Long-run Effects on Poverty of Public Expenditure in Education *

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Abstract

Household characteristics may have long-run effects on individual outcomes when adult. For instance, individuals who lived when young in households experiencing financial problems are more likely to be poor when adults. Public intervention in education is one of the most important means by which governments try to reduce these effects and to promote equality of opportunity. The objective of this paper is to check whether public expenditure in education has an effect in reducing the probability of being poor when adult, and to what extent. Our main finding is that public expenditure in primary education has a strong effect on raising individuals above the poverty line. We also find that this effect is particularly strong among those individuals whose parents had little education.

Keywords: Public expenditure in education, poverty rate, intergenerational transmission of poverty

JEL Classification: H52, I21, I23, J24, J31.

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1 Introduction

There is a growing literature that shows how inequality has increased during the last decades in most developed countries (see Atkinson, 2010 for the EU; Atkinson, Piketty, and Saez, 2011 or Jenkins et al. 2011 for the US). For instance, in most OECD countries the gap between the rich and the poor has widened continuously prior to 2008 (OECD, 2011). In addition, recent OECD data (OECD, 2013) show that the global economic crisis has squeezed incomes in most countries, but this reduction is not shared evenly across the two extremes of the income distribution, with larger reductions in the bottom part of the distribution, thus suggesting further increases in inequality and poverty. It is also well-known that poverty has long-run negative effects. Individuals who live in a poor household when young may suffer negative long-run effects on individual welfare. When adults, these individuals are more likely to be poor, they are also more prone to suffer health problems and less likely to stay at school after compulsory education. These long-run effects reflect the degree of intergenerational mobility in a society. In countries where social mobility is low, being poor when young is a good predictor of the probability of being poor when adult, or of the probability of suffering health problems.

There are two plausible mechanisms underlying the intergenerational transmission of poverty. On the one hand there may be genetic differences in ability that are transmitted from parents to children and that lead to intergenerational persistence in poverty. On the other hand, children of wealthy parents earn higher incomes in part because they invest more in human capital and have more education. To the extent that they are due to differential human capital investment, this suggests a role for public provision or financing of education to equalize opportunities. Indeed, public intervention in education is one of the most important means by which governments try to reduce these long-run effects of poverty and to promote equality of opportunity.

Our objective in this paper is to empirically study whether public expenditure in education helps to mitigate the long-run negative effects of poverty, and to what extent. In order to do so we combine individual and aggregate variables by merging data from two cross sections of the EU-SILC (2005 and 2011, since they include a special module on "Intergenerational transmission of poverty") with data on public expenditure in education that we retrieve from the UNESCO database to analyze what may contribute to cross-country and cohort differences in the probability of falling below the poverty line.

The main finding is that, focusing on expenditure in primary education, public expenditure in education seems to have a strong effect on raising individuals above the poverty line when adults. The reason for this can be that spending resources in primary education increases attendance to school beyond compulsory education and, therefore, helps to lift individuals above the poverty threshold when adults. We also find that the effect of public expenditure in education on poverty is not linear, but has diminishing returns. In addition we analyze the role of public expenditure on education on intergenerational mobility. We find that the effect that has public expenditure on education in reducing the probability of being poor today is mostly concentrated among individuals with low-educated parents. This suggest that public expenditure in education helps to increase intergenerational mobility.

Our identification strategy to assess the impact of government educational spending on individual's particular outcomes (poverty status) consists of exploiting country and time differences in expenditure. We identify the effect of public intervention by exploiting changes in spending across countries from the initial period. Several other papers have used a similar approach while considering other outcomes, as infant mortality and test scores. For example, state per pupil spending on elementary and secondary schooling is associated with higher post-schooling wages (Grogger, 1996). However, other studies find that expenditure on schools has little effect on test scores (e.g., Hanushek, 1996, 2001), while others find that spending increases test scores (e.g., Hedges et al., 1992). Mayer (2002), using data from New Zealand, finds that greater spending on elementary and secondary schools increases low-income but not high-income children's educational attainment. She also finds that greater spending on college financial aid increases schooling for high-income, but not for low-income children. This result points out that spending in elementary and secondary schooling but not spending in post-secondary schooling promotes intergenerational mobility. Within this literature on the relationship between education spending and educational outcomes, there are some works using other identification strategies. For example, Meghir and Palme (2004) evaluate the impact of a school reform, which took place in the 1950s in Sweden, on educational attainment and earnings. This reform consisted of increasing compulsory schooling, among other aspects. Thus the reform can alternatively be viewed as an increase in per capita public expenditure on education. They find that the reform increased both the educational attainment and the earnings of those whose fathers had just compulsory education.

This paper is related to two strands of the literature. First, the literature that studies the effects of schooling on several life outcomes as commented above. Second, the literature on intergenerational income mobility. In particular, it is related to several works that estimate the relationship between parents' economic status and a child's economic status in adulthood. There have been some important contributions in terms of measurement of correlations and the forces driving this relationship (see Black and Devereux, 2011). While most theoretical works on the intergenerational transmission of economic status consider only parental investments in children, governments also invest in children's human capital. Solon (2004) is among the few authors in that research line. He departs from a standard human capital model similar to Becker and Tomes (1979) by incorporating public human capital investments. Among other results he finds that intergenerational income elasticity decreases with the progresivity of public investment in human capital, thus suggesting that cross-country differences in intergenerational mobility could arise from differences in this factor. Mayer and Lopoo (2008), in the paper most closely related to ours, provide an empirical contribution that takes into account government expenditure. They assess the relationship between government spending and intergenerational economic mobility using PSID data together with data on state spending from the U.S. Census of Governments. They find greater intergenerational mobility in high-spending states compared to low-spending states. They also find that spending on elementary and secondary schooling has the largest impact on low-income children's future income.

A weak point of the previous literature is that individual and aggregate dimensions have been analyzed separately. This study aims at going beyond the standard approach and contributes to the related literature by checking the robustness of the results obtained following it. First, we analyze cross-country differences in intergenerational poverty transmission using a two-step model similar to Bell et al (2002) or Markaki and Longhi (2012). We first follow the traditional approach and estimate current poverty status including individual characteristics and a full set of country-cohort dummies. We then regress these estimated country-cohort differences in current poverty status on country-cohort attributes such as public expenditure in education. By doing so we address the problem of biased standard errors in individual level models including aggregate data (see Moulton (1990)). However, this modelling approach could be considered as restrictive too as it disregards that, for example, the parental background effect on poverty reduction might differ across country-cohorts. In order to analyze it, country-cohorts effects will be modelled as specific intercepts and slopes in the individual poverty status regression and a test on the equality of parameters across country-cohorts will be provided. Thus, multilevel or mixed effects modelling will be used.

Our paper contributes to this line of research is several other aspects. First, we focus on intergenerational poverty transmission rather than income, as most of this literature does. Surprisingly, there is no evidence on the potential mitigating effect of public expenditure in education on poverty despite the recent trends in poverty and income inequality. Second, we focus on a group of European countries using data from the EU-SILC. Finally, we also add to this debate by using a more narrowly defined measure of expenditure on children.

The paper is organized as follows. Section 2 describes the data used in the paper. Section 3 presents the empirical model. We discuss our empirical results in Section 4. Section 5 provides a robustness analysis of the main results. Finally, Section 6 concludes.

2 Data and descriptive statistics

Estimating whether government expenditure increases intergenerational mobility requires individual-level data on adult's income together with information on the characteristics of the household where that adult grew up. It also requires a source of variation in government expenditure. In this study we merge data drawn from both the 2005 and 2011 cross sections of the EU-SILC database with data from the UNESCO database for Education. We build a database comprising 17 European countries.[1] These are the countries in the EU-SILC database for which we have enough historical data on public expenditure in education.

The reason for using the 2005 and 2011 cross sections of the EU-SILC database is that they include special modules on inter-generational transmission of poverty.[2] These modules contain retrospective information on parental background and childhood circumstances. This information includes, in particular, family composition, year of birth of parents, occupation and level of education of parents. Individuals also provide retrospective information about the economic situation when teenagers. In principle we could use this variable as a summary of the household situation when young. We decided not to do so for three reasons. First, this variable does not take the same values in both cross sections.[3] Second, there are many missing values in the 2005 cross section. Four countries in the 2005 cross section (Austria, France, Greece, and Portugal) do not report information on economic circumstances when young. Also, the 2011 cross section has no data for Ireland. Third, this variable can be seen as a extremely subjective indicator. In any case, we use this information to check the validity of our results to alternative measures of childhood circumstances (see Section 5 below).

We use instead parental education as a measure of individuals' childhood circumstances. We build a dummy variable called "*educated_family*" that takes value 1 when at least one of the parents has secondary education.[4]

Since we want to use the intergenerational module, we have to exclude from the 2005 and 2011 cross sections all individuals who are not in the age range (25-65) or are not the selected respondent. Since we want to assess the long-run effect of household characteristics, we also exclude those individuals who lived in a collective house or in some institution when young.

As we said above, to the EU-SILC sample we merge data on public expenditure in edu-

[1] The list of countries is: Austria, Cyprus, Denmark, Finland, France, Greece, Hungary, Ireland, Italy, Luxembourg, Netherlands, Norways, Portugal, Spain, Sweden and United Kingdom.

[2] For an overview of EU-SILC, see Wolff, Montaigne, and Rojas González (2010). To access further information about EU's regulations concerning the SILC, data documentation provided by Eurostat, and SILC variable lists, we recommend the EU-SILC web portal provided by the GESIS research institute at http://www.gesis.org/.

