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Accounting for the Heterogeneity in Inter-generational Links in Educational Attainment Across Europe

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Abstract

We use data drawn from the European Social Survey to investigate the extent of inter-generational links in educational attainment across twenty-four European countries. We find that there is a lot of cross-country variation in the observed patterns especially when gender distinction is made at both the parents' and the children's generations. To account for the variation in the estimates obtained in separate country regressions, we propose the use of simple educational inequality measures as country-level control variables. While the variation in the children's educational attainment turns out to be positively associated with the level of inter-generational links, the opposite is the case for the variation in the parents' attainment. The introduction of country-level variables into the analysis brings about the estimation of the econometric models on the pooled sample of all countries and the use of multilevel modeling methods which we find to perform better than least squares estimation.

Keywords: *Educational attainment, inter-generational links, European Social Survey, HLM.*
JEL Classifications: *I21, J16, J24*

1. Introduction

One of the most commonly studied aspects of socio-economic inter-generational mobility within families is to what extent the educational outcomes of individuals are associated with the schooling levels of their parents. Though the examination of the relationship in question may at first seem to be a straightforward task, complex models have been developed for both conceptual and methodological reasons. Feinstein, Duckworth, and Sabates (2004) argue, for example, that parental education is a major influence both directly and through other channels such as income and parenting skills and that part of the effect of parents' education is in moderating the effects of other elements. The authors also point to the fact that the inter-generational transmission of educational attainment is not necessarily a desirable outcome as it implies the persistence of social class differences and a barrier to equality of opportunity.

The pattern generally agreed upon in the empirical literature is that parents' educational attainment has a positive impact on their children's educational outcomes, and that the human capital of the mothers is of more relevance than the

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fathers' (Haveman and Wolfe, 1995).[3] This is despite the contrary evidence presented in some recent studies in which the impact of unobserved inherited abilities and the assortative mating of the parents are controlled for. Using data for the U.S., Behrman and Rosenzweig (2002) and Plug (2004) have found, on samples of twins and adopted children, respectively, that the mother's schooling has little, if any, impact on the schooling of her children. Furthermore, Ganzach (2000) reports evidence for the interactions between parents' education, cognitive ability of the child, and educational expectations in determining educational attainment. This latter finding implies that obtaining reliable estimates can be tricky even when abilities are controlled for.

In this paper, we use data drawn from the European Social Survey (ESS) to examine the determinants of individuals' educational attainment across Europe. Our primary aim is to demonstrate and explain the cross-country heterogeneity in the effects of the various variables that are being considered as potential factors. We are particularly interested in exploring the nature of inter-generational links, i.e. the effect of the parents' schooling levels and employment statuses on the respondents' educational attainment. We propose country-level variables that account for the variation in the coefficient estimates relating to educational attainment across the countries under examination. Finally, we compare two alternative estimation methods, namely ordinary least squares and hierarchical linear modeling, in terms of their explanatory powers. Since our empirical work does not involve adjustments for unobserved characteristics and possible endogeneities, the reported estimates should be used primarily for the purpose of making cross-country comparisons and interpreted as representations of the associations between the variables rather than causal effects.

Depending on the theoretical assumptions being made, there are several ways the inter-generational transmission of educational outcomes can be explored empirically in a regression context. The econometric work could feature a restrictive model which omits the mother's schooling level altogether, but it could also utilize a comprehensive one which assumes both parents to have different effects for male and female children. Using data on multiple countries from the International Stratification and Mobility File (ISMF), Johnston, Ganzeboom and Treiman (2005) carry out an extensive study to operationalize and test the various models suggested in the literature. They conclude that a model that allows for gender differences at both generations should be used to ensure that all observable patterns are accounted for.

The findings of Jerrim and Micklewright (2009) based on data from the 2003 round of the Programme of International Student Assessment (PISA) for 30 OECD countries also reveal that gender distinctions at both generations provide valuable insights about the nature of inter-generational links. The authors relate children's learning achievement (as recorded in standardized tests at the age of 15) to the years

[3] See Jerrim and Micklewright (2009) for a summary of the findings of related studies. The authors also refer to the Haveman and Wolfe paper as the prominent study on this subject.

of education of their mothers and of fathers, trying many different specifications including one with an interaction term to allow for the complementarity of the parents' schooling. Even though it focuses on a different educational outcome, this study is especially relevant to our work as it concludes that the variation across countries in the inter-generational links is large enough to dissuade researchers from making generalizations on the basis of findings for a single country. This is why we focus on trying to account for the cross-country variation as much as estimating a practical model of inter-generational links.

2. The ESS Data and the construction of variables in the model

Initiated in 2001 with the cooperation of the European Commission, European Science Foundation, and 26 national Research Councils, the European Social Survey (ESS) aims to monitor attitudes and behaviors across countries and over time. We use data drawn from the second round of the ESS fielded in 2004-2005 in the following 26 countries: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Great Britain, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Spain, Slovakia, Slovenia, Sweden, Switzerland, Turkey, and Ukraine.[4] Besides the data on educational attainment, this rich data set contains many bits of information that are potentially relevant to the current study, such as whether the respondent was born in his/her country of residence or whether s/he belongs to an ethnic minority.

In order to work with a sample of individuals who have completed their schooling, we restricted our sample to respondents aged 25 and over (which seems to be the cut-off point used in many studies on this topic) and also to those who are currently not students, assuming that they will not be going back to school. Obviously, we also had to exclude the observations at which one or more of the variables was missing or responded to as "Don't know" which implies that single-parent families are excluded from the analysis.[5] The Great Britain sample was also left out of the analysis because the educational attainment variable for this country has been removed from the main data file for not being compatible with the classification scheme to be discussed below. We also had to exclude the data for Portugal which turned out to be a major outlier with respect to the relationships we are focusing on. One possible reason for this could be that over 90 percent of the fathers and mothers in this country have completed at most primary education.

