (glass ceiling). In the bottom occupation, the average $\theta_{ij}$ is equal for the worse- and the well-off and, hence, earnings should be the same. From this simple example, it is clear that a human capital explanation can hardly account for the parachute effect.

The next section describes the practical implementation of our partial identification strategy that uses relative social mobility to distinguish between ability and family background.

## 3. Empirical Implementation

### 3.1 Measuring family background and relative social mobility

Without a clear measure of ability in the EU-SILC dataset, the key obstacle to implementing our empirical strategy is to find a way to distinguish between a type of RBC that is primarily correlated with unobservable skills and a type of RBC that is primarily correlated with family networks. To this end, we first need to construct two distributions that capture the relative social position of the child and the parent with the highest occupational status[8]. Then, we measure where the child is with respect to his/her parent. Relative social positions are, unlike absolute positions (e.g., educational attainments), independent of the unit of measure. Moreover, relative social positions are independent from compositional changes of the occupational structure across generations and countries.

A first preliminary step consists of defining a baseline proxy of family background that can be used to estimate the RBC as in equation (1). This is important as a-priori the RBC can be either positive or negative and either statistically significant or not. In a nutshell, it is essential to first understand the effect we want to decompose.

[8]Considering the highest parental status, rather than only the father's one, allows accounting for the maternal influence (Erikson 1984) and to reduce the number of missing observations, which is particularly large in the UK where 38% of children did not report the father's occupation. However, the results presented in section 4 do not change if we exclude from the sample the individuals whose father occupation variable is missing (detailed results are available upon request).

As a proxy of family background, we use parental occupation. According to the sociological literature[9], parental occupation is not only a good proxy for unobservable aspects of human capital, but it also captures the individual's position in the social scale, its capacity to influence economic decisions or of being a part of certain social networks. We use a socio-economic index of occupations, the International Socio-Economic Index of occupational status (ISEI, proposed by Ganzeboom et al. 1992), rather than the occupational classes in order to have a synthetic index[10].

The ISEI index is constructed by computing a weighted sum of the socioeconomic characteristics of the incumbents of each occupation, namely education and income (Ganzeboom and Treiman 1996)[11]. A major advantage of this index is that it has been updated to capture changes in the socio-economic statuses of occupations over time, allowing the use of different rankings for individuals belonging to different generations. The "ISEI-88" was built according to estimates carried out on micro-data on worker's occupations, education and incomes concerning 31 datasets in 16 countries in the period 1968-1981 and converting ISCO-88 occupations in ISEI values (Ganzeboom and Treiman 1996), while recently, it has been updated in "ISEI-08" using micro-data provided in the 2002-2007 waves of the International Social Survey Programme (ISSP), which brings together detailed occupation data with education and earnings data covering 42 countries (Ganzeboom and Treiman 2012). Henceforth, this update allows the use in our paper of a specific conversion table for each generation to transform the ISCO two-digit occupation recorded in EU-SILC for both parents and children into the *parental ISEI* (following the ISEI-88 index) and the *child ISEI* (following the ISEI-08 index).

The second step consists of building two surrogate distributions of the parent's and child's social positions starting from their respective ISEI levels. In EU-SILC, ISCO occupations are only available at the two-digit level, and hence, these distributions are clustered in a few mass points. The percentiles of the two marginal distributions of, respectively, the better parent and the child are then not well balanced. Because we are mainly interested in relative social positions, we use other qualitative information to smooth the original ISEI distribution for both generations. In particular, we rank individuals with the same ISEI using other variables that also approximate their social positions, i.e., immigrant status, educational attainment, family composition and, for the parental

[9] See, e.g., Willis (1986), Ganzeboom and Treiman (1996), Erikson and Goldthorpe (1992), Granovetter (2005).

[10] In sociological literature (e.g. Ganzeboom et al. 1992), the main point in favour of continuous measures of occupational status rather than discrete ones rests in their capacity to overcome the problem of heterogeneity within social classes, an issue that is looming ever larger given the widespread social fragmentation following upon the process of tertiarization of economic systems.

[11] In more detail, the ISEI index is generated by the optimal scaling of ISCO occupations to maximize the role of occupation as an intervening variable between education and income (i.e. maximizing the indirect effect of education on income through occupation and minimizing the direct effect of education on income; Ganzeboom et al. 1992). In other terms, occupation is conceptualized as the activity that transfers education into earnings.

distribution, the occupational and educational attainments of the less-achieving parent. The exploitation of this additional information follows a hierarchical order: each additional variable is used to refine the ranking. More precisely, those individuals with the same ISEI are first ranked according to their immigrant status, those with the same ISEI and immigrant status are further ranked following their educational attainments, and so on[12]. This refinement allows us to derive two smooth distributions of social origins and destinations.

The third step of our empirical implementation consists of choosing the appropriate measure of relative social (or occupational, as ISEI is the primary ranking criterion) mobility. Our preferred measure considers the relative position of parents and children through interaction variables for each possible combination of the percentiles in the two distributions (e.g., the deciles). The advantage of this choice is to know both the starting and arrival point, e.g., the child in the top decile and the father in the bottom. The disadvantage is to have an excessive number of coefficients to comment. To address this trade-off, we choose the tercile. Our variable of interest is therefore:

$$P_j * C_i \text{ with } i, j = 1,2,3$$

where $P_j$ (resp. $C_i$) refers to the parent (resp. child) tercile of the marginal distribution built from their ISEI levels. As an alternative measure of mobility, we fully exploit all of the information in the two marginal distributions. In particular, we first construct the "Relative Social Mobility Index (RSMI)", built as the difference between the child's and the parent's deciles of their respective marginal distributions and normalised to vary between 0 and 2[13]. Second, the quintiles of the RSMI replace the RBC in equation (1) and allow us to measure the aggregate effect of upward and downward social mobility.

