EDUCATIONAL ATTAINMENT AND EQUALITY OF OPPORTUNITY IN PORTUGAL AND IN EUROPE: THE ROLE OF SCHOOL VERSUS PARENTAL INFLUENCE*

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1. INTRODUCTION

Economics of education is rooted in economic theories studying human capital. One of its branches is concerned with understanding what happens in schools, i.e. the way performance interacts with a multitude of factors such as the characteristics and family background of students, school resources and institutional features of the educational systems. This relates to several research agendas, beginning with the effective use of resources. Education accounts for a large share of government expenditure in almost all countries. People care about whether spending additional money will improve educational outcomes, or whether a given outcome can be attained by spending less. Research has suggested that pure resource policies may not be very effective, unless they are accompanied by changes in incentives. In this context, it is important to consider institutional features, e.g. school autonomy, among the determinants of performance. Another related research agenda arises from the stylized fact that family background plays a key role in achievement, repeatedly confirmed by research since the publication of the well-known Coleman report (Coleman, 1966). A high degree of dependence of outcomes on socioeconomic background is, however, an undesirable feature of educational systems, for in this case schooling does not contribute to attenuating social inequality. However, policy interventions can only work if the underlying mechanisms are well understood. For instance, socioeconomic status needs not determine achievement directly; it may determine instead which schools students select into, and inequality may be mostly between schools.

The objective of this study is to gather insight about such issues for Portugal and several European Union countries, on the basis of the data made available by the OECD Programme for International Student Assessment (PISA) of 2006. PISA comprises cross-country tests of educational achievement, assessing students' literacy in mathematics, science and reading at the end of their compulsory education. The tests assess students' capacity to use the acquired knowledge in situations that occur in the real world, rather than the learning of specific curricula. PISA is an ongoing survey that has been administered in three-year cycles; to date, surveys were conducted in 2000, 2003, 2006 and 2009. This study uses data from the last cycle available at the time of writing which is 2006.[1] Besides the OECD countries, an increasing number of partner countries have participated in the Programme (in 2006, this extended to 57 countries).

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(1) The results of PISA 2009 became available after the completion of this study.

International student achievement surveys such as PISA are important tools for countries to monitor the quality of their educational systems, to the extent that they make available data whose collection process and definition are comparable across countries. PISA outcomes have been exhaustively debated by the national media and the different players in the educational process in several of the participating countries (see Fuchs and Woessmann, 2007). At the same time, such surveys have become a key input to empirical analysis in economics of education (Hanushek and Woessmann, 2010). The PISA dataset includes, in addition to test scores, a great deal of information about the students and their socio-economic background and school characteristics and resources. An obvious advantage of this type of data *vis-à-vis* national datasets is the possibility of assessing the importance of an estimated impact by comparing it with the same estimate for other countries. For example, the coefficients of family background measures in country regressions explaining test scores can be seen as indicators of equality of opportunities. Moreover for some variables, as those relating to the institutional design of educational systems, within-country variation is typically small or absent. Cross-country datasets are needed to enable researchers to identify the influence of such variables.

This study estimates education production functions, regressing student performance measured by test scores on a wide set of explanatory variables. These comprise at the student level, for example, gender, grade, age, parents' education and occupations, immigration background, and indicators of wealth and educational resources at home. At the school level the covariates include the student/teacher ratio, class size, measures of teacher shortages, school size and location, public/private status and indicators of autonomy. Separate education production functions are estimated for test scores in mathematics and reading. In order to guarantee a higher socioeconomic and cultural homogeneity throughout the countries considered and minimize the importance of omitted factors, we have confined our attention to the OECD participants in the Program that are members of the European Union (with the exception of France owing to a total absence of school data).

As convenient for the analysis, this study focuses on either the full set of countries or groups of them. For instance, education production functions are estimated for Portugal and the sets of three countries with the best- and worst-performing students, respectively. This makes it possible to assess to what extent differences in achievement (as far as the model can explain it) have to do with differences in the contribution of specific covariates i.e. the coefficients of the production function. Such an approach differs from other studies (e.g. Woessmann, 2003) that estimate a single education production function for all countries as a whole, in order to exploit the cross-country variability in the explanatory variables. With this sort of regressions, one can also assess whether, after controlling for a wide set of covariates, the initial differences in relative performance across countries remain. For instance, one can investigate to what extent the low educational level of the population in Portugal can explain the gap to the average of scores of Portuguese students, given that parents' education is a determinant of achievement. The study ends with an analysis of the variance of scores and the role social inequality plays in it. In this context, given that students are grouped within schools, it is important to ascertain whether performance variability is a between-school or within-school phenomenon. The study starts with a descriptive digression through the PISA 2006 database.

2. THE PISA 2006 DATABASE AND SOME DESCRIPTIVE RESULTS

PISA tests are taken by a representative sample of the population of students around the age of 15[2] who attend schools in a given country and are in the 7th or higher grades. In general the design of the survey takes the form of two-stage stratified sampling, where schools are drawn randomly in a first stage and students within them in a second one. For instance, for Portugal 173 schools were selected at the first stage and 40 students (or all eligible students, when less than 40) were subsequently randomly selected in each of those schools. The bulk of PISA data other than test scores comes from two questionnaires, respectively filled out by students and by schools. The 2006 database encompasses 5 109 students in Portugal and 131 598 students in the set of countries under consideration.

Students included in the PISA sample are not equally representative in terms of the population, and the database is provided with final student weights that reflect sampling probabilities and other factors such as non-response. Point estimates of descriptive statistics or model parameters for the population have to be drawn weighting student observations accordingly. Test scores in PISA are reported in the form of five plausible values for each subject - mathematics, reading and science - which correspond to random draws from the estimated distribution of student's abilities (see OECD, 2009, Chapter 6). Population statistics, including model parameters, are generally obtained by averaging over the corresponding statistics computed separately for each plausible value. Their variance comes from two sources: the sampling variance and the so-called imputation variance which reflects the measurement error in the tests (OECD, 2009, Chapter 8).

We firstly present the mean of mathematics and reading scores (Charts 1A and 1B) for the set of countries considered which includes Austria, Belgium, the Czech Republic, Denmark, Finland, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Poland, Portugal, Slovakia, Spain, Sweden, and the United Kingdom. Note that test scores are standardized to have a mean of 500 and a standard deviation of 100 across OECD countries. Portuguese students ranked 16th in mathematics and 14th in reading among these 18 countries in PISA 2006. This poor outcome does not differ overly from previous surveys.[3]

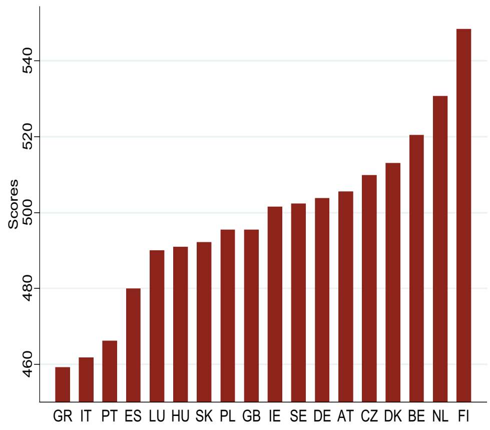
In order to benchmark the results for Portugal against those in other countries, we selected (weighting equally the rankings for the two subjects considered) two groups with the three best- and worst-performing countries. The first group includes Belgium, Finland and the Netherlands, and the second Greece, Italy and Spain. Portugal's achievement levels are very similar to the ones in this second set of countries, with which it also shares certain socio-economic and cultural traits. The

(2) More precisely, students are between 15 years and 3 months and 16 years and 3 months old. As explained below, such small age differences have an impact on performance because, combined with the student grade, they may capture a grade repetition effect.