[3] Individuals are asked how frequent financial problems in the household were when they were young teenagers. In the 2005 cross section there are five possible answers: 1 (most of the time), 2 (often), 3 (occasionally), 4 (rarely), and 5 (never). In the 2011 cross section there are six possible answers: 1 (very bad), 2 (bad), 3 (moderately bad), 4 (moderately good), 5 (good), and 6 (very good).

[4] The mean value of educated-family is .409 (st. dev. is .492). Requiring tertiary education would be too restrictive, since only a 14.36% of individuals in the sample have at least one parent with tertiary education.

cation from the UNESCO Database for Education. The UNESCO Database for Education contains, for several years, country data on public expenditure in education per student as a % of per capita GDP at three levels (primary, secondary, tertiary).[5] We cannot use directly these ratios between expenditure in education per student and per capita GDP since an increase in them can be due either to an increase in expenditure or to a reduction in per head GDP. What we do is to use data on per capita GDP to recover data on expenditure in primary, secondary and tertiary education for every country and year. Since data on per capita GDP are in US dollars of year 2000, the same applies to the resulting expenditure per individual.

Our objective is to construct a variable that imputes to each individual in the sample a measure of public expenditure in education (PEE) she has potentially enjoyed. In principle, there are many alternatives. In this paper we focus mainly on expenditure in primary education. The reason is that, since primary education was compulsory in all countries in the sample during the period we consider, we are confident that all individuals in the sample must have benefitted from this type of expenditure. The problem with expenditure in secondary education is that this type of expenditure refers to a period that was not compulsory for all individuals in our sample. This problem exacerbates with expenditure in tertiary education, since we cannot assume that attendance to post-compulsory levels of education is an exogenous decision.

We illustrate how we build our measure of PEE as follows. Suppose we know that a given individual in the sample attended primary education from 6 to 11 years old. As an example, an individual born in Spain in 1970 was in primary education between 1976 and 1981. We use our data on expenditure in primary education for Spain corresponding to the years 1976 to 1981, and simply compute the average of these six numbers.[6] We call this variable "*exp_p*".

To illustrate the data we use, Figure 1 shows per capita expenditure on primary and

[5] See http://www.uis.unesco.org/Education/Pages/default.aspx

[6] Since entry and exit ages in primary education may vary across countries, we compute average spending for different age intervals in each country. See Table A.1 in the Appendix for details.

secondary education for the 17 countries in our sample.

Figure 1 here

As can be seen in Figure 1, there is variation both across countries and through time. If we focus on primary education, Greece and Norway are the lowest and highest spending countries in this period, respectively. We also see that per capita expenditure in primary education was below per capita expenditure in secondary education for most countries (with the exceptions of Hungary, Norway and Sweden). Regarding per capita expenditure in secondary education over GDP per capita, Greece is again the lowest spending country, while Denmark is now the highest spending country.

Because of availability of data on public spending, we restrict our sample to include individuals born between 1960 and 1980 (2005 cross section) and between 1960 and 1986 (2011 cross section). We also exclude those individuals who were not born in the country, since we do not know whether they went to primary education in a different country. Our final sample consists of 142,030 individuals from 17 countries. A 45.96% belong to the 2005 wave (65,274 individuals) and the remaining 54.04% (76,756 individuals) to the 2011 wave.

Our objective is to study whether public expenditure in education helps to mitigate the effects on adult circumstances of being raised in a disadvantaged household. In particular, we focus on individual's current poverty status. This is the information contained in the variable HX080, which is an indicator of whether the individual lives in a family with income below the poverty threshold. The poverty line corresponds to 60% of equivalized household disposable income and corresponds to the standard measure of poverty in the European Union. The argument for using a relative measure of poverty is that individuals sometimes think of themselves as poor when they compare themselves with their neighbors. We define a dummy variable called "*poor*" which is 1 whenever HX080 is 1. The mean value of poor in our final sample is 12.4%. It is 12.1% in the 2005 wave and 12.7% in the 2011 wave. We represent in Figure 2 the percentage of individuals below the poverty line in each country. The maximum value corresponds to Spain (18.5%) and the minimum to Cyprus (7.3%). The red line is the mean value for the whole sample. It is important to remember that these numbers are not representative of the whole population, since we are considering only those individuals who at the time of the survey were 25-45 in the 2005 wave or 25-51 in the 2011 wave. In particular, the elderly are not included in our sample.

Figure 2 here

Finally, and in addition to parental education, we consider a set of household characteristics when the individual was young (unemployed father, number of siblings, single mother family, etc.). We do not include information on parents occupation, since these variables have many missing values. These household characteristics are included in the special module on intergenerational transmission of poverty of the 2005 and 2011 cross sections of EU-SILC. Table 1 shows the main descriptive statistics. A complete description of all the variables used in this analysis can be found in the Appendix.

Now we illustrate the correlation between current poverty status and past poor parental circumstances, measured by parental education. We compute probabilities for the current poverty status (measured by the variable *poor*), conditional on the two possible values of the possible values of the variable *educated_family.* We do it separately for the two cross sections and also pooling all the data. As Table 2 shows, there is a strong correlation between these two variables.

Table 2: Long-run effects of parental education

	Poor 2005	Poor 2011	Poor All
educated_family=0	14.86	16.59	15.83
educated_family=1	7.05	7.94	7.56
All	12.02	13.34	12.76

To read Table 2, let us focus on the first column (the one labeled "Poor 2005"). The proportion of individuals below the poverty line in the 2005 cross section that have low-educated parents is 14.86%. However, for those individuals with educated parents this probability is only 7.05%. We find similar differences in the 2011 cross section (16.59% vs. 7.94%) and with the two cross sections combined (15.83% vs. 7.56%). So, roughly speaking, the probability of being below the poverty line for individuals without educated parents is twice as big, compared with that of individuals with educated parents. We also illustrate these correlations in Figure 3 below. This figure shows the poverty rate among individuals with educated and non-educated parents for all countries in the sample.

Figure 3 here

There are striking differences across countries. While the general pattern is that poverty rates are higher among those who have non-educated parents, there are four countries (Denmark, Finland, Norway, and Sweden) where differences in poverty rates are not statistically significant between the two groups. These four countries have in common that in all of them poverty rates are very low.

In Figure 4 we represent the connection between public expenditure in education in the past and poverty rates today. We represent the average value of *exp_p* and *poor* for each country. Countries that spent more in primary education have typically lower poverty rates. We also fit a quadratic line to illustrate the fact that the negative relationship between these two variables has diminishing returns.

Figure 4 here

To see the effect of expenditure according to family type, we compute in each country poverty rates according to the education of parents. As seen in Figure 3, poverty rates are typically higher among individuals with non-educated parents. We represent in Figure 5 poverty rates for these two groups as a function of average public expenditure in education. We also fit a quadratic line for each group. We find that expenditure seems to reduce only poverty rates among individuals whose parents lack education.

Figure 5 here

In the rest of the paper we analyze whether these relationships observed at country level maintain at the individual level. In addition we also study the causal impact of the public expenditure on poverty rate reduction.

3 Empirical model

Our aim is to study the effect that has public expenditure in education on reducing the long-run negative effects of having when young a disadvantaged background. We need to control as accurately as possible for additional factors affecting our dependent variable. Household characteristics consist of parental education, number of siblings, and whether the individual was raised in a single-mother family. Our set of additional explanatory variables includes gender, time dummies, and a dummy variable that indicates not being a citizen of the country. A first possibility is to estimate a simple Linear Probability Model (LPM) as follows (Model A):

$$poor_{ic} = \beta_0 + \beta_1 PEE_{ic} + \beta_2 (PEE_{ic})^2 + \beta_3 educ\_fam_{ic} + X'_{ic}\gamma + \beta_c + \beta_t + \varepsilon_{ic}, \qquad (1)$$

where $poor_{ic}$ is the current poverty status (binary) variable for individual i who lives in country c. Variable PEE_{ic} is our measure of the size of the educational budget invested in a particular individual. In particular, we use the average public expenditure in primary education (exp_p). Since the country evidence from Figure 4 suggests the existence of diminishing returns, we include a quadratic term for PEE_{ic}. We will test the functional form of this relationship, captured by parameter β_2.

The vector X_{ic} contains the remaining explanatory variables, apart from parents education. First, there are variables that capture the current situation (gender, non-citizen status, etc.). Second, we also include a set of parental background variables (single mother family, etc.). Third, we include as a regressor in matrix X_{ic} average per capita GDP during individual's period of primary school attendance. If we do not do this, the impact of expenditure in education might be biased. Rich countries raise more revenue from taxes and can dedicate more resources to education. At the same time, they have lower poverty rates. Then, the impact of public expenditure in education will be over-estimated. The idea is that average per capita GDP may capture the general effect of government expenditure, while PEE_{ic} captures only expenditure in basic education. Four, we also include a measure of "initial inequality" ($ineq\_p_{ic}$). It is well known that some forms of spending are entitlements. But then, countries that are initially more unequal or with many poor households will have to spend more than countries with fewer poor families. If it is so, and we do not account for this effect, the impact of PEE could be underestimated. In the Appendix we provide a detailed description of all the variables we use.

The crucial issue for identification is the assumption regarding exogeneity of public expenditure. Variation in this variable arises because of differences in expenditure across countries at the same point in time and differences in country expenditure over time. Either difference could be partly endogenous with respect to the poverty rate and related to both country expenditure and children's eventual income. To partially account for this issue, we add country fixed effects to the model, captured by the term β_c which contains a set of dummy variables to control for invariant factors within countries. Finally, parameter β_t is a vector of year of birth indicator variables to capture any factors influencing country public expenditure at a point in time, in particular it addresses a possible trend toward increasing public expenditure.

