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Multidimensional poverty measures for analysing educational poverty in European countries

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Abstract

This paper studies the degree of educational poverty in European countries by focusing on data from two editions of the OECD Programme for International Student Assessment (PISA): 2006 and 2015. We focus on students' proficiency levels in various literacy domains and propose a multidimensional approach that enables the measurement of not only the incidence of educational poverty but also its depth and severity. Subsequently, we perform a micro-econometric analysis of school factors that are associated with the probability of educational poverty using a Partial Proportional Odds Model. The main results demonstrate that in recent years, the incidence of educational poverty became more relevant in many countries, while most of them experienced a reduction of poverty depth and severity. Several school factors can be manipulated to avoid the trap of educational poverty, such as improving the disciplinary climate, adopting an adaptive style of teaching, and increasing the amount of instructional time.

Keywords: educational poverty, students' learning, European countries

JEL Codes: I24, I32

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1. Introduction

The alleviation of educational poverty is largely recognized as a relevant issue that deserves the attention and intervention of both national and international institutions (European Commission, 2015; OECD, 2016). Low performance in school has a negative impact on the future educational and socio-economic status of students (Erikson *et al.*, 2005) and long-term consequences for society (OECD, 2016). In addition, this trend tends to be self-perpetuating across generations when the education system is unable to mitigate the negative impact of low socio-economic family background on students' schooling lives - and to break the vicious generational cycle of poverty (Corak, 2006).

Concern regarding educational poverty entered the policy agenda at the Lisbon Summit in 2000, when the Commission of the European Communities raised the challenge of reducing by at least 20% the number of 15-year-old students who are classified as low performers in reading literacy in the period up to 2010. The reduction of educational poverty, which is expressed in terms of learning outcomes and not only access to education, is one of the Sustainable Development Goals within the "2030 Agenda for Sustainable Development".

Although the concept of educational poverty is not new (Checchi, 1998), to the best of our knowledge, few papers address the specific issues that are related to the measurement of this phenomenon. Educational poverty is typically expressed in terms of years of schooling, certificates attained or competence level achieved. Once the concept of educational poverty was defined, the vast majority of research focused on the traditional headcount ratio (i.e., the proportion of a population that is below the poverty line) for measuring educational poverty, which is a simplistic index that has the advantage of being easy to interpret and understand. In this paper, we use a different perspective, which is based on considering direct measures of academic skills in three important domains: reading, mathematics and science. This way, we can define as poor those students who do not reach a predefined level of proficiency in the selected subjects. We take advantage of microdata that contain information about representative samples of 15-year-olds in various countries. Moreover, we propose the adoption of a set of indices that measure not only the level of educational poverty in a country but also its depth and severity, that is, how poverty varies at different points of the achievement distribution.

In this paper, we use the data on students' performance of various editions of the OECD Programme for International Student Assessment (PISA) to address two research questions: *i) What is the level of educational poverty in European countries? ii) What are the main school-level factors that are associated with the probability that a student is educationally poor in Europe?*

More specifically, the first research question is aimed at quantifying the extent of educational poverty. We posit that the students' educational "background" is a multidimensional concept and an exhaustive analysis of the complete learning deprivation status cannot be restricted to a single educational subject. Consequently, we should take into account that students could be low performers in one, two or more learning dimensions. Remarkably, this approach is particularly useful when a policymaker aims at obtaining a concise depiction of the poverty levels in various learning dimensions. Therefore, we propose applying the class of additive multidimensional poverty measures that were proposed by Alkire and Foster (2011). We employ these indices for the first time in the analysis of cognitive skills from an international perspective. This analysis is based on the latest OECD PISA edition (2015) and the corresponding edition with the same major domain as the learning dimension, namely, science, which is from 2006. This enables us to investigate how educational poverty has evolved over time.

The second research question moves beyond the description of the quantitative relevance of the phenomenon at the country level. In particular, by using micro-data from PISA 2015, we investigate the impacts of various factors that are related to both student socio-economic background and school resources, on the probability of being poor in one or more domains of the PISA test. In this way, we identify potential mechanisms that explain the risk of educational poverty at the individual level and derive implications for actionable school interventions that are aimed at reducing this risk.

The remainder of the paper is organized as follows: Section §2 reviews the literature. Section §3 illustrates the data that are used in this work and describes the methodological approach. Section §4 reports the main findings and Section §5 presents the conclusions and derives the key policy implications.

2. Related literature

The analysis of distributive aspects of education and their implications is becoming popular in the economics literature. Education is recognized as a fundamental determinant of individuals and societies' capacity for achieving their functioning. Education contributes to economic growth significantly (Psacharopoulos, 1984) and is positively related to individuals' income (Psacharopoulos, 1994) and health status (Cutler and Lleras-Muney, 2010). At the same time, society may benefit from education in terms of civic engagement (Milligan *et al*., 2004), social return (Acemoglu and Angrist, 2001) and more active political participation by its members. These effects suggest that an unequal distribution of cognitive achievement may have important consequences in other dimensions of societal life. This has stimulated the interest of researchers in measuring and investigating the inequality in learning outcome, as suggested by the increasing number of contributions (Rodrigues *et al*., 2013; Oppedisano and Turati, 2015; Crouch and Gustafsson, 2018). Other papers focus on the distribution of opportunity for acquiring education and investigate the extent to which educational outcomes can be explained by individuals' differential circumstances (Peragine and Serlenga, 2008; Gamboa and Waltenberg, 2012; Ferreira and Gignoux, 2014).

In the academic literature, the concept of educational poverty appeared at the end of 1990s when Checchi (1998) addressed the question of how educational poverty should be measured, namely, in absolute or relative terms. By adopting an absolute definition, the author characterizes educational poverty as the fraction of individuals who do not complete compulsory schooling. Since then, the concept and measurement of educational poverty evolved in various directions, even in the context of analyses across and within countries.

Bourguignon and Chakravarty (2003) consider education as a separate attribute of their multidimensional analyses of poverty. Allmendinger and Leibfried (2003) investigate educational poverty in OECD countries by adopting two alternative definitions of poverty: According to the first definition, poverty is expressed in terms of a missing certificate or diploma. The second definition is related to the level of the competencies that are acquired. That is, people below a given competence threshold are considered educationally poor. Moreover, poverty is measured in both absolute and relative terms. This work represents the first attempt to measure educational poverty in terms of acquired competencies by using PISA 2000 data. Recently, Lohmann and Ferger (2014) provided an overview of educational poverty from a comparative perspective by considering a set of European countries. In particular, poverty is expressed in terms of certificates, competencies or years of schooling. As in Allmendinger and Leibfried (2003), both absolute and relative definitions of poverty are adopted. Their results demonstrate that the educational poverty scenario changes with the adopted variable.

The headcount ratio is the most widely adopted indicator of educational poverty. Few works consider measures that take into account other aspects of poverty, such as intensity and severity (see Section 3.1). Denny (2002) represents the first attempt to analyse various aspects of educational poverty. In particular, by using the International Adult Literacy Survey (IALS) data, he computes various measures of illiteracy among the class of indicators that was proposed by Foster *et al.* (1984). Likewise, Rios-Neto and Rodrigues (2012) estimate various educational deprivation indices based on the PISA test scores on reading for the years 2000 and 2009.

Recently, Mynzuk and Russo (2016) adopt the multidimensional approach that was proposed by Alkire and Foster (2011) and Bourguignon and Chakravarty (2003) to measure educational poverty in Italy. We share similarities with this contribution, in that multidimensionality refers to the domains that characterize the overall student "educational background" and, hence, to the possibility that a student might be a low performer in various subjects.

The analysis of educational poverty is now enjoying a renewed and increasing interest, which is due also to the availability of better information and data on students' competencies in an international setting. Other recent contributions, which are based on the PISA dataset, have been proposed by Villar (2016) and Sanchez *et al.* (2016). In particular, Villar (2016) measures educational poverty in OECD countries by constructing a multidimensional index that is associated with a social evaluation function that combines the incidence, the intensity and the inequality of educational poverty. Sanchez *et al*. (2016) extend the class of sub-group consistent poverty indicators that was proposed by Foster *et al*. (1984) by developing a multidimensional poverty index that takes into account the non-poor educational attributes of a poor person, thereby enabling partial compensation.

Only a few studies focus on the effects of determinants of poverty in education. Both Rios-Neto and Rodrigues (2012) and Bruckauf and Chzhen (2016) study the determinants of poverty at the country level by using cross-sectional macro-regressions with educational poverty outcome measures as dependent variables. From this perspective, the OECD (2016) report provides estimates of the likelihood of low performance in mathematics based on simple, binary logistic micro-regression analyses that consider the characteristics of individuals. Based on these contributions, we extend the empirical application by modelling the probability that a student is deemed "poor" in one or more subject domains by employing an array of individual-level variables that describe the student's background and the characteristics of the schools that he or she attends.