(3) In PISA 2009 the position of the Portuguese students improved markedly, in particular for reading in which the average score is not significantly different from the OECD average in statistical terms. Portugal occupies, respectively, the 11th and 15th position in reading and mathematics within the same group of 18 countries in the last PISA.

Chart 1A

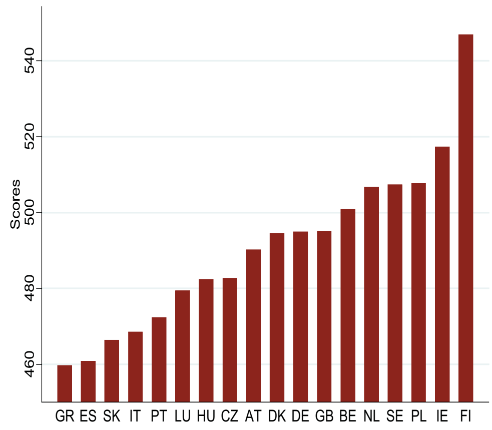
PERFORMANCE IN MATHEMATICS BY COUNTRY
Mean score



Source: Author's calculations on the basis of the PISA 2006 database.
Note: Average of the weighted averages for each plausible value.

Chart 1B

PERFORMANCE IN READING BY COUNTRY
Mean score



Source: Author's calculations on the basis of the PISA 2006 database.
Note: See previous chart.

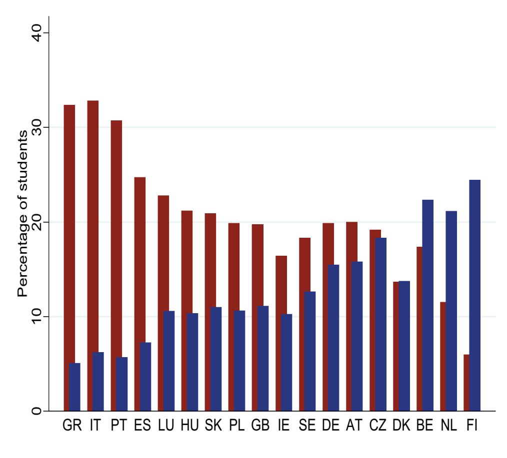
distributions of test scores (not shown) almost coincide for Portugal and the low performers. The distributions for the top performers are comparatively shifted to the right, but the dispersion is comparable. For instance, the inter-quartile range divided by the mean is 0.27 for mathematics scores in Portugal and the low-performing countries, and 0.25 for the high performers; for reading scores, these figures are between 0.26 and 0.28. The range of scores in PISA is divided into 6 successive proficiency levels which are associated with the increased difficulty of the tasks the students must perform. Charts 2A and 2B present the proportion of students, respectively, at level 1 and below and at level 5 and above, with the countries ordered in accordance with the mean score. As the mean score increases, the proportion of students at lower proficiency levels tends to go down and at higher levels to go up. However, some countries such as Austria, Belgium, the Czech Republic and Germany, have a great proportion of students at low proficiency levels for the country's average performance, indicating a higher dispersion of scores (we shall return to this issue in section 4).

Table 1 shows the characteristics of the student population, their families and schools for Portugal, breaking down further between public and private schools, and in the benchmark groups. These are the variables included in the education production functions to be estimated in the next section. In countries in which the compulsory school starting age is at six, students are mostly distributed between the 9th and the 10th grade (reflecting the specific rules regarding the birth date). This is the case of Portugal and all countries in the two groups except Finland, where school starts at seven and almost all students are in the 9th grade.[4] A reasonably high number of Portuguese students - around 20 per cent - are still in grades 7th or 8th due to higher repeating rates.

(4) More generally, in the full set of countries considered, the school starting age ranges from four or five in the United Kingdom to seven in Denmark, Finland, Poland and Sweden.

Chart 2A

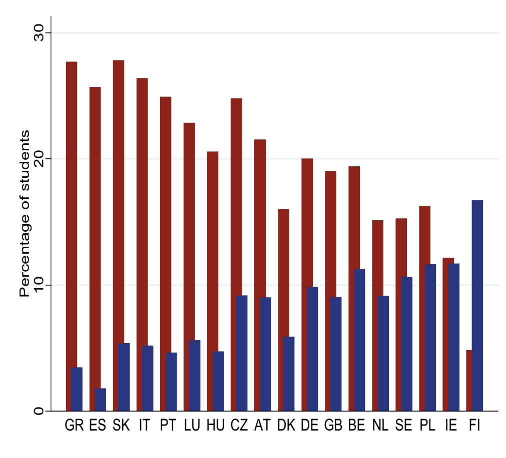
PROFICIENCY IN MATHEMATICS BY COUNTRY
Students at level 1 and below (in red) and at level 5 and above (in blue)



Source: Author's calculations on the basis of the PISA 2006 database.
Note: Average of percentages for each plausible value.

Chart 2B

PROFICIENCY IN READING BY COUNTRY
Students at level 1 and below (in red) and at level 5 and above (in blue)



Source: Author's calculations on the basis of the PISA 2006 database.
Note: See previous chart.

Concerning family background, the gap between Portugal and the best performers is particularly large in the case of parents' education and occupations. For instance, in Portugal around 25 percent of students have at least one parent in a white-collar/high-skilled occupation, and about 20 percent have at least one parent with a tertiary education level. These percentages are close to 60 per cent for the countries where students perform best. Furthermore, less than 5 percent of students in these countries indicated that the highest education level of their parents was primary education, against almost 40 per cent of Portuguese students. The same type of gap occurs, albeit to a lesser extent, *vis-à-vis* the low performing countries. The wealth indicator (computed from answers on household possessions of durable goods) has a higher average figure for the high-performing countries, as one would expect from the fact that they are richer. In contrast, the indicator for educational resources at home has a similar level throughout countries. The proportion of immigrant students is slightly higher in the best-performing countries than in Portugal and the worst-performing group (about 10 percent against 5 percent). For Portugal, students attending private schools come from advantaged households, as shown by the wealth indicator and particularly the upper cohorts of parents' education and occupations.

We now proceed to school variables. The share of private schools differs substantially between the best-performing countries (more than 50 percent),[5] and Portugal and worst performers (around 10 percent). Schools in Portugal are bigger, located in comparatively smaller towns and have a higher proportion of repeaters than those in both benchmark groups. Among the resource indicators, it is particularly striking the very low student/teacher ratio in Portuguese public schools. Portuguese schools have comparatively less autonomy of resource management and definition of curricula

(5) Note that most of these schools have private management but public financing.