We assume that the error term ε_{ic} is uncorrelated with public expenditure in primary education PEE_{ic}. In addition, the error term (conditional on the rest of explanatory variables) follows a normal distribution. Finally, since we combine individual-level data with group-level data in our variable of interest (PEE_{ic}), errors are clustered at the country and year of birth level.[7] Since our dependent variable takes only two values, we also estimate a Probit model.

To study the role of public expenditure on education on intergenerational mobility we test whether individuals that grew up in families in which both parents had little education benefit more from government investment in education. To do this, we estimate a model similar to Model A above but including an interaction term of expenditure in primary education with

[7] See Moulton (1986) for the importance of controlling for cluster effects.

the dummy variable *educated_family*, this is Model B:

$$\begin{aligned} poor_{ic} &= \beta_0 + \beta_1 PEE_{ic} + \beta_2 (PEE_{ic})^2 + \beta_3 educ\_fam_{ic} + X'_{ic}\gamma + \beta_c + \beta_t \\ &\quad + \beta_4 (PEE_{ic} \times educ\_fam_{ic}) + \beta_5 ((PEE_{ic})^2 \times educ\_fam_{ic}) + \varepsilon_{ic}. \end{aligned} \tag{2}$$

According to this model, if public expenditure in education increases intergenerational mobility then the expression $\beta_4 + 2\beta_5 PEE_{ic}$ should be positive. In the section below we provide not only the estimated coefficients of these models, but also the marginal impact of PEE for the two parental education levels and check the existence of intergenerational mobility. However, as it depends on the value of PEE_{ic} we think that providing just one estimate might not be clear enough and thus we also compute the marginal effect of PEE for the two parental education levels for several values of PEE.

4 Results

Table 3 presents the estimated coefficients of five alternative specifications in which the measure of PEE is the average public expenditure in primary education (exp_p). We estimate each model by OLS and Probit. Model 1 contains neither country nor year dummies. Model 2 adds country fixed effect whereas Model 3 only adds the year dummies. Models 4 and 5 correspond to Model B and A above, respectively. The first five rows in Table 3 show estimates of parameters β_1 to β_5. As can be seen in the table, the impact of most explanatory variables is similar under all these specifications. Expenditure in primary education has the hipothesized effect on the probability of being poor today. The estimate of β_1 is always negative, while the estimate of β_2 is always positive, confirming what we saw in Figure 4. Our variable PEE reduces the probability of being poor, but this effect becomes smaller as PEE increases. Women are more likely to be poor. All variables reflecting parental background have the expected sign. In addition, not being a citizen increases the probability of being poor. The same happens with the variable that reflects initial inequality, pointing out to persistence in poverty since poverty rates are typically higher in countries with more inequality. Observe that, by adding country fixed effects, we find a positive effect of the average GDP during the period of primary school attendance (*gdp_p)* on the probability of being poor today. We think that this is due to a convergence process among the country-cohorts analyzed. Those that enjoyed larger values of per capita GDP in the past have experienced less growth, compared to the ones with lower values.[8] Finally, the estimate for the dummy *cs2011* is positive, reflecting the effect of the financial crisis.

Table 3 here

In Table 4 we compute the average marginal effects corresponding to the variables PEE and parental education. In the case of Model B (the model with interactions) we can also compute a separated marginal effect of PEE for the two values of parental education.

Table 4 here

Except for Model 5 under the first specification, we always find a negative and significant effect of PEE. Observe that the estimated marginal impact of PEE are quite similar under the OLS and Probit specification. Focusing on the Probit model and depending on the specification we adopt, we obtain a marginal effect of PEE between -0.0117 and -0.0176. To illustrate the size of the effects we obtain, let us consider a mid-size estimate like the one in Model 2. The estimated marginal effect of is -.0144. This means that increasing PEE by $1,000 reduces the probability of being poor in 1.44 percentage points. Or, alternatively, increasing PEE in one standard deviation reduces that probability in 2.61 percentage points (1,817*1.44). This is a sizable effect, since it represents a 21.1% of the mean value of the variable poor (the mean of *poor* is 0.124).

The effect of having educated parents is also very strong. The marginal effect we obtain in

[8] We estimate a simple growth equation with the 405 country-cohorts in the sample. The independent variable is the logarithm of average per capita GDP during the period of primary school attendance (gdp_p). The dependent variable is the logarithm of the ratio between per capita GDP in 2008 and average per capita GDP during the period of primary school attendance (gdp_p). The estimation we get is (standard errors in brackets, $R^2 = .1125$):

$$\ln\left(\frac{gdp\_2008}{gdp\_p}\right) = \underset{(.233)}{7.862} - \underset{(.086)}{.1424}\ln(gdp\_p).$$

Although statistically insignificant the negative coefficient is in the direction that supports the hypothesis that cohorts with low initial per capita GDP grow faster than cohorts with high initial per capita GDP.

Model 2 under a Probit specification (-.0745) indicates that having at least one parent with secondary education reduces the probability of being below the poverty line in 7.45 percentage points. The effect of having educated parents is comparable to having an additional spending in primary education of \$5,173 (7.45/1.44), almost two times the standard deviation of PEE.

We also find that the effect of PEE concentrates mostly on individuals who had parents with little education. In all cases we do not find a significant effect on individuals with at least one parent with secondary education.

Figure 6 here

We illustrate this effect by plotting the predicted probabilities of being poor for different values of PEE and separated by the two levels of parental education. We do this in Figure 6. They correspond to the two versions of Model 4. We observe that the effect of PEE differs by parental education level. In particular, the effect of PEE seems to affect only those individuals with uneducated parents. In addition, individuals with poorly educated families only catch up those with educated parents when the value of PEE is high.

5 Robustness analysis

In this section we analyze the robustness of our analysis to alternative methods. The first one consists of analyzing country-cohort differences in the impact of PEE on poverty reduction using a two-step model similar to Bell et al. (2002) or Markaki and Longhi (2012). In a first step we run an OLS regression in which the dependent variable is the poverty rate and the regressors include all individual and family background variables, plus a set of dummies to capture year-country fixed effects. Since we have 17 countries and 27 years, in principle we should have to estimate up to 458 dummies. However, we lack data for 54 year-country combinations, so we have only 405 different combinations. This requires the estimation of 404 dummies, where the reference group is those born in Austria in 1960. In a second step, we regress these 404 dummy effects on the variable public expenditure in primary education (PEE), and on other variables of interest that characterize these countries and years. We include as regressors average per capita GDP and average inequality. The estimated coefficient we get for PEE in this second regression is the relevant part of the dummy effect in the first equation, since we have controlled for other observable characteristics of each year and country.

Then, in the first step we estimate:

$$poor_{ic} = \beta_0 + \beta_1 educ\_fam_{ic} + X'_{ic}\gamma + \beta_{ct} + u_{ic}, \tag{3}$$

where β_{ct} represents the country-cohort dummies. These dummies will be negative (resp. positive) for those country-cohorts in which the probability of being poor today is lower (resp. higher) than what we would expect given individual and family background variables.

Table 5 shows the estimated coefficients of Equation (3), except for those of the 404 dummies. They are very much in line with the results of Models A and B above. The F-test at the bottom of the table shows that the year-country dummies are jointly statistically significant. This means that there are residual (non-random) differences in the probability of being poor today across countries and cohorts that cannot been explained by just using the individual variables. Figure 7a below shows the distribution of the country-cohort dummies.

Figure 7 here

The mean residual impact of the country-cohort dummies is .1219, which is relatively high compared to the impact of most individual characteristics including parental education. As the reference group are those born in Austria in 1960, this is capturing two effects. One, that Austria has a poverty rate below average. Second, the fact that younger cohorts have higher poverty rates than the reference group. In Figure 7b we show the distribution of country-cohort dummies at the country level. In addition, Figure 8 shows the mean residual impact of country-cohort by country.

Figure 8 here

In both figures it can be observed that the residual impact of country-cohort dummies varies widely. This heterogeneity might be due to economic differences across countries and cohorts including differences in public expenditure in primary education. We address this point in the second step. where we use the estimated coefficients of the country-cohort dummies, $\widehat{\beta}_{ct}$ as dependent variable of an aggregated model. We model these country-cohort differences in average residual current poverty status by aggregate level measures of country-cohort variables:

$$\widehat{\beta}_{ct} = \alpha_0 + \alpha_1 PEE_{ct} + \alpha_2 (PEE_{ct})^2 + \alpha_3 gdp_{ct} + \alpha_4 ineq\_p_{ct} + \eta_{ct} \tag{4}$$

where PEE_{ct} is the public expenditure in education in country c in year t, gdp_{ct} is the average per capita GDP in country c during individual's born in year t period of primary school attendance and $ineq\_p_{ct}$ is average inequality in country c during individual's born in year t previous primary school attendance period.

The results of the estimation of Equation (4) are shown in Table 6. We lose some observations because we have some missing data for the variable $ineq\_p_{ct}$. We compute the marginal effects corresponding to each of the explanatory variables. The table shows that the public expenditure in primary education has again a statistically significant negative effect on the probability of being poor. The estimated marginal effect is -.01121, which means that for each additional $1,000 received by some country-cohort, the probability of being poor for some individual who belongs to it (and after controlling for individual variables) reduces in 1.12 percentage points. This result is similar to those found for Models A and B above (see Table 4).