### 3.2 Estimating Equations

First, we estimate the following empirical counterpart of equation (1) in order to compute the RBC[14]:

[12] Other characteristics included to rank the children are: supervisory responsibility, contractual arrangement (open-ended vs. fixed term, full-time vs. part-time), living in a urban area. For parents they are: ISEI of the worst parent, dummy for having both parents, the lower number of siblings, the lower year of birth of father and mother. Since the derived distributions are refinements of the original ISEI distribution, the results do not change if we change the hierarchical order of the other criteria considered to order origins and destinations. Actually, all results presented in the paper do not change if we use only the ISEI index as the ranking criterion. Moreover, we prefer to build an index that maintains a hierarchy of family circumstances rather than using a latent variable approach, i.e. principal components, as not all these circumstances are equally important in determining socio-economic success, even if all these variables are significantly associated with earnings.

[13] That is: $RSMI = \frac{d_c - d_p}{10} + 1$. For further details about the index and its distribution in EU countries see Raitano and Vona (2011).

[14] All estimates of this paper have been carried using using the sample weights provided in the intergenerational section of EU-SILC 2005.

$$(2) \qquad \log(w_i) = \sum_e \delta_e 1_e + \delta_i isei_i + \delta_j isei\_par_j + \boldsymbol{X\beta} + \varepsilon_i,$$

where *isei_par* is the highest parental ISEI level, i.e., our proxy of family background, $1_e$ are dummies for educational attainments, **X** is a vector of standard controls in wage equations[15], and $\varepsilon_i$ is a standard error term. In the vector **X**, we also include a dummy equal to 1 if both the child and her/his better parent get exactly the same ISCO two-digit job. This dummy accounts for the inadequacy of continuous measure of occupational status to address immobility (Ganzeboom et al. 1992) and captures the transfer of specific skills that represent another transmission channel (Galor and Tsiddon 1997). Although this dummy does not have a significant effect across the board, it allows us to exclude, at least partially, the role of the most obvious network (especially for self-employed) within the same occupation.

The second step consists of decomposing the RBC. Under our preferred measure of relative social mobility, we distinguish the parachute and glass ceiling effects by estimating the following model:

$$(3) \qquad \log(w_i) = \sum_e \delta_e 1_e + \delta_{ij} \sum_{ij} P_j C_i + \boldsymbol{X\beta} + \varepsilon_i,$$

where we replace *isei_par* with the interactions between terciles of origin and destination, i.e., $P_j C_i$. We interpret these variables as the combination of ability (worsening or not compared to the best parent) and family background (those who have a high $P_j$).

There are two alternative possibilities to decompose the RBC and partially identify the effect of unobservable skills related to background vis à vis the family network. A first option is to estimate equation (2) using quantile regressions rather than OLS. In this case, the coefficient associated with *isei_par* is to be interpreted as the RBC conditioned to the child's ability. Thus, because we expect unobservable skills to be stronger in the top of the ability distribution, a flat pattern of *isei_par* across deciles will denote a stronger influence of family network. A second option is to use the alternative proxy of relative mobility (the RMSI index), which fully uses all of the information contained in the distribution of children's and parents' social positions:

$$(4) \qquad \log(w_i) = \sum_e \delta_e 1_e + \delta_i isei_i + \delta_k \sum_k Q_k + \boldsymbol{X\beta} + \varepsilon_i,$$

[15] Namely: age, age squared, potential experience (actual experience is not recorded in many countries in EU-SILC), sex, immigrant status, marital status, typology of area of residence, working part time and working as self-employed. Potential experience is defined as the distance between 2004 (the income year in EU-SILC 2005) and the year when the highest educational degree was attained (so partially capturing also some individual abilities synthesized in the delay of attaining a degree).

where $Q_k$, the quintiles of the RSMI distribution, capture the effect of upward and downward mobility. Including the individual $isei$ allows us to interpret the effect of the quantiles as a direct decomposition of the RBC. This approach should be viewed as complementary to the main one of equation (3), as we estimate here only the overall effect of improving or worsening social position irrespective on the point of departure.

### 3.3 Data and Preliminary Analysis

The first cross-sectional wave of the European Union Survey on Income and Living Conditions (EU-SILC 2005) includes a specific module that focuses on intergenerational mobility. In all of the Member States, interviewed persons aged between 24 and 65 had to reconstruct the home environment when they were approximately 14 years old, providing a detailed picture of their family background, e.g., family composition, number of siblings, parents' education and occupation. In addition to these background variables, for each individual, the dataset provides information on labour income and several variables that are used to explain incomes in multivariate analyses.

Following the literature on intergenerational inequality (Haider and Solon 2006), we consider only prime-age workers to reduce the life-cycle bias. In particular, we consider workers aged 35-49 for whom the process of intergenerational transmission has fully displayed its effects. Also in line with the literature, our main dependent variable is the log of gross annual labour income from employment and self-employment. To reduce the impact of outliers, we dropped all individuals earning less than 750 euro in a year and for each country, the top 0.2% (resp. 0.5%) of the employees' (resp. self-employed) distributions. As a final remark, note that in EU-SILC 2005, earnings are recorded net of taxes in Spain and Italy; hence, for these two countries, the size of RBC constitutes a lower bound insofar as tax progressivity mitigates income differences.