Table 1

EXPLANATORY VARIABLES (MEANS) [a]

	Portugal			Low-performing countries [b]	High-performing countries [b]
	Total	Public	Private		
Student characteristics					
7th grade	6.6	6.9	3.9	0.2	0.2
8th grade	13.1	13.5	9.9	3.7	5.3
9th grade	29.5	29.7	27.6	21.0	47.5
10th grade	50.9	50.0	58.6	72.4	46.5
11th grade				2.8	0.5
age (years)	15.7	15.7	15.7	15.8	15.8
female	51.7	52.1	48.3	50.0	48.8
Family background					
wealth (index) ⊂ [-2.1,2.3][c]	-0.17	-0.20	0.11	-0.14	0.45
educational resourc. home (ind.) ⊂ [0,7]	6.2	6.2	6.4	6.1	6.2
books at home < 25	38.9	40.0	29.2	24.7	28.0
books at home 25-200	45.6	45.6	46.3	53.2	48.3
books at home > 200	15.5	14.5	24.5	22.1	23.7
native	94.1	93.7	97.4	94.6	89.7
second-generation immigrant	3.5	3.8	1.3	4.6	4.0
first-generation immigrant	2.4	2.5	1.2	0.8	6.3
test language at home	97.7	97.6	98.1	85.9	90.9
other national language at home	-	-	-	11.2	4.0
foreign language at home	2.3	2.4	1.9	2.9	5.1
parents' highest occuppat. level					
blue collar/low skilled	12.6	13.2	7.6	11.8	7.1
blue collar/high skilled	24.2	24.9	18.7	19.0	9.4
white collar/low skilled	36.3	36.6	33.4	23.7	22.4
white collar/high skilled	26.9	25.4	40.3	45.5	61.2
parents' highest education level					
primary or less	38.6	39.2	33.5	7.9	3.6
lower secondary	15.3	15.4	14.8	22.3	5.4
upper secondary	23.5	24.0	19.6	38.5	32.3
tertiary	22.5	21.5	32.1	31.2	58.6
School characteristics					
school size (1000 students)	0.957	0.922	1.268	0.694	0.824
proportion of girls	50.9	51.0	49.7	49.7	48.9
located in town with less 15 000 people	42.5	40.8	57.9	24.9	25.6
located in town with 15 000-100 000 people	35.9	38.2	15.1	42.0	51.0
located in city with more 100 000 people	21.6	21.0	27.1	33.1	23.4
grade amplitude (max-min grade)	5.1	4.7	8.3	4.9	4.8
proportion of repeaters	14.6	15.3	7.2	10.5	4.7
school faces competition[d]	72.9	71.9	81.7	78.4	84.4
autonomy resources (ind.) ⊂ [-1.1,2.0]	-1.0	-1.1	-0.8	-0.6	0.1
autonomy curric./assessm. (ind.) ⊂ [-1.4,1.3]	-0.5	-0.5	-0.3	0.1	0.4
school faces parental pressure[e]	7.1	4.9	26.5	16.1	7.4
public school	91.1			84.4	44.2
private school	8.9			15.6	55.8
School resources					
class size (students)	24.0	23.7	26.3	27.0	22.3
student/teacher ratio	8.9	8.4	13.3	10.4	12.9
proportion web-connected computers	80.2	79.7	84.5	84.9	89.1
computer/student ratio	0.07	0.07	0.06	0.11	0.15
regular lessons mathematics (hours)	3.5	3.5	3.8	3.5	3.2
regular lessons language (hours)	3.2	3.2	3.4	3.9	3.1
school faces lack of math. teachers	1.3	0.6	7.7	10.5	21.1
school faces lack of language teachers	0.0	0.0	0.0	9.2	13.5
Computer familiarity					
self-conf. internet tasks (ind.) ⊂ [-2.9,0.8]	-0.2	-0.2	-0.2	-0.4	0.4
time spent intern./entert. (ind.) ⊂ [-2.1,3.2]	0.2	0.2	0.1	-0.1	0.2

Source: Author's calculations on the basis of the PISA 2006 database.

Notes: **(a)** Weighted averages; figures as a percentage of totals unless otherwise stated (more details about the definition of variables are given in Appendix 1). **(b)** The low-performing countries include Greece, Italy and Spain; the high-performing countries include Belgium, Finland and the Netherlands. **(c)** The intervals show the percentiles 1. and 99. of the indicator. **(d)** School reports that there is at least one other school in the same area competing for its students. **(e)** School reports that there is pressure from a majority of parents to achieve higher academic standards.

and assessment practices, particularly in comparison to the best-performing countries. Curiously, schools in the two benchmark groups of countries report a shortage of qualified teachers, in contrast to their Portuguese counterparts. Note that there is no measure of teacher experience in the PISA 2006 database, so this could not be included in the education production function.[6]

3. THE EDUCATION PRODUCTION FUNCTION

3.1. Specification and possible sources of biases

The relationship between educational attainment and its determinants is typically studied by means of an education production function - see, for instance, Hanushek (1979) and Todd and Wolphin (2003) for detailed discussions about the specification and estimation of these functions. They can be generically specified as

$$Score_{ij} = b_0 + b_1 St_{ij} + b_2 Fm_{ij} + b_3 Sc_j + b_4 Re_j + e_{ij},$$

where i indexes the student and j the school. $Score$ is the outcome of the test, St is a vector of student characteristics, Fm includes family background measures, Sc comprises various school features and Re includes variables associated with school resources. The determinants of student performance we consider in this study are listed in Table 1.[7] The main problem affecting the estimation of education production functions is the endogeneity of some covariates, often arising from their correlation with unobservables, notably cognitive abilities of students. Although ideally measures of such abilities should be added to the equation above, this is almost never the case as they are hard to come by. Actually, one of the variables we consider - the indicator measuring self-confidence in internet tasks (under computer familiarity in Table 1) - is of particular interest in this respect because it can be seen as an indicator of student abilities,[8] although it may also reflect family possessions and/or school resources to the extent that these condition students' internet access. A second problem relates to the fact that the PISA database is cross-sectional, allowing the estimation of models in levels but not of value-added specifications that require panel data.

Student grade captures the exposure to more or less advanced curricula and, combined with student age, also a grade repetition effect (see the next section). Note that grade repetition does not appear in our regression. This variable would reflect past performance which is related to current performance. As a result student grade is itself partly endogenous to current performance. Therefore, one may expect an overestimation of its (positive) effect on attainment *vis-à-vis* a regression controlling also for the number of years the student has repeated.

(6) The database includes the share of teachers with tertiary education, but this variable shows reduced variability (the median is close to 90 percent). As it was, in addition, fully missing for some countries, it was not taken on board in the regressions.

(7) There are no missing values for the test scores; in contrast, most of the explanatory variables in the production have a small amount of missings. In order to avoid a great loss of information, we imputed these missing values prior to estimation, similarly to previous researchers (e.g. Fuchs and Woessmann, 2007). The details are given in Appendix 2.

(8) Note that this variable measures competence in tasks only loosely related to the use of computers as learning tools (see Appendix 1). Otherwise its explanatory power would be of less interest. Another variable available in the PISA database which measures self-confidence in general computer tasks (not used) appears more likely to suffer from this problem.

The explanatory variables relating to family background can be considered largely exogenous to educational achievement[9] and, at the same time, should make a steady contribution to the knowledge acquired by the student over the years, adequately captured by a level-type modelling. Most of schools' basic characteristics such as location and size, and institutional features such as autonomy, can also be deemed exogenous in the production function. Parental pressure, however, may not fulfil this and, besides the influence exerted on schools to improve standards, capture the selection of better schools by parents who are more concerned with their children's education. This may lead to an overestimation of the variable's expected positive impact on performance. Given that we control extensively for family and immigration background, even if students from favoured households select preferentially into private schools, this should not cause a bias in the measurement of the private-school effect.