The question of how the background variables in cross-national surveys can be compared has previously been addressed by several researchers. The educational attainment information presents its own specific set of problems as one needs to

[4] The fieldwork in Turkey and Italy took place in 2006.

[5] As would be expected, in most cases, it is the father's information that is missing from the data.

compare the respondents' education acquired under different national systems (Hoffmeyer-Zlotnik and Warner, 2008). The seven distinct levels of educational attainment appearing in the ESS data are based on a reduced version of the 1997 edition of the International Standard Classification of Education (ISCED) developed by UNESCO (UNESCO, 2006 [1997]). In a study testing the validity of ISCED-1997 as the classification criteria in the ESS, Schneider (2008) argues that the main drawback of the system is that it does not distinguish between vocational and general programs at the upper secondary and tertiary levels, but this does not seem to be a source of major concern as far as our empirical work is concerned.

The level of education variable in the ESS data set includes the following categories: "Not completed primary education", "completed primary or first stage of basic", "lower secondary or second stage of basic", "upper secondary", "post-secondary, non-tertiary", "first stage of tertiary", and "second stage of tertiary". In the case of the respondent's attainment, the categorization was obtained by 'post-harmonization', i.e. the recoding of more detailed country-specific data, whereas the parents' levels were obtained by 'pre-harmonization', i.e. the information was recorded in the survey in accordance with ISCED-1997 (Schröder and Ganzeboom, 2009). In order to facilitate the use of this information as a dependent or explanatory variable, the seven categories were converted into a single continuous variable such that they correspond to 2, 5, 8, 11, 13, 15, and 17 years of education, respectively. It would have been more appropriate to recode the ISCED levels into years of education equivalents using country-specific conversion coefficients, but we were unable to do this due to the lack of relevant data. However, since the same recoding scheme is used for the dependent and explanatory variables the association between which we are mostly concerned with, this is less of a problem than it would have been in another type of study.[6]

Determining the direction of the relationship between parents' employment and the cognitive and educational outcomes of their children has also been the purpose of several studies. Probably due to their different ways of handling the potential endogeneities involved, the evidence obtained in these studies has been mixed (Duncan et al., 1998; Harvey, 1999). However, the general belief is that mothers' employment has a negative impact on educational attainment even though the magnitude of the net effect is ambiguous due to the presence of an indirect positive effect through household income.[7] The information provided in the ESS pertains to the employment status of the respondent's parents when the respondent was at the age of 14. This information provides only a crude measure of the 'employment effect' since it ignores the intensity (i.e. number of hours) of work and the incidence of employment at different developmental stages of a child. Working

[6] The ESS data set also contains a 'years of education' variable, but the use of this information is likely to be more problematic.

[7] Using a sample of adopted children to obtain genetically unbiased estimates and correcting for biases arising from unobserved parenting qualities, Plug and Vijverberg (2005) find that family income has a significant effect on educational attainment.

with more detailed employment data to examine children's educational attainment, Ermisch and Francesconi (2000) distinguish between full-time and part-time employment and also employment when the child was aged 0-5, 6-10, and 11-15. In comparison with part-time employment and the employment of the father, they find a greater significant negative effect of the mother's full-time employment when the child was aged 0-5, but they also report that the effects persist when the parents' employment patterns over the entire childhood period are examined.

Besides their employment statuses, parents' occupations have also been linked to their children's educational attainment. Using data for the Netherlands, Ganzeboom (2009) finds that parents' occupations matter for both the educational attainment and the occupational choice of their children. The effect of occupation is found to be present even when the mother was not gainfully employed (which is the case for the majority of mothers) when the respondent was growing up. The author also finds evidence in favor of the 'same-sex role model hypothesis' which implies that fathers matter more for male children, and mothers matter more for female children. Despite some of its shortcomings as far as the employment information is concerned, the ESS data distinguishes between wage and salary work and self-employment which might prove useful in certain contexts. In an effort to pack the employment and occupation effects together without introducing too many variables into the analysis, we utilized a more aggregate grouping in our preliminary work and classified parents with respect to their employment status at their workplaces, i.e. based on whether they were engaged in wage and salary (employee) or own-account (self-employment) work when the respondent was 14. Since it turned out that there was quite a bit of cross-country variation in the related estimates, we decided to leave the employee vs. self-employment distinction out of the current study and pursue this point in future work.

The immigration status of the respondents or their parents may also produce different results across the countries depending on the nature of the relocation. While some countries may be more popular destinations for educational purposes, others may attract a greater proportion of potential unskilled workers. In their study on the effects of parental occupational status and education on the occupational attainment of immigrants and natives, Güveli and Ganzeboom (2007) distinguish between immigrants who emigrated before the age 12, between the ages of 12 and 21, and after the age of 21. They also distinguish between first and second generation migrants as well as those who move to neighboring and non-neighboring countries and find different patterns for immigrants and natives and also for different types of immigrants. In our preliminary work, we controlled for the respondents being a first or a second generation immigrant based on the 'country of birth' information available for both the respondents and their parents, but did not obtain significant results. This is why an immigration variable is not included in the models presented below.