The analysis is carried out for 8 countries, the 5 largest European economies (Germany, France, the UK, Spain and Italy) plus Ireland, Finland and Denmark[16]. These countries are representative of the four welfare regimes usually identified by the literature (Esping Andersen 1990, Ferrera 1996) and are characterised by different levels of intergenerational income inequality[17]. Apart from Ireland, the literature has produced a clear country ranking in term of intergenerational income

[16] Sweden has not been included because about 90% of the answers on parental occupation are missing. Questions on parental occupation display a very high response rate (higher than 95%) in 6 out of 8 countries; only in the UK and Ireland missing answers on the occupation of both parents reach a remarkable 20%. However, missing data do not appear concentrated among the more disadvantaged children.

[17] See d'Addio (2007), Andrews and Leigh (2009), Bjorklund and Jantti (2009), Corak (2006) and (2013). To the best of our knowledge, no study computed so far intergenerational income elasticity for Ireland that, for occupational mobility, is considered one of the less fluid European country (Breen and Luijkx 2004).

elasticities (estimated in log-log regressions of child income on parental income): Denmark and Finland, followed by Germany, are characterised by the lowest inequality; the UK and Italy exhibit the highest inequality, and Spain and France lie in the middle (e.g., Corak 2013). Similar country rankings are also found for the association between parents' and children's education (Hertz et al. 2007), whereas studies on occupational mobility find a slightly different ranking, with Germany among the least mobile countries (Breen 2004, Blanden 2013).

For each country, Table 1 displays the changes in the average *isei* and in its standard deviation from the parent to the child generation. A general improvement in the average *isei* occurs everywhere, but it is more pronounced in the two Southern countries, where the average occupational statuses were initially lower. The standard deviation in *isei* is positively correlated with the mean and the cross-country convergence, and the mean of the child *isei* appears to be associated with a convergence in the variance. Simple bivariate correlations between parent and child *isei* highlight interesting patterns: Germany emerges as the "most mobile" country, whilst Italy, France and Spain are the least mobile. To go a step further, in Figure 1, we present parent-child *isei* correlations obtained in a multivariate regression that includes additional controls. Everywhere, the association between parental and child *isei* is positive and highly statistically significant. Differences among countries emerge, but they are not statistically significant, apart from the difference between Germany and France.

Table 2 presents mobility patterns across terciles of the two marginal distributions of social positions. It is evident from looking at the values on the main diagonal that persistency in social positions is widespread. With the exception of Finland, persistency at the bottom is quite similar across countries. The same can be said for persistency at the top, which is slightly higher in Spain and France. Cross-country differences are also minimal in terms of long-distance upward mobility (from P1 to C3) and long-distance downward mobility (from P3 to C1). In turn, differences are slightly more evident for middle positions (P2): in France, Italy, Ireland and Denmark, downward mobility is more frequent than upward mobility, while in remaining countries, they are equally frequent.

We can summarise the finding of this preliminary analysis in two points: 1) The influence of family background on children's occupational attainments is statistically significant in all the countries, although the magnitude of the effect differs; and 2) Changes in relative social positions display a similar pattern across countries. However, as is well known, the degree of intergenerational inequality substantially differs across countries. We argue that these differences may reflect a "residual association" (the RBC) that has to be further decomposed to understand the fundamental mechanisms at play.

## 4. Results

### 4.1 Residual Background Correlation

As the initial step of our econometric analysis, we look at the association between parental ISEI and children's earnings. In particular, we assess whether a residual effect of *isei_par* on gross labour incomes persists once other intervening factors – child education and occupation – are included among the set of covariates.

Table 3 shows four models[18]. Model A estimates the effect of *isei_par* only including a set of basic controls (the vector X in eq. 2). Model B adds the first background-related intervening factor, i.e., child education, while model C adds the second intervening factor, i.e., child *isei*, and the "same job dummy" defined above and is equivalent to the specification in equation 2. Model C' is similar to model C except that we include only individuals working full-time for 12 months. Annual labour incomes of individuals employed full-time for the whole year as the net of employability differences can be considered to be a closer proxy of workers' productivity conditions[19].

The estimated coefficient of *isei_par* in Model A is the overall effect of family background on offspring earnings. The coefficient is positive and highly significant at the 1% confidence level in all countries. In line with the usual country ranking in terms of intergenerational inequality, the association between *isei_par* and child earnings is lower in the Nordic countries and in Germany, stands at an average level in France and Ireland and is higher in Italy, Spain and the UK. Differences are also large in terms of size. The effect of a standard deviation increase in *isei_par* on annual income is approximately 6% in Germany and Nordic countries, 9% in France, 10% in Italy and Ireland, 13% in Spain and 14% in the UK. Recall that for Italy and Spain, the effect is a lower bound as net earnings are considered.

The effect of *isei_par* is, as expected, considerably reduced when we add child education among the explanatory variables (Model B). First, the coefficient of *isei_par* is not significantly different from zero in Nordic countries. In addition, the coefficient more than halves in Ireland and Finland, roughly halves in France and Denmark, declines by 3/4 in Spain and Germany and by a thin 40% in the UK and Italy.

The RBC is estimated in Model C, where we include the child *isei* and a dummy equal 1 if parent and child are in the same occupation. The main result of this section is that the RBC

[18] For sake of space, we present only the main variables of interest, but results for the other control variables (available upon request) are robust across specifications.

[19] In order to control for employability conditions during the year, we prefer to focus on annual incomes of those working full-time for the whole year rather than on hourly wages because EU-SILC dataset does not provide very accurate measures of hourly wages for all countries. Actually, for most of them only information on incomes in the previous year is recorded, while the information on the usual number of hours worked refer to the current employment status.

disappears for every country except the less equal ones: Italy, Spain and the UK. Interestingly, the unexplained fraction of the overall effect of *isei_par* estimated in model A is significantly larger in Italy (45%) than in Spain (27%) and in the UK (33%). Finally, Model C' shows that in Italy and Spain, approximately 15% of the RBC is explained by general employability conditions (i.e., working hours and weeks), while in the UK, the RBC is 1/3 higher when only individuals working full-time for 12 months are included. The latter result suggests that for the UK, the RBC is not related at all to differences in employability conditions among workers with different backgrounds. Finally, note that the estimated country differences in RBCs are not driven by differences in within-occupation earning dispersion. Indeed, the share of inequality within ISEI classes is very similar in the countries of our sample, and it is slightly lower in immobile countries.