The variables measuring the use of resources by schools, e.g. class size and hours of regular lessons, are clearly less suitable for the specification in levels we use. In effect, such variables will usually change from one year to the other, and the current level of knowledge will also depend on the values they assumed in the past. With PISA data this shortcoming cannot be overcome. The volume of resources may itself respond to student performance: for instance, students with poor attainment may have supplementary classes.[10] Nevertheless, given the resource covariates we consider and their definition in terms of school averages (except for the hours of regular lessons), this is unlikely to be an issue for our estimates.

When estimating education production functions using data from more than one country, one has to reckon with country-specific effects that have an impact on school outcomes, e.g. social attitudes towards education. In the production functions estimated for the two benchmark groups, such effects are accommodated by the inclusion of binary variables at the country level.

3.2. Determinants of attainment in Portugal and in the benchmark countries

Student characteristics

Table 2 presents the estimates of the education production functions for Portugal and the two groups of countries where students had, respectively, the worst (Greece, Italy and Spain) and the best (Belgium, Finland and the Netherlands) scores. We start with the impact of student characteristics. In Portugal there is a positive effect on performance of the student grade, clearly significant (the same holds for the groups of high- and low-performing countries). A comparison with the coefficients of the other binary variables in the regression shows that its magnitude is very large. For the Portuguese PISA 2006 students, grade and age interact in the following way. Among all students of a given age, those in the top grade, which can be the 10th or the 9th depending on the date of birth,[11] never

(9) Assuming that ability is not correlated across generations; otherwise abler students could be associated with advantaged families.

(10) An example of a resource variable in the PISA database strongly affected by this sort of endogeneity is out-of-school-time lessons. We experimented with it in the production function, but the positive effect it may have on performance is completely offset by the selection of the low-performing students it entails.

(11) According to the rules governing the start of compulsory education, the students who never repeated and were six years old by 15 September 1996 are in the 10th grade, those who became six only after 31 December are in the 9th grade, and those who became six in-between are in either of those grades, depending on a decision of parents.

Table 2 (to be continued)

EDUCATION PRODUCTION FUNCTION, ESTIMATES[(a)]

	Portugal		Low-performing countries [(b)]		High-performing countries [(b)]	
	Mathematics	Reading	Mathematics	Reading	Mathematics	Reading
Student characteristics						
grade (7th)[(c)]						
8th	39.4	53.2	12.1	54.4	51.4/73.0	90.2/67.7[(d)]
	3.5	*4.1*	*12.6*	*18.0*	*7.7/12.6*	*14.8/19.0*
9th	83.1	95.7	58.8	93.5	86.0/124.6	132.1/111.8
	3.8	4.4	13.0	17.2	*6.7/13.1*	*15.5/18.3*
10th	144.1	158.7	115.2	144.1	142.2/-	186.1/-
	2.9	*3.7*	*13.1*	*17.5*	*6.7/-*	*15.6/-*
11th	-	-	119.7	150.3	202.6/ -	245.2/ -
			13.8	18.7	10.3/ -	15.7/-
age	-17.1	-23.4	5.5	0.5	-17.1	-18.8
	2.1	*2.6*	*1.2*	*1.6*	*1.4*	*1.6*
female gender (male)	-26.9	20.9	-26.8	18.7	-24.3	16.9
	1.6	*1.4*	*0.8*	*1.0*	*1.0*	*1.1*
Family background						
wealth	-3.5	0.3	-4.2	-7.9	-2.0	-3.8
	1.3	*1.1*	*0.5*	*0.8*	*0.7*	*0.9*
educat. resources at home	2.2	2.0	8.5	8.7	7.8	8.0
	0.7	*1.0*	*0.4*	*0.4*	*0.5*	*0.6*
books at home (less than 25)						
between 25 and 200	19.6	15.4	21.8	23.2	22.2	21.4
	1.5	*1.6*	*1.0*	*0.9*	*1.0*	*1.1*
more than 200	35.4	22.8	46.2	39.9	49.0	42.7
	2.1	*2.6*	*1.2*	*1.2*	*1.1*	*1.4*
immigration background (native)						
second generation immigrant	-17.4	-14.5	-7.1	-4.6	-24.0	-9.6
	3.3	*6.5*	*2.0*	*2.1*	*2.9*	*3.1*
first generation immigrant	-15.1	-9.8	-15.9	8.8	-27.7	-18.5
	6.6	*5.6*	*4.0*	*5.0*	*1.9*	*3.4*
language at home (test language)						
other national language	-	-	-0.8	-3.2	26.3	28.1
			1.3	1.6	2.0	2.2
foreign language	23.8	-10.1	12.2	-9.6	-1.2	-18.3
	5.2	*4.9*	*3.4*	*3.2*	*3.1*	*2.9*
hig. occup. parents (bl. col./low skil.)						
blue collar/high skilled	1.2	2.6	4.0	0.4	4.5	7.2
	2.8	*3.1*	*1.4*	*1.5*	*2.3*	*2.6*
white collar/low skilled	2.3	10.0	7.4	7.8	10.5	14.6
	2.8	*3.2*	*1.1*	*1.3*	*1.7*	*2.3*
white collar/high skilled	18.1	23.7	12.6	11.9	21.3	26.5
	2.7	2.9	1.2	1.5	2.2	2.5
highest educ. parents (primary or less)						
lower secondary	-0.4	3.6	13.5	17.8	13.2	16.3
	2.3	*2.6*	*1.8*	*2.1*	*5.2*	*3.7*
upper secondary	2.4	3.0	17.6	25.2	10.2	18.6
	1.3	*2.7*	*1.8*	*1.9*	*3.9*	*2.8*
tertiary	0.3	5.8	15.2	20.0	10.5	19.2
	2.6	*2.9*	*1.7*	*1.6*	*3.9*	*2.9*

Table 2 (continued)

EDUCATION PRODUCTION FUNCTION, ESTIMATES(a)