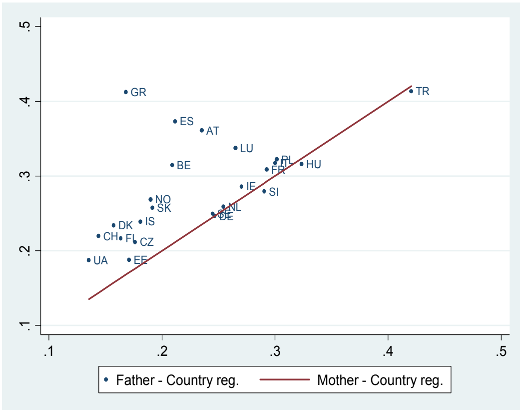
We also experimented with variables that indicate respondents who belong to a minority ethnic group in their countries and also variables that control for the religious affiliation of the respondent using dummy variables for Christians and followers of other religions, implying that those who presently do not associate themselves with any particular religion or denomination are the reference category. However, these were also taken out of the analysis for being statistically insignificant. Despite also being among the possible explanatory variable candidates, information relating to 'the language most commonly spoken at home' was not considered to be in the model since we expected it to be highly correlated with the immigrant and minority variables, and also because the more relevant information would be the language spoken at home when the respondent was a child, rather than at the time of the survey. Similarly, the household income information was not used either as it refers to the present income level. We do, however, have controls for the gender of the respondent as well as his/her age (along with 'age-squared') to account for the general increasing trend in educational attainment.

3. Empirical work

We begin the presentation of the empirical findings by summarizing the findings of the country regressions estimated separately. The first specification we consider distinguishes between the effects of the educational attainment of the father and the mother, while the second specification also allows the effects to differ by the gender of the child. Both specifications include controls for the age and gender of the child (The 'Female' dummy =1 if female) as well the employment statuses of the parents ('employed'=1 if employed) when the child was 14 (See Appendix 1 for variable means). As summarized in Figure 1, in most countries, the educational attainment of the father appears to have a greater impact on the attainment of the child even though the difference between the magnitudes of the coefficients is statistically significant only in 5 out of 24 countries. The reason for this pattern might be that the father's attainment is more closely related with household income which we are not able to control for. We also observe that there is a lot of cross-country variation in the magnitudes of both variables.

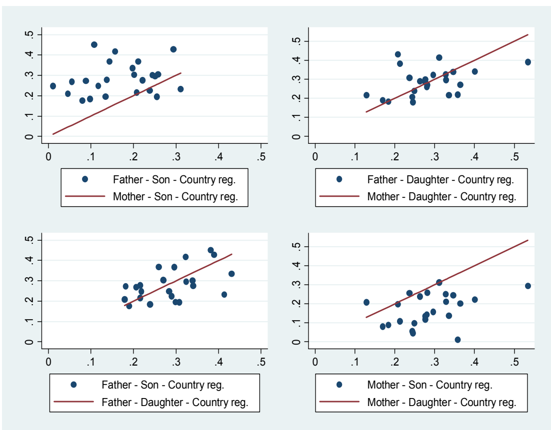
In Figure 2, the coefficient estimates from the second specification are summarized. We find that making the distinction between sons and daughters is justified in many cases and that the observed patterns are mainly in line with the same-sex gender role hypothesis mentioned earlier. While the equality of the coefficients for the sons and daughters is rejected in 14 countries in the case of the mother's attainment, the corresponding figure for the father is only 3 (See the two graphs in the bottom row). The pattern in the bottom-right graph suggests that the mother's education has a greater impact on daughters than on sons. Finally, the two graphs on the top row suggest that the pattern observed in Figure 1 was mainly due to the fact that the father's effect is larger than the mother's especially in the case of sons.

Figure 1: Coefficient Estimates for the Father's and Mother's Educational Attainment from Country Regressions



Note: Points above the 45I line indicate that the coefficient for the father's educational attainment (the y-axis variable) is larger than the coefficient for the mother's attainment (the x-axis variable). Country names are abbreviated as follows: AT = Austria, BE = Belgium, CZ = Czech Republic, DK = Denmark, EE = Estonia, FI = Finland, FR = France, DE = Germany, GR = Greece, HU = Hungary, IS = Iceland, IE = Ireland, IT = Italy, LU = Luxembourg, NL = Netherlands, NO = Norway, PL = Poland, ES = Spain, SK = Slovakia, SI = Slovenia, SE = Sweden, CH = Switzerland, TR = Turkey, and UA = Ukraine.

Figure 2: Coefficient Estimates for the Father's and Mother's Educational Attainment for Sons and Daughters from Country Regressions



Note: The graphs in the top row depict gender differences with respect to the parents' generation. The graphs in the bottom row depict gender differences with respect to the child's generation. The 45I line represents where the data points would have been placed if the y-axis and x-axis variables (named in the first and second rows of the legends, respectively) had been equal.

3.1 Accounting for the heterogeneity in inter-generational effects

In the second step of the empirical work, we try to come up with a useful and simple-to-implement way of explaining the heterogeneity in the extent of inter-generational links across the countries covered by the ESS. In other words, we would like to find country-level variables that do a good job of explaining the variation in the magnitudes of the coefficients on educational attainment variables. The reason we want to keep this point as simple as possible is that we will need to interact these country-level variables with the educational attainment variables when we re-estimate the earlier models on the pooled sample of 24 countries, rather than separately for each country.

In trying to explain cross-country variation, there are many 'macro' variables one can choose from depending on the type of relationship one assumes. For instance, measures of per capita income, income inequality, average returns to schooling, or social mobility can all be considered as potential candidates. Our preference, however, is not to rely on external data, but instead generate country-level variables from within the ESS data set, and if possible, from the variables already in the models. It turns out that we do not have to look very hard to find such variables we can work with.

