Family characteristics and early career outcomes in nine European countries[1]

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Abstract

In this paper I study how much family characteristics affect early career outcomes (wages) of children in nine European countries: Germany, France, United Kingdom, Ireland, Italy, Greece, Spain, Portugal and Austria using ECHP. To asses the overall importance of family influence I compute a broad indicator of family effect on earnings, the siblings earnings correlations, using the first eight waves of ECHP data on siblings. I find that Portugal, Italy and Greece are the countries with the higher correlations.
Rather than using the amount of education to explain family influence. I concentrate on how family characteristics affect returns to education and estimate both family fixed effect and random coefficients models that allow for heterogeneous returns to education in cross-country comparison point of view. I find that in many countries returns to education are affected by parents' education. In particular I find positive and significant effect of parents tertiary education on return to tertiary education in France, the UK, Italy, Greece and Spain and on return to secondary education in Ireland and Italy.

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1 Introduction

Many different disciplines like, psychology, sociology and economics have studied the way family characteristics can influence children outcomes. Extensive research analyzed the direct effect of family background on school achievement, schooling levels and wages as well as the casual effect of education on wages (Haveman and Wolfe, 1995 for a review)

It has been well established that an individual socio-economic success in labor market depends by his family background. Recent studies suggest the existence of strong intergenerational link in earnings driven by an high persistence in education within each family (Checchi et alii, 1999, Comi, 2003) and this seems to be particularly true in countries like Italy, Portugal and Belgium. It has been well established (Haveman and Wolfe, 1995 for a review) in the economic literature that families, through the educational channel, tend to transmit their socio-economic position, given that higher levels of education grant higher earnings. This is the so called intergenerational transmitted inequality and consider the case when the intergenerational links are stronger, rich families tend to have rich offspring and there is a low level of upward mobility: everybody should agree that this can be considered a violation of the equality of opportunity social norm. That's why it is important to know how strong the family-offspring link is and whether it is stronger in some countries.

Using ECHP I study how much family characteristics affect early career outcomes of children in nine European countries: Germany, France, United Kingdom, Ireland, Italy, Greece, Spain, Portugal and Austria. These are very different countries both in social habits and labor market characteristics. Cross country comparison can shade a light on how labor market characteristics and institutions can determine the relative importance of family background in the early career. First of all I will measure the overall importance of family background and then I will study whether family characteristics affect returns to education.

A good measure of the overall importance of family background is the siblings correlation in earnings which measures how much of the observed earnings can be attributed to what siblings share: family and community background observed and unobserved characteristics. It can be interpreted as the proportion of the variance in the outcome variable that is attributable to factors that siblings share. It a broader measure than parent-child earnings elasticity because it captures both observable and unobservable parents characteristic. Solon (1999) reviewed the empirical literature on siblings correlations in earnings: he find that very heterogeneous studies produce estimations in the range of .15 and .42 for the United States. More recent studies by Bjourklund and Mazumder, with more years of PSID and NLS finds correlations around .45 for the US. In my knowledge, the only other countries for which this statistics is available are the Nordic countries2 covered by Bjorklund et alii: in these countries the correlations are lower than the US and are between .2 and .3. Unfortunately I am not able to produce estimation for the same countries of Bjorklund et alii using ECHP because the structure of the data and the social habits to leave parents house very early do not allow me to have representative samples.

Family influence may be stronger in the early career steps, where families can provide to children not only an amount of schooling, but also an easy way to find a job as well as affect in the characteristics of the first job. To have an idea of how this shared background can act, just think to how much social networks can affect the school to work transition as well as the characteristics of the first job (Margolis and Simmonet, 2003). Informal contacts as a mean to find a job are quite common in Europe, as it is documented by Pellizzari 2004. It turns out that about one third[3] of the jobs in 1996 in Europe have been found through informal network. This percentage ranges from 23 percent in the UK to 45 percent in Spain.

According to the education investment literature, family background affects education mainly by influencing the choice of the amount of schooling , holding the rate of return constant. Implicitly these models imply that those family characteristics that can affect returns to education may induce individuals to invest in further education. But as Altonji and Dunn (1996) suggest the higher parental and siblings correlations in education may be due to the intra-family shared economic value of education. In the education literature only few contributions have examined whether and how much returns to education varies with family characteristics and allow for heterogeneous returns to education. Altonji and Dunn (1996) find evidence of heterogeneous returns to education in the US: My paper is more similar to Schnabel and Schnabel (2002), which use fixed and random effects estimations and find that both parents education and gender influence the returns to education in Germany. In the last section of this paper I estimate heterogeneous returns to education for nine European countries and I try to control for unobserved family –specific heterogeneity and to eliminate the bias due to family effects using siblings data and controlling for family fixed-effect. Furthermore a main difference from their work is that I will use multilevel models framework to estimate a random coefficient model.

2 The estimation strategy

[2] Denmark, Finland, Sweden, Norway.
[3] Author elaboration on the percentage reported in table 3, pag 31 of Pellizzari 2004. This figure is the average computed on the countries I use in this paper.

Siblings earnings correlation

Following previous literature, I first estimate the following equation:

$$y_{ijt} = \beta X_{ijt} + \varepsilon_{ijt} \quad (1)$$

where y_{ijt} is the logarithm of annual earnings in year t (t=1,...,T_{ij}) for the jth (j=1..J) sibling in family i (i=1,...N); X_{ijt} is a vector that contains (a polynomium in) age and years dummies to account for lifecycle effect and years effects such as business cycle. The residual purged from these effects captures permanent components of earnings. The residual is then decomposed as follows:

$$\varepsilon_{ijt} = a_i + u_{ij} + v_{ijt} \quad (2)$$

where the first term a_{ijt} is the permanent component common to all siblings in the family i; u_{ij} is the permanent component that is individual specific and v_{ijt} is the transitory component. In line with previous studies, I assume that these three components are "orthogonal by construction" and so we can split the permanent component in two parts one that is individual, and the other which is shared among siblings. This assumption imply that the variance then is:

$$\sigma^2_\varepsilon = \sigma^2_a + \sigma^2_u + \sigma^2_v \quad (3)$$

in this framework the of permanent earnings among siblings is:

$$\rho = \frac{\sigma_a^2}{\sigma_a^2 + \sigma_u^2} \quad (4)$$

and this correlation can be interpreted as the proportion of the population variance in long-run earnings due to what is shared by siblings.