	Portugal		Low-performing countries (b)		High-performing countries (b)	
	Mathematics	Reading	Mathematics	Reading	Mathematics	Reading
School characteristics						
school size	4.2	8.5	-2.6	-1.9	24.7	20.0
	3.1	*2.9*	*2.2*	*2.6*	*3.5*	*4.1*
proportion of girls	88.9	98.5	-5.0	34.3	34.7	52.7
	23.2	*25.2*	*4.7*	*5.7*	*5.5*	*6.8*
located in (town < 15 000 people)						
town 15 000 - 100 000 people	1.5	-3.7	3.1	6.2	-3.1	-1.2
	2.6	*2.7*	*2.1*	*2.7*	*2.5*	*3.3*
city > 100 000 people	6.4	10.9	11.7	14.5	-6.5	1.0
	2.9	*3.1*	*2.1*	*2.5*	*3.2*	*3.7*
grade amplitude	0.0	1.3	2.1	1.0	1.3	1.3
	0.6	*0.7*	*0.6*	*0.6*	*0.3*	*0.4*
proportion of repeaters	-26.2	-9.8	-60.0	-107.8	-75.0	-120.6
	11.6	*14.0*	*14.3*	*13.9*	*17.1*	*23.1*
school faces competition (no)	6.8	1.3	-0.1	3.7	0.5	4.3
	2.3	*2.2*	*2.0*	*2.3*	*3.4*	*4.5*
autonomy resource allocation	-8.9	44.5	1.1	2.1	3.4	3.1
	12.1	*13.6*	*1.4*	*2.0*	*1.5*	*2.0*
autonomy curriculum/assessment	-2.7	-7.6	-2.5	-1.6	-1.6	-2.8
	1.5	*1.5*	*0.9*	*1.1*	*1.2*	*1.6*
school faces parental pressure (no)	6.0	9.4	14.8	15.0	11.5	12.9
	3.5	*4.9*	*2.4*	*2.2*	*3.4*	*3.0*
private school (public)	13.4	-12.3	-35.2	-24.9	7.4	6.2
	4.7	*6.4*	*4.7*	*4.2*	*2.1*	*2.0*
School resources						
class size	0.5	0.3	-0.3	-0.1	1.5	1.8
	0.3	*0.3*	*0.1*	*0.1*	*0.4*	*0.5*
student/teacher ratio	0.1	-0.4	3.7	2.8	4.4	4.6
	0.5	*0.6*	*0.4*	*0.3*	*0.5*	*0.8*
prop. web-connected computers	-0.5	11.5	17.2	13.1	15.5	3.1
	4.0	*5.3*	*2.9*	*4.1*	*5.2*	*5.5*
computer/student ratio	23.9	17.9	13.6	-10.6	26.3	-2.2
	29.4	*29.5*	*7.4*	*9.8*	*10.2*	*12.5*
hours of lessons language/math.	6.8	5.4	9.0	7.4	9.4	3.5
	0.3	*0.5*	*0.3*	*0.2*	*0.2*	*0.3*
shortage teachers lang./math. (no)	-	-	3.5	11.5	-12.0	-19.1
			2.9	*3.2*	*2.4*	*3.5*
Computer familiarity						
self-confidence in internet tasks	10.3	16.2	14.8	18.2	13.1	17.5
	1.1	*0.9*	*0.4*	*0.5*	*0.7*	*1.0*
time spent on internet/entertainment	-5.2	-8.1	-12.6	-14.3	-7.2	-9.2
	0.9	*0.9*	*0.4*	*0.6*	*0.5*	*0.6*
coefficient of determination	0.56	0.56	0.36	0.34	0.48	0.45
observations in the sample	4981	4981	45660	45660	18319	18319

Source: Author's calculations.

Notas: (a) Average of the coefficients estimated by weighted least squares regressions of the five plausible values in mathematics and reading, respectively, on the covariates listed in the table and country dummies (not shown); standard errors shown in italics. The variance depends on the sampling variance, calculated in accordance with the Fay's variant of the balanced repeated replication method, and the imputation variance. **(b)** The low-performing countries include Greece, Italy and Spain; the high-performing countries include Belgium, Finland and the Netherlands. **(c)** Ommitted category in parenthesis, for binary variables. **(d)** The grade effect is estimated separately for Finland (figures on the right) where the school starting age is at 7, and in the other high-performing countries (figures on the left), where it is at 6.

repeated a year, those one grade below repeated once, and so on (this holds true for all students except those born between 15 September and 31 December whose parents could and did postpone school entry by one year). Therefore, as stated, the variable captures not only the impact of the student's current curricula, but also an effect associated with grade repetition.

The explanatory power of age, with grade held fixed, has to do with the students born between 15 September and 31 December: an increasing number of such students, as the birth dates approach the end of the year, waited a further year to enter school. Thus, as age goes down within that group and each grade, except the 10th, the proportion of children entering school at the age of 6 goes up and that of students who repeated once (9th grade) or one additional year (grades below) goes down, and thus the negative relationship with attainment. Gender has a clear influence on scores, with boys performing better in mathematics and girls in reading. The effect is precisely estimated and, as one would expect, similar across countries.

Family background

Our education production function includes several measures relating to the socioeconomic background of students, and results confirm that they have a strong impact on attainment. The contribution of the books at home variable stands out, which does not come as a surprise as it is very often the best single predictor of educational performance in similar regressions (Hanushek and Woessmann, 2010). Naturally, it is not the number of books at home *per se* that is causally associated with achievement, but this variable captures very well a home environment propitious to learning. The measured impacts in Portugal are lower than those for the two groups of benchmark countries, particularly in the upper category (more than 200 books). In all of the three regressions, as one moves up in the breakdown of parental occupations, a positive influence on performance emerges, particularly marked for white-collar/high-skilled jobs. As far as the formal education of parents is concerned, its contribution is barely or not significant for Portugal, in contrast with the strong impact in the two benchmark groups. Among family background covariates, academic qualifications may be specifically associated with parents' monitoring of school tasks of their children. The results may signal less capability or readiness by Portuguese parents to do so.

A second set of covariates in this group relates to nationality and language spoken at home. Immigrant status generally entails a disadvantage in terms of attainment, which is largest for the countries where students perform best. In the case of Portugal, the second-generation immigrant students fare worse than their first-generation counterparts in terms of point estimates (although the difference is statistically not significant at the usual levels). This implies that the negative impact of the status seems not to attenuate as students and their families have lived longer in the country. It is interesting to note that once the immigration status is controlled for, to speak a foreign language at home has a positive and significant impact on mathematics scores in Portugal (for reading scores this is still negative). Such result may reflect a very strong commitment to school of certain groups among the population of immigrant students, surpassing that of native students.

The contribution of educational resources at home to the performance of Portuguese students is positive and significant, but falls short of that in the two benchmark groups. The coefficient of the wealth indicator is either non-significant or even significantly negative, basically indicating that it has no impact of its own, once many other aspects of the socio-economic status of students are taken into account.

The impacts of family background variables can be interpreted in another dimension which relates to educational equity - an issue explored in more detail in section 4. The relationship between a summary measure of socioeconomic status (for instance, the number of books at home) and an achievement variable - sometimes called the slope of the *socioeconomic gradient* - is often used as an indicator of educational opportunity. A steeper socioeconomic gradient implies more unequal school outcomes for children from households of different statuses, holding the rest constant. In the education production function for Portugal, the coefficients of the variables measuring several aspects of family background suggest a weaker impact on achievement, in particular in comparison to the countries with the best performance. Two factors may account for this. The first is a more passive parental attitude toward education, featuring less involvement by parents in the school lives of their children. The second is an educational system that tends to offset more the unequal situation of children from different social classes.

School characteristics

We consider a multitude of school characteristics in our education production function. The point estimates of the influence of school size are positive for Portugal, albeit only significant in the case of reading tests. This indicates the existence of economies of scale, in line with the findings in Pereira and Moreira (2007). In the benchmark groups, the same sort of evidence is confined to high-performing countries. In contrast, school location for Portugal appears less important than in that study, since only the upper category - location in a city over 100 000 people - makes a significant (positive) difference to performance. Such results must be accounted for by the much larger set of controls used here. A higher proportion of repeaters produces the expected negative impact on performance, while a higher proportion of girls contributes to a school atmosphere conducive to favourable outcomes.

From a theoretical perspective, the effect of school autonomy on attainment is ambiguous. On the one hand, it can be positive because decision-makers at the school level tend to have better information. However, autonomy can also be used by local decision-makers to pursue their own aims, which may not coincide with an improvement of students' achievement levels (Hanushek and Woessman, 2010). In the empirical literature, it has been found that the room for manoeuvre in budget allocations (given the overall amount) including teacher hiring and rewarding, and in choosing textbooks and teaching methods, tends to enhance performance. In contrast, autonomy of schools over the budget size and autonomy of teachers over the curriculum to be covered in class appear negatively linked to performance, possibly because these lend themselves more to opportunistic behaviour. The regressions in this study are a less-than-ideal environment for analysing these effects, since they do not fully exploit cross-country variation that precisely helps to pinpoint them. Nevertheless, our point estimates generally fit with this sort of evidence. Autonomy in resource allocation makes a positive contribution to achievement (in Portugal this occurs for reading scores only) and autonomy of curriculum and assessment a negative one, although not always significant. Note that, in the Portuguese case, there is virtually no autonomy of teacher allocation and rewarding for public schools and so the first of the two indicators is close to the overall minimum throughout; it is private schools that lend some variability to it.