3. Data and methodological approach

3.1 Deriving indices of educational poverty at the country level

In this paper, we measure educational poverty in 26 European Union countries by using the OECD PISA 2006 and 2015 datasets. Since the first edition in 2000, every three years PISA collects highly standardized data to assess the competencies of a representative sample of 15-year-old students in three subject domains: reading, mathematics and science. Students' competencies are expressed in terms of "plausible values", which are obtained via a two-step procedure. The first step deals with the distribution of the students' latent abilities, which is obtained by adopting the item response theory (IRT) statistical technique.[1] Then, in the second step, a new distribution is derived by applying an affine transformation to the distribution that was generated in the first step. Let x_i denote the "raw" plausible value score of individual i in a generic learning attribute. The final adjusted plausible value score, which is denoted as y_i, is obtained via the following standardization:

$$y_i = \hat{\mu} + \frac{\hat{\sigma}}{\sigma}(x_i - \mu), \qquad (1)$$

[1] This distribution is obtained by drawing for each student a specified number of values, which are known as plausible values. By combining IRT scaling methods and a latent regression model (Mislevy, 1991), these values are drawn from a posterior marginal distribution of ability that is estimated on the basis of the students' answers and a set of background variables (which are obtained from the student context questionnaire).

where μ and σ denote the original raw mean and the standard deviation, respectively, across all OECD countries, while $\hat{\mu}$ and $\hat{\sigma}$ are the "arbitrary" mean and standard deviation for the standardized distribution, which are set (by OECD) to 500 and 100, respectively.

The analysis of poverty poses three fundamental tasks: the identification of the poor, the quantification of the intensity of their poverty and the aggregation of poverty across the distribution (see Sen, 1976; Lambert, 2001). Within an educational framework, the first two tasks require the choice of an appropriate threshold or poverty line in the distribution of students' learning levels that identifies as "educationally poor" all students whose level is lower than that threshold. In this regard, within the distribution of PISA scores, OECD identifies six proficiency levels, range from 1 (low-skilled student) to 6 (high-skilled student), with level 2 considered the minimum required competence level. In this paper, we adopt that threshold as the (absolute) poverty line for measuring educational poverty. In a multidimensional framework, a second poverty cut-off defines the minimum number of learning dimensions in which the student must be deprived to be identified as "globally poor". Here, we consider both the traditional multidimensional headcount ratio and the class of multidimensional indicators that was proposed by Alkire and Foster (2011; hereafter AF).[2]

Following Alkire and Santos (2013), let y_j denote the distribution of test scores in the learning dimension j, with $j = 1, \dots, d$. A poverty line Z_j identifies in *each* dimension the poor students (i.e., $Z_j > y_{ij}$, with $i = 1, \dots, N$), while the second poverty cut-off is labelled by k. Then, a generic student i is globally poor if his/her number of learning deprivations, which is denoted as c_i, is greater than or equal to k. Different levels of k are associated with different approaches

[2] For a review on the literature on multidimensional poverty, see Thorbecke (2008).

for identifying the globally poor. In particular, when each dimension is equally weighted, with $k = 1$ we have the "union method" and a student is considered poor if his/her learning outcome is below the poverty cut-off in *at least* one attribute, while with $k = d$ we adopt the "intersection method", which identifies student i as poor if he/she is poor in *all* attributes.

The multidimensional educational headcount ratio, which measures the incidence of poverty, namely, the share of poor students who are deprived in k, or more, learning dimensions, is:

$$MEH^{y} = \frac{1}{N} \sum_{i=1}^{N} \left[\sum_{j=1}^{d} g_{ij}(k) \right]^{0} \ , \tag{2}$$

where $g_{ij} = \frac{Z_j - y_{ij}}{Z_j}$ is the poverty gap for multidimensional poor student *i* in learning dimension *j,* with $g_{ij} > 0$ if $y_{ij} < Z_j$ and $c_i \geq k$; otherwise $g_{ij} = 0$.

The AF class of indicators is:

$$M_{\alpha}^{y} = \frac{1}{Nd} \sum_{i=1}^{N} \sum_{j=1}^{d} w_j (g_{ij}(k))^{\alpha} \ , \tag{3}$$

where w_j is the weight that is assigned to dimension *j*, with $\sum_{j=1}^{d} w_j = d$, and α is a non-negative parameter that measures the sensitivity to changes in intensity and inequality aversion within the group of poor students in each dimension *j*. Different values of the parameter α are associated with different multidimensional poverty measures that emphasize different aspects of poverty. When $\alpha = 0$, the AF index focuses on the incidence *and* the breadth of poverty, where the latter aspect refers to the number of learning deprivations that are experienced by poor students. In other words, when $\alpha = 0$, Equation 3 reduces to the *adjusted educational headcount ratio (AEH)*, which expresses the total number of learning deprivations over the total number of learning dimensions in which the whole student population can be deprived. From a purely methodological perspective, we consider the *AEH* more appropriate than the *MEH* for describing educational poverty in a more complete way.

When $\alpha = 1$, Equation 3 reduces to the *adjusted educational poverty gap index (AEPG)*, which corresponds to the weighted average of educational poverty gaps in each learning dimension. This index focuses on the incidence, the breadth *and* the depth of poverty (which refers to the magnitude of the poverty gaps that are experienced by poor students).

Lastly, when $\alpha = 2$, we obtain the *adjusted educational poverty severity index (AEPS)*, which is the weighted average of the educational squared poverty gaps in each learning dimension. For each dimension, this index also takes into account the inequality among the poor students by assigning to them increasing weights as their poverty gaps increase. [3]

Each AF indicator can be decomposed into the contribution of each learning dimension. This property is particularly relevant when a policymaker aims at determining which subject domain significantly contributes to the observed overall poverty. [4]

3.2 Modelling the determinants of educational poverty - a microeconometric approach

The poverty measures that were introduced and discussed in the previous section are useful for obtaining a detailed and in-depth picture of the problem of the educational emergency at the country level. A further step of the analysis consists of modelling the probability of being poor in education by exploiting the PISA micro-data (at the school and student levels). In so doing, we

[3] When $\alpha>1$, the economic literature on poverty justifies this choice according to the *Pigou-Dalton* principle of transfers. However, in the educational context, one cannot transfer a 'unit of learning' from one student to another. Therefore, we argue that if one has the possibility to improve the learning, e.g., in reading, of two students by the same amount, then it is better to choose the less educated of the two (Denny, 2002).

[4] Moreover, it is possible to calculate the contributions of various macro-areas or socio-economic groups to the national level of educational poverty. This topic will be explored in future research.

adopt the number of PISA domains (reading, mathematics and science) in which each student is below proficiency level 2 as a measure of educational poverty. The empirical analysis relies on the estimation of an unconstrained Partial Proportional Odds Model (PPOM) due to the orderly and categorical nature of the dependent variable, which can take values between 0 (if the student's score is not below the proficiency level 2 in any subject) and 3 (if the student's score is below this level in all three domains).

The econometric analysis draws upon the data from the latest edition of PISA (2015), which involved approximately 540,000 students from 17,600 schools in 72 countries and economies. We focused on the EU-26 area, as it contains the group of longest-standing member states, which share many similarities in terms of European-level policy-related activities. The PISA study complements information from the assessment of reading, mathematics and science with data that were gathered through questionnaires on students and schools. Focusing on several school-level factors, such as the learning environment, the school resources and the teaching practices, we aim at highlighting the unique role that schools and educators play in fighting educational poverty, while also accounting for individual characteristics and family backgrounds of students. Table 1 lists the definitions of the explanatory variables that are included in this study. The choice of variables was driven by the literature on the determinants of students' educational results. [5]

[Table 1] around here

[5] While providing a complete review of econometric studies in the field is beyond the scope of our paper, interested readers can refer to Hanushek (2002), who provides an overview of the conceptual framework of educational production function (EPF), which has been adopted here. Hanushek and Woessmann (2011) describe the use of international datasets for modelling the determinants of student achievement from a cross-country perspective. Agasisti et *al.* (2018) use PISA data for modelling the student and school factors that are associated with the performance of disadvantaged students.