Before moving to the main results of the paper, Table 4 shows that the terciles of the parental distribution capture the cross-country differences in terms of RBCs. This step is important, as we will use the terciles of the two surrogate distributions to estimate the effects of mobility on earnings. Including the P2 and P3 instead of *isei_par* (P1 being the reference category), the UK, Italy and Spain remain the only countries with significant RBCs. The inclusion of terciles' dummies also unravels nonlinear patterns: for Spain and the UK, the background advantage is concentrated in the third tercile, while in Italy, the background disadvantage is concentrated in the first tercile. Overall, these findings confirm our previous results on cross-country differences in RBCs using a different measure of background (Raitano and Vona 2013a)

### 4.2 Earnings and intergenerational social mobility

This section presents the estimate of our preferred specification to assess the returns to intergenerational social mobility: the specification presented in equation 3. In Table 5, we show the estimated coefficients of the interactions between the terciles of origin and destination using P2*C2 as a reference modality. We include Wald tests on the difference between each pair of origins, e.g., P1 vs. P3, in the same destination, e.g., C3. We comment in Table 5 first on immobile countries and then on mobile ones.

*Immobile countries*. In top social positions, Italy, Spain and the UK are characterised by a widespread and statistically significant glass ceiling effect. The effect is always associated with a penalty for long-distance mobility (P1*C3) compared with "stayers" in higher social positions (P3*C3). The additional return of P3*C3 compared to P1*C3 is 16% in the UK, 18% in Italy and only 8% in Spain. Long-distance upward mobility is particularly penalised in Italy, where P1*C3 earns 8% less than the reference group (P2*C2). In middle positions, upward movers are always penalised compared with downward movers. This parachute effect is again stronger in Italy, where upward movers are also penalised (-12%) compared to the reference group. In lower social positions, the parachute effect is evident only for Italy and Spain, although the effect is again stronger in Italy. In sum, a significant RBC is mainly associated with a glass ceiling effect in the UK where the educational system is known to be highly heterogeneous (Blanden and Machin 2004). Conversely, network effects in the labour market exert a stronger influence in Southern countries (Pellizzari et al. 2011, Raitano 2011). Note, however, that the glass ceiling and the parachute effect are both active in all of the immobile countries.

*Mobile countries.* Our approach also allows us to reveal heterogeneous patterns in terms of returns to occupational mobility in countries with insignificant RBC. First, the glass ceiling effect is widespread in top positions where stayers always earn more than upward movers. The effect is particularly large in Germany, where stayers (P3*C3) have a significant advantage over upward movers (P1*C3 and P2*C3). This pattern changes in middle position, where background-related advantages are statistically insignificant and, except in France, downward movers are slightly penalised compared to the reference group (P2*C2). Finally, in bottom positions, long-distance downward movers are significantly penalised in France, Germany and Finland compared to stayers (P3*C3) and short-distance downward movers (P2*C3). Denmark and especially Ireland are the only countries where a parachute effect emerges. However, it should be noted that the smaller sample size of these two countries makes the estimated coefficients more sensitive to changes in specifications.

Our main results suggest that the glass ceiling effect is widespread across all countries irrespective of their level of intergenerational inequality. This is most likely due to unavoidable features either of the educational system[20] or of the cumulative process of human capital accumulation (Cunha and Heckman 2007). The parachute effect is instead concentrated in immobile countries, especially in Southern ones, where the family network is known to influence children's labour market outcomes (Whelan and Maitre 2010). This does not exclude that family networks also matter for the glass ceiling effect observed in top occupations in the other groups of countries, as the recent literature on the club membership of the super-rich has shown (Bingley et al. 2011).

### 4.3 **Robustness**

As the first alternative specification, Table 6 presents estimates of equation 4. Recall that the estimated effect of the quintiles of the RSMI distribution should be interpreted as the overall returns

[20] For instance, in schooling systems where access is conditioned by the neighbourhood of residence, pupils end up in schools with fairly homogeneous peers, hence replicating the home environment at school. See Machin (2011) for a review.

to upward and downward mobility conditioned to the child *isei* and education. The first part of Table 6 shows the effect of two dummies capturing downward mobility (1st and 2nd quintile) and upward mobility (4th and 5th quintile)[21]. The results always point in the same direction: downward mobility is rewarded in Southern countries irrespective of the origin, while upward mobility is penalised in the UK and, albeit to a lesser extent, in Italy. The second part of the Table 6 considers only individuals working full-time for 12 months. The results change substantially for Italy and Spain, where the rewards of downward mobility disappear. When estimating equation (3) for the same sub-sample, the parachute effect becomes statistically insignificant for Spain, whereas it remains in Italy only when comparing P1*C1 and P3*C1 (detailed results are available upon request). In sum, general employability conditions appear to be a key driver of the parachute effect in Southern countries.

Another possibility consists of using Quantile Regressions that condition the effect of the RBC, proxied by *isei_par,* to child abilities. Table 7 shows that the RBCs tend to increase along the income distribution in almost every country except Spain. This suggests that perhaps naturally, family background complements individual abilities. Incidentally, this result corroborates our key identification assumption, i.e., $E(h_{ij,}a_i) > 0$. In addition, mobile countries display a sign reversion in the RBC, being negative for lower deciles and positive for higher ones. The only incoherent result is the one of Italy that displays an unexpected increasing pattern. However, when using P2 and P3 instead of *isei_par* in the quantile regression, a flat and significant pattern emerges for P2, whereas an increasing pattern remains only for P3. In sum, family background complements abilities in almost every country except Southern ones.