A consistent estimation of ε_{ijt} can be derived from least square estimation of equation (1), where I purge the annual real[4] earnings including in X a cubic in age and years dummies simply taking the residuals:

$$e_{ijt} = y_{ijt} - \hat{\beta} X_{ijt} \quad (5)$$

To estimate the three variance components I can then apply the classical analysis-of-variance methods to e_{ijt}. But, as shown by Solon et alii (1991), I need to correct the classical formulas because my samples contain different number of siblings per family J_i, different numbers of observations T_{ij} per person, and furthermore the transitory component may be serially correlated[5]. So I identify the transitory variance on the basis of the longitudinal variation year-to-year in the same individual earnings according to this equation:

[4] cpi used to deflate earnings (base years=1996) taken from Bank of Italy Governor Relation 2002

[5] An appendix in which I extend the model and explicitly take into account the autocorrelation in the transitory component v_{ijt} of equation 2 is available upon request from the author.

$$\hat{\sigma}_v^2 = \sum_i \sum_j \sum_t \left((e_{ijt} - \bar{e}_{ij} \right)^2 \bigg/ \left(\sum_i \sum_j T_{ij} - \sum_i J_i \right) \qquad (6)$$

where $\bar{e}_{ij} = \sum_t e_{ijt} \big/ T_{ij}$ and then I identify the permanent variance among siblings in the same family using the observed within-family variation according to this equation:

$$\hat{\sigma}_u^2 = \frac{\sum_i \sum_j T_{ij} \left(\bar{e}_{ij} - \bar{e}_i \right)^2 - \left(\sum_i J_i - N \right) \hat{\sigma}_v^2}{\sum_i \sum_j T_{ij} - \sum_i \left(\frac{\sum_j T_{ij}^2}{\sum_j T_{ij}} \right)} \qquad (7)$$

where $\bar{e}_i = \sum_j \sum_t e_{ijt} \big/ \sum_j T_{ij}$ and finally I identify the permanent variance across families using the observed between-family variation:

$$\hat{\sigma}_a^2 = \frac{\sum_i \left(\sum_j T_{ij} \right) \left(\bar{e}_i - \bar{e} \right)^2 - \left(\sum_i \left(\frac{\sum_j T_{ij}^2}{\sum_j T_{ij}} \right) - \frac{\sum_i \sum_j T_{ij}^2}{\sum_i \sum_j T_{ij}} \right) \hat{\sigma}_u^2 - (N-1) \hat{\sigma}_v^2}{\sum \sum T_{ij} - \frac{\sum_i \left(\sum_j T_{ij} \right)^2}{\sum_i \sum_j T_{ij}}} \qquad (8)$$

where $\bar{e} = \sum_i \sum_j \sum_t e_{ijt} \big/ \sum_i \sum_j T_{ij}$. I calculate the standard errors of the correlations bootstrapping 1000 times from the original family sample.

This estimations are very sensible to sample selection. In particular, the inclusion of singleton is controversial: it allows a better estimation of the variance between families (increasing the number of families) but if outliers tend to be more common among singletons than siblings it may lead to an underestimate of ρ because they are used to estimate σ^2_u, the denominator of ρ and not used to estimate σ^2_a, the numerator (Mazumder and Levine, 2003). So I will use only siblings samples, and then split them according to siblings sex and present separate estimations for males and females. In this case, siblings of different sex are split and include in the right sample as singletons.

Heterogeneous returns to education

Since we are interested in how family characteristics affect the education slope and unobserved family characteristics tend to be correlated with individual effect there is a strong possibility that omitted family variables will bias estimations and that's why I control for unobserved variables common to siblings using a family fixed effect estimator. An econometric family model that takes into account the heterogeneity of returns to education between families can be formulated as follows, where $\log y_{ii}$ is the log wage of individual *i* in family *h* and Z_{ih} includes all individual observed characteristics of individual *i* in family *h*:

$$\log y_{ih} = \beta_0 + \beta_1 Z_{ih} + r_h S_{ih} + \alpha_{hi} \qquad (9)$$

The variable S_{ih} is the educational variable of interest (set of dummies for educational levels or alternatively years of schooling); the individual error term α_{hi} can be split in two components: $\alpha_{hi} = \varepsilon_h + \varepsilon_{hi}$ where ε_h and ε_{hi} are family specific and individual specific error components. Returns to education r_h are not unique in the sample but vary across families. I can model these heterogeneous returns as a function of family background characteristics such as parents' education[6]. So I define :

$$r_h = d_1 + d_2 X_h + \eta_h \qquad (10)$$

where η_h is a mean 0 unobserved family specific error component affecting the rate of return to education, X_h is a vector of family background characteristics (parents' education) that influence the returns to education and d_1 is the average return to education. Using (10) to substitute in (9) leads to:

$$\log y_{ih} = \beta_0 + \beta_1 Z_{ih} + [\, d_1 + d_2 X_h \,] S_{ih} + \varepsilon_h + \varepsilon_{hi} + \eta_h S_{ih} \qquad (11)$$

As highlighted by Card (1999), S_{ih} is likely to be correlated with the additive family and person specific error component and so OLS estimate of (11) are biased. As a first estimation strategy, it is possible to eliminate ε_h from equation (11) by differencing it for pairs of siblings. Let Δ denote the "sibling difference" operator, for siblings indexed i and i' the differenced equation is :

[6] The main difference respect to Altonji and Dunn (1996) is that I allow returns to vary only between families, not within families.

$$\Delta log\, y_{ih} = \beta_1[\Delta Z_{ih}] + d_1\Delta S_{ih} + d_2\, X_h\, \Delta S_{ih} + \Delta\varepsilon_{hi} + \Delta\eta_{hk}\, S_{ih} \tag{12}$$

Since the number of children differs across family, a more efficient estimation approach is to work with (11) and include a separate intercept for each family (a fixed effect) to absorb ε_h. Given the large number of parameters to be estimated, fixed effects estimates may produce relatively large standard errors. As it can be seen by the term [$d_2X_h\Delta S_{ih}$], in the fixed effect estimation, heterogeneous returns are obtained simply interacting the education variable with the family variables of interest, in my case parents' education.