Parental pressure has a positive impact on performance although, as mentioned above, this may also reflect the effect of better schools being chosen by more attentive and informed parents, in addition to the pressure they may bring to bear upon schools. The coefficient of the private school indicator is negative, but on the brink of non-significance for reading, and positive and significant for mathematics. In the latter case, the impact measured in the mean of the dependent variable is around 3 percent. Pereira and Moreira (2007) - who used the average scores in the 12th grade national examinations for all subjects, 2003/04 and 2004/05 - estimated the private-school effect at 7 to 8 percent. We get a lower effect for mathematics (and an effect of the opposite sign for reading). Apart from the different dataset, this result can be explained by the absence of family controls in the aforementioned study, leading to an upward bias in the coefficient. While it is possible that the inclusion of such controls approximately empties the explanatory content of the private-school indicator, these results should not be considered as definitive. Given that private schools are a small part (about 10 percent) of the population of relevant students, there is the possibility of biases caused by the sampling process. A comparison between the averages of scores in private and public schools in the PISA 2006 database and those in the 9th grade national examinations (academic year 2006/07), indicates that this may be the case.[12]

School resources

Traditional measures of school resources such as average class size and student/teacher ratio do not enter significantly into the Portuguese education production function. In the two benchmark groups of countries, the coefficient of the student/teacher ratio has a counter-intuitive positive sign and is statistically significant (this also holds true for class size in high-performing countries). Hanushek (1986) surveys the findings in many studies over the contribution of resource variables and concludes that this is often not significant and, in some cases, opposite-than-expected effects are found. This fits in with the well known result that such variables have a much weaker (if any) influence on attainment than those relating to family background. The amount of regular lessons stands in contrast with this sort of evidence, featuring a clear positive and statistically significant impact on performance, in all of the three regressions. If interventions at the level of resources are to be carried out, this appears to be the only variable where they can be effective.

(12) In PISA 2006, the average scores in private schools are, respectively, 5.5 percent higher in mathematics and 3.2 percent in reading. The corresponding figures in the 9th grade national examinations, 2006/07, in mathematics and portuguese are 22.6 and 7.8 percent (Jornal Público, 2007).

Computer familiarity

We argued above that the variable internet skills could be a measure of student abilities. The fact that its impact is positive and significant, and not very different across countries, speaks in favour of such an interpretation. In contrast, the time spent in entertainment and internet browsing is negatively related to performance.

3.3. Differences in country performance with parental characteristics remaining constant

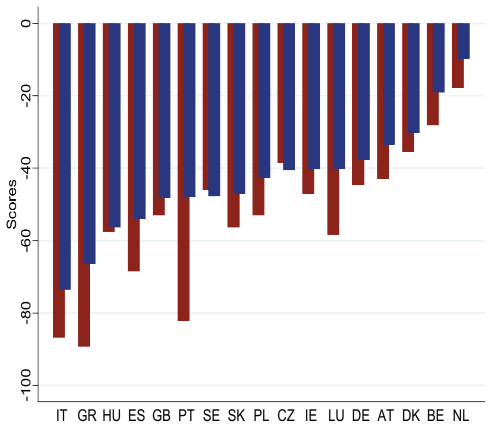
Rankings of countries constructed on the basis of PISA test scores, as presented in Charts 1A and 1B, obviously do not control for the factors determining test scores. At the same time, determinants such as the education level and the occupational structure of the population, which the student background variables capture, come from the past and are largely unaffected by current education policies. A question arising in this context is how rankings would change should the distribution of parental characteristics across countries be held constant. This is particularly pertinent for Portugal that has one of the lowest endowments among the European Union countries in terms of the education level of its population. In order to investigate the issue, we estimate an education production function for the full set of countries, including the family background measures as covariates (Table 1) plus country-specific binary variables.[13] The coefficients of the latter variables can be interpreted as the mean scores holding constant parental characteristics, and compared with the unconditional means presented in Charts 1A and 1B. Such an exercise is not without caveats, because our model is only an approximation of reality. In practice if the level of certain covariates, say, in a low-performing country, changed to the level prevailing in a high performer, the actual change in achievement would differ from that implied by the model. The results are set out in Charts 3A and 3B, in terms of each country's gap in comparison to the best performer, i.e. Finland.

Portugal is the country in which the gap to the best performer narrows most when the conditional mean of scores, instead of the unconditional mean, is considered. This confirms a strong negative impact of the composition of parental characteristics on attainment. The narrowing of the gap is more pronounced than in some of the other low-performing countries such as Spain and Italy which, as shown in Table 1, have a more favourable situation in terms of that composition than Portugal. Charts 3A and 3B indicate a less gloomy situation for Portugal in terms of school outcomes than Charts 1A and 1B. In mathematics, although still in the bottom half of the ranking, Portugal is close to the group of countries with middling levels of achievement. In reading, the change is more marked, with the Portuguese students rising to the upper half of the countries in terms of performance.

(13) The other regressors, such as school characteristics and resource variables, are not included because we do not want to control for them. The student background variables will capture the effect of these omitted regressors to the extent that there is correlation between both. However, this should be reasonably low (except possibly for the public or private status of schools) and cause a small distortion.

Chart 3A

MATHEMATICS PERFORMANCE BY COUNTRY, DIFFERENCE TO FINLAND
Unconditional mean (in red) and mean holding family background constant (in blue)

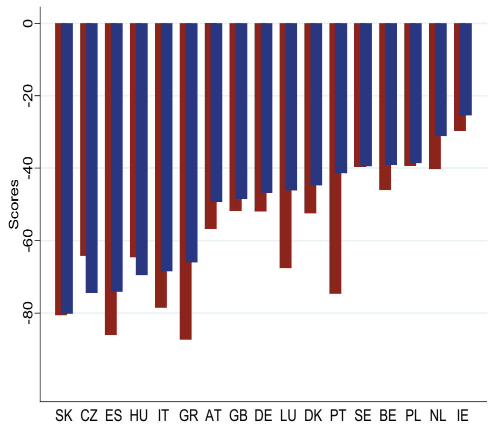


Source: Author's calculations.

Note: Based on weighted least squares regressions of mathematics scores on country-specific constants (unconditional mean) and on these constants plus all socioeconomic covariates (mean holding family background constant). The chart shows the difference between the coefficients for each country and Finland.

Chart 3B

READING PERFORMANCE BY COUNTRY, DIFFERENCE TO FINLAND
Unconditional mean (in red) and mean holding family background constant (in blue)



Source: Author's calculations.

Note: Same as the previous chart but for reading scores.

4. SOME ASPECTS OF VARIABILITY IN STUDENT PERFORMANCE

We now consider variability in student performance or academic inequality, complementing the preceding results which were mainly aimed at explaining the respective level. Analyses usually place much emphasis on social inequality as a source of academic inequality. This is justified by the importance of the socioeconomic status of parents for the educational performance of their children. In addition, the regressors in this group usually have higher variance than, notably, those related to school resources (particularly in the context of analyses within countries or involving countries with similar levels of development). At the same time, academic inequality feeds back on social inequality, as the education level of older generations is the single most important factor behind the current distribution of workers by occupations and earning levels. In fact, one of the main objectives of educational systems is to progressively attenuate such inequalities, by ensuring that the distribution of children's skills at the end of the period of education is less unequal than that of their parents. There are other important sources of variability in educational outcomes, such as students' cognitive skills and the quality of teaching.