For the sake of space, we do not include other exercises that substantially confirm the robustness of our main results and remain available upon request. Few aspects of these exercises deserve, however, a brief comment. First, using hourly wages as the dependent variable, penalties of long-distance upward mobility are offset by penalties of long-distance downward mobility in France. This result also emerges for Germany if we build the interactions' origin-destination using pre-defined occupational categories, i.e., managers, white-collar workers and blue-collar workers. Second, excluding all individuals with missing fathers, which are particularly numerous in the UK, we observe again a combination of penalties of long-distance mobility for Germany and France. Overall, these additional results reinforce our approach that allows us to unravel heterogeneous patterns in both mobile and immobile countries.

[21] Results do not change when we include the four quintiles of the RSMI distribution.

## 5. Conclusions

This paper proposes a simple method to interpret and decompose the residual correlation between family background and child earnings. Our preliminary analysis motivates this exercise by showing that salient cross-country differences in terms of intergenerational inequality concern RBCs rather than occupational mobility. In turn, our main result unravels significant country differences not only in RBC but also especially in the way in which RBC should be interpreted.

We find that highly significant RBC mainly reflects a glass ceiling effect in the UK and a parachute effect in Southern European countries, particularly in Italy. Interestingly, the parachute effect appears to be primarily related to general employability conditions and is substantially reduced when only full-time individuals working 12 months are considered. In turn, the glass ceiling effect appears to be more generally widespread as, to a certain extent, it also applies to Scandinavian and central European countries. This result suggests that the glass ceiling effect is most likely associated with an intrinsic complementarity between family background and individual abilities in the process of skill formation. From the theoretical perspective, this finding indicates that human capital theory does a good job of explaining a crucial aspect of the process of inequality transmission. However, further research is certainly required to understand the role of family networks both at the top and at the bottom of the income distribution and for countries at different stages of development.

Two final caveats should be explained. First, the two-digit classification of ISCO occupations available in our dataset, on which the ISEI index and the social positions are based, provides a crude and aggregate measure of occupational quality and conceals within-group heterogeneity. With a finer examination of occupational classes, part of the RBC is likely to emerge as an effect of occupational sorting rather than as a pure earning effect within the same occupation. Second, our analysis does not allow us to analyse the impact of family background along the entire carrier path. This is particularly important especially in Southern countries where labour market outcomes and employability conditions seem to crucially depend on family background. For instance, an issue at stake is to test whether seniority amplifies or mitigates the background effects (Husdon and Sessions 2011). In an on-going study on Italy, we merge the EU-SILC dataset with the panel of working histories from administrative sources and investigate this issue in greater detail (Raitano and Vona 2013b).

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Tab. 1: Parental and children ISEI and intergenerational correlation in ISEI levels.

| | Mean ISEI | | | ISEI Standard Deviation | | | |
|---|---|---|---|---|---|---|---|
| | Parent | Children | *% Change* | Parent | Children | *% Change* | *Correlation parental children ISEI* |
| Germany | 44.5 | 46.8 | 5.1% | 15.4 | 14.5 | -5.6% | 0.257 |
| France | 39.8 | 41.1 | 3.1% | 14.7 | 14.9 | 1.5% | 0.377 |
| Spain | 35.1 | 38.4 | 9.4% | 14.3 | 15.4 | 7.2% | 0.387 |
| Italy | 36.9 | 41.1 | 11.4% | 13.9 | 14.4 | 3.6% | 0.333 |
| UK | 44.4 | 44.6 | 0.4% | 15.7 | 15.2 | -3.7% | 0.294 |
| Ireland | 43.1 | 45.3 | 5.2% | 15.6 | 15.4 | -0.7% | 0.314 |
| Denmark | 43.4 | 44.2 | 1.9% | 16.8 | 15.3 | -8.8% | 0.303 |
| Finland | 40.6 | 44.2 | 8.7% | 16.2 | 15.4 | -4.9% | 0.325 |