As a second estimation strategy, I fit the same problem in a multilevel models framework. Multilevel models have been developed to deal with data with observations clustered in units and where observations within the same unit may be more similar than observations in separate units. These models assume hierarchical data with the dependent variable measured at the lowest level (earnings measured for each individuals) and explanatory variable at all existing level. In this case we have observations on siblings, clustered within families. We can write the model in multilevel language[7] rephrasing equations 17-18 considering individual *i* (level 0 unit) nested in family (level 1 unit) *h* as:

$$\log y_i = \beta_{0h} + \beta_1 Z_{ih} + r_{ih} S_{ih} + \varepsilon_{hi} \tag{13}$$

$$\beta_{0h} = (\beta_0 + \varepsilon_h) \tag{14}$$

$$r_h = d_1 + d_2\, X_h + \eta_h \tag{15}$$

where $\beta_{0h} = (\beta_0 + \varepsilon_h)$ is a random family intercept, and r_h is the random coefficient that multiply educational variable and, as before, that is explicitly modeled as a function of the average return to education (d_1), of family characteristics (X_h) and of a family error term (η_h). Substituting (14) and (15) in (13) I obtain the reduce-form model which will be next estimated:

$$\log y_{ih} = (\beta_0 + \varepsilon_h) + (d_1 + d_2\, X_h + \eta_h)\, S_{ih} + \beta_1 Z_{ih} + \varepsilon_{hi} \tag{16}$$

Rearranging the terms I obtain the following multilevel model:

$$\log y_{ih} = \beta_0 + d_1\, S_{ih} + d_2\, X_h\, S_{ih} + \eta_h\, S_{ih} + \beta_1 Z_{ih} + \varepsilon_h + \varepsilon_{hi} \tag{17}$$

[7] I do not adopt the correct multilevel language because I want to preserve the same notation as before.

Where β_0 is the intercept estimate and ε_h correspond to the disturbance term for the random intercept term, while d_1 is the estimated (average) return to education and η_h correspond to the disturbance term for the randomly varying (slope) coefficient, d_2 is the interaction coefficient, and finally ε_{hi} is the individual (level 0) residual (error) term.

3. Data and Sample selection

I use the first eight waves of the European Community Household Panel[8] which is a large household survey that covers most members countries in Europe and for this reason a very good data set for siblings study. Rather than trying to harmonise output from national surveys, the European statistical agency (Eurostat) adopts an input oriented approach and uses the same community questionnaire as the base for the national versions of the survey. The data are collected by the National Collection Units and finally checked by Eurostat (European Community (2003)). A desirable feature of ECHP is that the definitions of and questions on earnings, the reference period and the survey methods are common across countries. This format increases comparability, but does not eliminate all problems, as the interpretation of common questions can vary across countries because of country – specific institutions and history (OECD, 1991). Furthermore individuals of the original sample are followed over time even when they leave the original family and this allow me to match them with their siblings.

I attribute to each individual who was a children in the original sample and who left the house, the same family id as before. Using the link file I connect individuals with their siblings, exclude all the unmatched observations and then I keep those with an age lower than 40, with a positive earnings in at least a year and which declare themselves to be working with an employer in paid employment (more than 15 hours a week), in paid apprenticeship or training (more than 15 hours a week) (i.e individuals must not be in formal education or self-employed) . The earnings variable I use is the monthly (gross) earnings of the month prior to the interview, and I exclude individuals which have earned in the previous month less than 200 euros

To estimate heterogeneous returns to education according to family characteristics I need to merge parents information with my siblings samples. So I start with the samples used before and merge parents education information where available. After keeping those individual with information about parents education, I end up with samples reduced of

[8] ECHP UDB – version of December 2003.

about 30%. To estimated a family fixed or random effect model I don't need information for the same individual in different point in time. Furthermore I observe individual on average for four waves. So to increase sample size, rather than using only a wave I express wages in 2000 prices and keep just the last (in time) observation for each individual. I use the same earnings variable as before, the gross monthly wage which increases comparability across countries being gross and so disregarding the existing differences in tax system across countries.

ECHP first collects data on individuals of the original sample when they reach the age of 17, and this is the lower bound of my samples age, while I exclude individual with an age higher than 40.

In ECHP education is a categorical variable and it is classified in three ascending level on the basis of the ISCED classification scheme which is mainly based on years of education: less than secondary (ISCED 0-2), second stage of secondary level (ISCED 3) and tertiary level (ISCED 5-7). I define parents' education as the highest level of education of the parents. For example, a mother with a tertiary degree and a father with a secondary degree are treated as parents' with tertiary degree.

4. Results

To estimate the three earnings variance component as in equation (3) in order to calculate earnings siblings correlations I use the siblings samples selected as described in the previous section. Table 1 contains the samples mean and, as it can be seen, the average age is quite different across countries, higher in Italy, lower in the UK and Austria, reflecting cohabitation with parents habits (Iacovou, 2002). The average annual net incomes reflect the young age of my samples. In the middle and bottom panels I reports means also for sisters and brothers.

TABLE 1 AROUND HERE

In these samples I keep individual according to their sex and who is unmatched by a siblings of the other sex enter the sample as a singletons (to increase numbers of observations and to better identify σ_u and σ_a. Brothers show an higher monthly wage than sisters and but have a lower average age, except in Ireland, Spain and Portugal. These are clearly young people in their starting steps in the labor market, and that's why I cannot interpret the estimated correlations as overall correlation. Rather than correlations in the permanent income, they are correlations in the early career choices and earnings.

Good data containing information for many brothers in many years are scarce and so estimations of siblings correlations have almost been done using small sample. Solon 1999 in reviewing the literature on siblings correlations, shows that the vast majority of this studies have used few hundreds of family. More recently some bigger sample have been used to this purpose, as for example in Bijorklund et alii, 2000 in which the authors used registry files of Scandinavian countries with data from several thousand of families, but compare their results with estimation obtained from the PSID (US panel) in which they used about 9 hundreds of families.