Table 6: **Marginal effect of PEE, GDP and INEQ on country-cohort residuals.**

	OLS
PEE	$-.0112175^{***}$ (.0036906)
GDP	$.0016146^{*}$ (.0008741)
INEQ	$-.000049$ (.0007591)
Observations	395
R-squared	.0715

A second alternative modelling approach is that of hierarchical or multilevel models. This seems particularly appropriate in our case, since the data structure is hierarchical.[9] All individual born in Spain in 1970 have the same value for some of the explanatory variables, including expenditure in education, per capita GDP and the inequality measure. We propose to estimate the following model:

$$poor_{ic} = \beta_{0ct} + \beta_{1ct} educ\_fam_{ict} + X'_{ic}\beta + \epsilon_{ict} \tag{5}$$

where β_{0ct} is the average poverty rate in country-cohort ct, which might be affected by a set of year-country level variables:

$$\beta_{0ct} = \gamma_{00} + \gamma_{01} PEE_{ct} + \gamma_{02}(PEE_{ct})^2 + \gamma_{03} gdp_{ct} + \gamma_{04} ineq\_p_{ct} + u_{oct} \tag{6}$$

Now, as it might be the case that the impact of parental education on individual's current poverty status depends on year-country public expenditure in education, we model it as a

[9]Hierarchical or multilevel models explicitly address situations where the group-varying parameters estimated in one level are treated as the dependent variables in the next level equations. Haitovsky (1986) is one of the seminal works responsible for the development to k-level hierarchical models.

random effect and thus:

$$\beta_{1ct} = \gamma_{10} + \gamma_{11} PEE_{ct} + \gamma_{12}(PEE_{ct})^2 + u_{1ct} \tag{7}$$

By substituting Equations (6) and (7) into (5), a random-intercept and random-slope model including year-country variables and cross-level interactions is obtained:

$$\begin{aligned} poor_{ic} \;=\; & \gamma_{00} + \gamma_{01} PEE_{ct} + \gamma_{02}(PEE_{ct})^2 + \gamma_{03} gdp_{ct} + \gamma_{04} ineq\_p_{ct} + \gamma_{10} educ\_fam_{ict} \\ & + \gamma_{11}(PEE_{ct} \times educ\_fam_{ict}) + \gamma_{12}(PEE_{ct})^2 \times educ\_fam_{ict} + X'_{ic}\beta \\ & + u_{oct} + u_{1ct} educ\_fam_{ict} + r_{ict} \end{aligned} \tag{8}$$

The first part of the equation corresponds to the fixed effects component which describes average poverty rate in the population, given individual variables and country-cohort ones. The term $(u_{oct} + u_{1ct} educ\_fam_{ict})$ corresponds to the random component, thus capturing deviations from the average poverty rate due to year-country specific effects and individual deviations from his/her year-country average poverty rate. Note that, by estimating Equation (8) we allow for individual's parental education $(educ\_fam_{ict})$ having both fixed and random effects. The fixed effect refers to the overall expected effect of individual's parental education on his/her current poverty status whereas the random effects captures whether or not this effect differs by year-country.

Table 7 shows the results of the estimation of Equation (8).[10] The upper part shows the average estimated values for the fixed parameters. Results are very similar to the ones obtained in Section 4. There are some differences though, for example, the magnitude of the estimated coefficient for PEE is much larger here and income inequality during the primary school attendance period has a negative and significant effect of poverty today. The bottom part of Table 7 reports the estimates of variances and covariances of u_{oct} and u_{1ct} above, with the standard error in parenthesis. The significance of the variance of each of the slopes means that there is significant variability across year-country groups in the way

[10] Table 7 shows the OLS estimates of Equation (8). Results under Logit specification are very similar and available upon request.

parental education affects the probability of being poor today. This slope cannot therefore be considered as constant across years and countries, since parental education does not seem to influence poverty reduction following the same universal rule across country-cohorts. Testing this model against the specification which disregards the variability of the parental education parameter across country-cohort (Model 1 above), leads to a chi-squared statistic of 847.97, highlighting that the variation of these parameters across country-cohorts should not be disregarded. In Table 8 below we compute average marginal effects corresponding to the variables PEE and parental education, together with separated marginal effects of PEE for the two values of the parental education level.[11]

Table 8: Marginal effect of PEE on poor. Random effects model

	OLS Model
PEE	$-.0256773^{**}$ (.0038459)
Educ_fam	$-.068651^{***}$ (.0028792)
Effect of PEE	
Non-educ	$-.0385571^{***}$ (.0048678)
Educ	$-.0077944^{**}$ (.0029593)

Results in Table 8 are again in line with those commented above regarding the impact of PEE in general and for different parental education levels (see Table 4).

Finally, in order to check the validity of the above results regarding Model A and B we consider an alternative measure of parental background. In particular, we use the variable that tells us whether an individual experienced difficulties when teenager or not, this is *poor_past*. We estimate three alternative models. In Model 1 we estimate a model similar to Equation (2), but the only variable describing parental background is *poor_past*, thus we use data only from the 13 countries for which we have information on that variable in the

[11] Marginal effects obtained under a Logit specification are very similar in sign and size and available upon request.

two waves, 2005 and 2011 (see footnote 6 above). Model 2 is exactly the one in Equation (2). Finally, Model 3 is exactly the same as Model 2 but adding *poor_past* as an additional regressor. Table 9 below shows the marginal effects of PEE and the two parental background measures studied. In particular we provide the estimates for the Probit model. As can be observed the impact of PEE still remains significant, and its effect is larger for individuals with poor parental circumstances compared to individuals with better backgrounds regardless of how it is measured.

Table 9: Marginal effect of PEE on poor. Parental background measures.

	Model 1	**Model 2**	**Model 3**
PEE	$-.0129^{**}$ (.0064)	$-.0173^{***}$ (.0066)	$-.0143^{**}$ (.0066)
Educ_fam	-	$-.0749^{***}$ (.0025)	$-.0707^{***}$ (.0026)
Past_poverty	$.0840^{***}$ (.0047)	-	$.0492^{***}$ (.0031)
Effect of PEE			
Non-educ/poor_past	$-.0119^{**}$ (.0058)	$-.0307^{***}$ (.0091)	$-.0260^{***}$ (.0092)
Educ/non-poor_past	$-.0193$ (.0122)	.0012 (.0035)	.0015 (.0036)
Observations	105156	121868	110529

6 Concluding remarks

Being raised in a poor household may have negative long-run effects on individual welfare. In this paper we study whether these long-run effects of poverty are mitigated by public expenditure in education, and to what extent.

The main finding of this paper is that public expenditure in primary education has a strong effect on raising individuals above the poverty line. In addition we find that this effect is larger on individuals from poor parental background than on individuals that grew up in rich families. This result suggests that public expenditure in primary education increases intergenerational income mobility.

We believe that our results could be relevant for several recent debates in the literature on the economics of education. In particular, our findings provide support for policies that promote increasing expenditure in basic education, for example, by reducing the compulsory school entry age, or improving the quality of the education provided at early stages.

This study have some limitations. We do not have a direct measure of government investment in education and thus we follow previous research in using government spending as a proxy for government investments (see Mayer and Lopoo, 2008). However, this might be an imperfect measure of actual investment. For example, countries with similar public expenditure might be spending it differently and having different results with their spending depending on several other circumstances.

References

[1] Atkinson A. (2010): "Macerata Lectures on European Economic Policy. Poverty and the EU: the New Decade" Working Papers 24-2010, Macerata University, Department of Studies on Economic Development (DiSSE).

[2] Atkinson A., Piketty T., and E. Saez (2011): "Top Incomes in the Long Run of History." Journal of Economic Literature. 49 (1): 3-71.

[3] Becker G.S. and N. Tomes (1979): "An equilibrium theory of the distribution of income and intergenerational mobility" Journal of Political Economy 87 (6): 1153-1189.

[4] Bell B., Nickell S. and G. Quintini (2002): "Wage equations, wage curves and all that" Labour Economics 9: 341–360.

[5] Black, S. and P. Devereux (2011): "Recent Developments in Intergenerational Mobility." In: Ashenfelter, O., Card, D. (Eds.), Handbook of Labor Economics, Vol. 4, Part B. Elsevier, Amsterdam, 1487–1541.

[6] Evans W., Hout M. and M.E. Mayer (2008): "Assessing the effect of economic inequality" In: Neckerman K. (ED.) Social Inequality. Russel Sage Foundation Press, New York, 933-968.

[7] Grogger, J. (1996): "School expenditures and post-schooling earnings: evidence from the high school and beyond," Review of Economics and Statistics 78, 4, 628–637.

[8] Haitovsky Y. (1986) "The linear hierarchical model and its application in economic analysis". In Bayesian Inference and Decision Techniques-Essays in Honor of Bruno de Finetti, Goel P;, Zellner A (Eds). Elsevier: Amsterdam: 119-138.

[9] Hanushek, E. (1996): "School resources and student performance." In: Burtless, G. (Ed.), Does Money Matter? The Effect of School Resources on Student Achievement and Adult Success. Brookings Institution Press, Washington, D.C.

[10] Hanushek, E. (2001): "Spending on schools." In: Moe, T. (Ed.), A Primer on American Education. Hoover Institution Press, Palo Alto, CA, pp. 69–88.

[11] Hedges, L.V., Laine, R., Greenwald, R. (1992): "Does money matter? Meta-analysis of studies of the effects of differential school inputs on student outcomes." Educational Researcher 23, 3, 5–14.