Students are assigned to schools, and dispersion in student achievement may materialize to some extent through the existence of schools that differ substantially as far as that achievement is concerned. It is thus important to look, besides the overall variability in student performance, at the proportion evaluated between and within schools. If the between-school component is large *vis-à-vis* the within-school component, then students with lower achievement levels concentrate in some schools and students with higher levels in others. Such phenomenon may occur for a number of reasons, for example, schools may have a socioeconomic intake that covers students predominantly coming from either advantaged or disadvantaged households. When there is a great asymmetry in living standards across regions in a country, given that the mobility of students is limited, the social composition of schools located in poorer regions will differ markedly from their counterparts in richer areas. The same holds for asymmetries across neighbourhoods within large towns, particularly in the absence of catchment areas (which oblige students to attend their local school), as parents tend to enrol their children in schools attended by their peers.

A mechanism introducing differentiation in achievement between schools is early tracking of students as it exists in the educational systems of some of the countries we consider (Brunello and Checchi, 2007). Early tracking is the allocation of students to schools offering specific curricula, for instance, general *vs* vocational, at an early stage (say, between 10 and 12 years of age). This allocation can be made on the basis of criteria such as formal tests and teachers' recommendation or self-selection. Formal testing brings about sorting of students in accordance with their socio-economic background and individual capabilities, as these are important determinants of scores in the placement tests. Sorting in accordance with the background may occur even in the case of self-selection, as parents with blue-collar jobs may find it more natural to enrol their children in schools offering vocational curricula, and parents with white-collar jobs in schools offering university-oriented curricula.

As a first exercise, we consider the association between the variance decomposition of mathematics scores and a family background measure, the index of economic, social and cultural status (ESCS index). This index, available in the PISA database, summarizes several dimensions of family background (see Appendix 1 for details about its construction), except for immigration status. The decomposition of the variance for each of the two variables is obtained from the estimation of multilevel models without explanatory variables, including school-specific random intercepts[14] (see Goldstein, 2010). Chart 4A depicts the scatter plot of total variance of mathematics scores and the ESCS index (both normalized to have the means equal to 100) and Chart 4B the respective between-school shares. In countries in which these shares are larger, schools differ more substantially as regards student achievement and social composition.

We start by looking at the dispersion of mathematics scores. There is no obvious relationship across countries between attainment (Chart 1A), on the one hand, and variability of scores and its decomposition in these charts, on the other. The best performer - Finland - has both the lowest overall variance and between-school share; however, Belgium, also on the top of the performance ranking, has the highest variance and one of the highest between-school shares (the Netherlands, another top performer, has the highest). Low levels of attainment are as well compatible with rather different situations in terms of score variability, as illustrated by the cases of Italy and Spain. These conclusions generally hold for the dispersion of reading scores as well (not shown), which is greater than

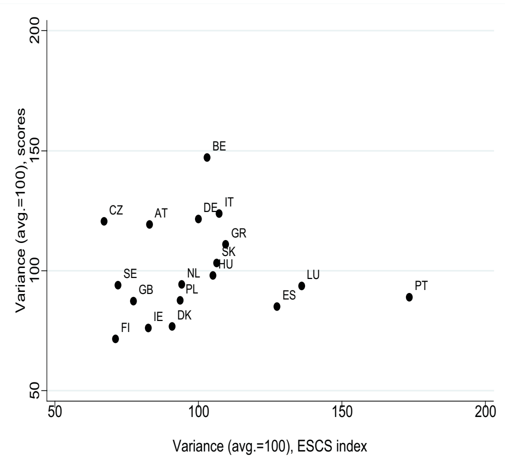
(14) This model explains the dependent variable as the sum of these intercepts (equal to a fixed grand mean plus each school's random deviation from it) and a student-level residual variable. The estimations were performed using the program GLLAMM (Rabe-Hesketh et al., 2004) that runs within STATA. Weighting was made in accordance with the first of the two schemes proposed by Pfeffermann et al. (2008). In the case of mathematics scores, the first plausible value was taken.

that of mathematics scores in most countries.

As far as the dispersion of the ESCS index is concerned, Portugal stands as an outlier with a figure of almost 75 percent over the cross-country average (Chart 4A). However, this dispersion is «passed on» to test scores to a much lesser degree than in other countries (a fact that also holds, to a certain extent, for Luxembourg and Spain). Such a finding must be accounted for by the smaller impact of family background variables on achievement in the education production function for Portugal (Table 2).[15] As a result the overall score variance for Portugal is a bit below the average, and the same applies to the share attributable to between schools (around 35 percent against an average of slightly more than 40 percent). A group of countries including Austria, Belgium, the Czech Republic, Germany and Italy seem to be in the opposite situation to Portugal, in that they have more variance of scores than implied by the ESCS index. All of these countries, except Italy, have early tracking of students (the other countries in the group sharing this institutional feature are Hungary, the Netherlands and Slovakia). Various studies - e.g. Hanushek and Woessman (2006) - have associated this feature with an increase in the variance of school outcomes.[16] The impact of early tracking is, as expected, more evident in the share of between-school variance (Chart 4B), as it implies a sorting of students in accordance with family background and, in some cases, cognitive abilities. Other factors may add to such differentiation between schools as, for instance, teacher sorting - better teachers may prefer to teach better students - and divergent curricula. The large overall variance of scores in comparison to the ESCS index in some of these countries may be also explained by a higher

Chart 4A

VARIANCE OF MATHEMATICS SCORES AND THE ESCS INDEX



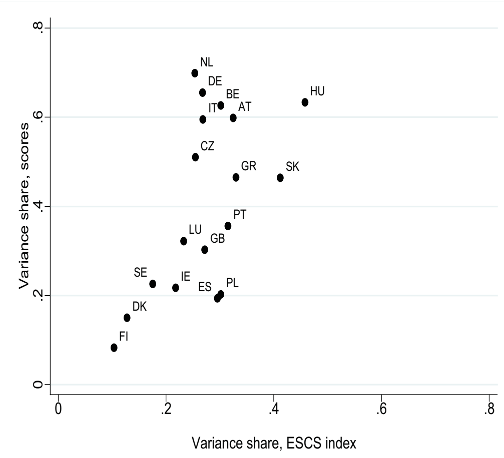
Source: Author's calculations.

Note: Based on the estimation of multilevel models for each one of the variables, including school-specific random parameters, whose variance accounts for the between-school component, and the student-level disturbance, whose variance accounts for the within-school component.

Chart 4B

VARIANCE OF MATHEMATICS SCORES AND THE ESCS INDEX

Between-school shares



Source: Author's calculations.

Note: See previous chart.

(15) In general, the contribution of a given regressor to the explained variance of the dependent variable results from the respective variance and regression coefficient.

(16) The influence on the level of outcomes is a more controversial issue, on which no firm evidence has been established.

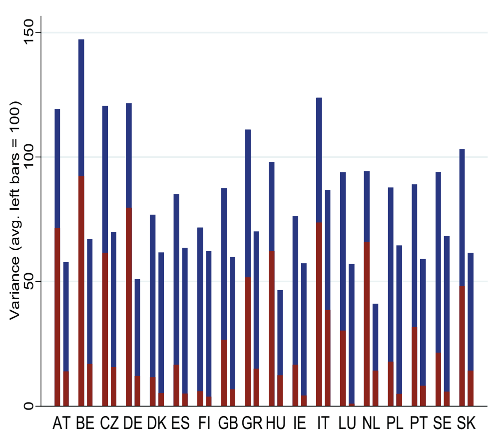
proportion of immigrant students, a dimension not captured by the index.