In our empirical application, we control for various individual and family characteristics that influence students' performance: gender (0=male, 1=female), language spoken at home (0=language of instruction, 1=different language), and immigrant status (0=native, 1=immigrate). We also control for the students' ICT interest, which is measured by an OECD synthetic indicator, and the career regularity of the students, as it may be linked to their cognitive development. To ensure a proper comparison among schools and to take into account the heterogeneity of students' family conditions, we include the OECD index of economic, social and cultural status (ESCS). This indicator includes information about parents' occupations and educations, along with data about goods that are possessed at home (such as the number of books). Lastly, a dummy indicates the type of school that is attended (0, public; 1, private).

The school explanatory covariates are classified into three categories: a) the learning environment; b) the school resources; and c) the teaching practices. The role of the learning environment is analysed through two key variables: i) the school average of students' individual perceptions of the classroom climate, as expressed by the PISA index of the disciplinary climate and ii) a measure of school truancy that is expressed by the school percentage of students who had not skipped a whole school day in the two weeks prior to the PISA test. Several studies that are based on cross-country analysis of PISA data have highlighted the importance of a positive classroom climate for students' academic achievement, for example, Güzel and Berberoğlu (2005) for a sample of OECD countries and Ma *et al.* (2013) for various Asian countries. Truancy, at the school level, is also strongly associated with student performance, as demonstrated by Fantuzzo *et al.* (2005) and Henry (2007). School resources are described by the number of extracurricular activities that are provided by each school, the proportion of certified teachers, the average class size of each school and the total learning time, which is expressed in hours per week. This set of covariates is useful for investigating the relationship between school resources and the degree of educational poverty and identifying potential patterns for policy interventions at the school level. The last set of school covariates focuses on the teachers' practices, due to their importance for modelling students' achievement, as described in the seminal contribution by Wenglinsky (2002). In detail, we consider the school average of the index of adaption of instruction, which expresses how much the instruction is tailored to the students' needs, and an index that is related to the use of ICT at school.

Table 2 lists the descriptive statistics of all covariates that are used in the empirical analysis for the entire sample of students and for each subgroup of students, which are identified according to the number of learning deprivations that are suffered by the poor students.

[Table 2] around here

The outcome of interest in this study is an ordinal polytomous variable that expresses the degree of educational poverty as the number of PISA domains (from 0 to 3) in which each student is below the minimum level of competency. The nature of our dependent variable enables the use of a partial proportional odds model to predict the degree of educational poverty as a function of student and school covariates. The PPOM falls within the broader category of generalized ordered models and it bridges the gap between the ordered and multinomial regression models. Compared to the multinomial approach, PPOM accounts for the ordinal nature of the outcome variables while overcoming the limitations of the parallel line assumption, which typically characterizes ordered logistic regression. Indeed, the parallel line assumption is too restrictive and is often violated in empirical studies since it assumes that the logit coefficients for each predictor variable are the same across the categories of the ordinal outcome variable. In contrast, the PPOM allows for independent predictors to affect each level of the response differently, whereas the effects of other independent covariates are constant if they satisfy the proportional line assumption. An unconstrained partial proportional odds model is adopted, which uses a multinomial distribution and a cumulative logit link function to compute the probability for each category of the response variable.

Following the gamma formalization that was proposed by Peterson and Harrell (1990), the cumulative probabilities are estimated as:

$$C_{ij} = \Pr(Y \geq j|\mathbf{X}_i) = \frac{1}{1+\exp\left(-\delta_j - \mathbf{X}_i'\beta - \mathbf{T}_i'\gamma_j\right)}, \qquad j = 1, \dots, d, \tag{4}$$

where δ_j is the threshold for each level j of the response variable, X_i is a $p\times1$-dimensional vector that contains the values of observation i for all p predictor variables, β is a $p\times1$-dimensional vector of regression coefficients, T_i is a $q\times1$-dimensional vector ($q \leq p$) that contains the values of observation i on the subset of the p covariates where the proportional odds assumption is rejected, and γ_j is a $q\times1$-dimensional vector of regression coefficients that are associated with T_i, such that $T_i\gamma_j$ corresponds only to generic cumulative level j of the response variable, with $j = 1, \dots, d$.

The elements of γ_j are denoted by γ_{jh}, $h = 1, \dots, q$, where $\gamma_{j0} = 0$. If $\gamma_j = 0$ for all j, then the model is equal to the standard ordered logistic model. The final specification of the model includes a Wald test, which was proposed by Brant (1990), for determining whether the effect of each variable is constant across all cuts of j ($H_0{:}\,\gamma_j = 0$; $H_1{:}\,\gamma_j \neq 0$). The parameters are estimated using a maximum likelihood approach with student weights and balanced repeated replication (BRR) replicates, while the standard errors are clustered by country and school to account for the hierarchical nature of the PISA data (see the technical suggestions that are provided by OECD, 2017).

4. Results

4. 1 Multidimensional poverty estimates

This section describes the main results of the multidimensional analysis, where all three learning domains are jointly considered. In Tables 3, 4, 5 and 6, poor students are identified according to the "union method" (i.e., $k = 1$). All learning dimensions are equally weighted ($w_j = 1$ for all j).

Table 3 reports the estimates of the traditional *multidimensional educational headcount ratio* (*MEH*) and Table 4 the results for the *adjusted educational headcount ratio* (*AEH*). According to the *MEH,* in more than half of the countries (fourteen out of twenty-five) there is a reduction in the share of deprived students over the period 2006-2015, with Italy and Portugal experiencing the highest reductions. In the remaining countries of the sample, there is an increase in the *MEH*, with Finland and the Netherlands recording the worst performances (however, these countries have very low levels of educational poverty, overall). The analysis of the *AEH* supports the main results that were obtained with the *MEH*. Countries that experience a reduction (increase) in the *MEH* also report a reduction (increase) in the *AEH*; France and Czech Republic are the only two exceptions to this trend. One interesting result is that, in general, the increase in the *AEH* is larger (in absolute terms) than the increase in the *MEH*. This trend is particularly dangerous from a policy perspective, as it reveals that there is a large share of educationally poor students who are experiencing, on average, more learning deprivations. Therefore, by focusing on the *MEH,* we obtain a partial description of the poverty that ignores the number of deprivations that are suffered by poor students, which can be interpreted as a measure of the breadth of poverty.

[Table 3] around here

The *AEH* provides a snapshot of the total educational poverty. However, from a policymaker's perspective, it would be particularly useful to know which subject domain significantly contributes to the observed poverty level. To obtain this information, we decompose the *AEH* and report in Table 4 the contribution of each of the three domains, namely, science, mathematics and reading, to the overall country level of multidimensional poverty. In particular, from 2006 to 2015, science (reading) increased (decreased) its contribution to the total level of poverty in all countries except Denmark and Great Britain (Denmark and Sweden). For the contribution of mathematics, we observe a positive variation in half of the countries and a negative change in the remaining half. More important, in more than half of the countries, mathematics is the learning dimension that contributes most to the multidimensional poverty in both periods. This is particularly true in Spain and Portugal, where mathematics was responsible for 40% of the overall multidimensional poverty in 2015.

[Table 4] around here

Table 5 and Table 6 present our estimates for the *adjusted educational poverty gap index* (*AEPG*) and the *adjusted educational poverty severity index* (*AEPS*), respectively.

For those countries (eleven out of twenty-five, excluding Slovenia) that experience a reduction in the *AEH* (the average of the number of learning deprivations that are experienced by poor students), the extent of multidimensional educational poverty also decreases in terms of the

AEPG (i.e., the average size of poverty gaps declines, thereby implying that poor students are, on average, closer to the poverty lines). In addition, poverty decreases in terms of the *AEPS*. In other words, the poverty gaps of extremely poor students narrow more than those of the less poor and, as a consequence, the poor student group becomes more homogenous in terms of learning achievements. Interestingly, the educational poverty drop is more evident for larger values of parameter α.

For eight countries, positive variations of the *AEH* are associated with positive, or null, variations of the *AEPG* and the *AEPS.* In particular, we observe a sharp rise in those indicators (at least by one-fourth) for Finland, Hungary, the Netherlands, Sweden and Slovak Republic. In Austria, Lithuania and Luxembourg, the average size of the poverty gaps increases*,* while the severity of educational poverty remains constant. More specifically, the former result is driven by the increase of the size of the poverty gaps of the less poor students, which more than compensates the reduction of the magnitude of the poverty gaps of the very poor. The latter result is due to negative variations of the poverty gaps being weighted more heavily than positive ones.