TABLE 2 AROUND HERE

Table 2 shows the estimated correlations, for all siblings and separately for sisters and brothers. My preferred results are those obtained with all siblings together, where I have more observations per family and I obtain a better measure of the within family variance and a more precise estimation of the correlation, as the low standard errors suggest. I have four countries with a correlation lower than .3, two Central Europe countries, Germany (which is know to be more mobile than the US, Couch and Dunn, 1998) and Austria and two Northern Countries, the UK and Ireland. France and Spain are somewhat in the middle (slightly higher than .3) , Greece and Italy are around .4 and finally Portugal has the higher siblings correlation which is over .5

The correlation sharply increases when I estimate it only for sisters in almost all countries except Ireland and France indicating that women tend to rely more on family and community maybe because of discriminating labor market, while it does not show a common pattern for brothers, and significantly decreases only in Austria. The observed gender based differences confirms previous findings on the different role of family behavior towards daughters and sons (Berman and Taubman, 1995 and Comi, 2003). Sisters correlations in early career earnings are particularly high in those countries where women participation rate in the labor market is lower, like Italy, Spain and Greece and extremely low in France.

A desirable feature of data to estimate earnings equations is an average labor experience of about ten years (Griliches, 1977). Table 3 shows the means of the (sub) samples used to estimate heterogeneous returns to education. Age ranges from 23.1 in the UK to 27.7 in Italy. The education distribution is very different across countries and it reflects the education system together with the age distribution. For examples in Germany, the sample is very young while tertiary education programs lasts many years: only 9 percent of the sample have a tertiary degree. In some countries (Italy, Portugal and Austria) the percentages of parents with a tertiary degree are very low. With the young sample ECHP provides, I may experience some problems in the identification of different return of educational level and of course these returns can be identified only inside the available age range and no inference can be done outside this support. Notwithstanding the caution needed in interpreting the results, heterogeneity in returns to education can still be investigated.

TABLE 3 AROUND HERE

In interpreting my results, we should keep in mind also the Ben-Poraht model of life-cycle decision to invest in education. According to this model, in the early stage higher level of education may be on average less rewarded by the labor market but earnings will growth at a faster rate during life. As table 3 shows, it does not seem to be my case because earnings is increasing with education in almost all countries except the UK In. France the average wage of those with a secondary degree is almost similar to the average wage of people without a secondary degree, while in Austria, there is a very small difference between the wages of secondary and tertiary education level. There is not a big difference between secondary and less than secondary average earnings in Italy, Spain and Portugal and it could be difficult to identify the secondary education dummy in these countries.

TABLE 4 AROUND HERE

To have a preview of how parents' education can affect children wages, table 4 show average wage according to individual and parents' level of education. In each country panel, wages should decrease moving down and right. There is not a single country who fulfill this expectation! Fro example, tertiary education wages seem to be clearly affected by parents education in France, Spain and Portugal while there is not a monotonic relationship in other countries. Furthermore, some cells have a very low number of observations, and this can create some problem in estimations.

Table 5 shows the OLS estimation of the classical Mincer equation, with educational dummies (tertiary and secondary, less than secondary is in the constant). In all the countries the coefficients of the educational levels are statistically significant (except the UK and France for the secondary level, as expected by the average wages showed in table 3) and increasing with the level of education (except Austria, as expected again by the raw means of wages by level of education in table3). This means that in these countries, even in the early career years, higher levels of educations have higher returns. Portugal, followed by Ireland and Germany is the country with the highest pay-off for tertiary education.

TABLE 5 AROUND HERE

As described in the previous section these estimates are likely to be biased and I can obtain less biased estimates using siblings differences estimations. Rather than using differentiated variables, I put in the OLS estimations a dummy for each family, controlling so for the family fixed effect (ε_{fj} in equation 19) and allowing each family to contribute with more as many siblings as possible. Table 6 shows the results of the fixed effect model, without interactions terms. Family fixed effects control for any characteristic shared by siblings, like parents education, family income etc and also for all individual characteristics linearly related to family characteristics, leaving only differences between individual of the same family (heterogeneity within the family). If we compare coefficients with OLS results, we can see that the OLS estimations where upward biased in all the countries except Austria.

TABLE 6 AROUND HERE

As previous literature, I allow for heterogeneous returns to education, introducing in the specification interactions terms (second order) of educational levels with parents education. Parents education is a measure of the cultural capital to which children are exposed to. I find almost no evidence of the effect of parents education[9] on return to education except for some rare countries: having a parent with a tertiary degree increases the return to tertiary education in Portugal and to secondary education in the UK, while in France having a parent with a secondary degree increases the returns to secondary education.

TABLE 7 AROUND HERE

Finally I estimate the random coefficients model as in equation (21) using the educational levels. At level 2 I allow for tree random terms: an intercept capturing family raw effect on earnings, a slope coefficient for tertiary education and one for secondary education. I also allow the three random terms to be correlated with each others[10]. Table 8 does not include interactions terms and, as it can be seen, the coefficients are highly significant in almost all countries, except France and the UK.

TABLE 8 AROUND HERE

This model accounts for the hierarchical structure of the data and we have information about both level of the hierarchy. Consider Italy as example we know that the earnings variance between individual (level 1) is .086 while the between family earnings variance is .055. Clearly, the level-1 residual variance is larger than the level-2 variance component; this

[9] Many other specification and parents education definition have been tried with the same results.
[10] The estimation are obtained using the gllamm command in STATA, as a references for random coefficients models in STATA with gllamm, see Rabe-Hesketh(2002)

will usually always be the case any time individual differences are larger than between-family differences and this imply that there is a significant between family variation in the dependent variable. The average return to tertiary and secondary education are respectively .220 and .110. The variances are respectively .002 (.002) and .037 (.007). The fact that the latter is statistically different from zero means that there is considerable variability in the returns to secondary education. The standard deviation (square root of variance) is about .192 and thus the range of the coefficient is quite large.