We conclude this section by estimating a multilevel model which includes the full set of family covariates as predictors of performance variability, both at the student level and, as school averages, at the school level.[17] These latter regressors capture the externalities for the school as a whole associated with its socioeconomic composition. The overall variance and its decomposition in this model are presented in Chart 5, where we also present the corresponding quantities in the model without covariates (measured in the y-axis of Charts 4A and 4B above) in order to facilitate the comparison of results. The lower part of each bar in red shows the between-school component of variance. All quantities are normalized by the cross-country average variance in the model without covariates, so that the sizes of the bars can be compared.

Socioeconomic covariates explain an important share of score variability. Therefore, the variance estimated in the second model is smaller than in the first one. In addition, the reduction in the between-school component clearly exceeds that in the within-school component, particularly in countries with school tracking. The amount of between-school variance that remains is, nevertheless, slightly larger for this set of countries than for the others, except for Italy and Greece, which presumably reflects the other aspects of differentiation between schools brought about by early tracking. Note that Italy and, to a lesser extent, Greece are special cases in that student achievement differs between schools more substantially than may be explained by social inequality. The between-school

Chart 5

MATHEMATICS SCORE VARIANCE, TOTAL AND BETWEEN-SCHOOLS
Model without covariates (left bars) and controlling for the family background (right bars)



Source: Author's calculations.

Note: Based on the estimation of multilevel models, respectively, without covariates (same model as in the note to Chart 4A), and including the socioeconomic covariates both as school averages and student variables (centred around the school averages). The variance captured by this last model is that unexplained by the covariates.

(17) The coefficients of all the covariates (i.e. the slopes) are modelled as constant parameters, while the intercepts continue to be random and school--specific.

variability of scores in Portugal is comparable to that of countries without early tracking (with the two exceptions just mentioned) and, within this group, higher than, for instance, in the Northern European countries as well as in Spain.

The evidence presented shows that the influence of social inequality, in the countries where it is largest, is mostlly felt through school composition effects and between-school differentiation in performance. The variance remaining after social inequality is controlled for, which as seen is mostly evaluated within schools, should be mainly accounted for by unobservables. These may include, for instance, student abilities and the quality and effectiveness of teaching (for instance, organization of classes and methods used by teachers). The covariates in the education production regressions estimated in section 3 that have been now omitted should only account for a fraction of the remaining variance, as they are mostly at the school level. This reading is also suggested by the sizeable portion of score variability that remains unexplained in those regressions, as shown by the relatively low value of the coefficients of determination in Table 2. Carneiro (2006) concludes similarly that covariates analogous to the ones we include in the production functions fail to explain a considerable amount of score variance in PISA 2003 for Portugal.

5. CONCLUSIONS

This study presents an analysis of the level and variability of educational performance in Portugal and European Union countries using the PISA 2006 database. The main conclusions are as follows:

• Portuguese students consistently come in the lower half of the performance ranking in the group of countries considered, both in mathematics and reading. These results are partly brought about by a disadvantaged situation in terms of household background, namely as far as parental education and occupations are concerned.

• In the education production function for Portugal, similarly to those in both groups of reference countries, the socioeconomic covariates are the main determinants of achievement, with a much less important contribution by resource variables (except for the hours of regular lessons).

• Socioeconomic covariates make, however, a weaker contribution to performance in Portugal than particularly in the high-performing countries. This is probably explained by less involvement on the side of parents in their children's education, and the role of the educational system in smoothing the performance of children of unequal social backgrounds.

• Some variables in the education production function for Portugal, namely, school location and private or public status are found to have a weaker impact than in previous studies, once one controls extensively for the family background.

• There is no obvious relationship between the level and dispersion of performance across countries, with both high and low levels being compatible with very different degrees of dispersion.

• Social inequality is shown to be an important source of variability in performance, particularly in countries whose educational systems have early tracking of students. This latter feature also brings about important differentiation in performance between schools due to peer effects and sorting of students in accordance with abilities.

• Portugal has a higher level of dispersion in the socioeconomic covariates but, given the flatter socioeconomic gradient, this is relatively less passed on to test scores, whose variance is close to the cross-country average.

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APPENDIX 1

Definition of some explanatory variables

Wealth (PISA database). Index computed on the basis of student answers on household possession of durable goods such as television, cars or cellular phones.

Educational resources at home (computed by the author). Index calculated by adding up binary variables on household possession of the following items: a study desk, a quiet place to study, a computer for schoolwork, educational software, own calculator, books to help with schoolwork and a dictionary.

Immigration background (PISA database). Binary variables for: native students - born in the country as well as at least one of the parents; second-generation immigrant students - born in the country but the parents born outside; first-generation immigrant students - born outside the country.

Grade amplitude (computed by the author). Calculated as the difference between the maximum and the minimum grades at each school.

School competition (PISA database). Binary variable for schools that report that there is at least one other school in the same area competing for its students.

Autonomy of resource allocation (PISA database). Index computed on the basis of school answers about who has responsibility for resource management e.g. teacher hiring, firing and rewarding, and formulation of the school budget.

Autonomy of curriculum and assessment (PISA database). Index computed on the basis of school answers about who has responsibility for student assessment policies, curricula, and textbooks used.

Parental pressure (delivered in the PISA database). Binary variable for schools that reported constant pressure from many parents regarding academic standards.

Self-confidence in internet tasks (PISA database). Index computed on the basis of student answers about how well they perform tasks such as chatting online, downloading files or music from the internet, and sending emails.

Time spent on the internet and entertainment (PISA database). Index computed on the basis of student answers about how often they use computers for tasks such as browsing the internet, playing games, downloading music, sending emails and chatting online.

Economic, social and cultural status (ESCS) index (PISA database). Index summarizing the information about household possessions of durable goods, household possessions of cultural goods, educational resources at home, number of books at home, highest parental education and the highest parental occupation.

APPENDIX 2

Data imputation

Data imputation was carried out using predicted regression imputation (see Kalton and Kasprzyk, 1982). The variables with missing values were regressed on a set of «fundamental» variables comprising grade, age, gender, school location and country (these regressions were run over the full set of countries). The observations for which at least one of these fundamental variables had no values were disregarded. It is worth noting that the student variables in this group had very few or no missings. The inclusion of school location allows to eliminate from the sample schools that had filled out the respective questionnaire very sparsely, with most variables - including location - missing.

In the imputation procedure, it was distinguished between student and school variables. The former were imputed by estimating regressions, at the level of the student, by weighted least squares in the case of continuous variables and weighted (ordered) probit regression in the case of ordinal and binary variables. When the variable to impute was continuous, predicted values were filled in for the missing data, when the variable was ordinal or binary, the predicted category was filled in. The school variables were imputed estimating regressions at the level of the school, with the student variables entering as school averages, by the unweighted versions of the same methods.

Only a small proportion of values need to be imputed for each variable: on average, 2 percent of the used sample. The maximum level of imputation was 7 percent. A comparison of the descriptive statistics before and after imputation shows very minor changes. Nevertheless, without the imputation procedure, considering the regressions in section 3, around 34 percent of the observations would have been lost.