However, there could be cases in which the three indicators that belong to the AF family offer an ambiguous interpretation of the trend of multidimensional educational poverty. Hence, the choice of the poverty measure is crucial in evaluating the educational poverty phenomenon over time. In Belgium, Czech Republic, Great Britain and Greece, for instance, the rise in the *AEH* is associated with a drop in the severity of multidimensional educational poverty. In other words, in these countries, the total number of learning deprivations increases, whereas the distance between the extremely poorly performing students and the educational poverty line narrows over time. These findings confirm that focusing only on a single indicator may lead to a misleading evaluation of the extent of multidimensional educational poverty over time in a country. For instance, if a policymaker aims at improving the conditions of the educationally poorest first, the *AEPS* is the most relevant indicator.

In Tables 5 and 6, we also report the contribution of each of the three domains to the overall country level of educational poverty. For the *AEH*, from 2006 to 2015, science (reading) increases (decreases) its contribution to the total level of poverty in almost all the sample. However, in contrast to the *AEH* case, reading is now the learning dimension that contributes most to multidimensional poverty, which is expressed in terms of the *AEPG* and the *AEPS*, in both periods.

[Tables 5 and 6] around here

Tables 7, 8 and 9 list the results for the *MHE*, [6] the *AEPG* and the *AEPS*, respectively, where the poor are identified according to the "intersection method" (i.e., $k = 3$) and all learning dimensions are equally weighted. As k increases from 1 to 3, which is a more demanding criterion, the estimates of educational poverty decrease; hence, not all students who are deprived in at least one subject are deprived in all learning dimensions. According to Tables 7 and 8, the overall learning deprivation intensifies for thirteen and eleven countries, respectively, with Finland, Hungary, the Netherlands and Slovak Republic showing the largest increases. When $k = 3$, the positive variations of the *MHE* and the *AEPG* are larger than the corresponding positive changes with $k = 1$ (excluding Great Britain for the *MHE* and Luxembourg for the *AEPG*). This trend represents a relevant challenge for policymakers, as it reveals substantial problems, especially for the most educationally poor students (who are identified according to the

[6] With the "intersection method", the estimates of the *MHE* and the *AEH* coincide and, thus, all learning dimensions contribute equally to multidimensional educational poverty.

“intersection method”). According to Table 9, most of the countries experience a reduction (thirteen out of twenty-five) or a null variation (seven out of twenty-five) of the severity of multidimensional educational poverty. Overall, this is an encouraging trend from an equity point of view. Lastly, among the globally poor students, the decompositions of the *AEPG* and the *AEPS* demonstrate that in both periods, reading is the learning dimension that contributes most to the depth (Table 8) and the severity (Table 9) of multidimensional educational poverty in almost all countries.

[Tables 7, 8 and 9] around here

In summary, the multidimensional estimates of poverty highlight a very heterogeneous situation across European countries. While detecting a common pattern is impossible, we observe that in many countries, overall educational poverty has increased over time. Considering the roles of various subjects in affecting multidimensional poverty, mathematics appears to be the most responsible in terms of the number of learning deprivations in most countries, while reading contributes more to multidimensional educational poverty when the aspects of depth and severity are considered. The severity of educational poverty follows a positive decreasing pattern over time in most countries.

4.2 School factors that are associated with educational poverty

This section empirically investigates the impact on educational poverty of various covariates at the student and school levels. Poverty is measured as the number of subject domains in which a student’s score is below the poverty line (i.e., the dependent variable increases from zero to three with the degree of educational poverty). An econometric analysis is conducted on a subsample of

24 EU countries. Two countries (Romania and Malta) are excluded from the original sample of EU 26 countries due to the high incidence of missing data. Table 10 reports results that are based on the unconstrained partial proportional odds model, which was introduced in Section 3.2. The first panel presents the estimates of the comparison of the first category of the dependent variable (no low proficiency, Y=0) with the other three (low performer in 1, 2 or 3 PISA domains; Y=1 ∪ Y=2 ∪ Y=3). In the second panel, the comparison is between the first two categories (Y=0 ∪ Y=1) and the remaining two (Y=2 ∪ Y=3). Lastly, the third panel compares the first three categories (Y=0 ∪ Y=1 ∪ Y=2) with the last one (Y=3). In the PPOM, the coefficients of variables that violate the parallel line assumption change according to the category of the dependent variable, while they remain constant for the covariates that satisfy that assumption. The β coefficients of the first panel in Table 10 are constant for the eight variables that satisfy the parallel line assumption (*immig*, *escs*, *priv*, *notruancy*, *proatce*, *clsize*, *total_hours* and *adinst*). The remaining panels, following the gamma parameterization that was discussed in Section 3.2, report the γ coefficients for the eight variables that violate the parallel line assumption (*female*, *forgn_lang*, *repeat*, *escs_avg*, *intict*, *disclima_avg*, *extrac_sum* and *usesch*). These coefficients represent deviations from proportionality, i.e., the difference between coefficient β_j (related to the generic cumulative level j of the response variable) and the β coefficient that is reported in the first panel. In general, coefficients β and γ indicate the strength and direction of the relationship between each variable and the probability of students being educationally poor(er). Since the dependent variable indicates the degree of educational poverty, the increase of covariates that have a positive (negative) slope is associated with a higher (lower) probability that a student will become poorer in educational terms.

We estimated the model in accordance with a stepwise logic by adding each group of variables one by one, so that the final model includes all the variables. The list of variables and their theoretical justification has been presented in section §3.2. The baseline model (Column 1) includes controls that are related to students' socio-economic backgrounds and various "general" school characteristics. The model in Column 2 demonstrates how the school learning climate affect the probability of being poor(er) in education. In the third model, we extend the baseline model with three variables that are related to school resources. In the fourth model, this group of variables is replaced by a set of variables that describe teachers' practices. Lastly, Column 5 reports the so-called "full" model, which includes all blocks of variables.

[Table 10] around here

When considering the β coefficients of panel 1, interesting findings emerge from Model 1 and remain stable across the various specifications. Students with an immigrant background and/or who do not speak the language of instruction at home are more likely to become poor in education. As expected, socio-economic status (ESCS) is strongly associated with the probability of a student being poor in education. This relationship is significant at both the student level and the school level. Therefore, students who attend schools with more advantaged peers have significantly higher chances of success. This relationship may arise for several reasons: (i) because of the direct influence of peers (peer effects), e.g., on motivation for learning; (ii) because more advantaged schools may benefit from additional resources (e.g., better teachers and local services) that are not included in the model and whose effects are therefore not distinguishable from the effect of the schools' socio-economic profile; and (iii) because students who attend more advantaged schools tend to receive stronger support from their parents and teachers. No data are available for exploring these factors further. Therefore, explanations of these patterns deserve attention as they can lead to important policy consequences. Future research will be devoted to this issue.

Model 2 sheds light on the importance of the school-learning climate. The results demonstrate that students who attend schools that have a better disciplinary climate in classrooms are significantly less likely to be poorer in education. Students are also less likely to be poorer when they attend schools where fewer students skip days of school. Both results call into action potential interventions by school management for improving the learning climate that is experienced by the students, in addition to the traditional focus on teaching quality.

Model 3 considers the relationship between school resources and the likelihood of educational poverty. The proportion of certified teachers in the school, as a proxy of the quality of human resources, is inversely related to the probability of students becoming poorer. This result confirms the importance of teacher quality, which is well discussed in the literature (Darling-Hammond, 2000). Schools with more qualified teaching staff are able to help students overcome the risk of educational poverty. It is not so much quantity as quality that matters for reducing the degree of educational poverty. Moreover, the number of extracurricular activities does not seem to play a statistically significant role in the context of educational poverty, which contrasts with previous findings about disadvantaged students who succeed academically - the so-called resilient students who were investigated by Agasisti and Longobardi (2017).

The role of variables that deal with teaching practices is examined in Model 4. All variables significantly affect the likelihood of being poor in education. In particular, both the amount of time that is devoted to learning in the three considered subjects and the capacity of teachers to adapt to the needs of students have a positive influence on insulating students from the risk of higher educational poverty. In contrast, the index on the use of ICT at school shows a significant and positive coefficient; hence, the probability of being poorer grows as the use of ICT at school increases. Although this result may seem counterintuitive, it confirms, as was already investigated in other studies, that the use of ICT at school has not yet revealed its full potential for increasing student achievement and that the positive effects are strongly dependent upon the details of ICT usage (see the discussion in Skyrabin *et al*., 2015).