There is evidence of variability between family in the returns to education in all countries as regards secondary education and in Ireland, Portugal and Austria in returns to tertiary education.

TABLE 9 AROUND HERE

In the last specification I estimate, I explicitly modeled the random coefficients as a function of a level two covariate, parents education. Table 9 shows the results. I find that in many countries the interaction term is statistically significant and this confirms that the random coefficients can be treated as a function of parents education. In particular I find positive and significant effect of parents tertiary education on return to tertiary education in France, the UK, Italy, Greece and Spain and on return to secondary education in Ireland and Italy.

Accounting for differences

To interpret these results we should think to existing differences in the countries under study. As a first attempt it can be useful to use the Esping Andersen classification of Welfare State. He define as Welfare State the state behavior towards citizen, market and families. He cluster countries in three different types of welfare state: *liberal*, clearly market oriented these states are extremely concerned about efficiency and let the markets work to reach equilibria and tend to infere just with few social –insurance towards low-income people, exclusively individual-oriented (Anglo-Saxon countries: US, Canada Australia and increasingly Great Britain); *corporatist* (conservative) less market oriented with a state ready to displace the market as a provider of welfare, in some cases they are also shaped by the Church and so family-oriented (Central Europe countries, like Germany, France and Italy); and *socio-democratic*, where the state solve the dualism between market and state promoting an equality of the highest standard (mainly Scandinavian countries).

In corporatist countries where the welfare state is family oriented, young people tend to cohabit longer with their parents because it can be difficult to leave parents' house and the state do not protect them, fro example with unemployment benefit if they loose their jobs. Furthermore these countries typically tend to have stricter employment protection laws to protect the breadwinner and disregards young people. In such a context, families react creating a network to protect their offspring and siblings correlations in earnings are higher and the effect of family characteristics on returns to education may be stronger.

My findings confirm this interpretation because the liberal countries UK and Ireland have lower siblings earnings correlations and milder effect of parents education on returns. Among the corporatist countries we need to further consider the role of the Church. Algan& Cahuc , 2004 deeply analyze the positive link between traditional family values and job protection legislation. Studying the interaction between religions, preferences and institutions they find that Mediterranean Catholic countries are more likely to support "macho values" than Protestant. This social status gives rise to job protection and families policies. My findings that Portugal, Italy and Greece are the countries with the higher correlations and. the (Catholic) Religion has shaped the societies upon the family are in line with this hypothesis.

Finally, also Fogli (2000) argues that in countries with imperfect credit markets, young agents realize consumption smoothing living with their parents longer, family size increases and there is a sort of intergenerational redistributions of consumption. In such a context, employment protection is welfare improving because protecting the old worker, it allows children still living with their parents to have an higher level of consumption and can reduce inefficiency. She concludes that in countries where credit market imperfections are more severe young people cohabit with their parents longer and employment protection is stricter. And in fact, plotting the siblings earnings correlations with an indicator of strictness of employment protection law[11] as in figure 1 I find that the higher is the EPL, the higher is siblings correlation in earnings, i. e. families tend to have a greater influence in early career.

FIGURE 1 ABOUT HERE

5. Concluding remarks

This paper is a comparative study of how much family characteristics affect early career outcomes (wages) of children in nine European countries: Germany, France, United Kingdom, Ireland, Italy, Greece, Spain, Portugal and Austria. To asses the overall importance of family influence I compute a broad indicator of family effect

[11] Taken from OECD Employment Outlook (1999) table 2.5 last column: overall EPL strictness weighted average of indicators for regular contracts, temporary contract and collective dismissals.

on earnings, the siblings earnings correlations, using the first eight waves of ECHP data on siblings. This indicator measures how much of the observed earnings can be attributed to what siblings share: family and community background observed and unobserved characteristics. I find that Portugal, Italy and Greece are the countries with the higher correlations. In these countries the Religious traditions as well as culture and traditional habits shaped the societies upon the family, moreover, they are characterized by very strict employment protection laws, and so young people tend to live longer with their parents and family influence in the early career period is greater.

According to the education investment literature, family background affects education mainly by influencing the choice of the amount of schooling , holding the rate of return constant and some studies has concentrated on the amount of education to explain family influence. Implicitly these models imply that those family characteristics that can affect returns to education may induce individuals to invest in further education. In this paper I measure the direct impact of family characteristics on the returns to education estimating models that allow for heterogeneous returns to education in cross-country comparison view. I find that in many countries parents education affect returns to education. In particular I find positive and significant effect of parents tertiary education on return to tertiary education in France, the UK, Italy, Greece and Spain and on return to secondary education in Ireland and Italy.

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Table 1. Siblings correlations: Samples means

	Germany	France	UK (2)	Ireland	Italy	Greece	Spain	Portugal	Austria
All									
Age	23.8	24.9	22.9	24.1	27.0	26.1	26.1	25.1	23.1
Average Monthly Gross Wage (1)	1372.31	1227.98	1863.72	1578.28	1131.56	693.50	1006.70	547.18	1371.34
N individuals	1411	1182	1048	2200	2359	1524	2855	1877	1386
N family	893	760	630	1088	1456	867	1646	971	720
N obs	5301	3688	3824	6476	8564	4149	8802	7840	4354
Average ind. per family	1.9	1.8	2.0	2.7	2.0	1.8	2.2	2.3	2.2
Sisters									
Age	23.1	24.7	22.9	24.2	26.5	25.6	26.3	25.2	22.6
Average Monthly Gross Wage (1)	1142.23	1163.34	1662.72	1462.74	1028.27	657.15	914.26	519.65	1163.49
N individuals	586	457	454	967	987	513	1176	755	496
N family	483	383	376	771	750	431	924	598	376
N obs	2145	1261	1599	2747	3431	1580	3454	2865	1751
Average ind. per family	1.4	1.4	1.4	1.5	1.6	1.4	1.5	1.5	1.5
Brothers									
Age	24.2	25.0	23.0	23.9	27.1	26.3	26.1	24.8	23.3
Average Monthly Gross Wage (1)	1493.99	1270.82	2022.92	1625.26	1203.86	716.01	1083.48	579.90	1515.30
N individuals	825	706	594	1248	1393	763	1680	1150	1121
N family	626	550	439	1044	928	586	1200	782	632
N obs	3143	2288	2230	3717	5136	2569	5358	4990	2603
Average ind. per family	1.6	1.5	1.6	1.9	1.6	1.5	1.7	1.8	1.7

Notes: (1) in euro in 2000 prices.