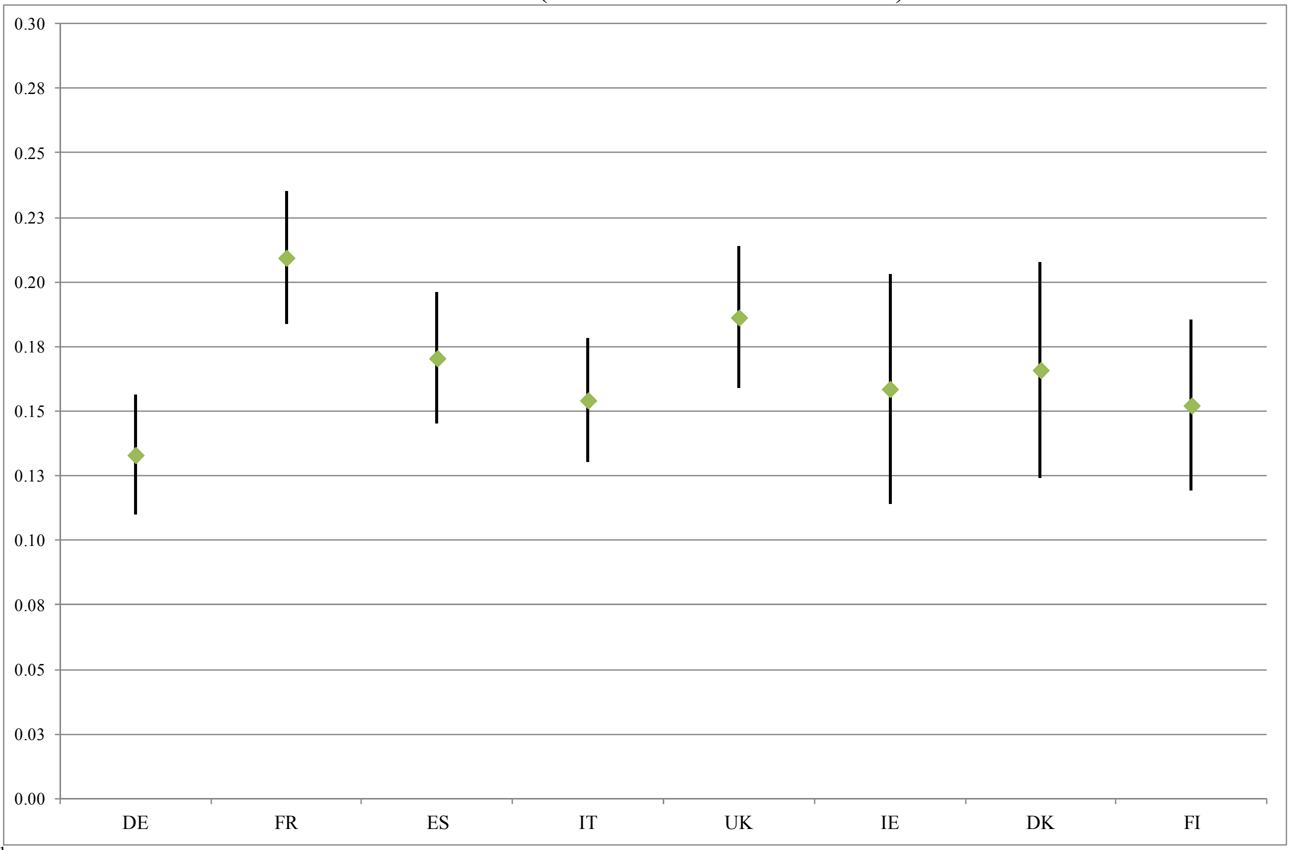
Source: elaborations on EU-SILC 2005 data

Tab. 2: Intergenerational mobility tables among the terciles of the occupational position (row %)

| | | | *Children position* | |
|---|---|---|---|---|
| | *Parental position* | 1° tercile | 2° tercile | 3° tercile |
| **Germany** | 1° tercile | 47.3 | 31.5 | 21.2 |
| | 2° tercile | 35.6 | 33.5 | 30.9 |
| | 3° tercile | 22.0 | 30.7 | 47.3 |
| | | | *Children position* | |
| | *Parental position* | 1° tercile | 2° tercile | 3° tercile |
| **France** | 1° tercile | 47.4 | 33.4 | 19.2 |
| | 2° tercile | 35.2 | 38.8 | 26.0 |
| | 3° tercile | 18.6 | 28.3 | 53.1 |
| | | | *Children position* | |
| | *Parental position* | 1° tercile | 2° tercile | 3° tercile |
| **Spain** | 1° tercile | 49.6 | 31.6 | 18.9 |
| | 2° tercile | 32.6 | 37.9 | 29.5 |
| | 3° tercile | 16.7 | 31.3 | 52.0 |
| | | | *Children position* | |
| | *Parental position* | 1° tercile | 2° tercile | 3° tercile |
| **Italy** | 1° tercile | 47.0 | 32.6 | 20.4 |
| | 2° tercile | 35.6 | 39.2 | 25.2 |
| | 3° tercile | 20.9 | 28.4 | 50.7 |
| | | | *Children position* | |
| | *Parental position* | 1° tercile | 2° tercile | 3° tercile |
| **UK** | 1° tercile | 48.4 | 30.5 | 21.1 |
| | 2° tercile | 32.0 | 38.1 | 30.0 |
| | 3° tercile | 21.7 | 32.1 | 46.2 |
| | | | *Children position* | |
| | *Parental position* | 1° tercile | 2° tercile | 3° tercile |
| **Ireland** | 1° tercile | 48.6 | 31.3 | 20.0 |
| | 2° tercile | 39.0 | 34.3 | 26.7 |
| | 3° tercile | 19.9 | 34.2 | 45.9 |
| | | | *Children position* | |
| | *Parental position* | 1° tercile | 2° tercile | 3° tercile |
| **Denmark** | 1° tercile | 51.3 | 29.4 | 19.3 |
| | 2° tercile | 39.6 | 34.9 | 25.5 |
| | 3° tercile | 18.8 | 34.9 | 46.4 |
| | | | *Children position* | |
| | *Parental position* | 1° tercile | 2° tercile | 3° tercile |
| **Finland** | 1° tercile | 43.7 | 37.4 | 18.9 |
| | 2° tercile | 31.9 | 43.0 | 25.2 |
| | 3° tercile | 19.0 | 36.5 | 44.4 |

Source: elaborations on EU-SILC 2005

Fig. 1: OLS "depurated" estimated coefficient[1] of the total association between parental and children ISEI (90% interval of confidence)[2].