Our hypothesis is that the magnitudes of the inter-generational effects depend on the degree of inequality in the educational attainment variables themselves. First of all, the idea makes sense for purely mechanical reasons. Under the assumption that parents' and children's attainments are positively related, a larger variation in the child's educational attainment variable implies a larger slope estimate, holding the distribution of the father's (or mother's) attainment constant. Similarly, a larger variation in the father's (or mother's) educational attainment implies a smaller regression coefficient, holding the distribution of the child's attainment constant. In addition to this 'arithmetic' reasoning, the inequality in the child's attainment could also be interpreted as a proxy for the degree to which the members of this generation had equal access to schooling opportunities (for economic or cultural reasons). A larger variation could be reflecting more unequal opportunities which, in turn, suggest that there is less room for social mobility, hence a greater impact of parents' attainment. In fact, the existing literature provides empirical evidence on the validity of using the distribution of educational outcomes rather than average levels of education to explain societal characteristics. Green, Preston, and Sabates (2003) find, in a cross-country context, that educational inequality is a better predictor of societal cohesion (which includes measures of trust and cooperation) than income inequality.

To check the validity of our hypothesis, we run a regression of the relevant coefficient estimates (of which we have 24 for each variable) on the standard deviations of the child's and father's (or mother's) educational attainment in the respective countries and obtain the following results:

$$\text{C-FATHER} = 0.241 + 0.092 \cdot \text{SD-CHILD} - 0.080 \cdot \text{SD-FATHER}, \ R^2 = 0.59,$$
$$\text{C-MOTHER} = 0.227 + 0.057 \cdot \text{SD-CHILD} - 0.062 \cdot \text{SD-MOTHER}, \ R^2 = 0.39,$$

where C-FATHER and C-MOTHER are respectively the coefficients on the father's and mother's educational attainment in the country regressions, SD-CHILD is the standard deviation of the children's educational attainment, and SD-FATHER and SD-MOTHER are the standard deviations of the fathers' and mothers' educational attainment. All coefficient estimates are statistically significant with *p*-values less than one percent, and they all have the expected signs. Especially in the case of the coefficients for the fathers, the proposed variables do a decent job of explaining the variation in the coefficient estimates. As for the coefficients in the second specification, the results we obtain for sons and daughters are:

Male child:

$$\text{C-FATHER} = 0.235 + 0.084 \cdot \text{SD-CHILD} - 0.067 \cdot \text{SD-FATHER}, \ R^2 = 0.37,$$
$$\text{C-MOTHER} = 0.053 + 0.068 \cdot \text{SD-CHILD} - 0.036 \cdot \text{SD-MOTHER}, \ R^2 = 0.37,$$

Female child:

$$\text{C-FATHER} = 0.255 + 0.106 \cdot \text{SD-CHILD} - 0.100 \cdot \text{SD-FATHER}, \ R^2 = 0.68,$$
$$\text{C-MOTHER} = 0.391 + 0.046 \cdot \text{SD-CHILD} - 0.086 \cdot \text{SD-MOTHER}, \ R^2 = 0.33,$$

where the explanatory variables have been computed separately for the subsamples of sons and daughters. With the exception of SD-MOTHER which has a *p*-value of 0.15 in the subsample of sons, all slopes are statistically significant at the ten percent level of significance, and once again they all have the expected signs. The R^2 values suggest that the proposed variables have reasonable explanatory power when gender distinction is made also at the child's generation.

3.2 Results from the pooled sample of all countries: The OLS vs. HLM estimates

In the last step of the empirical work, we incorporate the country-level variables presented above into our models and estimate the models on the pooled sample of all 24 countries. Our aim is to come up with coefficient estimates that apply to the whole ESS data set and also to observe whether the use of country-level variables allows us to approximate the results of the country regressions in a compact manner. Since our hypothesis is that the magnitude of the effects of parents' educational attainment depends on the degree of inequality in the attainment variables, we generate interaction terms using the attainment and standard deviation variables presented in the previous section. We do not include the main effects of the country-level variables as our hypothesis implies only that their interactions are relevant.

In estimating the pooled regressions, there are two options that we can take. One is to use the ordinary least squares (OLS) method allowing for fixed intercept differences between the countries and the other is to employ the hierarchical linear modeling (HLM) method which relies on maximum likelihood estimation. Also known as multilevel modeling, the HLM method is a more sophisticated technique that distinguishes between explanatory variables defined at different 'level's, which, in our case, are the individuals and the countries. This method also allows for the presence of mixed, i.e. both random and fixed, effects in the determination of the dependent variable. The HLM method has become increasingly popular with the availability of estimation routines in widely-used software packages. In the HLM jargon, the interaction terms that appear in our models are called 'cross-level effects'. These effects are included in HLM models when it is assumed that the coefficients on individual-level variables can be expressed as linear functions of higher-level variables, which is exactly what we have in mind here.

We now estimate our models using both methods and compare their results in terms of explanatory power as well as the patterns they imply. Note that in these regressions, the educational attainment variables (including the dependent variable) have been centered around their country-level means to make the figures comparable across the countries. Recall also that the original educational attainment variable has been converted into years of education equivalents so that the slopes can be interpreted as predicted changes in the 'effective' years of schooling.