Table 2: Siblings correlations and components of earnings inequality

	Germany	France	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
All									
Siblingss correlation	**.263 (.051)**	**.313 (.073)**	**.238 (.055)**	**.244 (.029)**	**.407 (.045)**	**.383 (.076)**	**.319 (.035)**	**.534 (.032)**	**.100 (.048)**
σ^2_a	.051	.031	.022	.027	.034	.026	.036	.045	.008
σ^2_u	.143	.068	.071	.085	.050	.042	.077	.039	.079
σ^2_v	.140	.076	.075	.085	.039	.046	.069	.028	.075
Sisters only									
Sisters correlation	**.446 (.196)**	**.145 (.279)**	**.427 (233)**	**.234 (.100)**	**.541 (.148)**	**.541 (.315)**	**.560 (.126)**	**.561 (.143)**	**.260 (.217)**
σ^2_a	.086	.011	.042	.024	.054	.036	.081	.056	.020
σ^2_u	.107	.069	.054	.081	.046	.030	.063	.044	.057
σ^2_v	.143	.050	.073	.078	.041	.044	.070	.023	.079
Brothers only									
Brothers correlation	**.210 (.117)**	**.445 (.192)**	**.344 (.126)**	**.309 (.068)**	**.439 (.119)**	**.506 (.149)**	**.456 (.079)**	**.623 (.062)**	**.058 (.124)**
σ^2_a	.038	.038	.029	.034	.028	.034	.037	.046	.004
σ^2_u	.142	.047	.056	.077	.036	.033	.044	.028	.072
σ^2_v	.140	.076	.075	.096	.038	.046	.068	.031	.072

Notes: Bootstrapped standard error within parenthesis

Table 3: Returns to education: samples means.

	Germany	France	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
Individual characteristics									
Age	24.3	25.2	23.1	24.0	27.7	26.6	26.6	25.6	23.6
% with tertiary education	9.66	45.13	66.19	27.96	11.3	31.82	43.15	12.6	4,23
% with secondary education	54.64	33.88	11.09	54.80	58.96	53.73	26.23	25.06	70.49
% with less than secondary education	35.70	20.99	22.72	17.24	29.74	14.44	30.62	62.34	25.82
Average wage tertiary education	2298	1326.1	2001.7	1824.5	1385.4	855.9	1195.8	962.6	1508.1
Average wage secondary education	1500	1078.6	1215.6	1305.9	1133.3	661.3	876.9	537.3	1486.9
Average wage less than secondary educ	834	1074.3	1410.8	1080.9	1006.9	605.6	832.3	454.8	819.3
Average Monthly Gross Wage	1339.4	1189.3	1780.3	1412.2	1124.2	715.2	1000.8	539.5	1319.1
% Female	49.4	48.7	49.3	49.6	48.9	48.8	48.8	48.8	49.6
Nobs	1014	782	572	1520	1540	817	1891	1333	803
Family background characteristics									
% Parents with tertiary degree	27,79	17,77	66,78	16,62	4,98	13,96	17,39	4,35	3,21
% Parents with secondary degree	48,79	46,93	13,99	40,00	32,47	27,56	14,86	4,20	78,42
% Parents with less than secondary deg.	23,42	35,29	19,23	43,38	62,55	58,48	67,76	91,97	18,37

Notes: all the wages are in euro and in 2000 prices

Table 4: Returns to education: average monthly wage by individual and parents' education.

Country	Individual education	Parent with tertiary education	Parents with secondary education	Parents with less than secondary education
Germany	Tertiary	2264.1 (47)	2327.7 (38)	2335.4 (13)
	Secondary	1335.3 (140)	1515.3 (283)	1642.8 (131)
	Less than secondary	617.3 (93)	722.2 (175)	1257.3 (94)
France	Tertiary	1496.5 (97)	1296.6 (152)	1175.9 (80)
	Secondary	1046.1 (24)	1079.9 (124)	1084.95 (99)
	Less than secondary	981.6 (14)	1071.8 (68)	1095.8 (71)
UK	Tertiary	2034.9 (261)	1839.3 (49)	1990.3 (60)
	Secondary	1271.4 (38)	1188.6 (11)	1075.6 (13)
	Less than secondary	1283.9 (75)	1529.4 (20)	1634 (32)
Ireland	Tertiary	1826.1 (123)	1847.7 (198)	1778.2 (104)
	Secondary	1410.6 (101)	1332.9 (350)	1253.5 (382)
	Less than secondary	1147.7 (20)	1067.6 (60)	1077.9 (182)
Italy	Tertiary	1413.4 (39)	1463.9 (78)	1258.6 (57)
	Secondary	1327.2 (37)	1131.8 (334)	1120.8 (537)
	Less than secondary	903 (1)	1025.2 (89)	1002.8 (368)
Greece	Tertiary	990.5 (52)	885.1 (84)	779.7 (124)
	Secondary	672.5 (59)	637.5 (129)	670.9 (251)
	Less than secondary	518.4 (3)	601.1 (12)	608.7 (103)
Spain	Tertiary	1392.4 (240)	1166.5 (139)	1097.9 (437)
	Secondary	877.9 (65)	927.2 (83)	864.7 (348)
	Less than secondary	870.8 (24)	821.5 (59)	831.7 (496)
Portugal	Tertiary	1100.8 (43)	872.1 (13)	919.9 (112)
	Secondary	611.5 (14)	519.5 (25)	535.3 (295)
	Less than secondary	334.6 (1)	482.3 (18)	454,4 (812)
Austria	Tertiary	1484.9 (6)	1514.1 (27)	1486.1 (1)
	Secondary	1404.5 (14)	1482.3 (448)	1517.9 (104)
	Less than secondary	660.0 (6)	760.2 (153)	1046.3 (44)

Notes: Number of observations per cell within parenthesis.