[12] Jenkins, S., Brandolini, A., Micklewright, J. and Nolan, B. (Eds) (2013) "The Great Recession and the Distribution of Household Income". Oxford University Press.

[13] Markaki Y. and S. Longhi: (2012) "What Determines Attitudes to Immigration in European Countries? An Analysis at the Regional Level" Norface Migration Discussion Paper No. 2012-32.

[14] Mayer, S. E. (2002): "The Influence of Parental Income on Children's Outcomes: A Review." Report to the New Zealand Ministry of Social Development.

[15] Mayer, S. E., and Lopoo, L. M. (2008): "Government spending and intergenerational mobility," Journal of Public Economics 92, 139–158.

[16] Meghir, C., Palme, M. (2005): "Educational Reform, Ability, and Family Background," American Economic Review 95, 1, 414-424.

[17] Moulton, B. (1986): "Random group effects and the precision of regression estimates" Journal of Econometrics, 32(3): 385-397.

[18] Moulton, B. (1990): "An illustration of a pitfall in estimating the effects of aggregate variables on micro units" The Review of Economics and Statistics 72: 334-338.

[19] OECD (2011): An Overview of Growing Income Inequalities in OECD Countries: Main Findings. OECD Publishing, Paris.

[20] OECD (2013): Crisis squeezes income and puts pressure on inequality and poverty. OECD Publishing, Paris.

[21] Solon G. (2004): A model of intergenerational mobility variation over time and place. In: Corak, M. (Ed), Generational Income Mobility in North America and Europe. Cambridge University, Cambridge, UK, 38-47.

[22] Wolff, P., Montaigne, F., and Rojas González, G. (2010): "Investing in statistics: EU-SILC," Chapter 2 in A. B. Atkinson and E. Marlier (eds), Income and Living Conditions in Europe. Luxembourg: Eurostat, 38-55.

7 Appendix

7.1 Compulsory education in Europe

Table A.1. Compulsory school reforms:1960-1990

Country	Reform in period	1st. cohort pot. affected	Interval compulsory	Interval primary
AT	NO		6 to 15	6 to 11
BE	YES	Till 1969	6 to 14	6 to 11
BE	YES	Since 1970	6 to 18	6 to 11
CY	NO		6 to 15	6 to 11
DK	NO		7 to 16	7 to 11
ES	YES	Till 1981	6 to 14	6 to 11
ES	YES	Since 1982	6 to 16	6 to 11
FI	YES	Till 1960	7 to 13	6 to 11
FI	YES	Since 1961	7 to 16	6 to 11
FR	NO		6 to 16	6 to 11
GR	YES	Till 1964	6 to 12	6 to 11
GR	YES	Since 1965	6 to 15	6 to 11

Table A.1. Compulsory school reforms:1960-1990 (cont.)

Country	Reform in period	1st. cohort pot. affected	Interval compulsory	Interval primary
HU	YES	Till 1982	6 to 16	6 to 11
HU	YES	Since 1983	6 to 18	6 to 11
IE	YES	Till 1984	6 to 15	6 to 11
IE	YES	Since 1985	6 to 16	6 to 11
IT	YES	Till 1985	6 to 14	6 to 11
IT	YES	Since 1986	6 to 15	6 to 11
LU	NO		4 to 15	4 to 11
NL	YES	Till 1978	7 to 17	7 to 11
NL	YES	1979	6 to 17	6 to 11
NL	YES	Since 1980	5 to 17	5 to 11
NO	YES	Till 1982	6 to 15	6 to 11
NO	YES	Since 1983	6 to 16	6 to 11
PT	YES	Till 1974	6 to 12	6 to 11
PT	YES	Since 1975	6 to 15	6 to 11
SE	NO		7 to 16	7 to 11
UK	NO		5 to 16	5 to 11

7.2 Variable Description

Expenditure per student, primary, secondary and tertiary (% of GDP per capita): Public expenditure per student is the public current spending on education divided by the total number of students at that level, as a percentage of GDP per capita. Public expenditure (current and capital) includes government spending on educational institutions (both public and private), education administration as well as subsidies for private entities (students/households and other privates entities). Source: United Nations Educational, Scientific, and Cultural Organization (UNESCO) Institute for Statistics.

GDP per capita: It is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in constant 2000 U.S. dollars. Source: World Bank national accounts data, and OECD National Accounts data files.

Parental education: It is a binary variable that captures if either the education the father or mother had attained when the individual was around 14 years old is at least upper secondary education. Source: EU-SILC

Past poverty: For the EU-SILC special module on "Intergenerational transmission of poverty" individuals were asked how frequent financial problems in the household were when they were young teenagers. In the 2005 cross section it is a categorical variable that takes five possible values: 1 (most of the time), 2 (often), 3 (occasionally), 4 (rarely), and 5 (never). In the 2011 cross section there are six possible answers: 1 (very bad), 2 (bad), 3 (moderately bad), 4 (moderately good), 5 (good), and 6 (very good). We summarize the information of these questions by constructing a binary variable that takes value 1 when the corresponding variable is either 1 or 2 in the 2005 cross section and when it is 1, 2, or 3 in the 2011 cross section. We call this variable "poor_past".[12] Source: EU-SILC.

Father unemployed: It is a binary variables that captures if the father was unemployed when the individual was 14 years old. Source: EU-SILC.

[12] We recognize that this is completely arbitrary, and our only justification is that by doing in this way, frequencies for poor_past are similar across the two cross sections.

Siblings: It is the number of siblings the individual's had when he/she was around 14 years old. Source: EU-SILC.

Citizenship: It generally corresponds to the country issuing the passport. It shall refer to current (at the time of survey) national boundaries. It is a binary variable that indicates if the citizenship corresponds to the same country as the country of residence. Source: EU-SILC

Inequality: It is the country average inequality during the previous years (3-5) to the period of individual's primary school attendance. Source: Estimated Household Income Inequality Data Set (EHII), global dataset on inequality derived by the University of Texas Inequality Project (UTIP).

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Poor	0.124	0.330	0	1	142016
PEE (exp_p)	2.210	1.817	0.259	10.443	142030
GDP	12.292	5.139	2.481	36.054	142030
INEQ	34.899	4.726	26.079	43.525	135705
Female	0.511	0.500	0	1	142030
Family educated	0.409	0.492	0	1	136828
Number of siblings	1.585	1.544	0	40	139169
Single mother family	0.082	0.275	0	1	140146
Poor_past	0.140	0.347	0	1	124675
Father unemployed	0.009	0.093	0	1	131032
Non citizen	0.004	0.067	0	1	141831
Year 2011	0.540	0.498	0	1	142030

Table 3: Estimated coefficients. Dependent variable is *poor*

	OLS					Probit				
VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
PEE	-0.0279***	-0.0303***	-0.0366***	-0.0337***	-0.0128*	-0.105***	-0.139***	-0.157***	-0.167***	-0.113***
	(0.00776)	(0.00855)	(0.00624)	(0.00919)	(0.00768)	(0.0405)	(0.0465)	(0.0327)	(0.0489)	(0.0436)
PEE2	0.00174**	0.00219***	0.00258***	0.00260***	0.00116*	0.00464	0.00922**	0.00948***	0.0122***	0.00982***
	(0.000709)	(0.000699)	(0.000576)	(0.000781)	(0.000629)	(0.00372)	(0.00375)	(0.00303)	(0.00416)	(0.00344)
Family educated	-0.132***	-0.135***	-0.142***	-0.137***	-0.0716***	-0.631***	-0.657***	-0.681***	-0.673***	-0.400***
	(0.00877)	(0.00845)	(0.00833)	(0.00843)	(0.00324)	(0.0493)	(0.0460)	(0.0470)	(0.0461)	(0.0159)
Family educated#PEE	0.0319***	0.0370***	0.0365***	0.0384***		0.111***	0.144***	0.136***	0.155***	
	(0.00597)	(0.00534)	(0.00560)	(0.00536)		(0.0333)	(0.0292)	(0.0312)	(0.0294)	
Family educated#PEE2	-0.00168***	-0.00242***	-0.00218***	-0.00256***		-0.00279	-0.00748**	-0.00553*	-0.00855***	
	(0.000622)	(0.000551)	(0.000582)	(0.000553)		(0.00356)	(0.00315)	(0.00333)	(0.00316)	
Female	0.0113***	0.0122***	0.0116***	0.0122***	0.0122***	0.0591***	0.0646***	0.0607***	0.0651***	0.0648***
	(0.00191)	(0.00191)	(0.00191)	(0.00191)	(0.00191)	(0.00974)	(0.00990)	(0.00977)	(0.00992)	(0.00994)
Non citizen	0.0500**	0.0541***	0.0512***	0.0553***	0.0431**	0.246***	0.290***	0.256***	0.297***	0.246***
	(0.0194)	(0.0190)	(0.0195)	(0.0189)	(0.0192)	(0.0859)	(0.0842)	(0.0867)	(0.0840)	(0.0850)
Single mother family	0.0235***	0.0294***	0.0205***	0.0293***	0.0287***	0.127***	0.166***	0.111***	0.165***	0.161***
	(0.00524)	(0.00516)	(0.00522)	(0.00517)	(0.00517)	(0.0265)	(0.0266)	(0.0264)	(0.0265)	(0.0266)
Number of siblings	0.0186***	0.0215***	0.0191***	0.0214***	0.0218***	0.0768***	0.0904***	0.0793***	0.0901***	0.0915***
	(0.00117)	(0.00112)	(0.00113)	(0.00113)	(0.00113)	(0.00433)	(0.00428)	(0.00423)	(0.00431)	(0.00434)
Father unemployed	0.151***	0.144***	0.148***	0.144***	0.142***	0.555***	0.516***	0.539***	0.518***	0.512***
	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0423)	(0.0426)	(0.0420)	(0.0425)	(0.0428)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 (cont.): Estimated coefficients. Dependent variable is *poor*