Model 5 supports the robustness of previous findings. All the variables that were significantly associated with educational poverty remain so and the magnitudes of the estimated associations remain stable, even in the full model. Focusing on the gamma coefficients (panel 2 and panel 3) that are related to the variables that violate the parallel line assumption[7], most of the coefficients are related to background variables, while among the school-level factors, only the disciplinary climate shows significant differences across the cumulative categories of our outcome variable. In particular, the negative sign of the γ coefficients that are associated with the school disciplinary climate demonstrates that the school climate acts as protective factor of educational poverty and its effect increases when the highest degrees of educational poverty are considered. Due to the cumulative nature of PPOM, the results of Table 10 are not highly informative about the effects of covariates on the intermediate categories of our dependent variable. In this light, to obtain further insight into the relationship between school factors and educational poverty, we estimate the marginal effect for each school covariate at representative values of other variables (mean values for continuous variables and mode values for dichotomous variables). The marginal effects are reported in Table 11 separately for the lowest- (Bulgaria), average- (France) and highest-performing (Estonia) countries in terms of PISA scores among the EU 26 countries.

[Table 11] around here

[7] To check the parallel assumption empirically, a Wald test is performed for each variable by using the gologit (Williams, 2006) procedure of STATA software.

Overall, the marginal effects demonstrate the existence of several variables at the school level that can be manipulated to fight educational poverty. The marginal effects that are related to the first category (no low proficiency, Y=0) have a positive sign when the corresponding school factor has a positive relationship with students' achievement. Consequently, an increase of these factors leads to an increase in the probability that the (average) student is not poor in education. The magnitudes of the marginal effects are very similar in the highest categories of educational poverty; this indicates that the effect of school factors does not change as the degree of severity of educational poverty increases. As also highlighted in Table 2, the covariates with the greatest impact are those that are related to the school climate and to the ability of teachers to adapt the teaching to the needs of the students. Interestingly, these effects are stronger in the low-performing countries compared to countries that have average or high performance.

5. Policy implications and concluding remarks

In this study, the degree of learning poverty that is experienced in European countries is analysed. The analysis draws upon OECD PISA data on 15-year-old pupils' educational performances in mathematics, science, and reading in 2006 and 2015. We adopted a multidimensional approach, which has enabled us to synthetize various learning dimensions of the deprivation that is suffered by students to provide a more comprehensive measure of educational poverty. We have not limited the focus to the proportion of the student population that falls below a benchmark educational level for various learning dimensions; we have added information about the "breadth" (the number of learning deprivations that are experienced by poor students), the "depth" (how far the student's learning performance falls short of reaching the poverty line) and the “severity” of poverty (the sensitivity to inequality of learning levels amongst the poor).

The main findings can be summarized as follows: Although each country has its own peculiarities, the proportion of “educationally poor” students increased in many of them. This is not good news for European societies and should be particularly worrisome for countries that had particularly low levels of educational poverty in 2006 (see, for example, the Netherlands), which experienced sharp increases until 2015. At the same time, the gap and severity indices are reported to be decreasing in most countries during the considered period. In this light, educational poverty seems to be more under control, or at least its incidence among the most disadvantaged students appears to be slightly lower in 2015 than it was in 2006. The factors that are behind such changes have yet to be fully understood and such an understanding is well beyond the scope of this paper – and deserves future attention. Various patterns can be observed regarding the roles of single subjects (disciplines) in determining educational poverty. Mathematics appears to be the main subject that is responsible in terms of the number of learning deprivations in most countries, while reading contributes more to multidimensional educational poverty when the aspects of depth and severity are considered.

Therefore, the econometric results demonstrate that various school-level factors might have a role in affecting educational poverty. The important finding here consists of providing practical suggestions to decision-makers about measures that can be taken for fighting educational poverty effectively. Many features (especially the learning climate, quality of education and resources) can be manipulated by teachers and principals, with the aim of reducing the likelihood of students becoming educationally poor. Therefore, individual-level variables such as socio-economic background, gender and immigrant status continue to influence achievement and should be kept in mind when designing policies for reducing educational poverty.

The findings of this paper have several important policy implications:

First, the preliminary step for any governmental intervention that aims at reducing educational poverty consists of measuring the phenomenon and its evolution over time. From this perspective, the present research is innovative in adapting the empirical literature about poverty to the case of education. We leverage the opportunities that are offered by the measures of educational achievement that were developed by OECD PISA, which enable standardized comparisons of proficiency across countries. The findings that are presented here pave the way towards further research on whether changes in the countries' levels of educational poverty are associated with policy reforms during the period that is under scrutiny.

Second, educational poverty is a phenomenon that is characterized by multiple dimensions and cannot be reduced to counting the proportion of students who do not meet a sufficient level of proficiency. The (public) policy perspective that is designed for facing learning poverty should influence the choice among the various measures that are proposed in this paper. Policymakers who are paying attention to the level of learning inequality among the poor should be particularly sensitive to poverty measures that assign higher weights to students in the bottom part of the learning distribution. Putting too much emphasis on reducing the multidimensional educational headcount ratio could lead to a failure to fully address poverty among students: distributional components should also be considered when designing countries' education policies for helping disadvantaged students.

Third, school management might be a significant factor in influencing educational opportunities and, consequently, poverty. The econometric estimates that are presented in this work identify areas of school-level functioning that can reduce poverty: the disciplinary climate experiences in classes, the regular attendance of lessons, the presence of stimulating extracurricular activities, the total time that is devoted to instruction, the adaptive mode of instruction, and a higher proportion of fully certified teachers. These characteristics of schools are not realized by chance but are due to intentional actions by school teachers, leaders and heads. Recent economic literature demonstrates that school management has a significant effect and that various practices are likely conducive to better educational performance (see Bloom et *al.*, 2015 and Di Liberto et *al*., 2015). The evidence that is reported in this paper accords with this new stream of studies and adds that school organizational practices not only improve standards but can also have a subsidiary role for disadvantaged students - helping to reduce educational poverty in various aspects.

In conclusion, the study provides optimistic results for policy-makers who are dealing with the problem of educational inequity. The phenomenon of poverty is not inevitable, and policies and practices can make a difference for many students who struggle with their educational results. Measuring the extent and gravity of educational poverty is a first step in this direction, along with studying some of its main determinants. We hope to have contributed to raising awareness and suggesting avenues of change, which can be helpful for improving scholarly and policy efforts in the field.

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Table 1. Variables used for the econometric model.

Category	Variable	PISA questionnaire	Label
Familiar and school socio economic background	female	st004d01t	Gender (0=male; 1=female)
	immig	immig	Immigrant student (0=no;1=yes)
	forgn_lang	st022q01ta	Foreign language at home (0=no;1=yes)
	repeat	repeat	Grade repeat (0=no;1=yes)
	escs	ESCS	Index of Economic, Social and Cultural Status (ESCS)
	escs_avg	ESCS	School average of ESCS index
	private	sc013q01ta	Private school (0=no;1=yes)
	intict	intict	Students'ICT interest (PISA index)
School climate	disclima_avg	disclisci	School average of PISA index of disciplinary climate
	notruancy	st062q01ta	School percentage of students which never skipped a school day in the last two weeks
School resources	extrac_sum	sc053q01(-02-03-04-09-10)ta	Number of extracurricular activities at school
	proatce	proatce	Proportion of teachers fully certified
	clsize	clsize	Class size (school average)
	total_hours	MMINS, LMINS, SMINS	Total learning time expressed in hours per week (sum of learning time in reading, math and science)
Teachers practices	adinst	adinst	Adaption of instruction (PISA index)
	usesch	usesch	Use of ICT at school (PISA index)

Table 2. Descriptive statistics.

Covariates	Pooled dataset (EU-26 countries)		Number of PISA domains for which the student is poor (lower than proficiency level 2) 0		1		2		3	
	Mean	*std.dev*	*Mean*	*std.dev*	*Mean*	*std.dev*	*Mean*	*std.dev*	*Mean*	*std.dev*
female	0.496	0.5	0.502	0.5	0.496	0.5	0.5	0.5	0.457	0.498
immig	0.107	0.308	0.086	0.28	0.132	0.339	0.152	0.359	0.177	0.382
forgn_lang	0.102	0.302	0.076	0.266	0.129	0.335	0.149	0.356	0.198	0.399
repeat	0.148	0.355	0.083	0.276	0.211	0.408	0.278	0.448	0.406	0.491
escs	-0.07	0.95	0.109	0.899	-0.332	0.903	-0.491	0.921	-0.647	0.939
escs_avg	-0.067	0.547	0.06	0.518	-0.242	0.485	-0.349	0.484	-0.481	0.474
intict	0.099	1	0.123	0.916	0.12	1.116	0.036	1.188	-0.061	1.296
private	0.12	0.325	0.137	0.344	0.094	0.292	0.08	0.271	0.069	0.254
disclima_avg	-0.081	0.395	-0.033	0.37	-0.138	0.405	-0.175	0.42	-0.252	0.44
notruancy	0.791	0.183	0.812	0.171	0.755	0.196	0.739	0.202	0.72	0.204
extrac_sum	3.371	1.963	3.465	1.972	3.285	1.942	3.174	1.926	3.024	1.902
proatce	0.88	0.252	0.891	0.238	0.859	0.272	0.862	0.274	0.84	0.291
clsize	25.332	6.126	25.886	5.925	24.538	6.122	24.239	6.468	23.406	6.503
total_mins	636.941	231.464	644.415	205.029	622.91	264.49	617.483	287.90	610.165	314.49
adinst	-0.066	0.999	-0.056	0.999	-0.099	1.01	-0.112	0.979	-0.075	1.003
usesch	0.007	0.938	-0.06	0.86	0.134	1.03	0.172	1.099	0.246	1.161

Table 3. Multidimensional educational headcount ratio (MEH) - union method ($k = 1$).