Table 5: OLS estimations of earnings equation by country.

	Germany	France	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
Tertiary education	.451*** (.070)	.215*** (.038)	.109** (.051)	.460*** (.037)	.221*** (.033)	.270*** (.043)	.273*** (.024)	.674*** (.030)	.162** (.077)
Secondary education	.310*** (.046)	-.049 (.040)	-.100 (.070)	.196*** (.032)	.115*** (.021)	.129*** (.037)	.056** (.025)	.170*** (.022)	.289*** (.040)
Age	.336*** (.039)	.310*** (.040)	.381*** (.046)	.209*** (.023)	.103*** (.016)	.054*** (.023)	.117*** (.017)	.076*** (.016)	.277*** (.024)
Age2	-.004*** (.0006)	-.005 (.0005)	-.006*** (.0009)	-.003*** (.0004)	-.005*** (.0002)	-.0004 (.0004)	-.001*** (.0003)	-.001*** (.0002)	-.004*** (.0004)
Female	-.205*** (.036)	-.177 (.029)	-.161*** (.039)	-.150*** (.023)	-.179*** (.018)	-.122*** (.026)	-.240*** (.020)	-.203*** (.019)	-.212*** (.027)
Constant	1.64*** (.448)	2.20 (.377)	2.06*** (.556)	3.83*** (.292)	5.26*** (.226)	5.25*** (.318)	4.77*** (.237)	4.9*** (.213)	3.13*** (.289)
R2	.47	.39	.37	.28	.17	.24	.25	.37	.49
Nobs	1014	729	559	1520	1540	817	1891	1333	803

Table 6: Family fixed effect estimates of earnings equations by country.

	Germany	France	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
Tertiary education	.296*** (.128)	.040 (.071)	-.030 (.081)	.263*** (.062)	.161*** (.056)	.172** (.086)	.102** (.041)	.417*** (.052)	.267** (.119)
Secondary education	.210*** (.071)	-.104 (.063)	-.196* (.112)	.039 (.049)	.067** (.036)	.074 (.069)	-.021 (.039)	.022 (.031)	.309*** (.058)
Age	.391*** (.052)	.293*** (.061)	.302*** (.086)	.229*** (.037)	.062** (.025)	.078** (.041)	.099*** (.029)	.072*** (.022)	.326*** (.040)
Age2	-.006*** (.0009)	-.004*** (.001)	-.004** (.002)	-.004*** (.001)	-.001* (.000)	-.001* (.001)	-.001 (.001)	-.001*** (.000)	-.006*** (.001)
Female	-.210*** (.057)	-.106*** (.051)	-.203*** (.062)	-.168*** (.032)	-.149*** (.027)	-.127*** (.041)	-.238*** (.029)	-.213*** (.025)	-.195*** (.039)
Constant	-.092 (.810)	2.52*** (.868)	4.14*** (1.076)	3.024*** (.557)	5.97*** (.459)	4.92*** (.623)	4.813*** (.442)	5.09*** (.337)	2.92*** (.577)
Family fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	.87	.87	.84	.72	.85	.86	.81	.85	.82
Nobs	1014	729	559	1520	1540	817	1891	1333	803

Notes: Dependent variable: logarithm of the monthly gross earnings. * means significant at 10%; **significant at 5%; ***significant at 1

Table 7: Family fixed effect estimates of earnings equations by country with interaction terms

	Germany	France	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
Tertiary education	.157 (.292)	-.043 (.113)	-.036 (.125)	.196*** (.087)	.147*** (.080)	.148 (.093)	.072 (.045)	.441*** (.055)	.503 (.475)
Secondary education	.138 (.105)	-.004 (.086)	-.593** (.243)	-.044 (.060)	.103*** (039)	.079 (.075)	.024 (.043)	.028 (.032)	.422*** (.102)
Tertiary educ. * parent tertiary educ.	.217 (.341)	.364 (.280)	.109 (.142)	.111 (.149)	-.132 (396)	0.040 (.342)	-.102 (.116)	.610*** (.4258)	.348 (.735)
Tertiary educ. * parents sec. educ.	.131 (.329)	.003 (.156)	-.058 (.153)	.185* (.108)	-.026 (.115)	.021 (.133)	.084 (.085)	-.637** (.241)	-.319 (.489)
Sec. educ. *parents tertiary educ	.006 (.178)	.002 (.325)	.611** (.287)	.172 (.132)	-.078 (.411)	-.121 (.303)	-.436*** (.135)	.425 (.341)	.113 (.478)
Sec. educ. * parents sec educ	.155 (.132)	-.221* (.131)	.220 (.353)	.206** (.086)	-.150** (.071)	-.014 (.124)	-.076 (.10)	-.065 (.131)	-.145 (.107)
Age, Age squared female and constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	.88	.83	.84	.73	.85	.86	.82	.86	.83