[1] Estimated coefficients have been divided by the ratio between the standard deviation of parental and children ISEI.
[2] Control variables on children characteristics: age and its square and dummies on gender, immigrant status, marital status, living in an urban area and education.
Source: elaborations on EU-SILC 2005

Tab. 3: Estimated coefficients of parental highest ISEI level.
OLS on logs of yearly gross labour income (net for Italy and Spain)[1].

| | DE | FR | ES | IT | UK | IE | DK | FI |
|---|---|---|---|---|---|---|---|---|
| ***Model A - only parental ISEI*** | | | | | | | | |
| Coeff. | 0.0037*** | 0.0061*** | 0.0089*** | 0.0073*** | 0.0092*** | 0.0064*** | 0.0040*** | 0.0040*** |
| $R^2$ | 0.250 | 0.213 | 0.291 | 0.210 | 0.298 | 0.335 | 0.111 | 0.165 |
| ***Model B - parental ISEI & child education*** | | | | | | | | |
| Coeff. | 0.0021** | 0.0032*** | 0.0050*** | 0.0051*** | 0.0064*** | 0.0030* | 0.0021 | 0.0015 |
| $R^2$ | 0.273 | 0.261 | 0.353 | 0.242 | 0.334 | 0.388 | 0.156 | 0.222 |
| ***Model C - parental ISEI, child education & child ISEI*** | | | | | | | | |
| Coeff. | -0.0004 | -0.0008 | 0.0024*** | 0.0033*** | 0.0030*** | 0.0012 | 0.0002 | -0.0007 |
| $R^2$ | 0.344 | 0.349 | 0.412 | 0.289 | 0.414 | 0.428 | 0.210 | 0.275 |
| *Obs.* | *5,973* | *4,053* | *5,585* | *8,460* | *3,269* | *1,564* | *1,586* | *2,393* |
| ***Model C' – considering the sub-sample of individuals working full-time for 12 months*** | | | | | | | | |
| Coeff. | -0.0008 | 0.0011 | 0.0020*** | 0.0028*** | 0.0043*** | 0.0012 | -0.0007 | 0.0005 |
| $R^2$ | 0.247 | 0.302 | 0.381 | 0.239 | 0.294 | 0.313 | 0.227 | 0.263 |
| *Obs.* | *3,592* | *3,016* | *4,433* | *6,517* | *2,328* | *1,041* | *1,309* | *1,924* |

[1] Control variables of model "A" are age, age squared, potential experience, gender, immigrant status, marital status, a dummy if living in an urban area, if working part-time and a dummy if income from self-employment is larger than income from employment. In model "B" two dummies on children educational attainment are added (upper secondary or tertiary graduated). In model "C" children ISEI level and a dummy if parental and children occupations are the same are added.
Observations are weighted using sample weights provided by EU-SILC. Standard errors are robust to heteroskedasticity. * p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on EU-SILC 2005 data

Tab. 4: Estimated coefficients of terciles of the distribution of parental position (reference category: parents in the 1° tercile). OLS on logs of yearly gross labour income (net for Italy and Spain)[1].

| | Germany | France | Spain | Italy | UK | Ireland | Denmark | Finland |
|---|---|---|---|---|---|---|---|---|
| 2° Tercile | -0.0162 | 0.0272 | 0.0338 | 0.1172*** | 0.0282 | 0.0059 | -0.0082 | 0.0142 |
| 3° Tercile | -0.0242 | -0.0081 | 0.0680*** | 0.1185*** | 0.0973*** | 0.0298 | -0.0028 | -0.0385 |
| 3° Tercile ≠ 2° Tercile | no | no | * | no | ** | no | no | no |
| $R^2$ | 0.344 | 0.349 | 0.412 | 0.292 | 0.414 | 0.428 | 0.210 | 0.275 |
| *Obs* | *5,973* | *4,053* | *5,585* | *8,460* | *3,269* | *1,564* | *1,586* | *2,393* |

[1] Control variables: age, age squared, potential experience, gender, immigrant status, marital status, a dummy if living in an urban area, if working part-time and a dummy if income from self-employment is larger than income from employment, two dummies on children educational attainment (upper secondary or tertiary graduated), children ISEI level and a dummy if parental and children occupations are the same.
Observations are weighted using sample weights provided by EU-SILC. Standard errors are robust to heteroskedasticity. F-tests are presented to test the equality of estimated coefficients of children of parents in the 2° and 3° tercile. * p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on EU-SILC 2005 data

Tab. 5: Estimated coefficients of the interaction between parental and children terciles (omitted category "parents and children in the second tercile"). OLS on logs of yearly gross labour income (net for Italy and Spain)[1]. Full sample.

| *Parental tercile/ Child tercile* | DE | FR | ES | IT | UK | IE | DK | FI |
|---|---|---|---|---|---|---|---|---|
| P3*C3 | 0.237*** | 0.304*** | 0.300*** | 0.098*** | 0.421*** | 0.311*** | 0.119* | 0.302*** |
| P2*C3 | 0.162*** | 0.290*** | 0.171*** | 0.065** | 0.374*** | 0.307*** | 0.072 | 0.253*** |
| P1*C3 | 0.131*** | 0.261*** | 0.220*** | -0.091*** | 0.252*** | 0.225*** | 0.108 | 0.199** |
| P3*C2 | -0.021 | 0.02 | 0.037 | -0.008 | 0.069 | -0.082 | -0.091 | -0.059 |
| P1*C2 | 0.016 | 0.011 | -0.053 | -0.129*** | -0.037 | -0.041 | -0.076 | -0.06 |
| P3*C1 | -0.567*** | -0.365*** | -0.205*** | -0.239*** | -0.283*** | -0.078 | -0.201* | -0.318*** |
| P2*C1 | -0.441*** | -0.198*** | -0.162*** | -0.244*** | -0.328*** | -0.293*** | -0.320*** | -0.139*** |
| P1*C1 | -0.432*** | -0.303*** | -0.260*** | -0.348*** | -0.313*** | -0.237*** | -0.269*** | -0.148*** |
| P3*C3≠P2*C3 | ** | no | *** | no | no | no | no | no |
| P3*C3≠P1*C3 | * | no | * | *** | *** | no | no | no |
| P2*C3≠P1*C3 | no | no | no | *** | ** | no | no | no |
| P3*C2≠P1*C2 | no | no | ** | *** | ** | no | no | no |
| P3*C1≠P2*C1 | ** | *** | no | no | no | ** | no | ** |
| P 3*C1≠P1*C1 | ** | no | no | *** | no | no | no | ** |
| P 2*C1≠P1*C1 | no | *** | *** | *** | no | no | no | no |
| $R^2$ | 0.344 | 0.332 | 0.39 | 0.278 | 0.408 | 0.423 | 0.191 | 0.268 |
| Obs. | 5,973 | 4,053 | 5,585 | 8,460 | 3,269 | 1,564 | 1,586 | 2,393 |