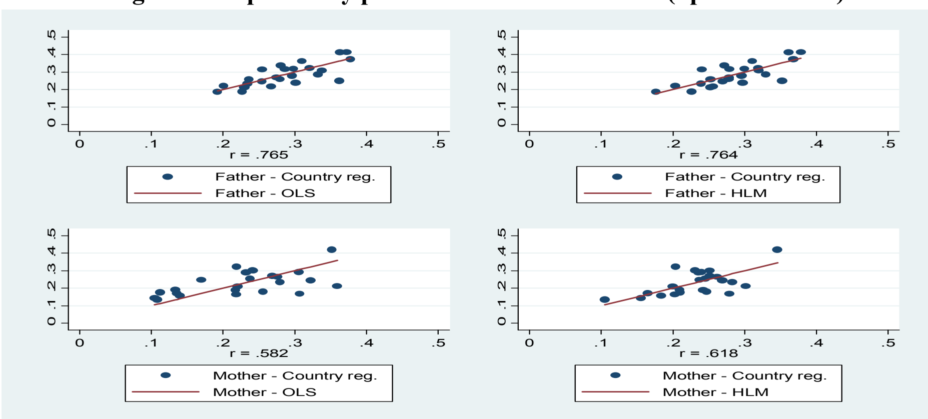
Results from specification 1:

Despite the different distributional assumptions made, the OLS and HLM estimates are quite similar with respect to most of the explanatory variables. Both sets of estimates reveal that being a female has a negative impact on education attainment even though the magnitude is only about 0.25 years. Since both age variables are found to be significant, we conclude that the quadratic relationship they impose is valid. The coefficient estimates imply that age has a negative effect on educational attainment beyond the age of (around) 34. The employment statuses of both parents (at the time the child was 14 years old) have a significant effect on the child's educational attainment. While the coefficient for the fathers is positive, the coefficient for the mothers is negative. Even though there must be several underlying factors that are at play here, we might attribute these findings to the fact that (i) an employed father implies a stable family structure, and (ii) mother's employment implies that she is less able to monitor the child's schooling-related efforts.

The findings of the two methods differ more with respect to the educational attainment variables, though they imply the same general patterns. The HLM estimates of the coefficients on the father's and mother's educational attainment are very close to each other whereas the OLS estimate for the mother's educational attainment is much smaller than the father's. The coefficients on the cross-level effects, i.e. the interaction terms, are quite similar across the two models, and they all have the expected signs. As in our preliminary estimations, we find that the impact of the parents' educational attainment increases with the variation in the distribution of the children's attainment while it decreases with the variation in the distribution of the parents' attainment.

What is more important for our purposes, however, is whether the combinations of the main effects and interaction terms translate into marginal effects that are close approximations for the ones obtained in the country regressions. In order to address this point, we calculate the marginal effects of the educational attainment variables separately for each country using the country-specific values of SD-CHILD, SD-FATHER, and SD-MOTHER (See Appendix 2 for these values). The marginal effect is obtained by multiplying the values of the relevant explanatory variables by the coefficients on the interaction terms and adding these products to the coefficient on the relevant educational attainment variable. We then plot the coefficient estimates from the country regressions against these marginal effects. This gives us a chance to observe how much of the cross-country variation in intergenerational links has been explained by our model and also to see if one of the methods used outperforms the other in terms of explanatory power. The graphs presented in Figure 3 reveal that the pooled regressions do a good job of predicting the coefficients in the country regressions.[8] The correlation coefficients between the corresponding estimates are just over 0.75 in the case of the father's effect and around 0.60 in the case of the mother's. While the explanatory power of two methods is nearly identical with regard to the father's effect, HLM outperforms OLS with a correlation coefficient of 0.62 vs. 0.58 with respect to the mother's attainment variable.

Figure 3: Explanatory power of the OLS vs. HLM (Specification 1)



[8] Here, we are following the lead of Jerrim and Micklewright (2009) in the use of scatter plots to depict the gender aspects of cross-country variation in the coefficient estimates.

Note: The graphs in the top row depict differences between OLS and HLM with respect to the father's educational attainment variable. The graphs in the bottom row depict differences with respect to the mother's educational attainment variable. The 45° line represents where the data points would have been placed if the y-axis and x-axis variables (named in the first and second rows of the legends, respectively) had been equal.

Table 1: The OLS and HLM estimates of the educational attainment model on the pooled sample (Specification 1)

	OLS		HLM	
	Coef.	*p*-value	Coef.	*p*-value
Father's educational attainment	0.216	0.000	0.268	0.000
Father's educ. att. × SD-CHILD	0.098	0.000	0.095	0.000
Father's educ. att. × SD-FATHER	-0.078	0.000	-0.090	0.000
Mother's educational attainment	0.071	0.071	0.266	0.000
Mother's educ. att.× SD-CHILD	0.112	0.000	0.061	0.001
Mother's educ. att.× SD-MOTHER	-0.075	0.000	-0.079	0.000
Age	0.075	0.000	0.078	0.000
Age^2 / 100	-0.111	0.000	-0.113	0.000
Female	-0.285	0.000	-0.248	0.055
Father employed	0.453	0.000	0.464	0.000
Mother employed	-0.191	0.000	-0.111	0.061
Constant	-3.016	0.000	-0.799	0.233

Notes: The dependent variable is the child's educational attainment. The educational attainment variables have been centered around country-level means. The number of observations is 31,681. The R^2 of the OLS regression is 0.307. The country dummies have been omitted from the OLS output. Five of them are statistically insignificant at α= 5%. The Wald chi-squared statistic (11 d.f.) for the HLM is 1562.53. In HLM, in addition to the intercept, independent random effects parameters are estimated for all variables except the interaction terms. All of the random effect estimates are statistically different from zero at α=5%. The estimated variance for the intercept is 2.89, and the estimated variance for the residual of the model is 8.25.