	OLS					Probit				
VARIABLES	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0423)	(0.0426)	(0.0420)	(0.0425)	(0.0428)
GDP	-0.00157**	0.00543***	-0.00177***	0.00476***	0.00684***	-0.00729*	0.0338***	-0.00755**	0.0286***	0.0387***
	(0.000734)	(0.00131)	(0.000649)	(0.00182)	(0.00191)	(0.00413)	(0.00829)	(0.00366)	(0.0103)	(0.0109)
INEQ	0.000634	0.00278***	-6.36e-05	0.000923	0.00238***	0.00330	0.0149***	-0.000364	0.00341	0.00898*
	(0.000609)	(0.000934)	(0.000535)	(0.000911)	(0.000899)	(0.00306)	(0.00474)	(0.00274)	(0.00505)	(0.00504)
Year 2011	0.0237***	0.0188***	0.0167***	0.0171***	0.0184***	0.114***	0.0869***	0.0766***	0.0773***	0.0819***
	(0.00291)	(0.00275)	(0.00298)	(0.00287)	(0.00283)	(0.0146)	(0.0140)	(0.0150)	(0.0146)	(0.0143)
Country dummies	NO	YES	NO	YES	YES	NO	YES	NO	YES	YES
Year dummies	NO	NO	YES	YES	YES	NO	NO	YES	YES	YES
Constant	0.143***	-0.0546	0.249***	0.0390	-0.0880*	-1.121***	-2.199***	-0.561***	-1.597***	-2.069***
	(0.0258)	(0.0369)	(0.0237)	(0.0548)	(0.0522)	(0.129)	(0.202)	(0.120)	(0.289)	(0.280)
Observations	121,868	121,868	121,868	121,868	121,868	121,868	121,868	121,868	121,868	121,868
R-squared	0.035	0.043	0.036	0.043	0.042					

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Marginal effects of PEE and educated_family on poor

VARIABLES	OLS Model 1	OLS Model 2	OLS Model 3	OLS Model 4	OLS Model 5	Probit Model 1	Probit Model 2	Probit Model 3	Probit Model 4	Probit Model 5
PEE	-0.0110**	-0.0110**	-0.0151***	-0.0123**	-0.00765	-0.0117**	-0.0144**	-0.0176***	-0.0173***	-0.0146**
	(0.00430)	(0.00539)	(0.00342)	(0.00565)	(0.00534)	(0.00503)	(0.00647)	(0.00406)	(0.00659)	(0.00641)
Family educated	-0.0760***	-0.0732***	-0.0791***	-0.0735***	-0.0716***	-0.0771***	-0.0745***	-0.0799***	-0.0749***	-0.0772***
	(0.00272)	(0.00289)	(0.00279)	(0.00287)	(0.00324)	(0.00270)	(0.00258)	(0.00271)	(0.00256)	(0.00307)
Effect of PEE										
Family Educated=0	-0.0219***	-0.0227***	-0.0277***		-0.00876	-0.0217***	-0.0262***	-0.0305***	-0.0307***	
	(0.00545)	(0.00645)	(0.00439)		(0.00581)	(0.00713)	(0.00885)	(0.00577)	(0.00909)	
Family Educated =1	0.00428	0.00535	0.00226		-0.00611	0.00219	0.00201	0.000270	0.00116	
	(0.00338)	(0.00438)	(0.00283)		(0.00473)	(0.00271)	(0.00359)	(0.00233)	(0.00356)	
Observations	121,868	121,868	121,868	121,868	121,868	121,868	121,868	121,868	121,868	121,868

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Impact of individual characteristics on poverty

VARIABLES	poor
Family educated	-0.0710***
	(0.00204)
Female	0.0125***
	(0.00180)
Non citizen	0.0469***
	(0.0140)
Single mother family	0.0300***
	(0.00524)
Number of siblings	0.0206***
	(0.000635)
Father unemployed	0.140***
	(0.00977)
Year 2011	0.0184***
	(0.00200)
Constant	0.0453***
	(0.0170)
Index dummies	405
F-statistics	5.35
Prob>F	0.000
Observations	127,485
R-squared	0.045

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Poverty regression with country-cohort specific random intercept and slopes, and parental education-specific random slopes

VARIABLES	OLS
PEE	-0.0524***
	(0.00697)
PEE2	0.00403***
	(0.000657)
Educated_family	-0.128***
	(0.00775)
Educated_family#PEE	0.0363***
	(0.00500)
Educated_family#PEE2	-0.00257***
	(0.000546)
Female	0.0118***
	(0.00184)
Non citizen	0.0530***
	(0.0143)
Single mother family	0.0290***
	(0.00546)
Number of siblings	0.0206***
	(0.000655)
Father unemployed	0.144***
	(0.00985)
GDP	0.00200***
	(0.000670)
INEQ	-0.00112***
	(0.000536)
Year 2011	0.0181***
	(0.00200)
Constant	0.185***
	(0.0224)

Random-effects Parameters | Variance-covariance matrix

	var(educat_family)	**var(intercept)**
var(educat_family)	.001155 (.0001959)	
var(intercept)	-.0016946 (.0002167)	.0027427 (.0002881)

var(Residual) .1032172 (.0004193)

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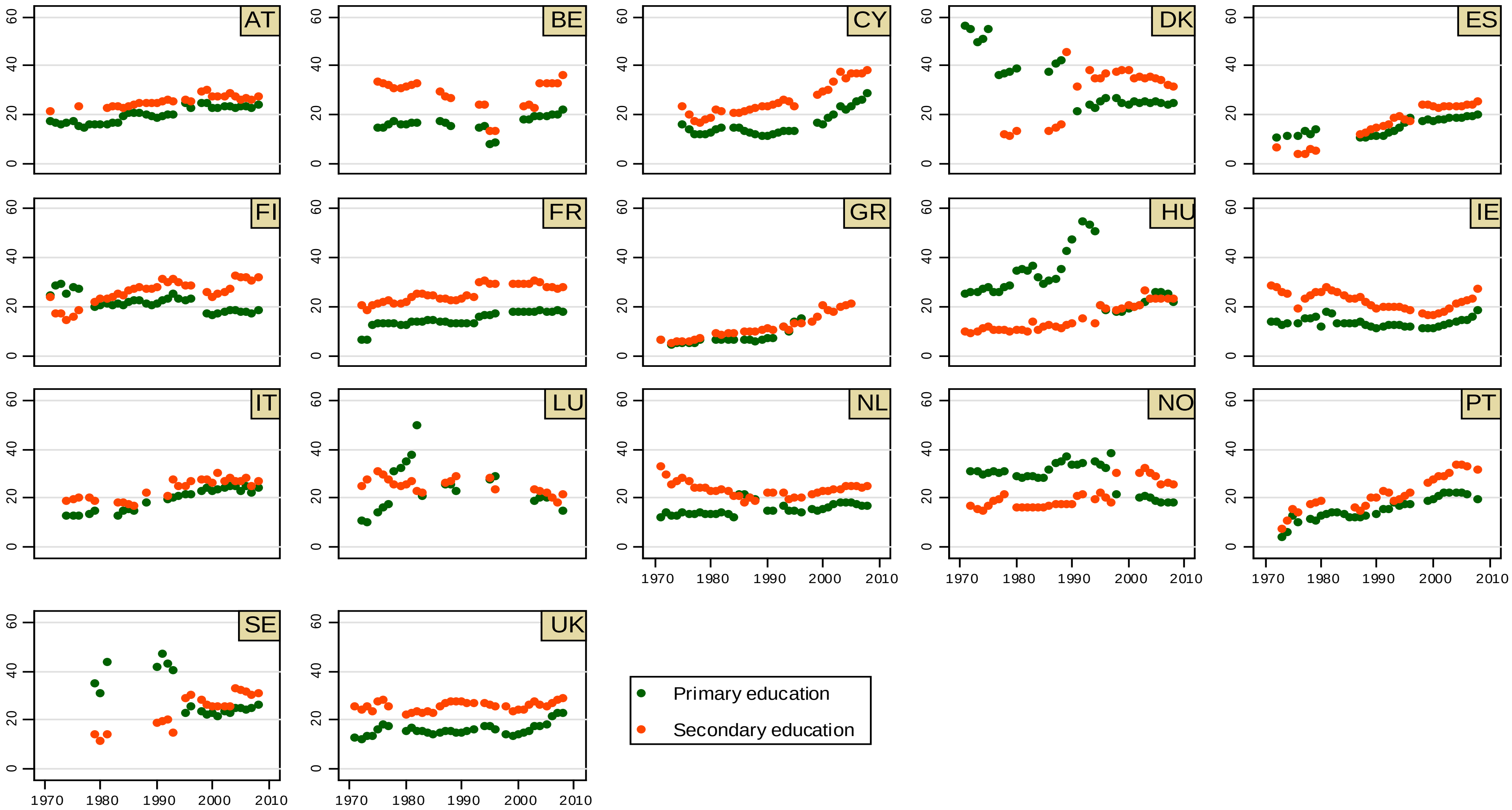
LR test vs. linear regression: chi2(3) = 847.97 Prob > chi2 = 0.0000

Figure 1: Expenditure in education as % of per capita GDP



Source: UNESCO database.