Notes: see table 5

Table 8: Multilevel model with random coefficients estimations

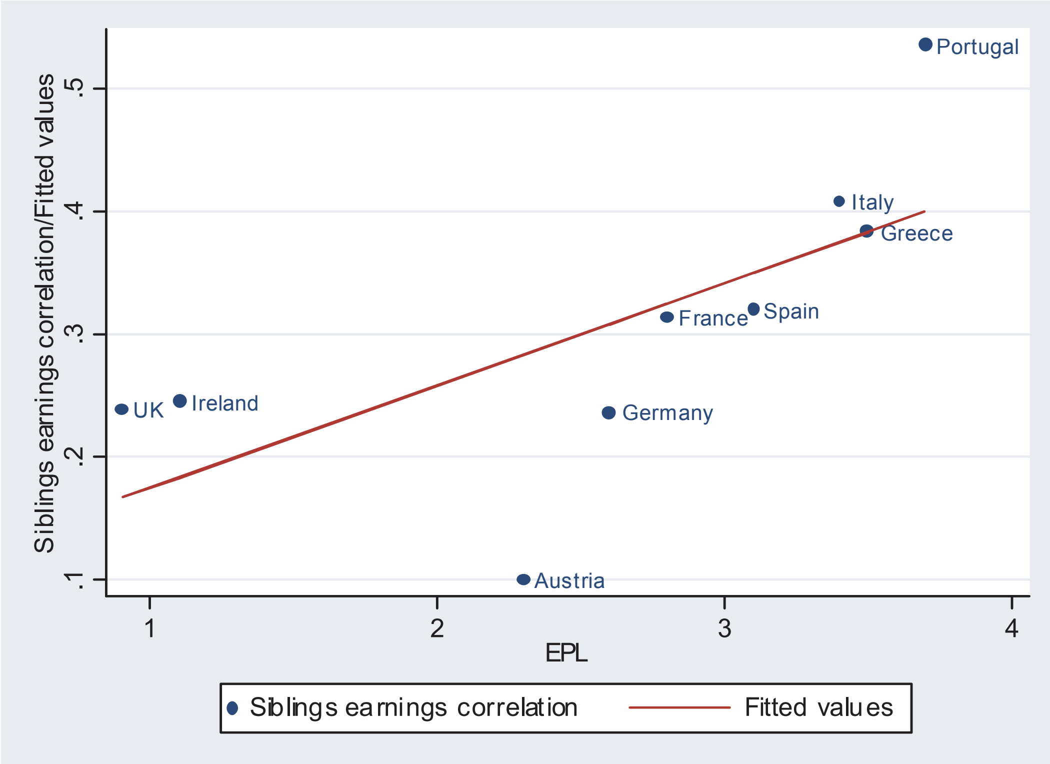
	Germany	France	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
Tertiary education degree	.372*** (.066)	.203*** (.037)	.092*** (.049)	.460*** (.041)	.220*** (.035)	.254*** (.044)	.256*** (.024)	.624*** (.033)	.309*** (.068)
Secondary education degree	.236** (.041)	-.057 (.037)	-.111 (.071)	.190** (.036)	.110*** (.020)	.105*** (.037)	.051** (.023)	.146*** (.020)	.308*** (.038)
Constant	1.80*** (.409)	2.66*** (.355)	2.15*** (.530)	4.05*** (.293)	5.61*** (.219)	5.73*** (.301)	4.98*** (.220)	5.14*** (.171)	3.63*** (.264)
N level 1 units	1014	729	559	1520	1540	817	1891	1333	803
N level 2 units	700	517	367	824	1066	588	1198	803	482
Variance level 1	.214 (.017)	.105 (.010)	.145 (.016)	.169 (.008)	.086 (.005)	.076 (.007)	.117 (.006)	.050 (.003)	.099 (.006)
Variances of level2 (family) random effects									
(A) Random intercepts	.014 (.139)	.074 (.041)	.009 (.056)	.079 (.0038)	.055 (.0029)	.084 (.047)	.032 (.017)	.124 (.025)	.025 (.039)
(B)Random slope of tertiary education	.008 (.020)	.0008 (.0004)	.030 (.061)	.047 (.033)	.002 (.002)	.010 (.011)	.005 (.009)	.021 (.010)	.050 (.025)
(C)Random slope of secondary education	.029 (.017)	.024 (.014)	.032 (.023)	.086 (.021)	.037 (.0007)	.049 (.015)	.023 (.006)	.024 (.004)	.024 (.012)

Notes: each regression contains a second order polynomium in age and a gender dummy.

Table 9: Multilevel model with random coefficients estimations with parents' education interaction.

	Germany	France	UK	Ireland	Italy	Greece	Spain	Portugal	Austria
Random coefficient of tertiary education									
Tertiary education degree	.461*** (.145)	.114** (.052)	.012 (.070)	.419*** (.055)	.127** (.054)	.192*** (.049)	.194*** (.028)	.610*** (.041)	.303* (.321)
Secondary education degree	.258** (.059)	-.078* (.046)	-223*. (.134)	.143*** (.046)	.096*** (.022)	.102*** (.053)	.052** (.025)	.143*** (.020)	.307*** (.049)
Tertiary educ *parent tertiary	-.120 (.154)	.133** (.058)	.107* (.063)	.058 (0.58)	.139* (.081)	.178*** (.059)	.183*** (.036)	.070 (.069)	.024 (.343)
Tertiary educ *parent sec. Educ	-.066 (.158)	.106** (.053)	.007 (.084)	.055 (.052)	.146** (.066)	.082 (.051)	.059 (.042)	-.059 (.111)	.004 (.323)
Secondary educ *parent tert. Educ.	-.122* (.066)	-.024 (.081)	.116 (.151)	.113** (.051)	.166*** (.057)	.038 (.046)	-.028 (.051)	.085 (.081)	-.182 (.093)
Secondary educ *parent sec. Educ.	.021 (.058)	.046 (.049)	.220 (.190)	.080** (.034)	.021 (.023)	-.008 (.034)	.029 (.046)	-.011 (.062)	.007 (.036)
N level 1 units	1014	729	559	1520	1540	817	1891	1333	803
N level 2 units	700	517	367	824	1066	588	1198	803	482
Variances									
Variance level 1	.214 (.017)	.105 (.010)	.146 (.014)	.169 (.008)	.086 (.005)	.076 (.007)	.117 (.006)	.050 (.003)	.099 (.006)
Variances of level2 (family) random effects									
(A) Random intercepts	.025 (.107)	.068 (.042)	.00001 (.001)	.080 (.039)	.056 (.029)	.078 (.046)	.022 (.013)	.119 (.025)	.025 (.033)
(B)Random slope of tertiary education	.009 (.027)	.0007 (.0039)	.027 (.075)	.043 (.029)	.002 (.002)	.010 (.011)	.004 (.008)	.020 (.010)	.047 (.025)
(C)Random slope of secondary education	.029 (.018)	.023 (.014)	.032 (.019)	.088 (.021)	.037 (.007)	.048 (.015)	.021 (.006)	.023 (.004)	.024 (.012)

Figure 1: Siblings earnings correlation and EPL



Notes: Siblings earnings correlation as in the first raw of table 2. EPL taken from OECD Employment Outlook (1999) table 2.5 last column: overall EPL strictness weighted average of indicators for regular contracts, temporary contract and collective dismissals.