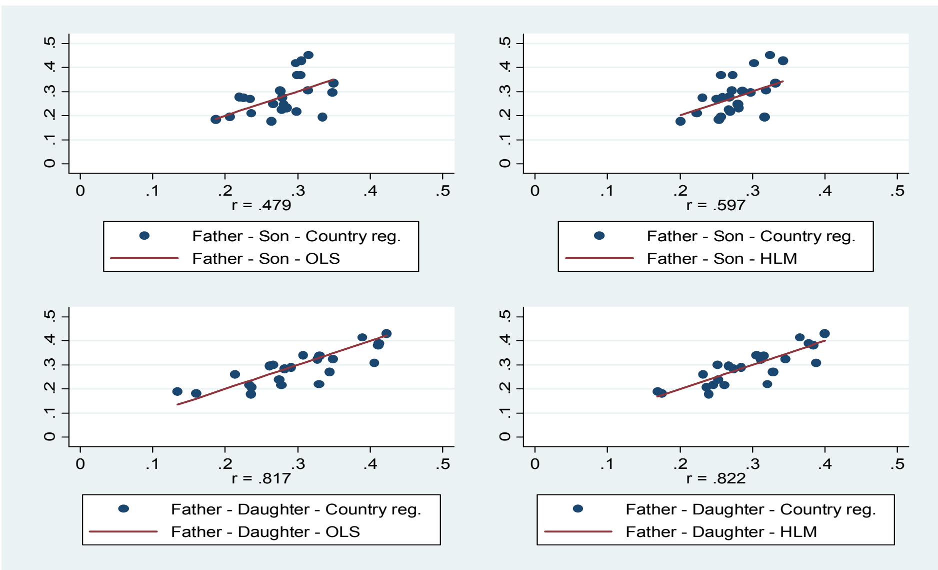
Results from specification 2:

When we distinguish between the sons and daughters in estimating the effects of the parents' educational attainment, we find once again that the OLS and HLM estimates are similar with respect to the individual-level control variables, and that the implied patterns are the same as in the first specification. One notable difference, however, is that the coefficient on the female dummy is much larger here, meaning that the simpler model underestimates the impact of the gender of the child as a result of restricting the slopes of the education attainment variables to be the same for sons and daughters.

Moving on to the educational attainment variables, we find that the HLM estimates are statistically more significant than the OLS estimates in some instances, and they are completely in line with our expectations regarding the signs of the coefficients. However, in the presence of as many interaction terms as in this model, it would be inappropriate to rely on a comparison of coefficients to conclude that the two methods yield very different results with regard to inter-generational transmission patterns. In fact, when the necessary computations are made to obtain the marginal effects implied by the two set of results, we find that they are highly correlated. Therefore, it is more appropriate to say that the HLM and OLS results differ in the importance they attribute to the various components that make up the total impact.

As far as the explanatory power of the pooled regressions is concerned, we perform the same exercise as before to observe whether they yield close approximations for the educational attainment coefficients obtained in the country regressions. Since male and female children are treated distinctly here, the country-level values have also been calculated separately for the subsamples of sons and daughters. This time, we have a total of eight graphs presented in Figures 4a and 4b because of the gender distinctions made at both generations. The correlation coefficients (reported in the graphs) reveal that the HLM and OLS estimates have similar explanatory powers in the case of the father-daughter and mother-son combinations, but the HLM performs considerably better for the father-son and mother-daughter combinations. Both methods perform poorly when predicting the 'mother-daughter' coefficients which is probably because this coefficient exhibits the greatest variation across the countries. The variance of the 'mother-daughter' coefficient is almost 50 percent greater than the variances of the remaining three attainment coefficients in the model. Apparently, a more detailed analysis is required to account for the factors that determine the extent of the inter-generational link between mothers and their daughters.

Figure 4a: Explanatory power of the OLS vs. HLM (Specification 2 - Fathers)



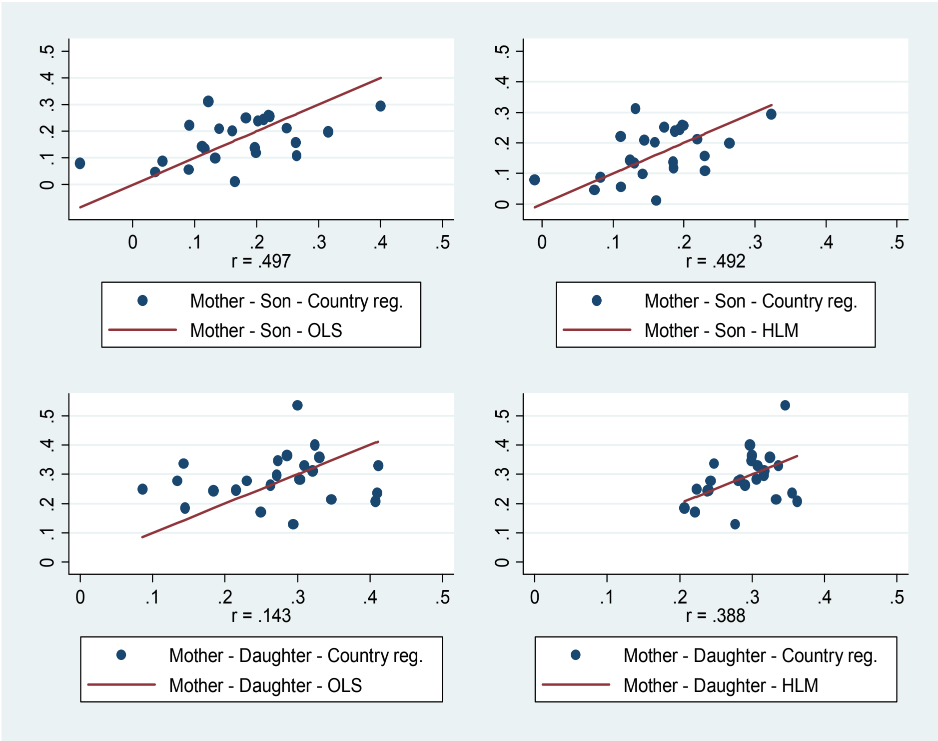
Note: The graphs in the top row depict differences between OLS and HLM with respect to the father's educational attainment variable in the case of sons. The graphs in the bottom row depict differences with respect to the father's educational attainment variable in the case of daughters. The 45I line represents where the data points would have been placed if the y-axis and x-axis variables (named in the first and second rows of the legends, respectively) had been equal.