[1] Control variables: age, age squared, potential experience, gender, immigrant status, marital status, a dummy if living in an urban area, if working part-time and a dummy if income from self-employment is larger than income from employment, two dummies on children educational attainment (upper secondary or tertiary graduated) and a dummy if parental and children occupations are the same.
Observations are weighted using sample weights provided by EU-SILC. Standard errors are robust to heteroskedasticity. F-tests are presented to test the equality of the interactions between parents and children terciles.
* p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on EU-SILC 2005 data

Tab. 6: Estimated coefficients of quintiles of Relative ISEI[1]. OLS on logs of yearly gross labour income (net for Italy and Spain).

| | DE | FR | ES | IT | UK | IE | DK | FI |
|---|---|---|---|---|---|---|---|---|
| *Full sample* | | | | | | | | |
| Q1-Q2 | 0.0316 | 0.0223 | 0.0728*** | 0.0593*** | 0.0020 | -0.0349 | 0.0196 | 0.0140 |
| Q4-Q5 | 0.0253 | 0.0252 | -0.0033 | -0.0664*** | -0.1138*** | -0.0142 | 0.0058 | -0.0107 |
| $R^2$ | 0.344 | 0.349 | 0.413 | 0.291 | 0.415 | 0.428 | 0.210 | 0.275 |
| Obs. | 5,973 | 4,053 | 5,585 | 8,460 | 3,269 | 1,564 | 1,586 | 2,393 |
| *Individuals working full-time for 12 months* | | | | | | | | |
| | **DE** | **FR** | **ES** | **IT** | **UK** | **IE** | **DK** | **FI** |
| Q1-Q2 | 0.0069 | 0.0221 | 0.0043 | 0.0311 | -0.0002 | -0.0503 | 0.0491 | 0.0431 |
| Q4-Q5 | 0.0114 | -0.027 | -0.0440* | -0.0714*** | -0.1425*** | -0.0097 | 0.018 | 0.0197 |
| $R^2$ | 0.254 | 0.304 | 0.384 | 0.241 | 0.294 | 0.316 | 0.239 | 0.264 |
| Obs. | 3,592 | 3,016 | 4,433 | 6,517 | 2,328 | 1,041 | 1,309 | 1,924 |

[1] Control variables: age, age squared, potential experience, gender, immigrant status, marital status, a dummy if living in an urban area, if working part-time and a dummy if income from self-employment is larger than income from employment, two dummies on children educational attainment (upper secondary or tertiary graduated), children ISEI level and a dummy if parental and children occupations are the same.
Observations are weighted using sample weights provided by EU-SILC. Standard errors are robust to heteroskedasticity. F-tests are presented to test the equality of the interactions between parents and children terciles.
* p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on EU-SILC 2005 data

Tab. 7: Estimated coefficients parental ISEI[1]. Quantile regressions on logs of yearly gross labour income (net for Italy and Spain). Full sample.

| | DE | FR | ES | IT | UK | IE | DK | FI |
|---|---|---|---|---|---|---|---|---|
| 10 | -0.0006 | -0.0040** | 0.0039** | 0.0022** | 0.0019 | -0.0005 | -0.0004 | -0.0043 |
| 20 | -0.0016* | -0.0008 | 0.0032*** | 0.0020*** | 0.0028*** | 0.0000 | -0.0004 | -0.0025** |
| 30 | -0.0016* | -0.0001 | 0.0027*** | 0.0024*** | 0.0031*** | 0.0018 | 0.0009 | -0.0014* |
| 40 | -0.0009 | 0.0006 | 0.0025*** | 0.0030*** | 0.0030*** | 0.0030* | 0.0002 | 0.0003 |
| 50 | -0.0004 | 0.0010* | 0.0027*** | 0.0032*** | 0.0032*** | 0.0033*** | 0.0007 | -0.0002 |
| 60 | -0.0002 | 0.0013** | 0.0028*** | 0.0034*** | 0.0041*** | 0.0027*** | 0.0008 | -0.0003 |
| 70 | 0.0002 | 0.0013** | 0.0022*** | 0.0040*** | 0.0038*** | 0.0028** | 0.0011* | 0.0002 |
| 80 | 0.0008* | 0.0015*** | 0.0020*** | 0.0037*** | 0.0047*** | 0.0021** | 0.0009 | 0.0007 |
| 90 | 0.0010 | 0.0026*** | 0.0023*** | 0.0045*** | 0.0049*** | 0.0007 | 0.0024** | 0.0013 |

[1] Control variables: age, age squared, potential experience, gender, immigrant status, marital status, a dummy if living in an urban area, if working part-time and a dummy if income from self-employment is larger than income from employment, two dummies on children educational attainment (upper secondary or tertiary graduated), children ISEI level and a dummy if parental and children occupations are the same.
Observations are weighted using sample weights provided by EU-SILC. Standard errors are robust to heteroskedasticity. * p<0.10; ** p<0.05; *** p<0.01. Source: elaborations on EU-SILC 2005 data