European Country	PISA 2006 estimate	PISA 2015 estimate	Var.%
AUT	0.288	0.306	6.25%
BEL	0.255	0.274	7.45%
BGR	0.634	0.521	-17.82%
CZE	0.307	0.304	-0.98%
DEU	0.267	0.242	-9.36%
DNK	0.247	0.229	-7.29%
ESP	0.347	0.282	-18.73%
EST	0.185	0.174	-5.94%
FIN	0.084	0.189	125%
FRA	0.311	0.303	-2.57%
GBR	0.275	0.296	7.63%
GRC	0.43	0.436	1.39%
HUN	0.289	0.366	26.64%
IRL	0.228	0.207	-9.21%
ITA	0.425	0.334	-21.41%
LTU	0.341	0.353	3.52%
LUX	0.312	0.347	11.22%
LVA	0.308	0.281	-8.77%
MLT	m	0.437	m
NLD	0.195	0.255	30.77%
POL	0.274	0.245	-10.58%
PRT	0.381	0.295	-22.57%
ROU	0.67	0.541	-19.25%
SVK	0.346	0.411	18.79%
SVN	0.251	0.234	-6.77%
SWE	0.256	0.297	16.01%

Note: The estimates are based on data from PISA 2006 and 2015 cycles. Data on learning achievements are not available in PISA 2006 dataset for Malta. The results are produced by author's calculations by using DASP (Distributive Analysis Stata Package; Abdelkrim and Duclos, 2007) software.

Table 4. Adjusted educational headcount ratio (AEH, $\alpha = 0$) and its decomposition by learning dimensions - union method ($k = 1$).

European Country	PISA 2006 estimate	PISA 2015 estimate	Var.%	Decomposition 2006			Decomposition 2015		
				reading	*math*	*science*	*reading*	*math*	*science*
AUT	0.191	0.217	13.61%	37.36	33.97	28.66	34.05	33.82	32.13
BEL	0.180	0.197	9.44%	35.67	32.44	31.89	32.83	33.24	33.93
BGR	0.487	0.408	-16.22%	34.50	36.55	28.95	34.04	34.16	31.79
CZE	0.198	0.215	8.58%	41.14	32.57	26.29	34.30	33.67	32.03
DEU	0.187	0.165	-11.76%	35.42	35.95	28.63	31.47	34.19	34.34
DNK	0.157	0.147	-6.37%	33.64	27.92	38.44	34.68	29.32	36.00
ESP	0.234	0.190	-18.80%	36.51	35.12	28.37	27.61	39.68	32.71
EST	0.111	0.104	-6.31%	41.07	35.58	23.34	35.99	37.39	26.62
FIN	0.047	0.120	155.31%	32.91	39.50	27.59	29.20	38.49	32.31
FRA	0.221	0.221	0.00%	32.97	34.26	32.76	31.99	35.05	32.96
GBR	0.185	0.196	5.94%	33.57	35.47	30.95	31.21	38.83	29.96
GRC	0.281	0.322	14.59%	33.01	37.91	29.09	28.35	37.06	34.59
HUN	0.190	0.272	43.15%	36.03	37.33	26.64	33.97	34.35	31.68
IRL	0.148	0.135	-8.78%	27.88	36.99	35.13	24.16	36.97	38.87
ITA	0.281	0.225	-19.93%	31.04	38.8	30.17	30.03	35.30	34.67
LTU	0.232	0.251	8.19%	37.02	33.11	29.87	33.31	34.01	32.68
LUX	0.226	0.257	13.72%	34.00	33.44	32.56	33.48	32.84	33.68
LVA	0.200	0.186	-7.00%	36.60	34.10	29.30	30.56	38.78	30.66
MLT	m	0.324	m	m	m	m	36.03	30.73	33.24
NLD	0.131	0.176	34.35%	38.66	28.8	32.54	33.79	31.26	34.95
POL	0.179	0.162	-9.50%	30.19	37.44	32.37	30.62	35.41	33.97
PRT	0.269	0.198	-26.39%	31.39	38.28	30.33	28.99	40.56	30.45
ROU	0.514	0.394	-23.35%	34.54	34.77	30.69	33.05	34.38	32.57
SVK	0.230	0.304	32.17%	40.21	30.28	29.51	35.26	31.15	33.59
SVN	0.159	0.154	-3.14%	34.13	36.21	29.66	32.68	34.55	32.77
SWE	0.165	0.200	21.21%	30.12	36.69	33.19	30.37	33.45	36.18

Note: The estimates are based on data from PISA 2006 and 2015 cycles. Data on learning achievements are not available in PISA 2006 dataset for Malta. The results are produced by author's calculations by using DASP (Distributive Analysis Stata Package; Abdelkrim and Duclos, 2007) software.

Table 5. Adjusted educational poverty gap index ($AEPG, \alpha = 1$) and its decomposition by learning dimensions - union method ($k = 1$).

European Country	PISA 2006 estimate	PISA 2015 estimate	Var.%	Decomposition 2006			Decomposition 2015		
				reading	*math*	*science*	*reading*	*math*	*science*
AUT	0.028	0.030	7.14%	44.31	31.34	24.35	38.32	32.93	28.75
BEL	0.029	0.027	-6.90%	41.95	31.15	26.90	35.21	31.36	33.43
BGR	0.100	0.075	-25.00%	40.33	34.16	25.52	39.65	31.88	28.47
CZE	0.029	0.028	-3.45%	48.72	30.18	21.10	38.81	32.50	28.69
DEU	0.029	0.021	-27.59%	44.85	31.73	23.42	34.80	32.04	33.16
DNK	0.019	0.017	-10.53%	37.23	25.07	37.71	37.49	24.56	37.95
ESP	0.032	0.023	-28.13%	41.12	33.38	25.50	34.16	29.22	36.63
EST	0.012	0.010	-16.67%	48.22	32.82	18.95	38.78	33.32	27.90
FIN	0.004	0.014	250.00%	33.26	38.58	28.16	33.32	34.59	32.09
FRA	0.033	0.033	0.00%	38.78	29.84	31.38	36.44	32.55	31.02
GBR	0.025	0.025	0.00%	38.83	29.71	31.46	32.37	40.53	27.11
GRC	0.046	0.048	4.35%	37.75	36.48	25.77	30.55	36.33	33.12
HUN	0.025	0.039	56.00%	42.69	35.52	21.79	35.56	33.8	30.63
IRL	0.017	0.014	-17.65%	30.07	33.04	36.89	24.41	35.31	40.28
ITA	0.045	0.030	-33.33%	37.51	36.69	25.80	31.87	34.69	33.44
LTU	0.031	0.032	3.23%	42.21	31.66	26.13	37.62	31.82	30.56
LUX	0.033	0.035	6.06%	37.91	30.52	31.57	38.84	29.77	31.39
LVA	0.024	0.020	-16.67%	40.44	32.41	27.15	34.07	37.32	28.61
MLT	m	0.064	m	m	m	m	40.47	28.40	31.13
NLD	0.016	0.022	37.50%	48.7	22.26	29.04	37.40	29.53	33.07
POL	0.021	0.018	-14.29%	36.64	33.82	29.54	32.49	35.06	32.45
PRT	0.039	0.025	-35.90%	35.71	37.88	26.41	29.76	42.95	27.29
ROU	0.087	0.058	-33.33%	40.25	33.10	26.65	37.89	33.20	28.91
SVK	0.036	0.050	38.89%	46.72	28.57	24.71	39.40	28.81	31.79
SVN	0.018	0.018	0.00%	38.84	33.04	28.11	36.75	31.62	31.64
SWE	0.021	0.028	33.33%	35.44	32.53	32.02	29.64	38.97	31.39

Note: The estimates are based on data from PISA 2006 and 2015 cycles. Data on learning achievements are not available in PISA 2006 dataset for Malta. The results are produced by author's calculations by using DASP (Distributive Analysis Stata Package; Abdelkrim and Duclos, 2007) software.