Table 2: The OLS and HLM estimates of the educational attainment model on the pooled sample (Specification 2)

	OLS		HLM	
	Coef.	*p*-value	Coef.	*p*-value
Male child:				
Father's educational attainment	0.104	0.019	0.272	0.000
Father's educ. att. × SD-CHILD	0.055	0.000	0.061	0.014
Father's educ. att. × SD-FATHER	-0.003	0.846	-0.058	0.030
Mother's educational attainment	0.252	0.000	0.226	0.002
Mother's educ. att.× SD-CHILD	0.110	0.000	0.074	0.000
Mother's educ. att.× SD-MOTHER	-0.145	0.000	-0.100	0.000
Female child:				
Father's educational attainment	0.307	0.000	0.256	0.000
Father's educ. att. × SD-CHILD	0.135	0.000	0.114	0.000
Father's educ. att. × SD-FATHER	-0.140	0.000	-0.106	0.000
Mother's educational attainment	-0.086	0.059	0.197	0.021
Mother's educ. att.× SD-CHILD	0.121	0.000	0.067	0.006
Mother's educ. att.× SD-MOTHER	-0.024	0.069	-0.048	0.065
Age	0.074	0.000	0.077	0.000
$Age^2 / 100$	-0.110	0.000	-0.112	0.000
Female	-1.598	0.000	-1.308	0.008
Father employed	0.445	0.000	0.456	0.000
Mother employed	-0.186	0.000	-0.109	0.068
Constant	-2.314	0.000	-0.626	0.340

Notes: The dependent variable is the child's educational attainment. The educational attainment variables have been centered around country-level means. SD-CHILD, SD-FATHER, and SD-MOTHER are computed separately for the subsamples of male and female children. The number of observations is 31,681. The R^2 of the OLS regression is 0.311. The country dummies have been omitted from the OLS output. Six of them are statistically insignificant at α=5%. The Wald chi-squared statistic (17 d.f.) for the HLM is 2368.84. In HLM, in addition to the intercept, independent random effects parameters are estimated for all variables except the interaction terms. All of the random effect estimates are statistically different from zero at α=5%. The estimated variance for the intercept is 2.64, and the estimated variance for the residual of the model is 8.22.

Figure 4b: Explanatory power of the OLS vs. HLM (Specification 2 - Mothers)



Note: The graphs in the top row depict differences between OLS and HLM with respect to the mother's educational attainment variable in the case of sons. The graphs in the bottom row depict differences with respect to the mother's educational attainment variable in the case of daughters. The 45I line represents where the data points would have been placed if the y-axis and x-axis variables (named in the first and second rows of the legends, respectively) had been equal.

4. Concluding remarks

The aim of this study was to serve three main goals: (i) observing the extent of inter-generational transmission of educational attainment across twenty-four European countries, (ii) accounting for the cross-country variation in the observed patterns using country-level variables, and (iii) comparing the explanatory powers of two alternative estimation methods employed in carrying out the final portion of the empirical analysis. With regard to the first point, the country regressions revealed not only that gender differences should be taken into account at both generations to uncover the patterns regarding inter-generational links, but also that there was a lot of cross-country heterogeneity that called for further analysis.

To account for the cross-country variation in the extent of inter-generational links, we proposed the use of the degree of inequality in the educational attainment figures as the country-level control variables. In line with our expectations, we found that a larger variation in the child's attainment variable was associated with greater impacts of both parents' attainment while the opposite was the case for the variation in the parents' attainment variables. We argued that this results made sense not only for mechanical reasons, but also because the proposed variables could be interpreted as proxies for the degree to which the respondents had equal access to schooling opportunities. One additional result that provides support for this argument is that, when employed as an alternative country-level variable, the Gini coefficients (of household income) of the countries produced similar results as the variation in the child's educational attainment variable, though this variable had less explanatory power.[9] Another finding which suggests that the proposed variables control for more subtle relationships is that when the original educational attainment variables were replaced with their standardized versions (i.e. zero mean, and variance equal to 1) to achieve uniformity across countries in the amount of variation in these variables, there was little change in the estimated coefficients for the countries. We interpret this finding to mean that, it is only when they are utilized as explanatory variables in the regression context that the proposed measures are able to proxy for the underlying socio-economic structure that influences educational outcomes. Further explorations of this finding are likely to yield more concrete explanations and also discover finer measures that can be employed.