Figure 2: Poverty rate by country

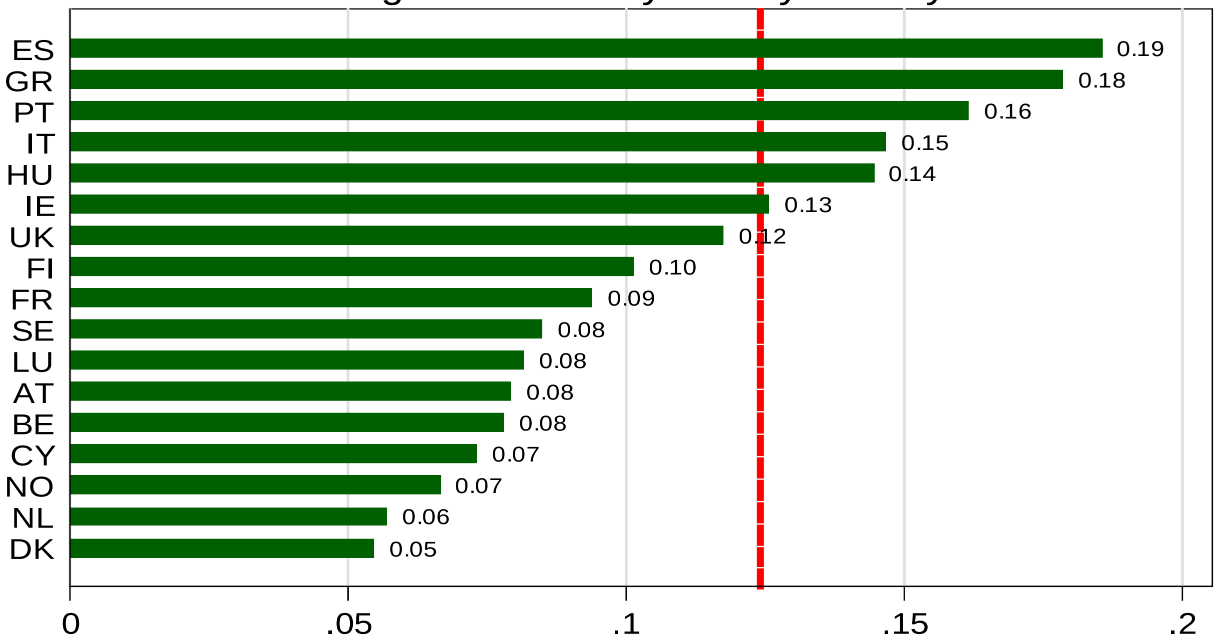


Figure 3: Poverty status by parental education

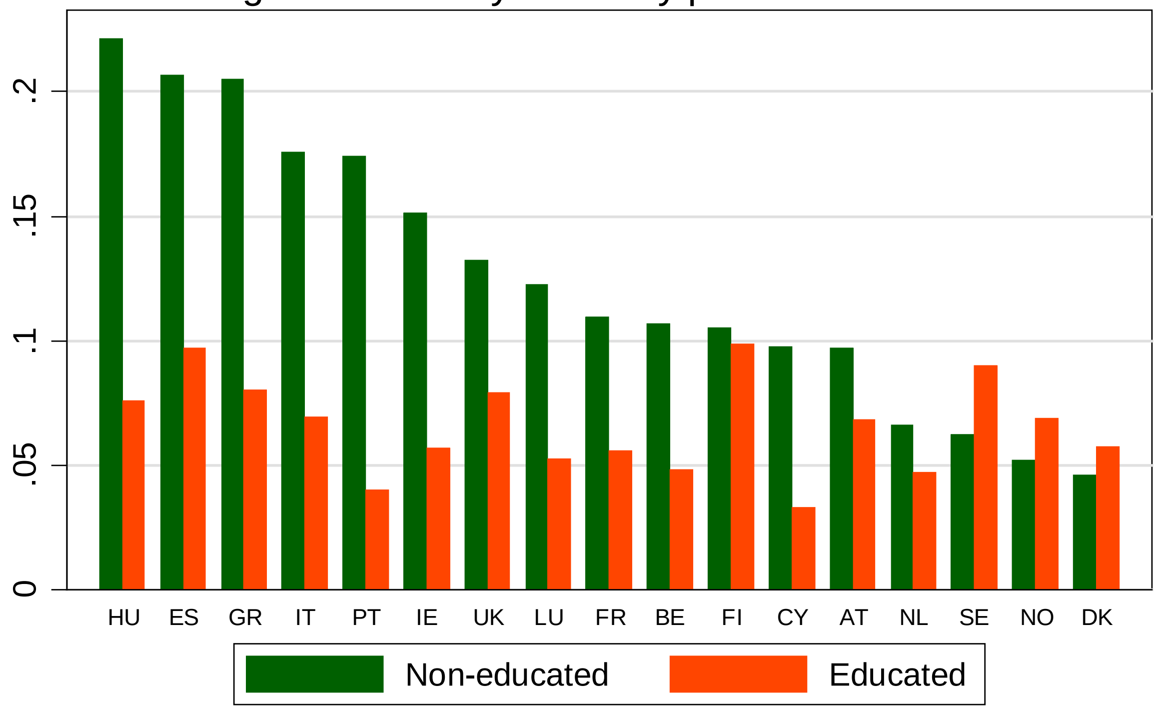


Figure 4: Expenditure in education and poverty rates

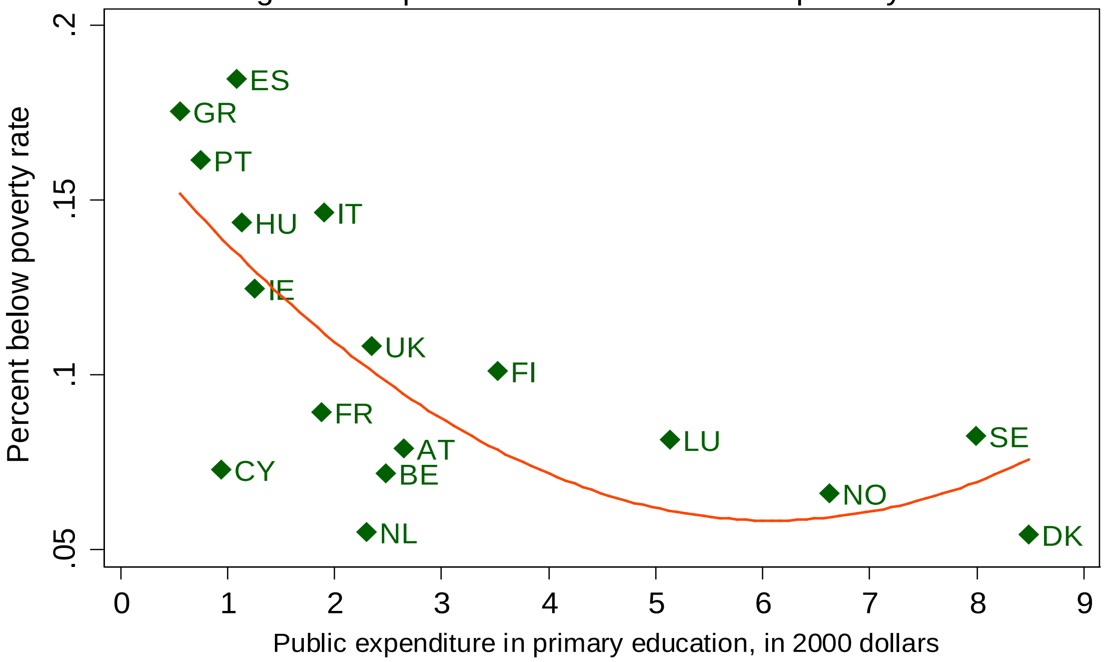


Figure 5: Public expenditure in education
and poverty today by parental background