Table 6. Adjusted educational poverty severity index ($AEPS, \alpha = 2$) and its decomposition by learning dimensions - union method ($k = 1$).

European Country	PISA 2006 estimate	PISA 2015 estimate	Var.%	Decomposition 2006			Decomposition 2015		
				reading	*math*	*science*	*reading*	*math*	*science*
AUT	0.007	0.007	0.00%	52.69	27.18	20.13	41.99	32.81	25.20
BEL	0.008	0.006	-25.00%	46.26	31.28	22.46	37.61	30.20	32.19
BGR	0.031	0.021	-32.26%	46.54	31.51	21.95	45.08	29.71	25.21
CZE	0.008	0.006	-25.00%	55.87	27.32	16.81	44.33	31.64	24.03
DEU	0.008	0.005	-37.50%	56.52	25.96	17.52	38.22	30.94	30.84
DNK	0.004	0.003	-25.00%	41.25	22.54	36.2	41.49	20.67	37.84
ESP	0.008	0.005	-37.50%	45.78	31.58	22.63	39.22	25.23	35.56
EST	0.002	0.002	0.00%	54.90	30.21	14.89	40.88	31.02	28.10
FIN	0.001	0.003	200.00%	35.55	36.62	27.83	38.93	30.51	30.56
FRA	0.008	0.008	0.00%	45.01	25.55	29.44	40.64	30.20	29.16
GBR	0.006	0.005	-16.67%	43.60	24.48	31.92	33.82	42.05	24.12
GRC	0.013	0.012	-7.69%	42.80	34.59	22.61	33.19	36.01	30.80
HUN	0.006	0.009	50.00%	49.73	33.21	17.06	36.88	33.14	29.98
IRL	0.003	0.002	-33.33%	32.35	29.64	38.01	24.67	33.94	41.39
ITA	0.012	0.007	-41.67%	44.94	33.58	21.47	32.65	35.66	31.68
LTU	0.007	0.007	0.00%	46.32	30.58	23.10	42.17	30.06	27.77
LUX	0.008	0.008	0.00%	42.42	27.81	29.77	44.85	26.99	28.15
LVA	0.005	0.004	-20.00%	44.40	30.77	24.83	37.90	36.32	25.78
MLT	m	0.020	m	m	m	m	44.39	26.81	28.80
NLD	0.004	0.005	25.00%	61.54	15.66	22.80	41.76	28.06	30.19
POL	0.004	0.003	-25.00%	43.61	30.09	26.30	34.59	34.41	31.00
PRT	0.009	0.005	-44.44%	40.65	37.02	22.33	31.06	44.88	24.06
ROU	0.023	0.014	-39.13%	45.96	31.40	22.64	43.78	31.39	24.83
SVK	0.010	0.013	30.00%	52.42	27.48	20.10	43.97	26.91	29.12
SVN	0.004	0.004	0.00%	44.82	29.6	25.58	41.48	28.78	29.74
SWE	0.005	0.007	40.00%	41.10	28.64	30.26	32.87	37.81	29.32

Note: The estimates are based on data from PISA 2006 and 2015 cycles. Data on learning achievements are not available in PISA 2006 dataset for Malta. The results are produced by author's calculations by using DASP (Distributive Analysis Stata Package; Abdelkrim and Duclos, 2007) software.

Table 7. Multidimensional educational headcount ratio (*MEH*) - intersection method ($k = 3$).

European Country	PISA 2006 estimate	PISA 2015 estimate	Var.%
AUT	0.103	0.137	33.01%
BEL	0.111	0.125	12.61%
BGR	0.349	0.3	-14.04%
CZE	0.106	0.133	25.47%
DEU	0.114	0.094	-17.54%
DNK	0.075	0.07	-6.67%
ESP	0.134	0.103	-23.13%
EST	0.052	0.049	-5.77%
FIN	0.017	0.06	252.94%
FRA	0.135	0.143	5.92%
GBR	0.108	0.108	0%
GRC	0.155	0.209	34.84%
HUN	0.103	0.184	78.64%
IRL	0.073	0.065	-10.96%
ITA	0.153	0.121	-20.91%
LTU	0.137	0.156	13.87%
LUX	0.148	0.166	12.16%
LVA	0.108	0.105	-2.78%
MLT	m	0.221	m
NLD	0.073	0.106	45.20%
POL	0.096	0.083	-13.54%
PRT	0.166	0.109	-34.34%
ROU	0.363	0.248	-31.68%
SVK	0.131	0.204	55.72%
SVN	0.08	0.082	2.50%
SWE	0.086	0.108	25.58%

Note: The estimates are based on data from PISA 2006 and 2015 cycles. Data on learning achievements are not available in PISA 2006 dataset for Malta. The results are produced by author's calculations by using DASP (Distributive Analysis Stata Package; Abdelkrim and Duclos, 2007) software.

Table 8. Adjusted educational poverty gap index ($AEPG$, $\alpha = 1$) and its decomposition by learning dimensions - intersection method ($k = 3$).

European Country	PISA 2006 estimate	PISA 2015 estimate	Var.%	Decomposition 2006			Decomposition 2015		
				reading	*math*	*science*	*reading*	*math*	*science*
AUT	0.019	0.024	26.32%	41.55	31.15	27.30	37.81	32.28	29.92
BEL	0.023	0.021	-8.70%	40.38	31.64	27.98	35.04	31.51	33.44
BGR	0.085	0.065	-23.53%	39.62	32.81	27.57	38.97	31.60	29.43
CZE	0.020	0.022	10.00%	43.04	31.35	25.61	38.29	32.18	29.53
DEU	0.022	0.016	-27.27%	43.19	30.80	26.01	35.65	31.41	32.93
DNK	0.013	0.011	-15.38%	36.81	27.14	36.05	36.59	26.12	37.29
ESP	0.023	0.016	-30.43%	38.79	32.93	28.27	33.04	33.74	33.23
EST	0.007	0.006	-14.29%	42.88	32.73	24.39	35.47	31.40	33.13
FIN	0.002	0.010	400.00%	33.45	33.86	32.69	35.93	31.22	32.86
FRA	0.025	0.027	8.00%	38.91	28.78	32.31	36.88	31.09	32.03
GBR	0.020	0.017	-15.00%	38.32	28.59	33.09	33.92	36.57	29.51
GRC	0.033	0.039	18.18%	38.19	33.57	28.24	33.33	33.65	33.02
HUN	0.018	0.032	77.78%	40.94	33.89	25.17	34.83	32.91	32.26
IRL	0.012	0.009	-25.00%	33.25	30.94	35.81	29.75	32.01	38.24
ITA	0.032	0.021	-34.38%	38.73	33.48	27.79	32.89	33.08	34.04
LTU	0.023	0.025	8.70%	38.65	32.42	28.93	37.35	31.27	31.38
LUX	0.027	0.028	3.70%	37.96	29.85	32.19	38.39	29.85	31.76
LVA	0.017	0.015	-11.76%	37.54	32.48	29.98	35.76	33.52	30.71
MLT	m	0.054	m	m	m	m	38.80	29.60	31.60
NLD	0.012	0.017	41.67%	46.52	23.84	29.63	37.31	30.67	32.02
POL	0.015	0.012	-20.00%	38.22	30.84	30.94	33.88	32.65	33.47
PRT	0.030	0.018	-40.00%	36.77	35.13	28.10	32.37	37.94	29.69
ROU	0.072	0.045	-37.50%	38.99	32.64	28.37	38.33	32.59	29.08
SVK	0.026	0.041	57.69%	41.73	31.05	27.21	38.24	29.79	31.97
SVN	0.012	0.012	0.00%	37.47	31.30	31.23	36.44	29.74	33.82
SWE	0.015	0.020	33.33%	37.40	30.18	32.42	35.65	28.89	35.46

Note: The estimates are based on data from PISA 2006 and 2015 cycles. Data on learning achievements are not available in PISA 2006 dataset for Malta. The results are produced by author's calculations by using DASP (Distributive Analysis Stata Package; Abdelkrim and Duclos, 2007) software.

Table 9. Adjusted educational poverty severity index ($AEPS$, $\alpha = 2$) and its decomposition by learning dimensions - intersection method ($k = 3$).