As for the comparison the two estimation methods used in the empirical work, our finding was that the HLM and OLS methods produced similar results and implied the same patterns with regard to inter-generational links. However, there were some instances where the HLM estimates outperformed the OLS estimates in explaining cross-country variation. They also tended to produce findings that are statistically more significant. Considering that the HLM method allows for a more complex distributional structure taking into account the multilevel nature of the determination of inter-generational links, and consequently the data being used, there seems to be no reason why one would opt against using the methodology in this context. Examinations of educational outcomes certainly deserve the most rigorous methods available for academic research.

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[9] We also experimented with the 'per capita GDP' as the country-level variable, but found that this variable has no association with the coefficient estimates.

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	Child's educational attainment	Father's educational attainment	Mother's educational attainment	Age of 'child'	Female	Father employed	Mother employed
Austria	9.1	7.6	6.5	49.7	0.56	0.96	0.43
Belgium	11.2	8.3	7.4	50.8	0.50	0.95	0.36
Switzerland	11.5	10.2	8.6	51.3	0.55	0.97	0.38
Czech Rep.	11.0	10.3	9.7	52.3	0.53	0.94	0.78
Germany	11.8	11.3	9.6	51.8	0.53	0.96	0.50
Denmark	11.9	10.1	9.2	52.3	0.52	0.98	0.57
Estonia	11.8	8.7	8.7	52.4	0.59	0.95	0.82
Spain	8.0	5.1	4.3	49.6	0.49	0.96	0.20
Finland	10.8	6.9	6.7	52.1	0.53	0.96	0.74
France	10.3	6.2	5.5	52.2	0.54	0.97	0.44
Greece	8.4	5.2	4.6	52.7	0.56	0.99	0.42
Hungary	9.1	6.7	5.7	50.9	0.56	0.96	0.59
Ireland	9.8	6.4	6.5	51.7	0.58	0.96	0.21
Iceland	12.2	9.4	8.0	49.5	0.53	0.98	0.57
Italy	9.2	6.1	5.5	51.4	0.51	0.96	0.28
Luxembourg	9.7	7.6	6.0	49.1	0.45	0.97	0.29
Netherlands	10.7	8.0	7.0	51.9	0.57	0.97	0.25
Norway	12.5	10.3	9.6	50.2	0.48	0.97	0.52
Poland	9.7	6.7	6.4	47.9	0.52	0.96	0.71
Sweden	10.4	6.9	6.7	52.7	0.48	0.97	0.56
Slovenia	9.0	6.9	5.9	51.7	0.54	0.79	0.44
Slovakia	11.1	9.6	9.1	48.4	0.49	0.94	0.67
Turkey	6.2	4.3	3.1	44.2	0.53	0.87	0.05
Ukraine	12.4	8.1	7.6	52.2	0.63	0.94	0.80

Appendix 1: The country-level means of individual-level variables

Appendix 2: The values of country-level variables

	All sample			Subsample of male children			Subsample of female children		
	SD-CHILD	SD-FATHER	SD-MOTHER	SD-CHILD	SD-FATHER	SD-MOTHER	SD-CHILD	SD-FATHER	SD-MOTHER
Austria	3.55	3.25	2.51	3.70	3.41	2.73	3.40	3.13	2.33
Belgium	3.91	4.42	3.84	3.87	4.37	3.90	3.95	4.47	3.79
Switzerland	2.56	3.41	3.36	2.39	3.23	3.22	2.58	3.53	3.47
Czech Rep.	1.73	2.00	2.03	1.62	2.03	2.04	1.81	1.98	2.02
Germany	2.33	2.44	2.16	2.23	2.44	2.07	2.32	2.45	2.24
Denmark	2.70	3.16	3.11	2.54	3.07	3.04	2.85	3.24	3.18
Estonia	2.96	3.59	3.55	2.59	3.60	3.45	3.19	3.57	3.62
Spain	4.69	3.82	3.14	4.67	3.93	3.10	4.70	3.69	3.19

Finland	3.83	4.16	3.73	3.76	4.04	3.62	3.88	4.26	3.83
France	4.79	4.46	4.00	4.68	4.53	4.02	4.88	4.39	3.99
Greece	4.13	3.31	3.01	4.02	3.37	2.96	4.16	3.26	3.06
Hungary	3.81	3.89	3.71	3.39	3.83	3.68	4.11	3.95	3.74
Ireland	3.90	3.42	3.18	4.01	3.44	3.26	3.81	3.40	3.13
Iceland	3.74	3.61	3.11	3.40	3.48	3.18	4.02	3.71	3.03
Italy	3.42	3.24	2.81	3.31	3.27	2.78	3.51	3.21	2.84
Luxembourg	3.85	4.01	3.02	3.76	3.97	2.87	3.88	4.06	3.18
Netherlands	3.45	3.52	2.92	3.35	3.64	2.88	3.45	3.44	2.94
Norway	3.12	3.18	2.70	3.12	3.17	2.72	3.13	3.19	2.68
Poland	3.75	3.38	3.32	3.48	3.54	3.53	3.96	3.22	3.11
Sweden	4.58	3.88	3.48	4.40	3.90	3.54	4.76	3.87	3.42
Slovenia	3.50	3.37	3.07	3.30	3.52	3.13	3.65	3.25	3.02
Slovakia	2.14	2.42	2.35	2.00	2.38	2.45	2.26	2.46	2.25
Turkey	3.78	2.75	1.90	3.81	2.83	1.86	3.56	2.68	1.93
Ukraine	3.50	4.70	4.72	3.16	4.58	4.72	3.68	4.77	4.71