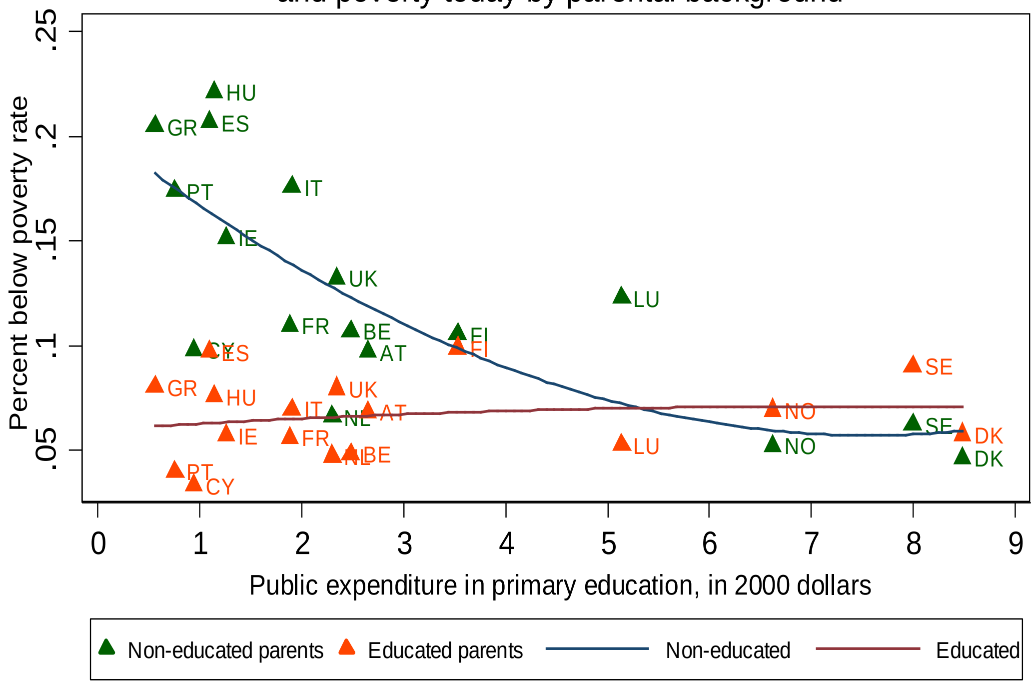
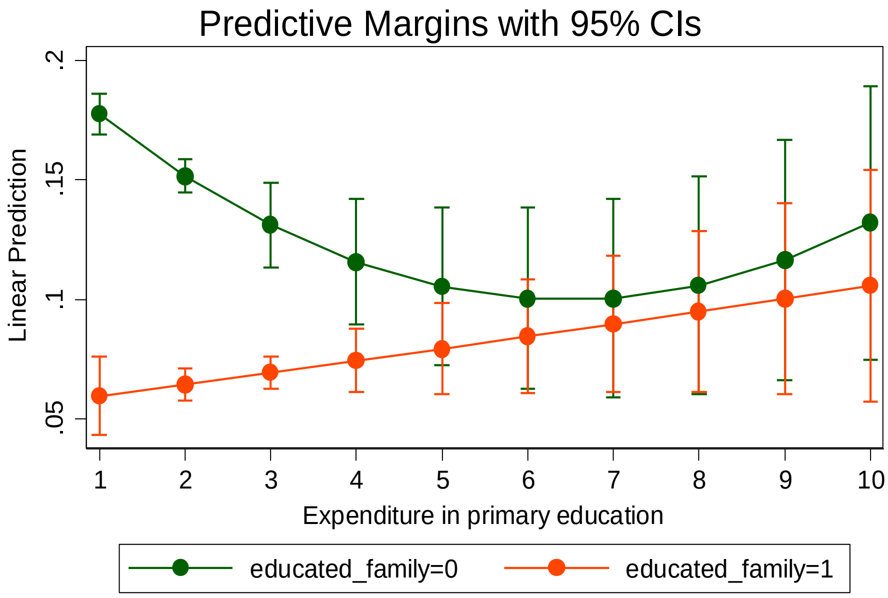


Figure 6: Predicted probabilities of being poor for different values of PEE (Model B)

OLS



PROBIT

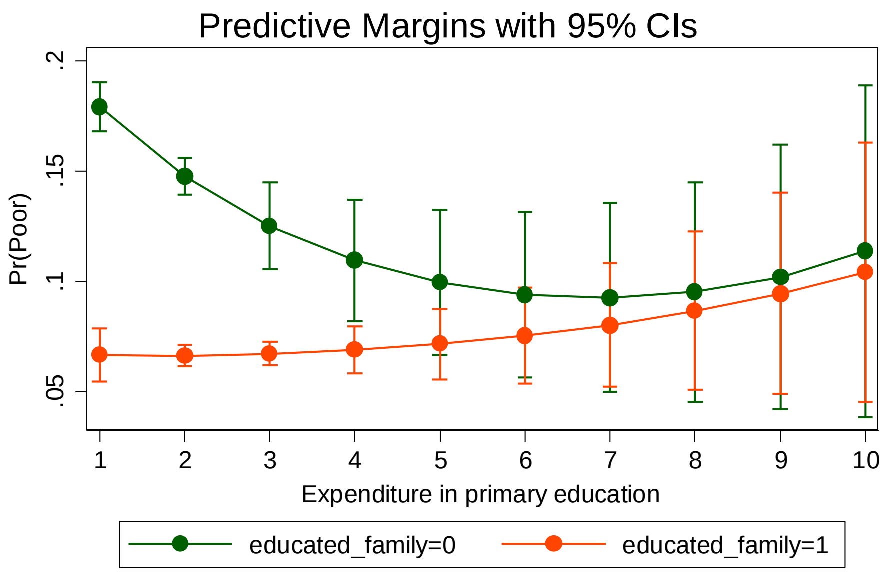


Figure 7a: Residual impact of country-cohort on poor

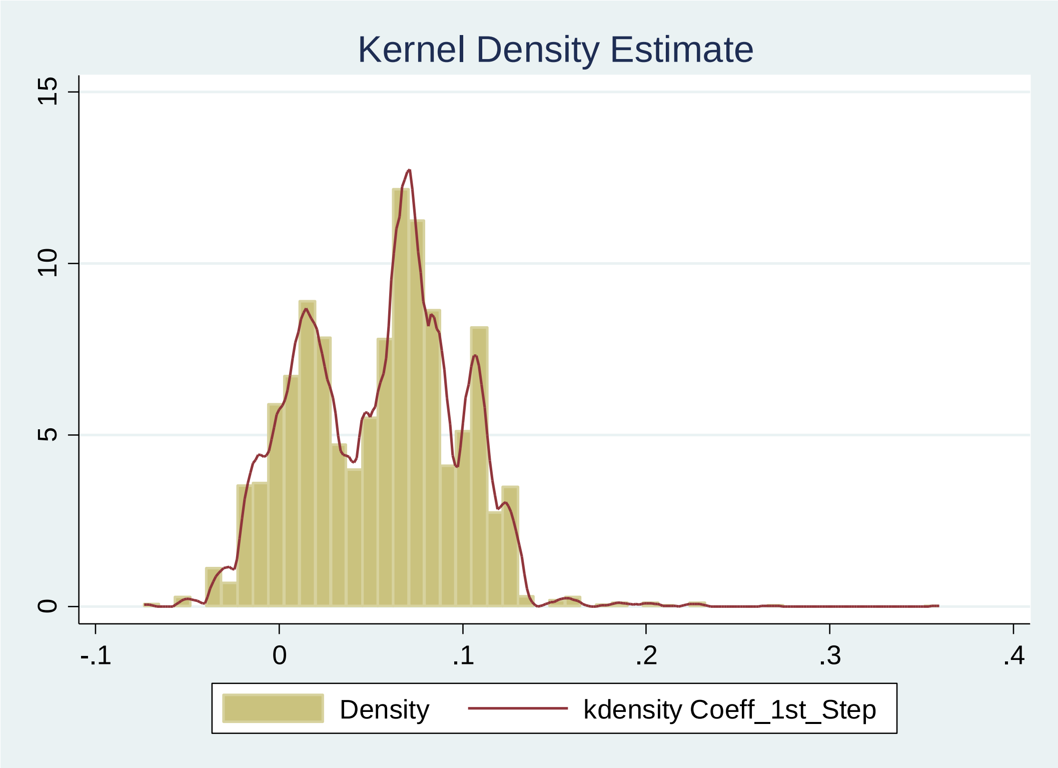


Figure 7b: Mean residual impact of year-country by country

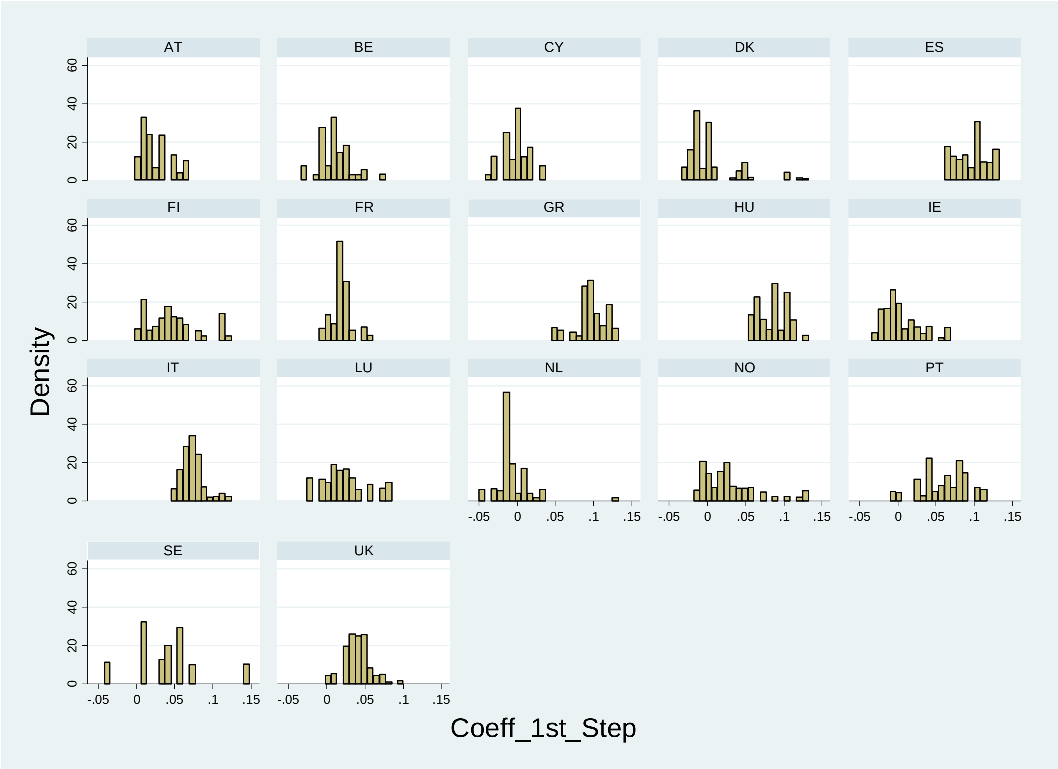


Figure 8: Average of estimated dummies by country