European Country	PISA 2006 estimate	PISA 2015 estimate	Var.%	Decomposition 2006			Decomposition 2015		
				reading	*math*	*science*	*reading*	*math*	*science*
AUT	0.006	0.006	0.00%	50.67	27.44	21.89	41.80	32.02	26.18
BEL	0.007	0.005	-28.57%	45.16	31.56	23.27	37.25	30.45	32.30
BGR	0.029	0.020	-31.03%	46.09	30.88	23.04	44.57	29.58	25.86
CZE	0.006	0.005	-16.67%	52.11	28.37	19.53	44.14	31.30	24.56
DEU	0.007	0.004	-42.86%	54.86	26.08	19.05	38.56	30.54	30.90
DNK	0.003	0.002	-33.33%	40.82	23.45	35.74	40.95	21.28	37.77
ESP	0.006	0.004	-33.33%	43.96	31.70	24.34	35.27	33.35	31.38
EST	0.002	0.001	-50.00%	50.79	31.02	18.19	37.48	30.58	31.94
FIN	0.001	0.002	100.00%	35.14	33.33	31.54	40.86	28.25	30.89
FRA	0.007	0.007	0.00%	45.15	24.58	30.27	40.65	29.30	30.05
GBR	0.005	0.004	-20.00%	43.19	23.88	32.93	34.90	39.19	25.91
GRC	0.010	0.010	0.00%	43.14	32.62	24.24	35.02	34.09	30.89
HUN	0.005	0.008	60.00%	48.54	32.60	18.86	36.34	32.35	31.31
IRL	0.003	0.002	-33.33%	34.06	28.51	37.42	27.94	31.41	40.65
ITA	0.010	0.005	-50.00%	45.56	31.65	22.79	32.59	34.27	33.14
LTU	0.006	0.006	0.00%	43.44	31.36	25.20	41.58	29.72	28.70
LUX	0.007	0.007	0.00%	42.66	27.16	30.18	44.10	27.10	28.80
LVA	0.004	0.003	-25.00%	42.60	30.85	26.55	38.94	33.52	27.54
MLT	m	0.019	m	m	m	m	43.49	27.35	29.16
NLD	0.003	0.004	33.33%	60.56	16.23	23.21	41.94	28.72	29.34
POL	0.003	0.003	0.00%	44.26	28.04	27.70	35.31	32.51	32.18
PRT	0.008	0.004	-50.00%	41.33	35.36	23.31	32.9	41.44	25.66
ROU	0.021	0.012	-42.86%	44.88	31.41	23.71	44.26	30.93	24.81
SVK	0.008	0.012	50.00%	48.88	29.39	21.73	43.18	27.45	29.37
SVN	0.003	0.003	0.00%	43.18	28.50	28.32	40.96	26.81	32.23
SWE	0.004	0.005	25.00%	42.66	26.59	30.74	40.01	24.88	35.11

Note: The estimates are based on data from PISA 2006 and 2015 cycles. Data on learning achievements are not available in PISA 2006 dataset for Malta. The results are produced by author's calculations by using DASP (Distributive Analysis Stata Package; Abdelkrim and Duclos, 2007) software.

Table 10. School factors associated with the probability of students being educationally poor.

			Y= 0 vs Y=1 ∪ Y= 2 ∪ 3		
	β coeff.	*β coeff.*	*β coeff.*	*β coeff.*	*β coeff.*
female	0.018	0.051***	0.025	0.071***	0.104***
immig	0.229***	0.204***	0.234***	0.224***	0.205***
forgn_lang	0.383***	0.409***	0.373***	0.350***	0.365***
repeat	1.516***	1.476***	1.499***	1.525***	1.471***
escs	-0.320***	-0.325***	-0.316***	-0.341***	-0.346***
escs_avg	-1.513***	-1.275***	-1.457***	-1.469***	-1.196***
intict	-0.123***	-0.123***	-0.123***	-0.185***	-0.183***
priv	0.072	0.105**	0.071	0.085*	0.107**
disclima_avg		-0.592***			-0.554***
notruancy		-1.790***			-1.683***
extrac_sum			-0.03***		-0.018**
proatce			-0.137***		-0.113***
clsize			-0.010***		-0.012***
total_hours			-0.019***		-0.017***
adinst				-0.099***	-0.080***
usesch				0.370***	0.353***
			Deviations from proportionality (Y= 0 ∪ 1 vs Y= 2 ∪ 3)		
	γ coeff.	*γ coeff.*	*γ coeff.*	*γ coeff.*	*γ coeff.*
female	-0.017	-0.013	-0.017	-0.008	-0.005
forgn_lang	0.041**	0.038*	0.044**	0.039**	0.040*
repeat	-0.038***	-0.031	-0.041**	-0.036*	-0.033*
escs_avg	-0.050***	-0.042***	-0.048***	-0.043***	-0.035**
intict	-0.033***	-0.031***	-0.033***	-0.036***	-0.035***
disclima_avg		-0.050***			-0.045**
extrac_sum			-0.007*		-0.007
usesch				0.003	0.001
			Deviations from proportionality (Y= 0 ∪ 1 ∪ 2 vs Y= 3)		
	γ coeff.	*γ coeff.*	*γ coeff.*	*γ coeff.*	*γ coeff.*
female	-0.094***	-0.088***	-0.094***	-0.085***	-0.080***
forgn_lang	0.073**	0.067**	0.078***	0.073**	0.073**
repeat	-0.047	-0.034	-0.049*	-0.048*	-0.036
escs_avg	-0.087***	-0.073***	-0.085***	-0.073***	-0.059**
intict	-0.062***	-0.059***	-0.062***	-0.067***	-0.064***
disclima_avg		-0.099***			-0.093***
extrac_sum			-0.003		-0.002
usesch				-0.003	-0.007
			thresholds		
	α coeff.	*α coeff.*	*α coeff.*	*α coeff.*	*α coeff.*
threshold1	-1.041***	0.515***	-0.464***	-1.244***	0.794***
threshold2	-1.772***	-0.239**	-1.338***	-1.998***	0.043
threshold3	-2.532***	-1.021***	-1.946***	-2.770***	-0.767***

Note: Results from the Partial Proportional Odds Model (PPOM) - stepwise logistic regression, by macro-category of explanatory variables. The econometric analysis is conducted on a subsample of 24 Eu-countries. Two countries (Romania and Malta) are excluded from the original sample of Eu 26 countries due to high presence of missing data. Significance: * 10 %; ** 5 %; *** 1 %. Labels about the variables' names are reported in the Table 1, with the descriptive statistics reported in Table 2.

11. Marginal effects of school covariates on the students' probability to be educationally poor.

	Bulgary (lowest performing country)				**France (average performing country)**				**Estonia (highest performing country)**			
	Number of PISA domains for which the student is poor (lower than proficiency level 2)				*Number of PISA domains for which the student is poor (lower than proficiency level 2)*				*Number of PISA domains for which the is poor (lower than proficiency leve*			
	0	*1*	*2*	*3*	*0*	*1*	*2*	*3*	*0*	*1*	*2*	
a	0.083***	-0.032***	-0.023***	-0.028***	0.048***	-0.021***	-0.013***	-0.014***	0.037***	-0.017***	-0.01***	-0
cy	0.252***	-0.109***	-0.071***	-0.072***	0.145***	-0.071***	-0.039***	-0.035***	0.112***	-0.056***	-0.03***	-0
	0.003**	-0.001	-0.001***	-0.001**	0.002**	0.000	-0.001***	0.000**	0.001**	0.000	-0.001***	0.
e	0.017**	-0.007**	-0.005**	-0.005**	0.01**	-0.005**	-0.003**	-0.002**	0.008**	-0.004**	-0.002**	-0
	0.002***	-0.001***	-0.001***	-0.001***	0.001***	-0.001***	0.000***	0.000***	0.001***	0.000***	0.000***	0.
rs	0.003***	-0.001***	-0.001***	-0.001***	0.002***	-0.001***	0.000***	0.000***	0.001***	-0.001***	0.000***	0.
	0.012***	-0.005***	-0.003***	-0.003***	0.007***	-0.003***	-0.002***	-0.002***	0.005***	-0.003***	-0.001***	-0
	-0.053	0.023	0.015	0.015	-0.03***	0.015***	0.008***	0.007***	-0.024***	0.012***	0.006***	0.

he econometric analysis is conducted on a subsample of 24 Eu-countries. Two countries (Romania and Malta) are excluded from the original sa ountries due to high presence of missing data. Significance: * 10 %; ** 5 %; *** 1 %. Labels about the variables' names are reported in the Table riptive statistics reported in Table 2.